Week 4: Visualising Two Variables

Visual Data Analytics

University of Sydney

Outline

- Categorical v Catgorical
  - Side by side bar
- Categorical v Numerical
  - Side by side boxplots
- Numeric v Numerical
  - Scatter plot

Motivation

- Understand the distributions of two variables
  - Find outliers
  - Find multi-modality
  - Find skew
- Also understand the relationship between the variables

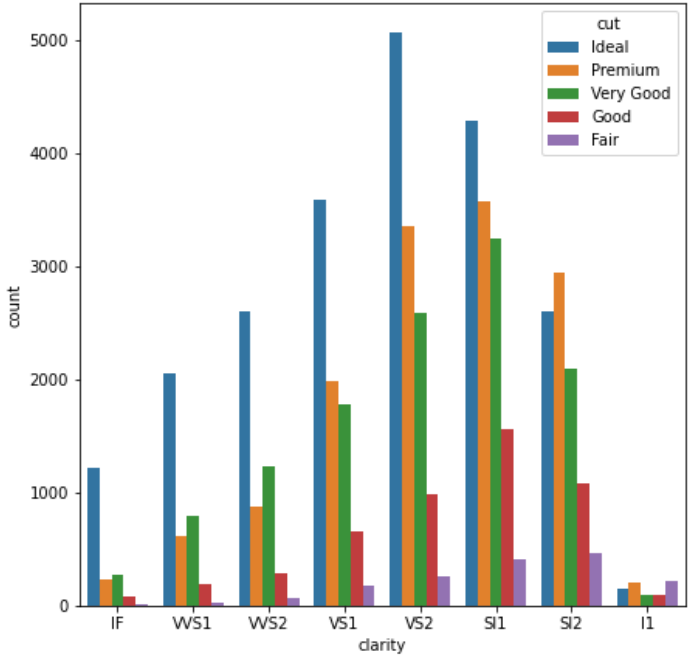
Categorical v Categorical variables

Bar charts

- To visualise two nominal/ordinal variables bar charts can still be used to plot the frequency of each category.
- There are two options
  - Grouped bar charts
  - Stacked bar charts
- We will investiate using the taxis and diamonds data also used last week.

Grouped bar chart

```
sns.countplot(data=diam, x='clarity', hue='cut')
```



Grouped bar chart

- Can easily make comparisons such as
  - Fair diamonds are relatively more common for worse levels of clarity (e.g. SI2)
  - For IF diamonds, these overwhelmingly have an ideal cut.
- Harder to make a comparison for
  - The most common category of clarity.

Stacked bar chart

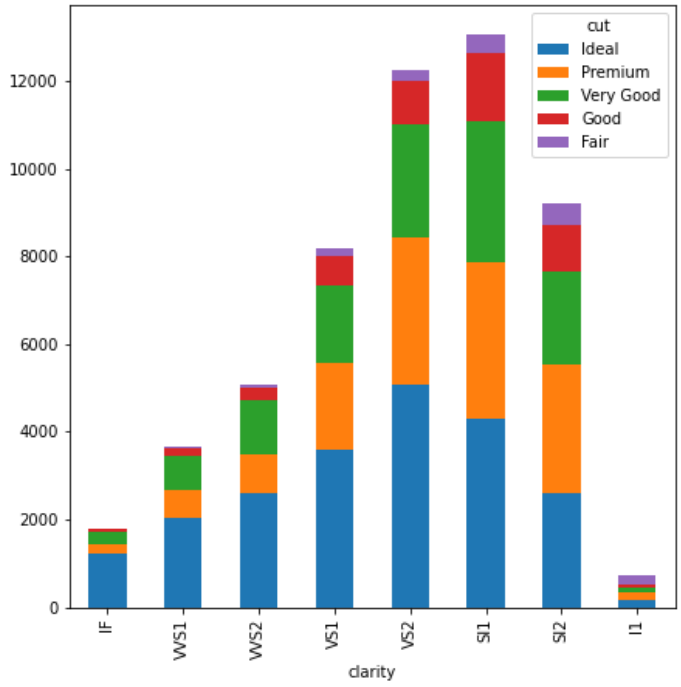
First must prepare data by creating corss tab

```
diamct = pd.crosstab(diam['clarity'],diam['cut'])
diamct
```

```
## cut      Ideal  Premium  Very Good  Good  Fair
## clarity
## IF        1212      230        268    71     9
## VVS1      2047      616        789   186    17
## VVS2      2606      870       1235   286    69
## VS1       3589     1989       1775   648   170
## VS2       5071     3357       2591   978   261
## SI1       4282     3575       3240  1560   408
## SI2       2598     2949       2100  1081   466
## I1         146      205         84    96   210
```

Stacked bar chart

```
diamct.plot(kind = 'bar', stacked = True)
```



Stacked bar chart

- Can easily see
  - Frequencies of categories for clarity
  - Relative freqeuncy of cut within a single category of clarity
- Harder to make a comparison for
  - Frequency of cut across categories of clarity (e.g. hard to quickly tell if there are more Good/VS2 or Good/SI2)

Percentage stacked bar chart

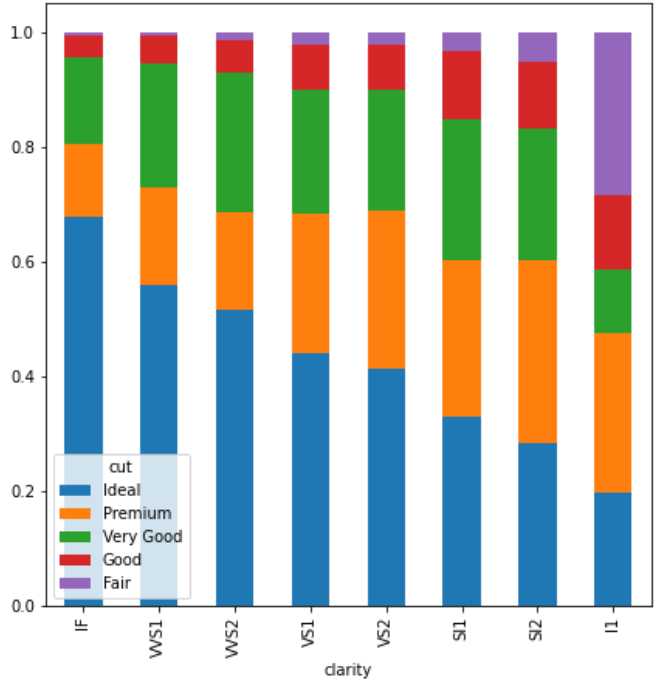
First must prepare data

```
diamct = pd.crosstab(diam['clarity'],diam['cut'], normalize='index')
diamct
```

```
## cut          Ideal   Premium  Very Good      Good      Fair
## clarity
## IF       0.677095  0.128492   0.149721  0.039665  0.005028
## VVS1     0.560055  0.168536   0.215869  0.050889  0.004651
## VVS2     0.514410  0.171733   0.243782  0.056455  0.013620
## VS1      0.439236  0.243422   0.217232  0.079305  0.020805
## VS2      0.413689  0.273862   0.211372  0.079785  0.021292
## SI1      0.327746  0.273632   0.247991  0.119403  0.031228
## SI2      0.282576  0.320753   0.228410  0.117577  0.050685
## I1       0.197031  0.276653   0.113360  0.129555  0.283401
```

Stacked bar chart

```
diamct.plot(kind = 'bar', stacked = True)
```



Percentage stacked bar chart

- Can easily see
  - The relationship between cut and clarity
- Harder to see
  - Anything about the distribution of the categories

Bar charts

- Three options
  - Grouped
  - Stacked
  - Percentage stacked
- No one is right or wrong, it all depends on what you are trying to communicate.

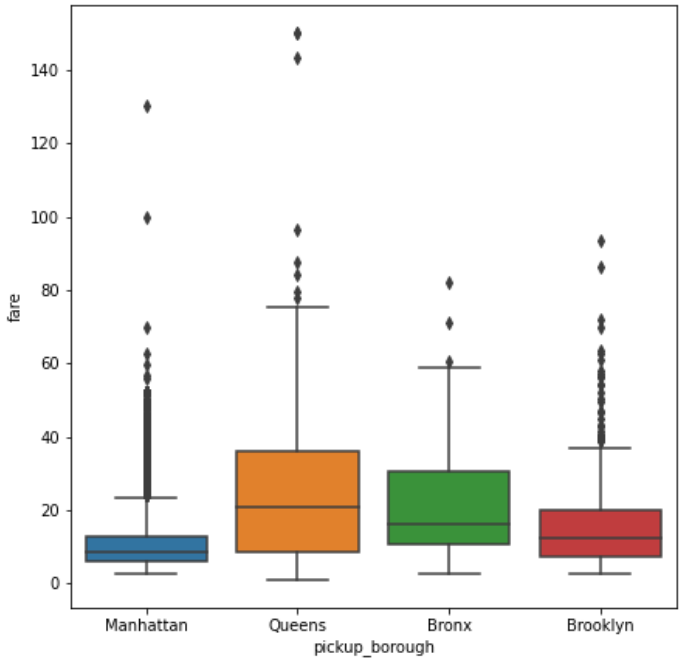
Categorical v Numeric

Side-by-side

- Will consider side-by-side
  - Boxplots
  - Violin plots
  - (Jittered) rug plots
- Seaborn syntax well suited to these

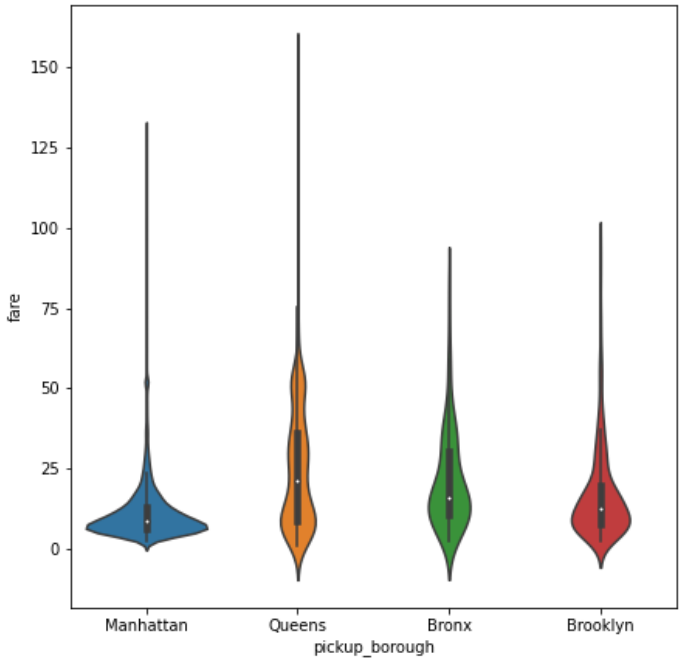
Side by side boxplots

```
sns.boxplot(data = taxisdat, y = 'fare', x = 'pickup_borough')
```



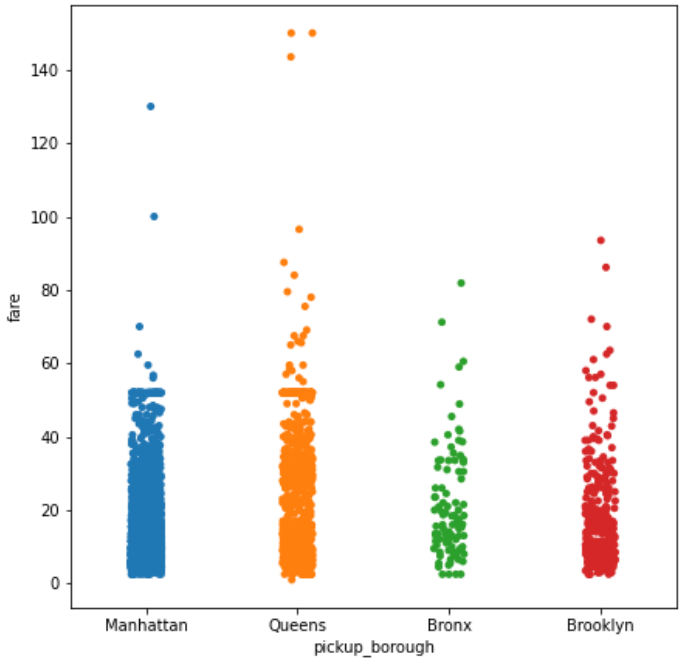
Side by side violin plots

```
sns.violinplot(data = taxisdat, y = 'fare', x = 'pickup_borough')
```



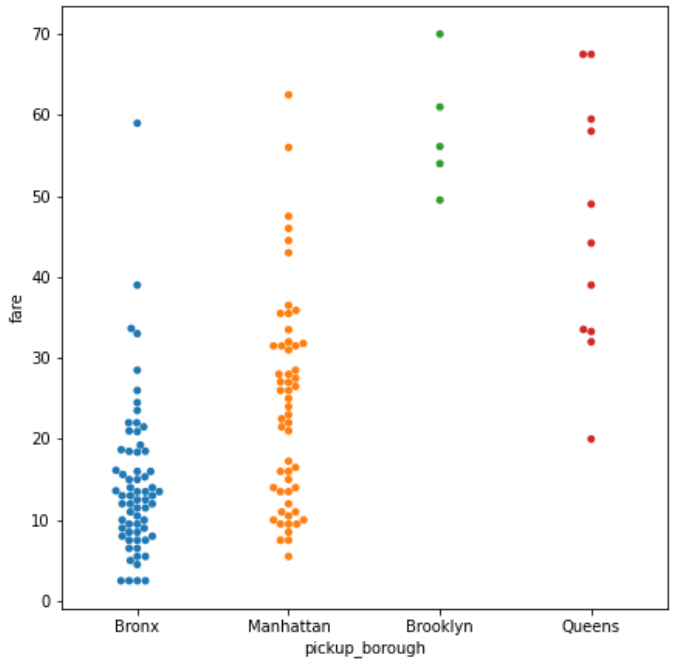
Side by side strip plots

```
sns.stripplot(data = taxisdat, y = 'fare', x = 'pickup_borough')
```



Side by side swarm plots (slow)

```
sns.swarmplot(data = taxisdat[taxisdat['dropoff_borough']=='Bronx'], y =
```



Different plots

- Boxplots clearly show that Manhattan has the lowest median fare and less volatility in the fare.
- Violin plots show three modes in the Queens distribution (cannot be seen using boxplots).
- Strip plots show that frequent value at around $50 occurs for Manattan and Queens.
- No single correct plot, use the plot that tells your story.

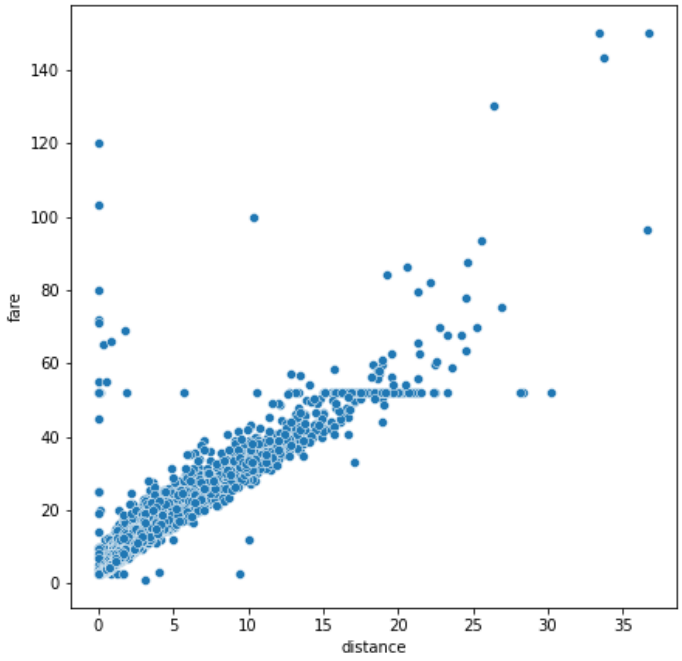
Numerical v Numerical

Scatter plot

- The scatter plot plots one numerical variable on the x axis and the other on the y axis.
- It is a very common plot and useful for
  - Finding outliers
  - Understanding the relationship between two variables.
- We will also look at
  - Log transformations
  - Strategies for dealing with big data.

Scatterplot

```
sns.scatterplot(data = taxisdat, y = 'fare', x = 'distance')
```

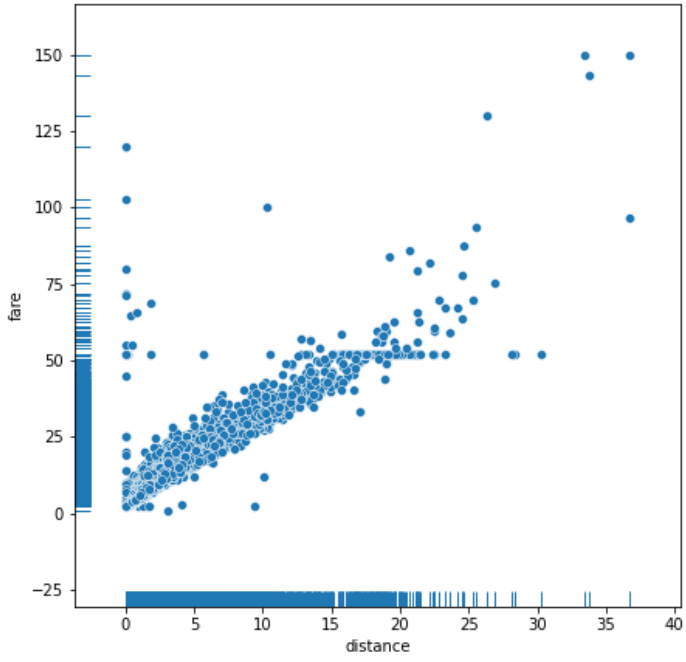


What do we see?

- Can still see certain distributional characteristics
  - Frequent values around $50
  - Outliers
- Relationship is positive and linear
- There are some observations with low distance but high fares.
  - This could not be seen by only looking at each distribution individually.

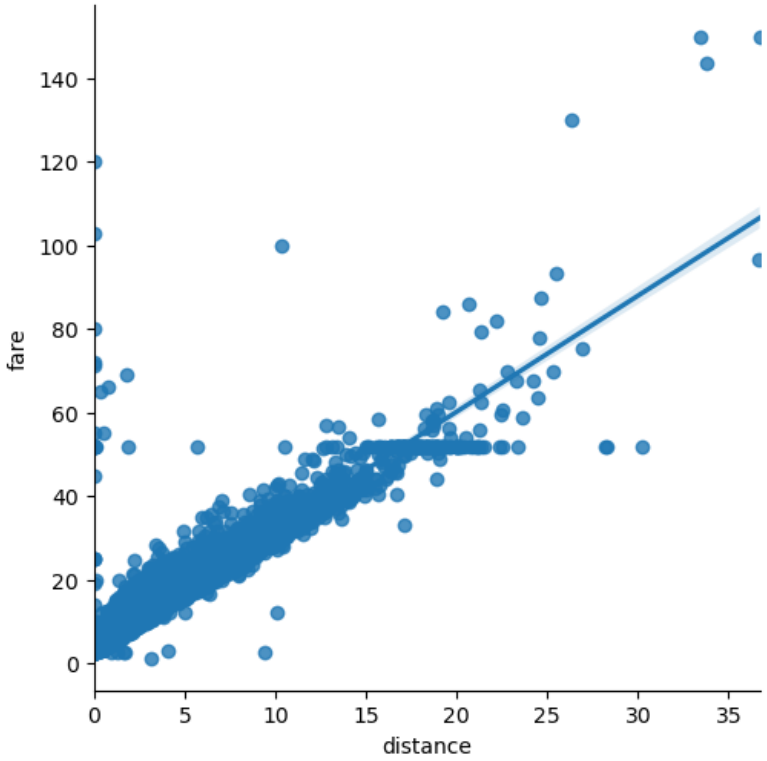
Adding rug plot

```
sns.scatterplot(data = taxisdat, y = 'fare', x = 'distance')
sns.rugplot(data = taxisdat, y = 'fare', x = 'distance')
```



Adding regression line

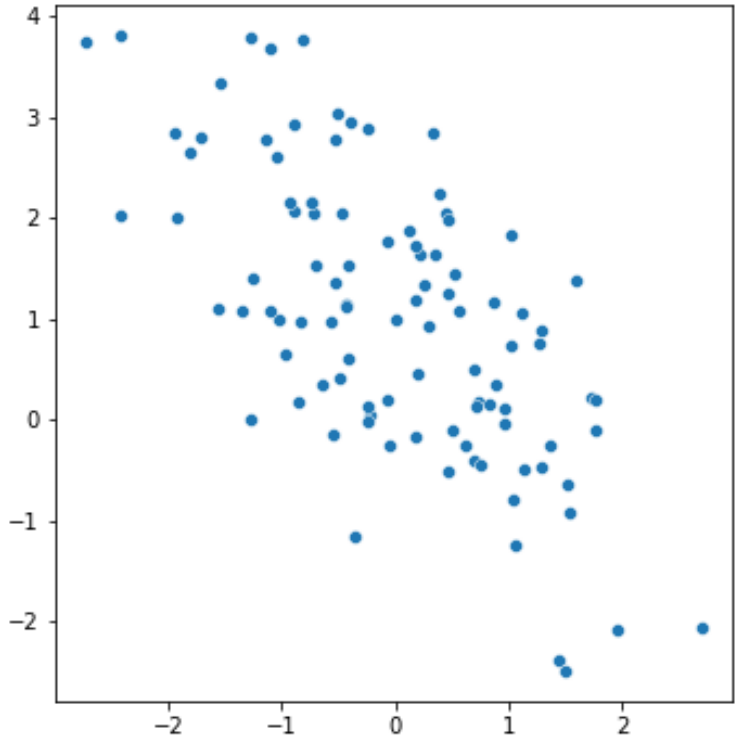
```
sns.lmplot(data = taxisdat, y = 'fare', x = 'distance')
```



Regression

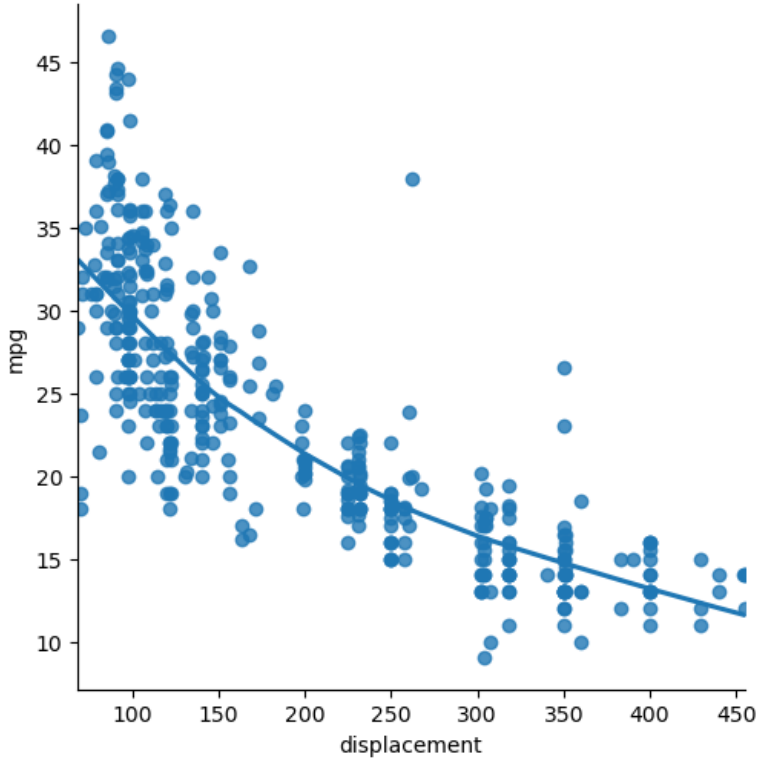
- We usually think of x as an independent variable and y as a dependent variable.
- Even if you do not include regression lines, if there are natural choices of independent and dependent variable then use them on the x and y axes respectively.
- For instance, in this example, distance determines price rather than the other way around.
- Always remember that correlation does not imply causality.

Example of negative correlation



Example of non-linear relationship

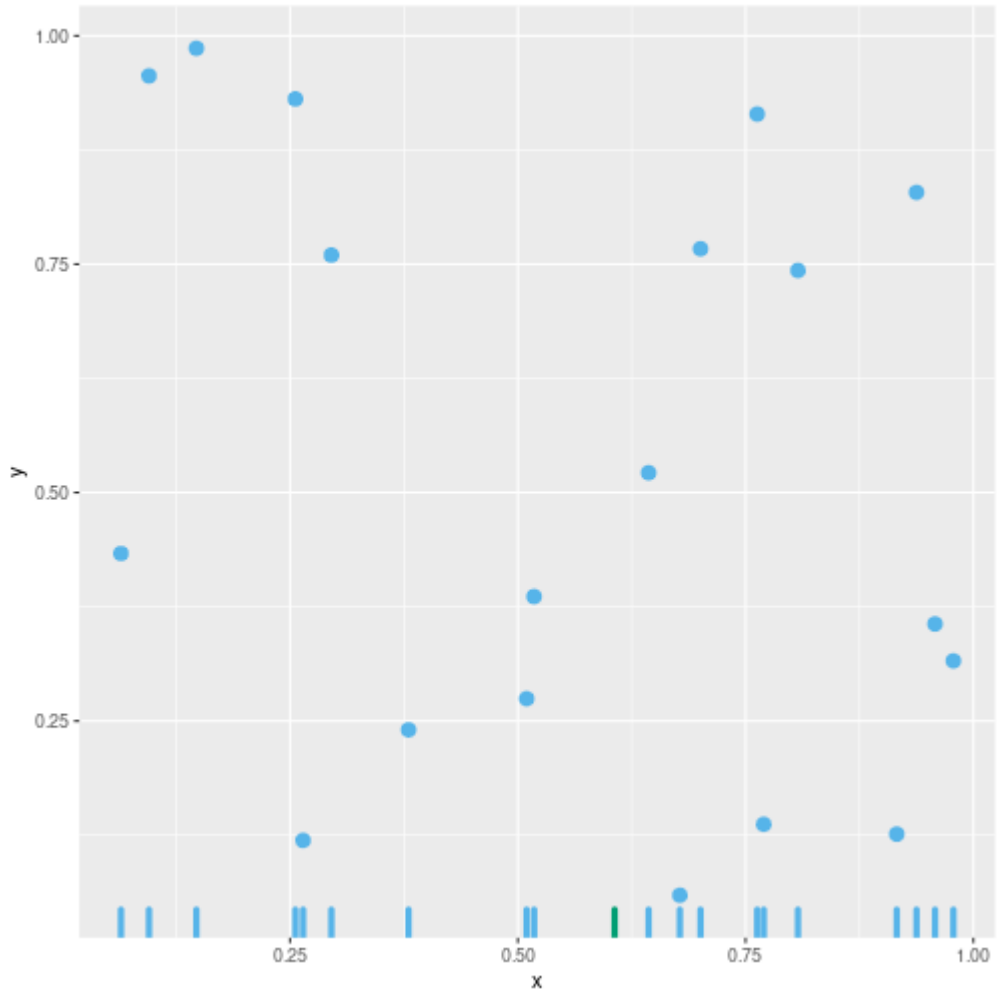
```
mpg = sns.load_dataset('mpg')
sns.lmplot(data = mpg, y = 'mpg', x = 'displacement', lowess=True)
```



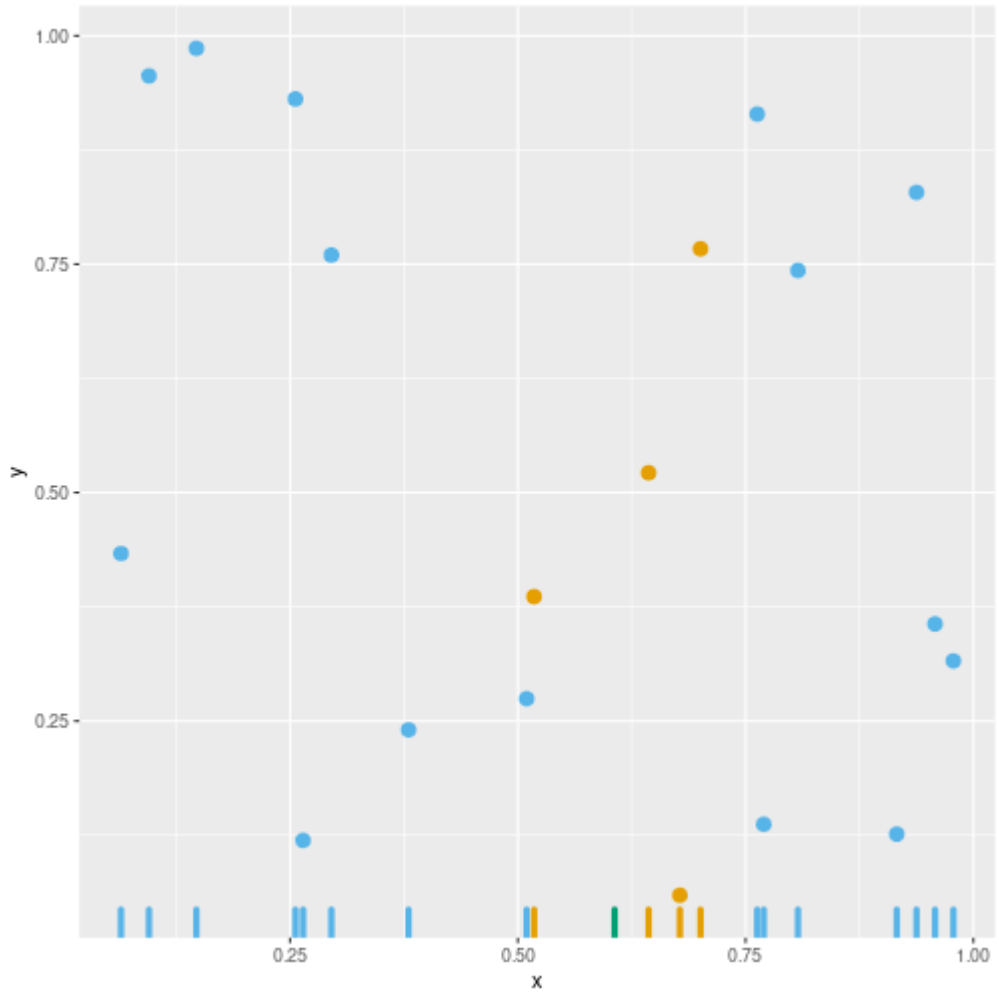
Smooth fit

- The fitted line comes from the LOcal Weighted Estimated Scatterplot Smoothing (LOWESS) method.
- This technique combines the idea of nearest neighbours with regression.
- Nearest neighbours are found (along the x-axis)
- A constant, linear or quadratic regression is fit to the nearest neighbours.

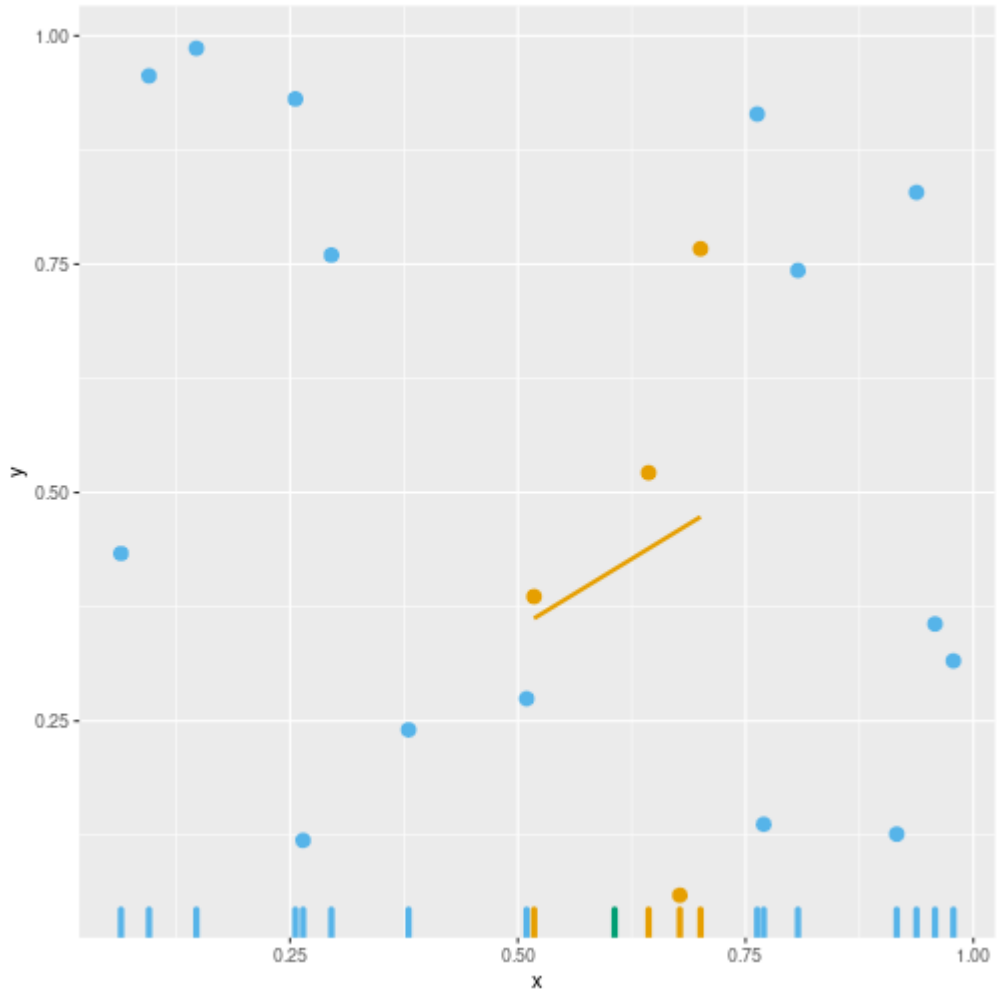
Nearest Neighbours



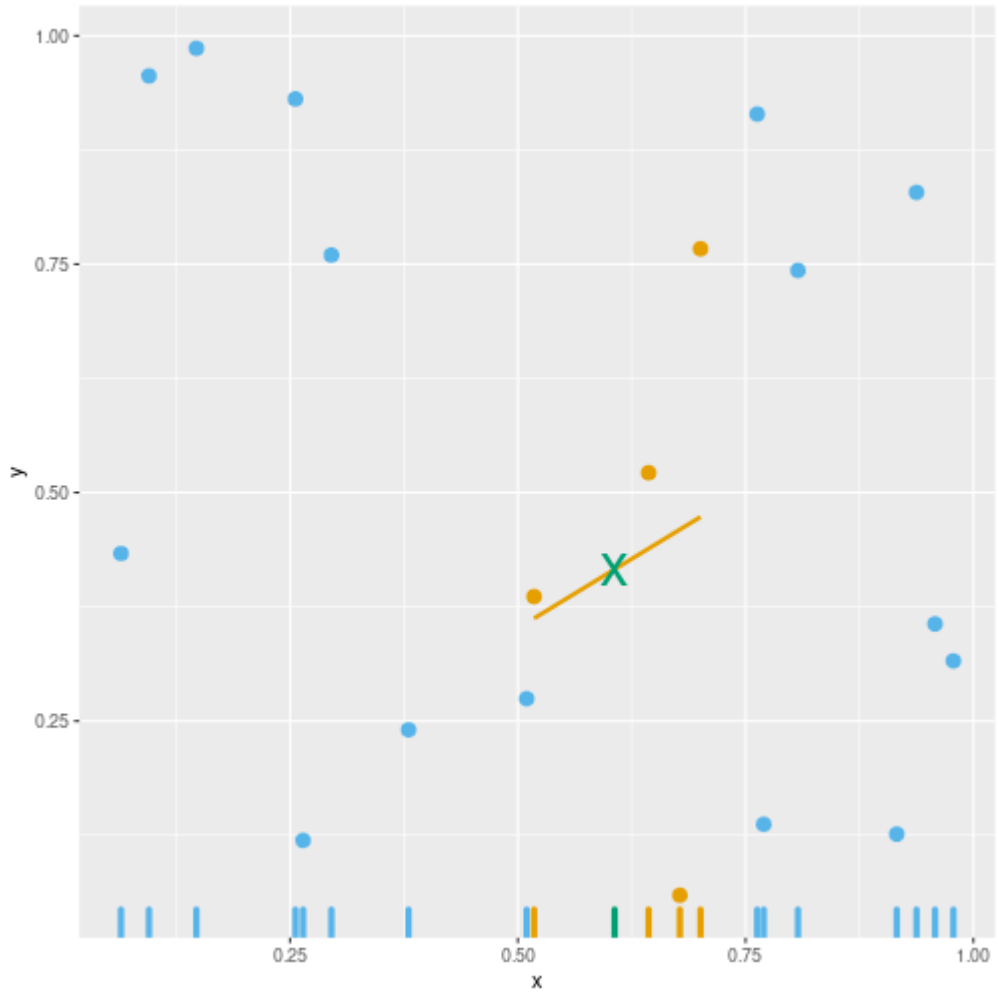
Nearest Neighbours



Local fit



Nearest Neighbours



Details

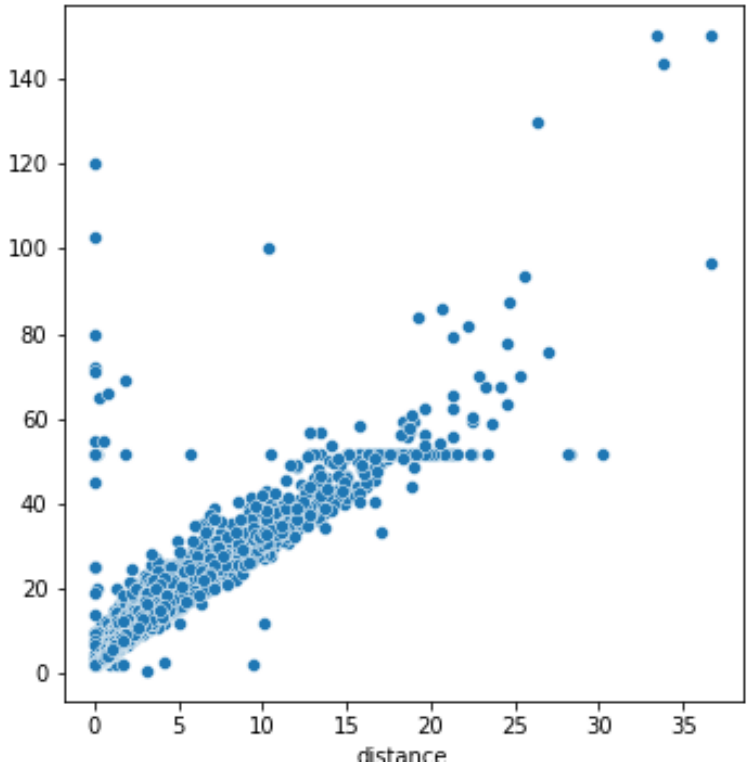
- In the LOWESS algorithm, the smoothing parameter we estimate a regression function ($\hat{y} = f(x)$) rather than a regression line.
- The smoothness of this function can be tuned by changing the number of nearest neigbours.
- Local regressions estimated by weighted least squares so that closer neighbours are given more influence.
- LOWESS is not ideal for large datasets.

Log transformations

- For positively skewed data it is often worth looking a a log transformation
- It particularly makes sense for relationships best understood in terms of percentage changes
  - For example prices change by 1%, demand changes by 5%.
- This transformation only works for positive data.

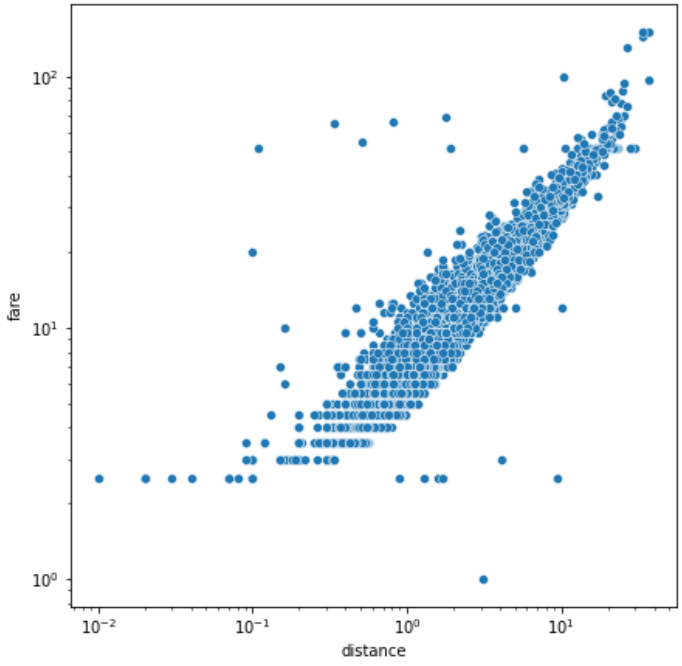
Without transformation

```
sns.scatterplot(data = taxisdat, y = 'fare', x = 'distance')
```



With transformation

```
## [None, None]
```



Using log scales

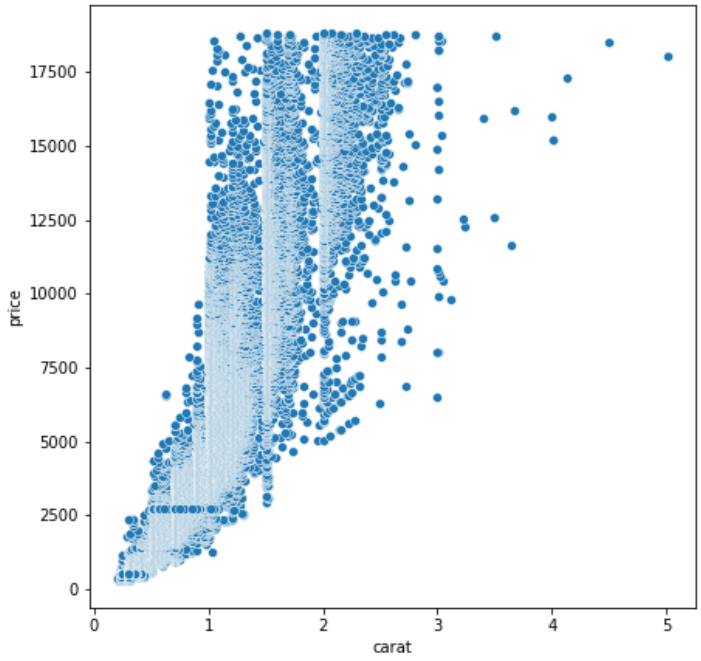
- Before using the log scale the values in the bottom left corner were too close to one another.
- By using the log-log scale these values can be seen more clearly.
- One thing to notice is that the fare has clusters around certain values.
- You will cover using log scales in a tutorial.

Overplotting

- With datasets with a large number of observations, points are plotted on top of one another.
- This is known as *overplotting*
- There are a few strategies to avoid this
  - Smaller points.
  - Transparent points.
  - Contour plot (of 2D KDE).
  - Binning.
- Can demonstrate using diamonds data (53940 observations).

Scatterplot

```
sns.scatterplot(data = diam, y = 'price', x = 'carat')
```

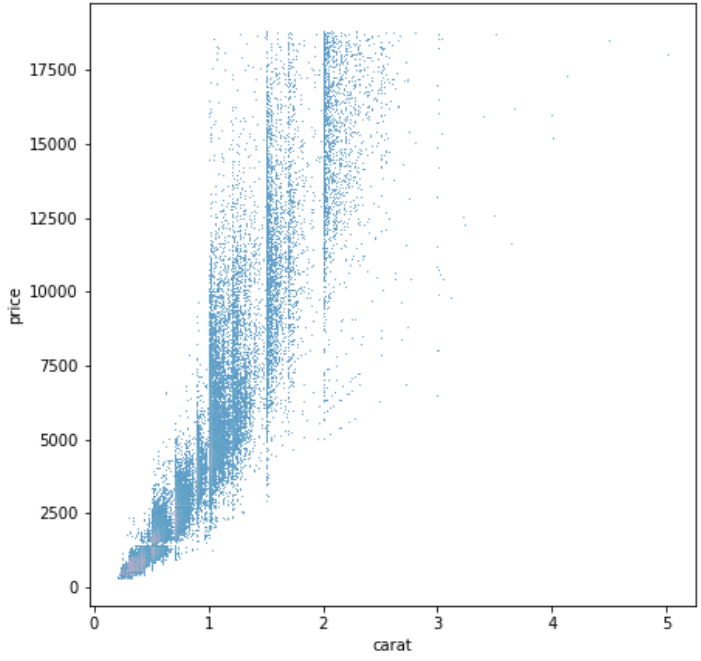


Overplotting

- There are so many points in the region towards the bottom left of the plot that points are on top of one another.
- This causes issues with how the plot is rendered.
- It is difficult to tell where any modes are.
- We will construct the same plot but with different strategies to deal with overplotting.

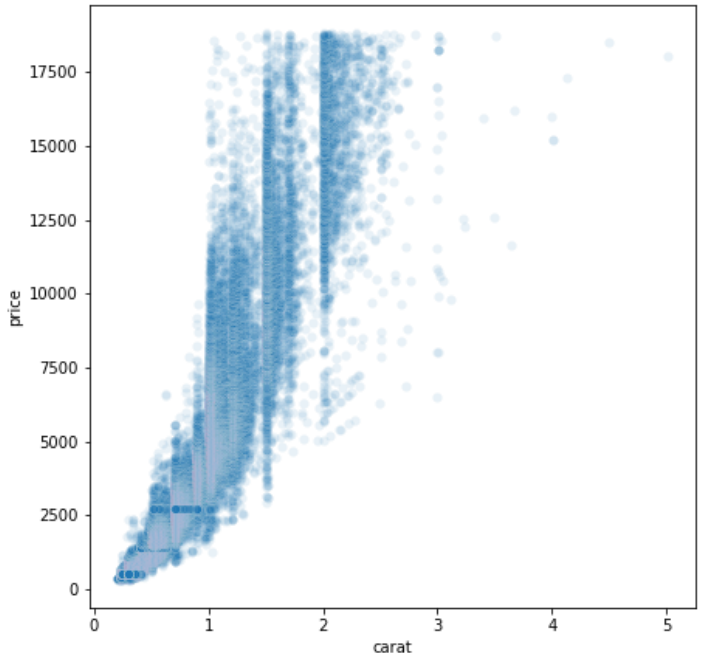
Smaller points

```
sns.scatterplot(data = diam, y = 'price', x = 'carat', s=1)
```



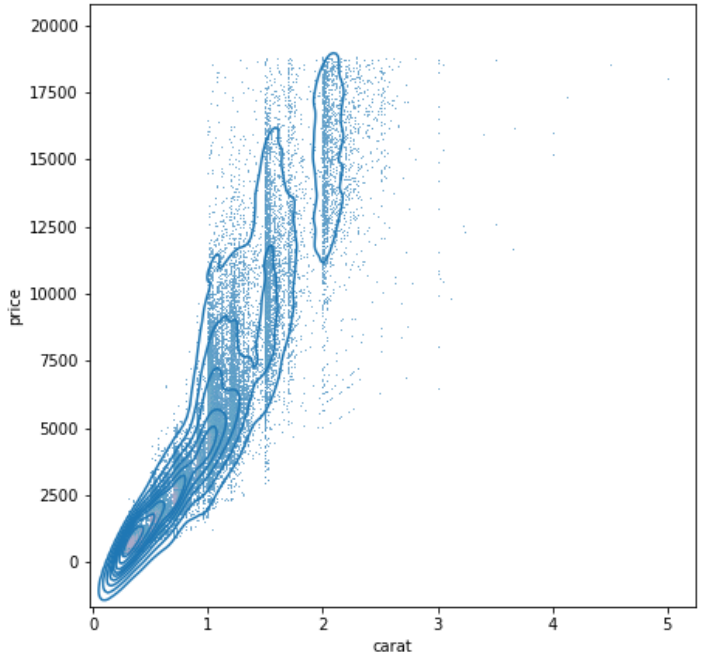
Transparent points

```
sns.scatterplot(data = diam, y = 'price', x = 'carat', alpha=0.1)
```



Add KDE contours

```
sns.scatterplot(data = diam, y = 'price', x = 'carat', s=1)
sns.kdeplot(data = diam, y = 'price', x = 'carat')
```

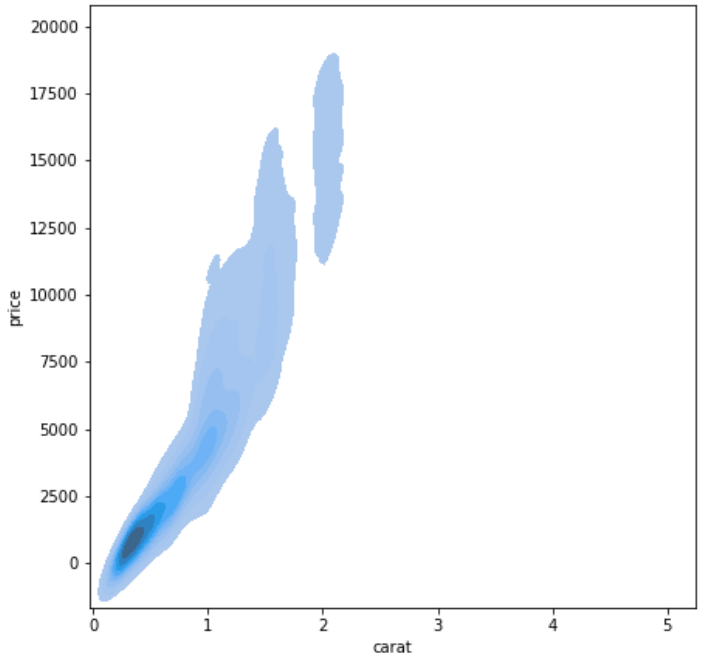


Two dimensional KDE

- Kernel function now takes a vector as an input and returns a single number as an output.
- Think of each kernel as a pile of sand on a table, and the value of the function is the height of the sand.
- The contour lines give all the values of price and carat that evaluate to the same density value.
- If any of you are familiar with elevation maps used in geography (e.g for mountain climbers), this is the same idea.

With shading

```
sns.kdeplot(data = diam, y = 'price', x = 'carat', shade = True)
```

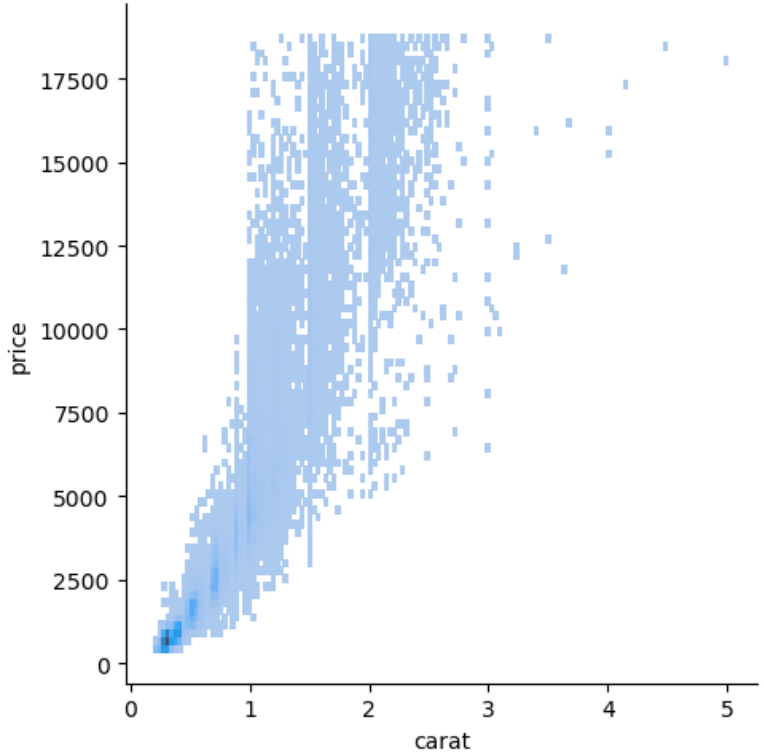


Binning

- Recall a KDE is a smooth version of a histogram.
- We can plot a "2D histogram" by binning the data into rectangles and using color to represent the frequncy of observations in each rectangle.
- This can be useful for locating modes in bivariate data.

Binning

```
sns.displot(data = diam, y = 'price', x = 'carat')
```



Discussion

- The advantage of binning (compared to a KDE) is that you can still see outliers
- However the KDE is a "smoother" plot that can still be overlaid with a scatterplot.
- Again there is no right or wrong plot, it depends on the story you want to tell.

Wrap-up

Conclusions

- Visualising two variables helps us to understand about the distribution of the variables including
  - Modes
  - Outliers
- In adddition we can understand more about the relationship between the two variables
  - Direction of relationship.
  - Whether relationship is linear
- Log transformations can be useful to help visualise variables.
- With big data, important to avoid overplotting.

Questions