# Diamonds Projeto

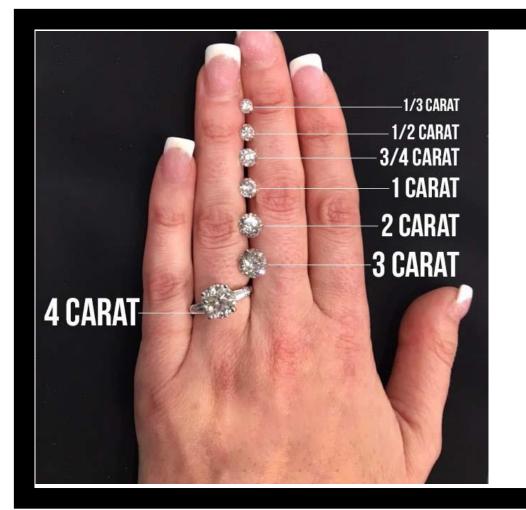


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# Entendendo as variáveis



|      | Column  | Description   |
|------|---------|---|
|      | Price   | Price in US dollars (326-18,823)  |
|      | Carat   | Weight of the diamond (0.25.01)   |
| 4C's | Cut     | Quality of the cut (Fair, Good, Very Good, Premium, Ideal)  |
| 703  | Color   | Diamond colour, from J (worst) to D (best)  |
|      | Clarity | A measurement of how clear the diamond is (I1 (worst), SI2, SI1, VS2, VS1, VVS2, VVS1, IF (best)) |
|      | х       | Length in mm (010.74)   |
|      | у       | Width in mm (058.9)   |
|      | z       | Depth in mm (031.8)   |
|      | Depth   | Total depth percentage = $z$ / mean( $x$ , $y$ ) = 2 * $z$ / ( $x$ + $y$ ) (4379)                 |
|      | Table   | Width of top of diamond relative to widest point (4395)   |



"Diamond carat weight is the measurement of how much a diamond weighs. A metric "carat" is defined as

200 milligrams."







https://www.brilliance.com/education/diamonds/depth-table



Essentially, anything between 50 and 69 percent is considered alright. However, the <u>most ideal</u> <u>TABLE PERCENTAGES are between 54 and</u> <u>60 percent.</u> At this proportion, the table is large enough to allow light to enter the stone at the correct angles to reflect and refract off the smaller facets below."

#### **Análises do Dataset**



- Criação de novas features;
- Regressão Linear.

#### **Inserindo novas colunas:**

- Volume;
- Densidade;
- Carat x Volume;
- **3Cs:** Clarity x Cut x Color
- 3Cs x Vol

## Dataset pronto para Regressão:

|   | carat | cut     | color | clarity | depth | table | price | x    | у    | z    | clarityNew | colorNew | cutNew | volume    | density  | carat*Vol | 3Cs | 3Csxvol    |
|---|-------|---------|-------|---------|-------|-------|-------|------|------|------|------------|----------|--------|-----------|----------|-----------|-----|------------|
| 0 | 0.23  | Ideal   | Е     | SI2     | 61.5  | 55.0  | 326   | 3.95 | 3.98 | 2.43 | 2          | 6        | 5      | 10.001411 | 0.022997 | 2.300325  | 60  | 600.084672 |
| 1 | 0.21  | Premium | Е     | SI1     | 59.8  | 61.0  | 326   | 3.89 | 3.84 | 2.31 | 3          | 6        | 4      | 9.033990  | 0.023246 | 1.897138  | 72  | 650.447276 |
| 2 | 0.23  | Good    | Е     | VS1     | 56.9  | 65.0  | 327   | 4.05 | 4.07 | 2.31 | 5          | 6        | 2      | 9.968566  | 0.023073 | 2.292770  | 60  | 598.113939 |
| 3 | 0.29  | Premium | - 1   | VS2     | 62.4  | 58.0  | 334   | 4.20 | 4.23 | 2.63 | 4          | 2        | 4      | 12.232621 | 0.023707 | 3.547460  | 32  | 391.443883 |
| 4 | 0.31  | Good    | J     | SI2     | 63.3  | 58.0  | 335   | 4.34 | 4.35 | 2.75 | 2          | 1        | 2      | 13.591922 | 0.022808 | 4.213496  | 4   | 54.367689  |

## Definindo uma função para Múltiplas Análises

```
## Function for comparing different approaches
 2 from sklearn.model selection import train test split
   def score dataset(df):
       model = LinearRegression()
       y = df.price
       results = []
       for i in list(df.columns):
           if type(df[i][0]) != str:
 9
               X = df[[i]]
10
               X train, X test, y train, y test = train test split(X, y, test size=0.2, random state = 0)
11
               model.fit(X train, y train)
               preds = model.predict(X test)
12
13
               results.append( (i, mean absolute error(y test,preds), model.score(X train, y train) ) )
       return results
14
```

#### **Analisando a performance**

```
[('carat', 1010.6385120654585, 0.8496675874577887),
('depth', 3062.993107599667, 0.0001524325286271777),
('table', 3013.202731588257, 0.01649906126461831),
('price', 4.2722411210737817e-13, 1.0),
('x', 1371.3344701089952, 0.7869746343926203),
('y', 1369.231589508964, 0.7891432918567728),
('z', 1390.5284414225846, 0.7778587353338537),
('clarityNew', 2970.645934437729, 0.021697735375831306),
('colorNew', 2987.5658365267927, 0.030145110949522436),
('cutNew', 3048.1165441561043, 0.002819880901487881),

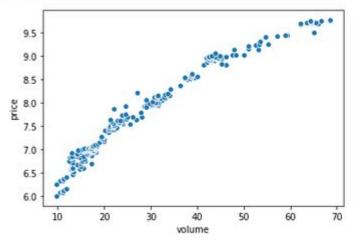
('volume', 1001.8440202571396, 0.8528797670926731),
('density', 2993.550579312727, 0.02004459763267541),
('carat*Vol', 1036.6571502159306, 0.7989266741237522),
('3Cs', 2921.741694038112, 0.037645135414547504),
('3Csxvol', 2474.637933069794, 0.2849633172127253)]
```

score dataset(diamondsNew)

#### Aplicando a realidade

```
1 data = diamondsNew.query('clarityNew == 5 and colorNew == 6 and cutNew == 4')
1 sns.scatterplot(x = data.volume , y= np.log(data.price));
```





**Mean Absolute Error: 0.1328** 

**Score:** 0.9580

r2\_score ScikitLearn: 0.963

# Regressão usando múltiplas variáveis

```
1  X = diamondsNew[['clarityNew','colorNew','cutNew','volume']]
2  y = diamondsNew.price
3  X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state = 0)
4  model = LinearRegression()
5  model.fit(X_train, y_train)
6  preds = model.predict(X_test)
7  print(f'Mean Absolute Error: {mean_absolute_error(y_test,preds)}')
8  print(f'Score: {model.score(X_train, y_train)}')
9  print(f'r2_score ScikitLearn: {r2_score(y_test, preds)}')
```

$$R_{adj}^2 = 1 - (1 - R^2) \frac{n-1}{n-p-1}$$

**Mean Absolute Error:** 856.4662

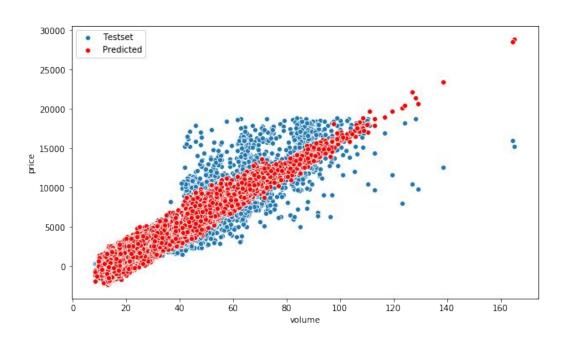
**Score:** 0.9050

r2\_score Scikit Learn: 0.9052284

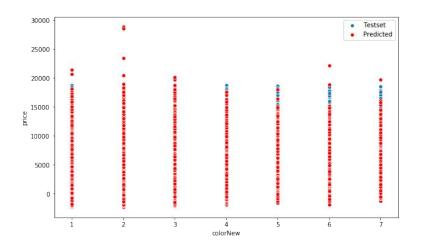
N = is the number of points of data sample. p = is the number of independent regressors.

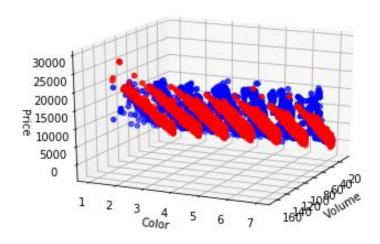
**R2 adjusted:** 0.9051933

## Analisando os gráficos



## Analisando os gráficos









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