Group 11 Final Presentation

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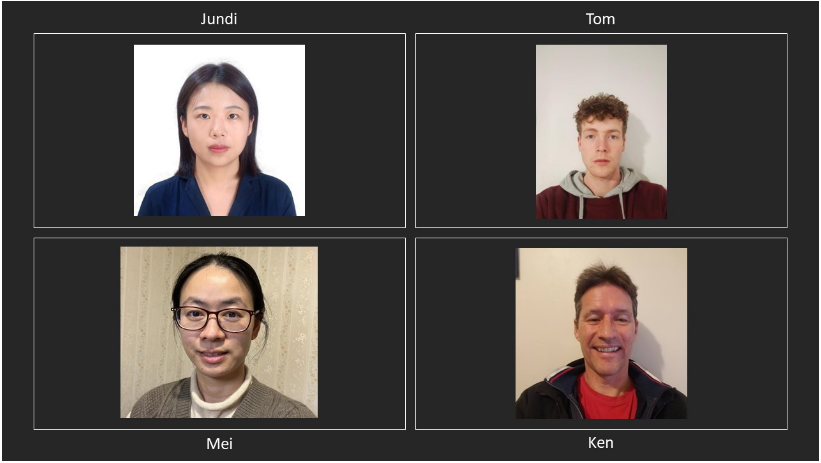
Group 11: Diamonds Dataset

Group Members (photos)



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The Diamonds dataset

- This large dataset has 53940 rows (diamonds) of ten variables (approx 540,000 values)
- Slow to process!
- There are seven numeric variables and three categorical variables
- We selected diamonds because it was conceptually simple to understand what each variable was measuring, and to have the opportunity to use the analytical techniques taught in STAT394 with a large dataset

The Variables

red font = categorical variable

- carat: the diamond's weight
- cut: a measure of quality (4 levels)
- color: a measure of colour quality (7 levels)
- clarity: a measure of clearness (6 levels)
- x: length in mm
- y: width in mm
- z: depth in mm
- depth: total depth percentage
- table: width of top of diamond relative to widest point
- price: the price of the diamond in US dollars

(List adapted from list at kaggle.com).

Pairs Plot

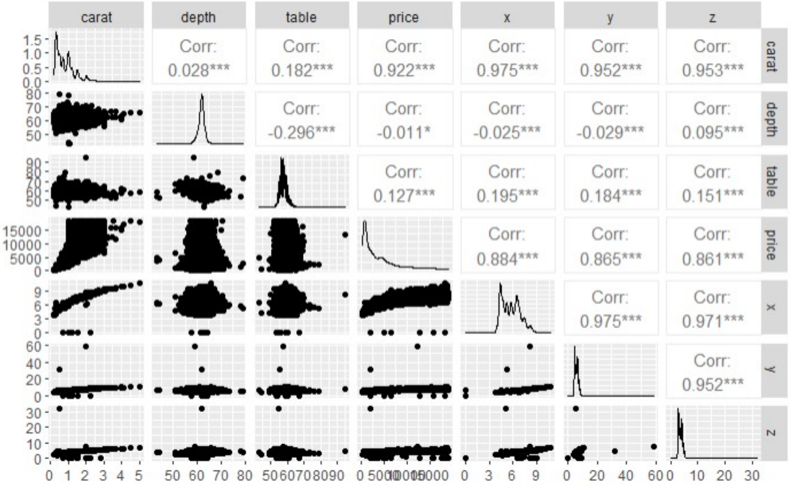

Figure 1: Pairs plot

Correlation Plot

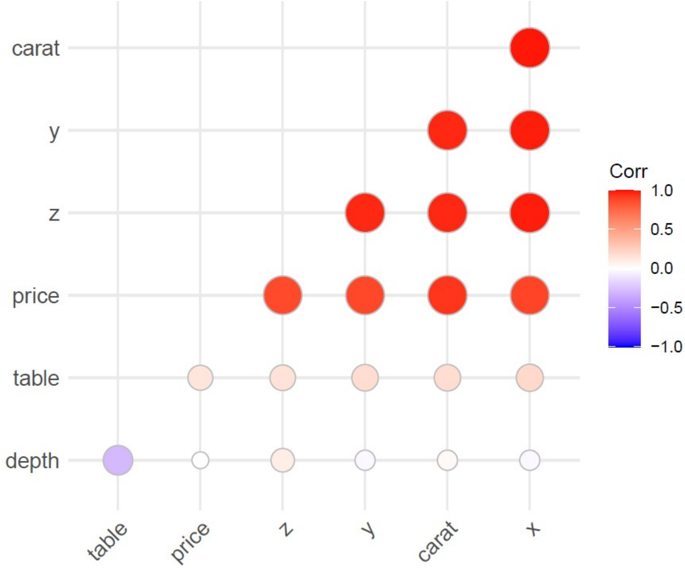

Figure 2: Correlation Plot

Normal QQ Plots

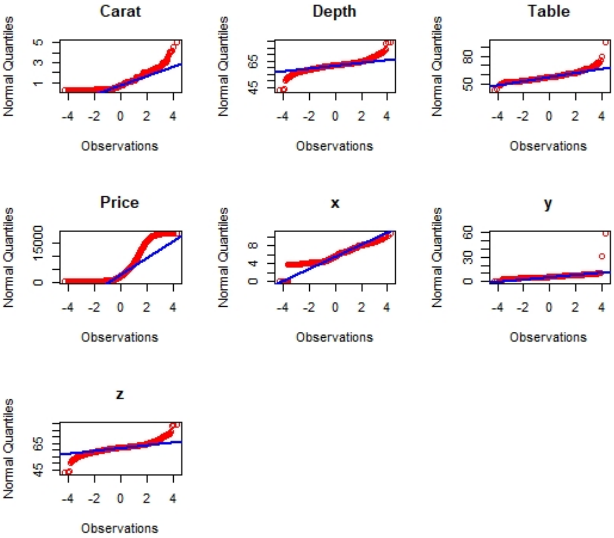

Figure 3: Normal QQ Plots

Price by Categorical

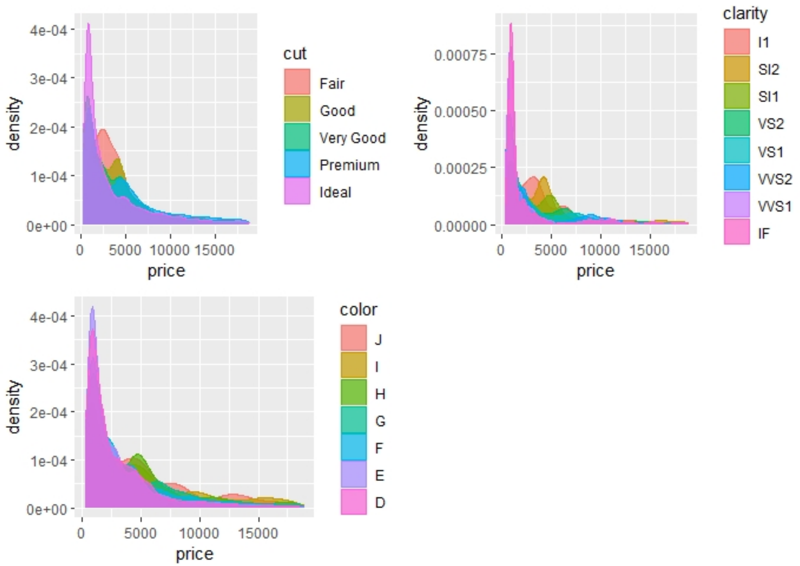

Figure 4: Price by Categorical

Leading Question 1

- How can we best predict diamond price using the other variables?
- We intend to use the following techniques to investigate this question:
- Stepwise Regression, Principal Components Analysis, Principal Components Regression

Multiple Regression

- Starting with the full model we used a stepwise regression procedure to find the best model for predicting diamond price.
- According to AIC the best model was:
- price ~ carat + cut + color + clarity + depth + table + x
- All variables excluding y and z are significant in the model
- The 'best' model had an Adjusted R^2 of 91.98%

Regression Assumptions

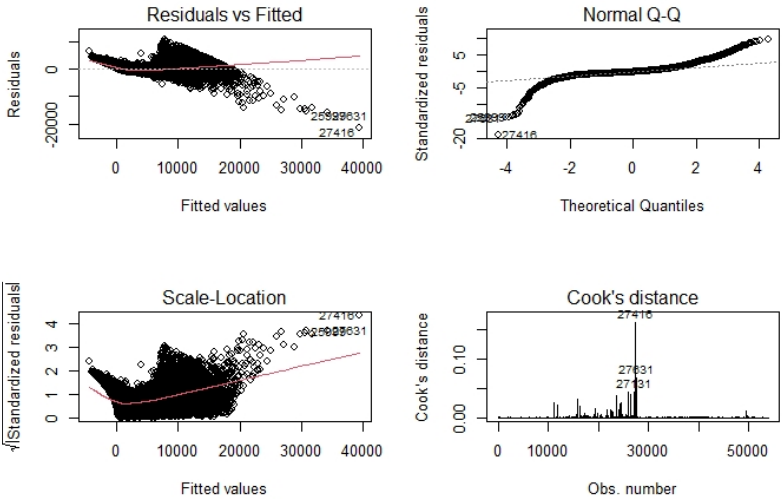

Figure 5: Regression Diagnostics

Principal Components Analysis: Screeplot

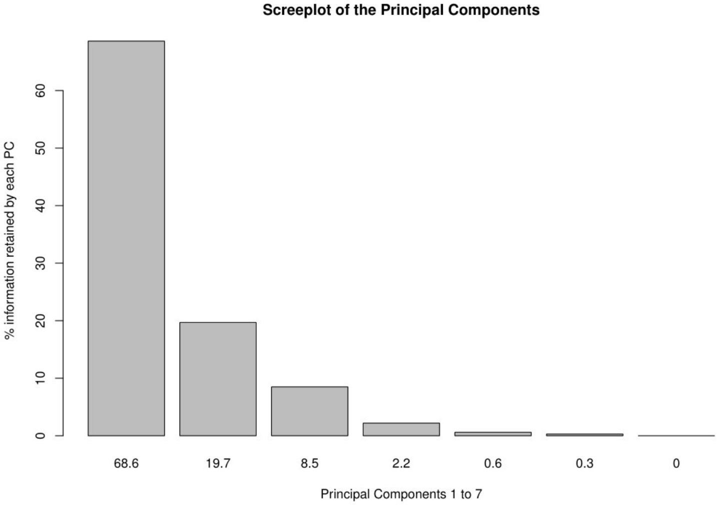

Figure 6: PCA Screeplot

Principal Components Analysis: Eigenvectors

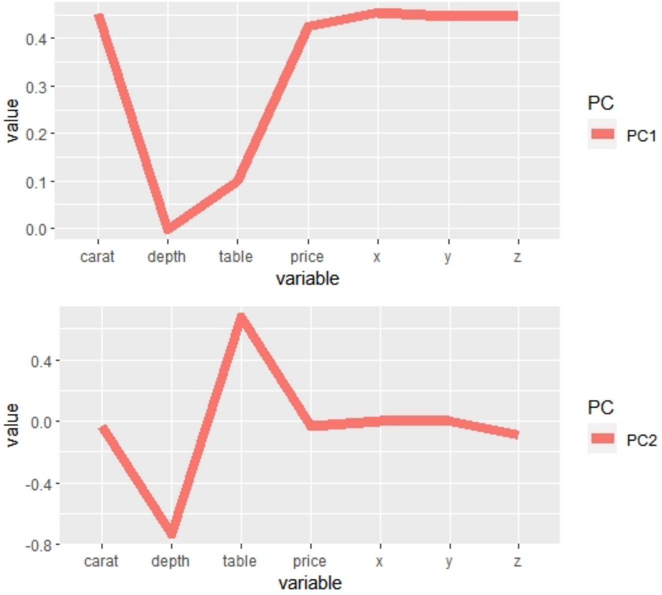

Figure 7: Plot of EigenVectors

Biplot

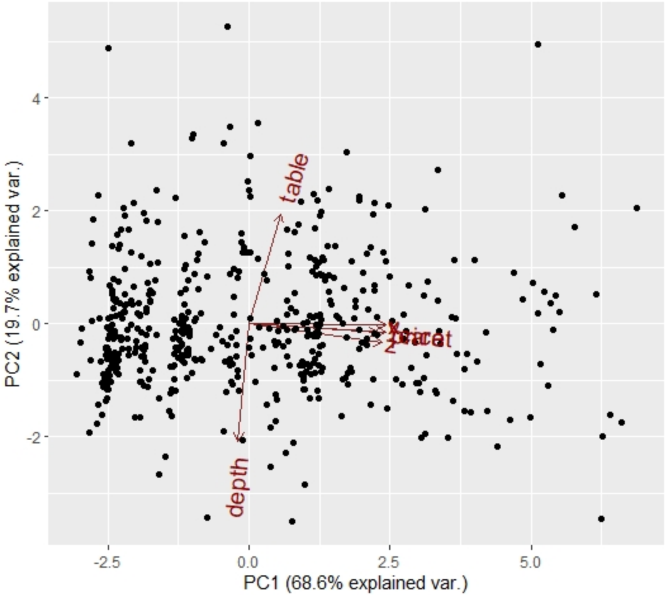

Figure 8: PCA Biplot

Principal Components Regression

- We conducted a Principal Components Regression with diamond price as the response variable
- The PCA excluding price was almost identical to the original PCA
- We were able to explain over 80% of the variation in price using just the first two principal components as predictors
- A more parsimonious model!

Summary of Models Predicting Diamond Price

Model	No. of Predictors	Adjusted R^2
Full Model	9	0.9198
Best Model	7	0.9198
Numeric Model	7	0.8592
Two PC	2	0.8092
All PC	6	0.8695

Leading Question 2 . . . and the issues we encountered. . .

- The diamonds dataset includes 280 interactions between different levels of the categorical variables
- Our second leading question was to investigate if we could classify the diamonds data more simply using analytical techniques such as LDA and CA

LDA

Problems encountered

- Despite a correlation of 0.9216, ‘carat’ was not a great predictor of ‘price’
- LDA not able to separate different levels of the categorical variables

Slicing the dataset 1

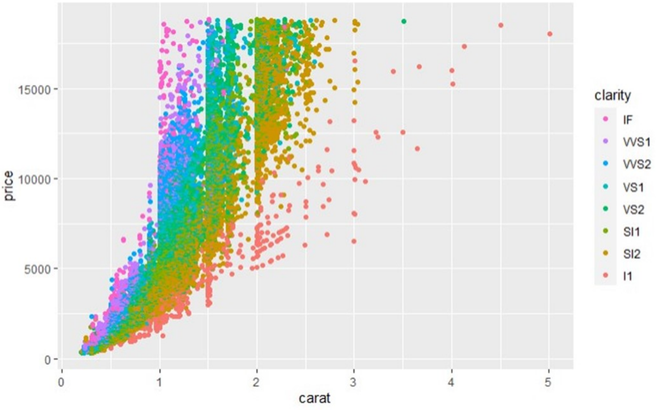

Figure 9: Carat vs Price vs Clarity

Slicing the dataset 2

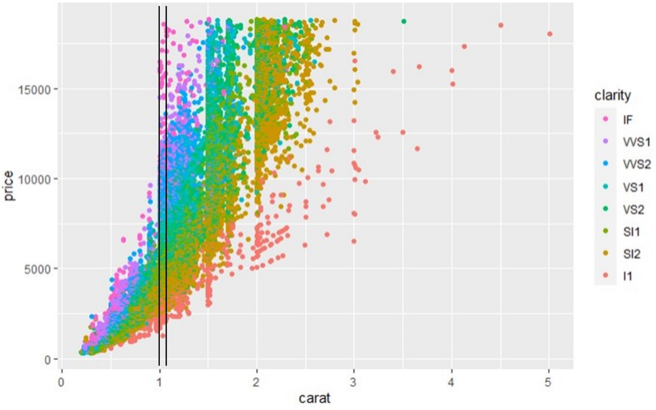

Figure 10: Carat vs Price vs Clarity: vertical slice

Colour bands evident in sliced version

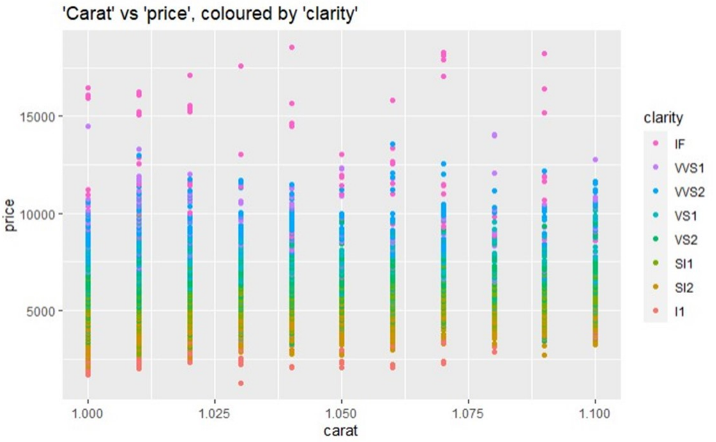

Figure 11: Carat vs Price vs Clarity: sliced 1

Colour bands evident in sliced version 4

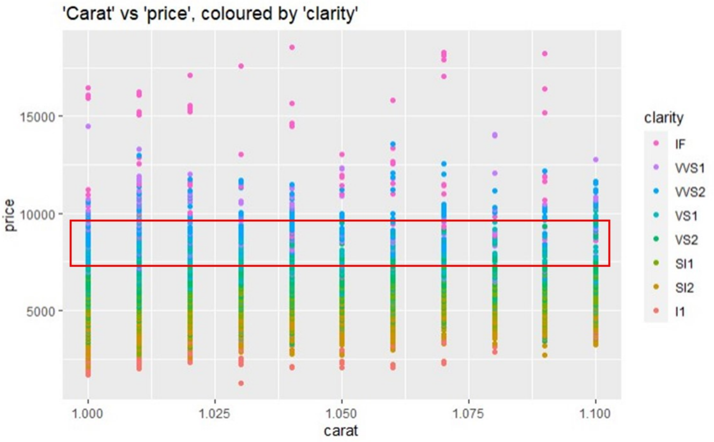

Figure 12: Carat vs Price vs Clarity: sliced 2

Linear Discriminatory Analysis

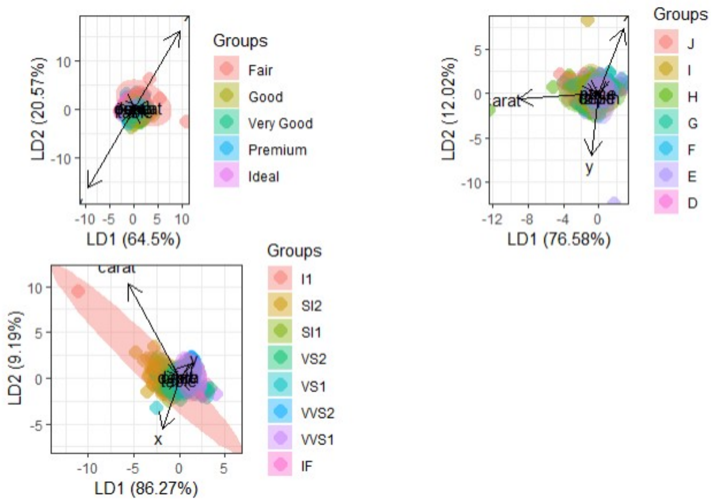

Figure 13: LDA ordination plots

Conclusion