Predicting Diamonds Price

Statistical Learning Mod. B, Final project

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Università degli Studi di Padova

Goal of the project

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Main Goal $\Rightarrow$ build an appropriate model to predict prices of diamonds.

In particular we will make use of:

1. Feature Selection;
2. Shrinkage Methods;
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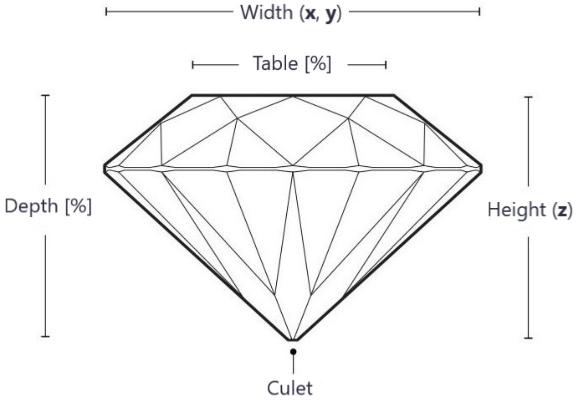
Obtaining the Data

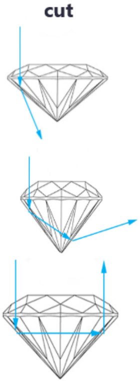
kaggle

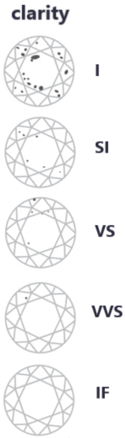
Diamonds Dataset from *kaggle*

https://www.kaggle.com/shivam2503/diamonds

Diamond Structure







Diamonds Dataset

Around 54000 diamonds with the following attributes:

- **Carat** (*numerical*): weight of a diamond (1 carat = 0.2 g);
- **Cut** (*factor*): *Fair*, *Good*, *Very Good*, *Excellent*, *Ideal*;
- **Color** (*factor*): *J*, *I*, *H*, *G*, *F*, *E*, *D*;
- **Clarity** (*factor*): *I1*,*SI2*, *SI1*, *VS2*, *VS1*, *VVS2*, *VVS1* and *IF*;
- **Depth** (*numerical*): percentual height over average width;
- **Table** (*numerical*): percentual width of the table over total width;
- **Price** [$] (*numerical*)
- **x**, **y**, **z** [mm] (*numerical*): three spatial dimensions.

Cleaning and preparing the data through the following:

- Check for Null Values;
- One-Hot-Encoding;
- Removal of absurd data;
- Check for possible outliers.

Data Preprocessing

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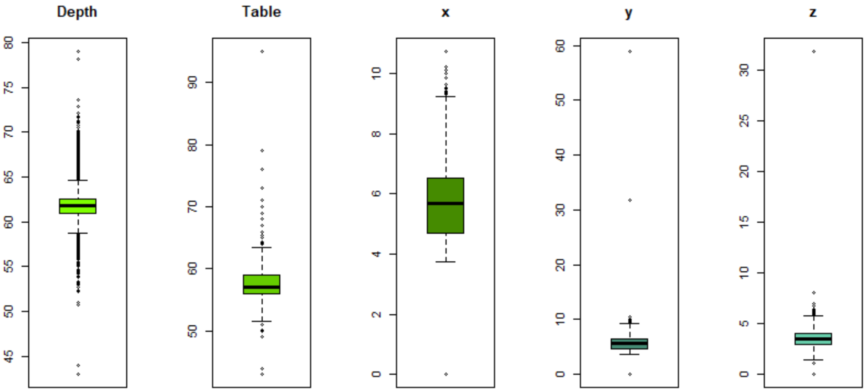

For a more complete data visualization, take a look at the attached paper and **R** code.

Defining objectives

- Goal: Price prediction;
- How? Linear models ⇒ limited capacity, high interpretability;
- Why? Costumer advisory, market analysis, insurance quote.

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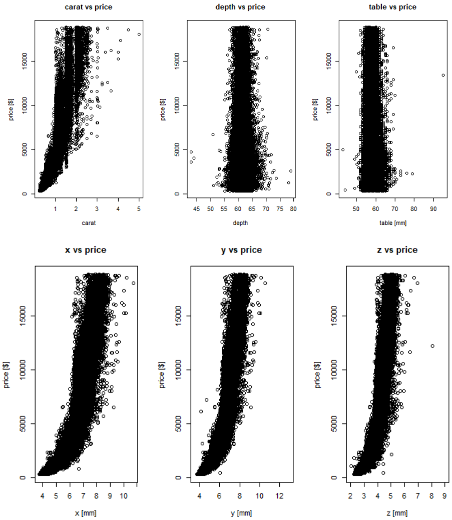
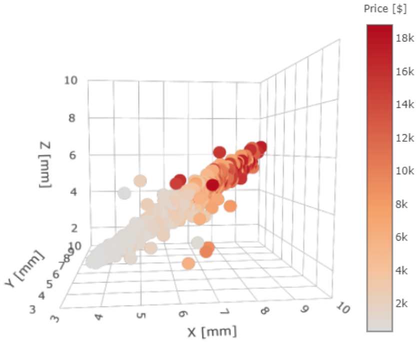
Explorative - Price vs Numerical





Explorative - Price vs Categorical

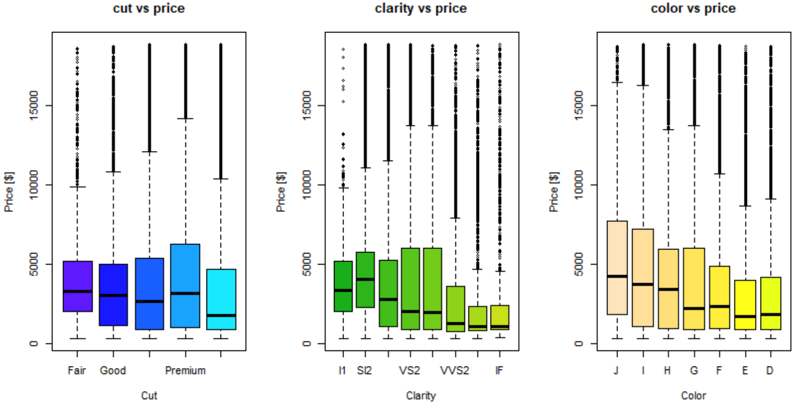


Figure: Boxplots of categorical features

Naive approach

First approach: we normalized our data (except for the target variable) and we tried to fit a linear model:

- Coefficients correctly describe the *expected* relationship between features and target variable;
- Analysis of residuals however shows they are clearly not randomly distributed, especially for the largest predicted values.

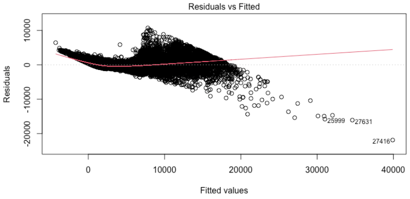


Figure: Plot of residuals for the naive approach

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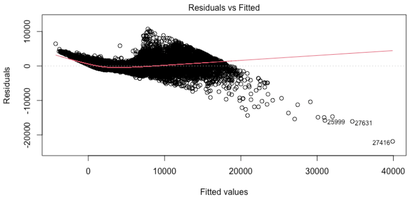

Figure: Plot of residuals for the naive approach

Solution: Variable transformation

To overcome this problem we followed two steps:

1. log(*price*): residuals become flat and uniformly distributed but now the coefficients are "wrong";

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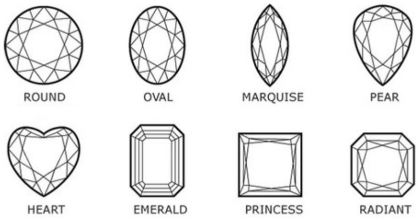
A new variable



We introduce a new variable $r = \dfrac{x}{y}$

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Now we can capture the shape of the diamond.

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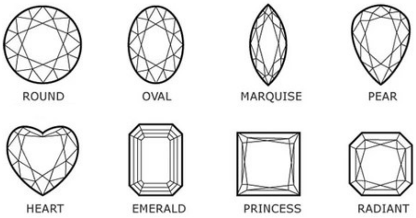

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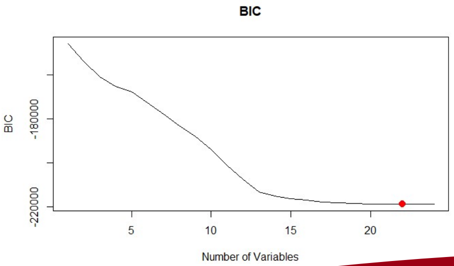
Best Subset Selection & Linear Model

We apply different techniques and criteria to select only the truly relevant features for our prediction.

$\Longrightarrow$ a simpler and more efficient model is obtained!

The final reduced linear model is given by:

$$\log(\text{price}) \sim \log(\text{carat}) + \text{cut} + \text{color} + \text{clarity} + x + y + r.$$



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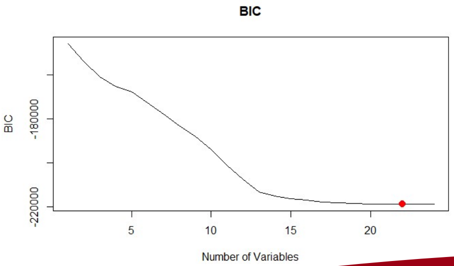
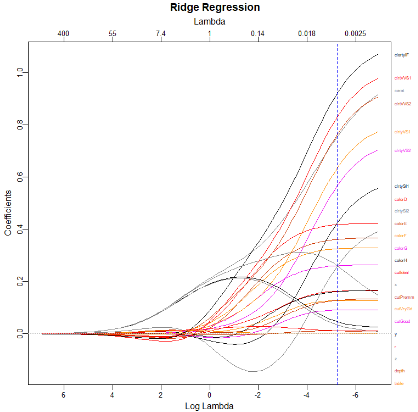


Shrinkage Methods

Other way to tackle feature reduction? Ridge regression and Lasso regression: two alternatives to Best Subset Selection in order to reduce model complexity.

$\Downarrow$

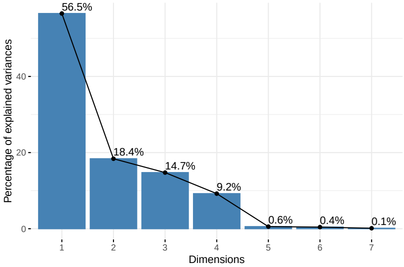
Features are not removed according to some metrics but instead the contribution of the irrelevant ones is shrinked toward zero.



One last method applied to obtain a model: PCA.

It is a technique that affects the data, not the model itself, and reduce their dimensionality.

From 7 numerical features to 4 components!



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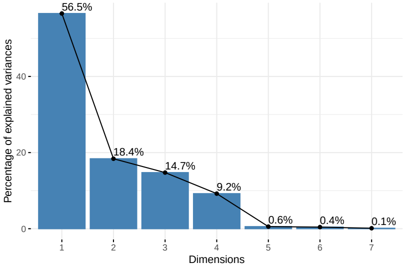

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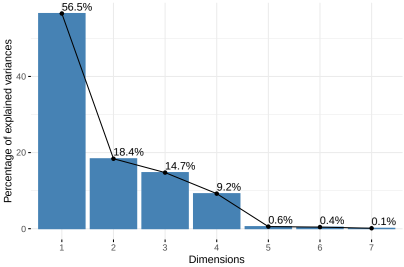

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Principal Component Analysis

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Summary of what we obtained in this project:

	MAE [$]
Naive linear model	740
Linear model (reduced)	418
Ridge regression	472
Lasso regression	448
PCA	1245
PCA + cat. vars.	875
PCA with log(*carat*)	989
PCA with log(*carat*) + cat. vars.	564

Mean Absolute Error: the smaller, the better.

Further Development

In the attached report you can find way deeper insights with much more technical results.

Anyway, there is still much space for improvement!

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