

DS-ML Mini-Project - Diamonds

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1 Dataset Choses

The dataset I'm planning to use is called Diamonds and can be found on Kaggle using the following link: <https://www.kaggle.com/shivam2503/diamonds>

This dataset describes all kinds of different diamonds with their quality (cut, color, carat and clarity) and size (x, y, z, dept and table). Also it describes the price of the diamond. I would like to use different machine learning techniques to calculate the price of a diamond given one or more of these measurements. Also I would like to be able to do the reverse and see what quality a diamond may be given it's size and price.

2 Example Data

In Pandas the cut, color and clarity column will be separated into separate columns or be represented as a number.

Example data:

Table 2.1: Data

id	carat	cut	color	clarity	depth	table	price	x	y	z
1	0.23	Ideal	E	SI2	61.5	55	326	3.95	3.98	2.43
2	0.21	Premium	E	SI1	59.8	61	326	3.89	3.84	2.31
3	0.23	Good	E	VS1	56.9	65	327	4.05	4.07	2.31
4	0.29	Premium	I	VS2	62.4	58	334	4.2	4.23	2.63
5	0.31	Good	J	SI2	63.3	58	335	4.34	4.35	2.75
6	0.24	Very Good	J	VVS2	62.8	57	336	3.94	3.96	2.48
7	0.24	Very Good	I	VVS1	62.3	57	336	3.95	3.98	2.47
8	0.26	Very Good	H	SI1	61.9	55	337	4.07	4.11	2.53
9	0.22	Fair	E	VS2	65.1	61	337	3.87	3.78	2.49
10	0.23	Very Good	H	VS1	59.4	61	338	4	4.05	2.39
11	0.3	Good	J	SI1	64	55	339	4.25	4.28	2.73
12	0.23	Ideal	J	VS1	62.8	56	340	3.93	3.9	2.46
13	0.22	Premium	F	SI1	60.4	61	342	3.88	3.84	2.33
14	0.31	Ideal	J	SI2	62.2	54	344	4.35	4.37	2.71

2.1 Table Description

carat	Carat weight of the diamond
cut	The cut quality of the diamond. Quality in increasing order Fair, Good, Very Good, Premium, Ideal
color	Color of the diamond, with D being the best and J the worst
clarity	How obvious inclusions are within the diamond:(in order from best to worst, FL = flawless, I3= level 3 inclusions) FL,IF, VVS1, VVS2, VS1, VS2, SI1, SI2, I1, I2, I3
depth	Total depth percentage = $z / \text{mean}(x, y) = 2 * z / (x + y)$
table	Width of top of diamond relative to widest point
price	The price of the diamond
x	Length mm
y	Width mm
z	Depth mm

3 Real World

Source: www.info-diamond.com/polished/calculate-diamond-prices.html

In the real world a chart named the Rapaport chart is commonly used to calculate the price of a diamond. This chart is distributed by the Rapaport organization and costs around 50 USD per chart. These charts are created using the supply and demand statistics from around the world.

A short description of how to calculate the price:

1. Select the correct chart given the shape and carat of the diamond.
2. Locate the multiplier on the chart using it's color(vertical) and clarity(horizontal).
3. Multiply the multiplier by the carat of the diamond and then by a 100 to get the price in USD.

4 Exploration

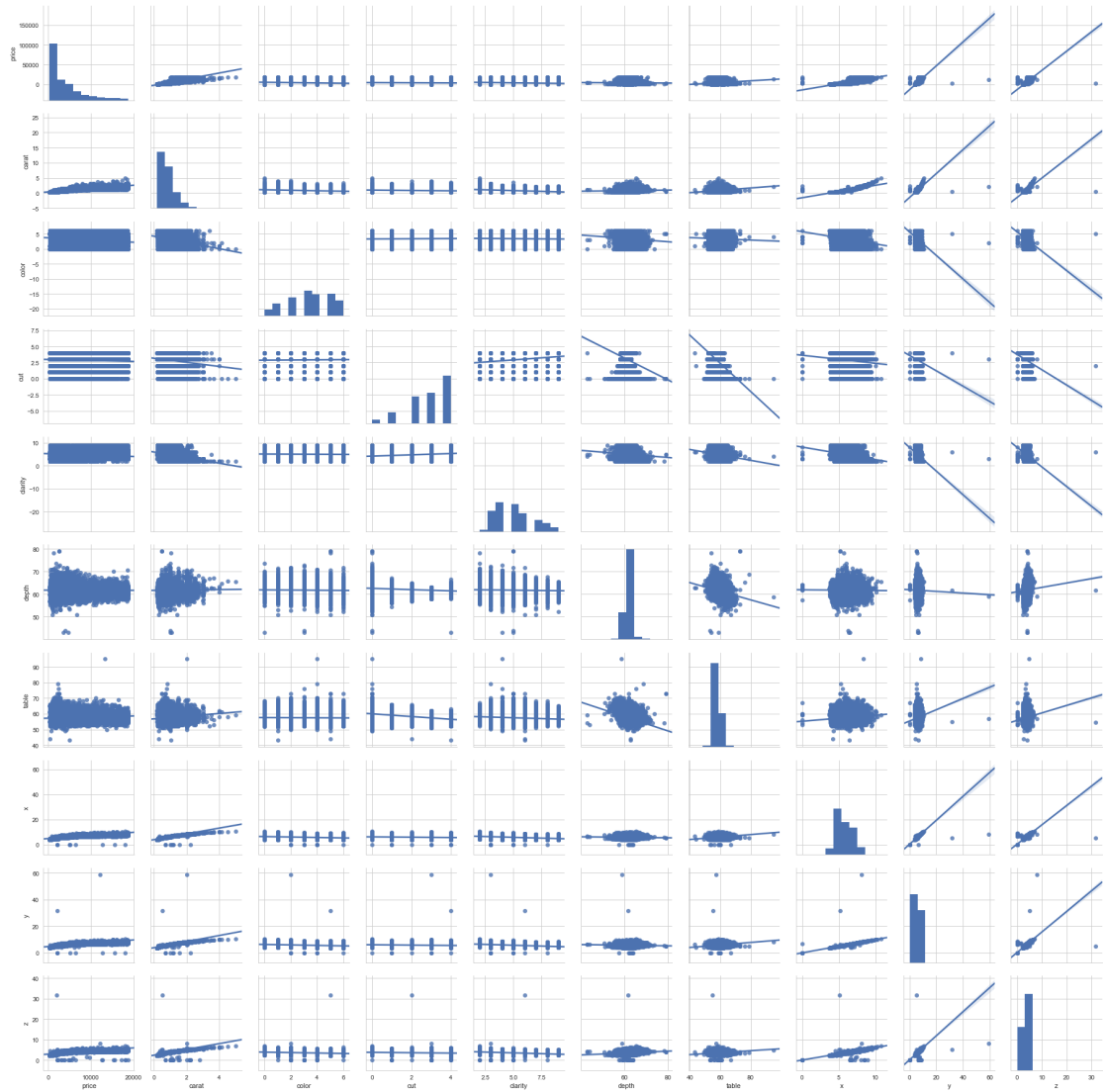


Figure 4.1: Pairplot all features

I have plotted all features against each other in Figure 4.1. What I am interested in is the first row and/or the first column, these both relate to the price of the diamonds. In this plot I also executed a regression on all the features to detect any relations.

You can see that the X, Y, Z, table and carat columns have a clear influence on the price. As these values increase, the price also increases. It is strange that the color and clarity do not seem to relate to the price, since they are used in the official price calculation.

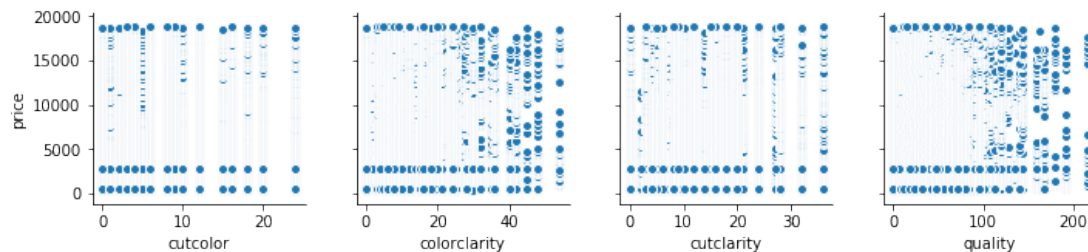


Figure 4.2: Combination of Cut, Color and Clarity to price

In Figure 4.2 I combined the cut, color and clarity in different ways and compared them to the price. Unfortunately there seems to still not be any evidence to correlation. While I did expect to see some correlation.

5 Learning

5.1 Hypothesis

Using the columns carat, cut, color, clarity, depth, table, x, y and z I can calculate the price of the diamond using one or more machine learning methods.

5.2 Execution

I have tried 3 different algorithms on the dataset, because I found that these best fit the original price determination. These are Decision Trees, Random Forest and Neural Networks.

I have used GridSearch to find the best parameters for the Decision Tree, but the Random Forest wouldn't even finish the grid search, so I used the same parameters for it. The parameters for the Neural Network were found by trial and error. I used Keras for the Neural Network because it has great customizability.

5.2.1 Decision Tree and Random Forest

The Decision Tree and the Random Forest have been trained and tested using a KFold split with a K of 5. This helps to reduce over-fitting because each row of data is used for both training and testing but not simultaneously.

The accuracy score for these two algorithms are calculated using the `r2_score` of `sklearn`.

5.2.2 Neural Network

The Neural Network score is calculated using the `mean_squared_error` function and plotted using the `live_loss_plot` module provided by the Intel workshop. It is optimized using the `nadam` function. I used this function because after some research on the Keras documentation website I found it was the best fitted function for my usecase. After testing it among some other functions it was clear that this one performed the best. Afterwards the network is also scored using the `r2_score` function of sklearn.

The Neural Network is structured as follows.

1. Dense layer.
Nodes: $2 \times \text{Input}$
Activation: Relu
2. Dense layer:
Nodes: Same as input
Activation: Relu
3. Dense layer:
Nodes: 1
Activation: Linear
Output node

6 Findings

I found that to some extent the machine learning algorithms are able to predict the price of the diamonds. But often they are a bit off, and sometimes even by a lot. Using the table provided by Rapport seems to be a better option.

The Decision Tree and the Random Forest score with 88% and 92% respectively. This already quite accurate, but still have a significant delta in a lot of the cases.

The Neural Network performed pretty good. Using the `r2_score` it got an accuracy of approximately 97.5%. This seems like a really good score. But when I look at the predictions I see deltas that are quite significant in my opinion.

When combining the three methods, the score actually decreases from the Neural Network. It becomes 96.8%. However when looking at the percentiles, a different story is told. These are way closer then before. And when calculation how many there where within 200 euro accurate, the amount increases from 62% to 66%.

In short, even though the `r2` score is a bit lower, the actual accuracy seems to be better when combining the three methods.

7 Conclusion

Even though these methods approximate the actual price quite accurately, they are a bit too far off to be of any actual use in my opinion. Using the Rapaport charts is a better option when you need to calculate the price of a diamond.

Nevertheless was it a fun experiment to perform and I have learned a lot while performing it.