Intro to data exploration and visualization

SDS 323

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Types of features in a data set

Categorical: the answer to a multiple choice question:

- Chevy/Honda/Tesla
- ice cream/cake/pie

Ordinal: categorical, where the answers have an ordering but not a magnitude

- Poor, Moderate, Good, Great
- Private, Corporal, Lieutenant, Colonel, General

Numerical: numbers, whether integer or real-valued

• Beware the "faux numerical" ordinal scale

The basics of data exploration

- Boxplots
- Scatter plots
- Line graphs
- Faceting

- Tables
- Grouping/piping/summarizing
- Bar plots
- Histograms/density plots

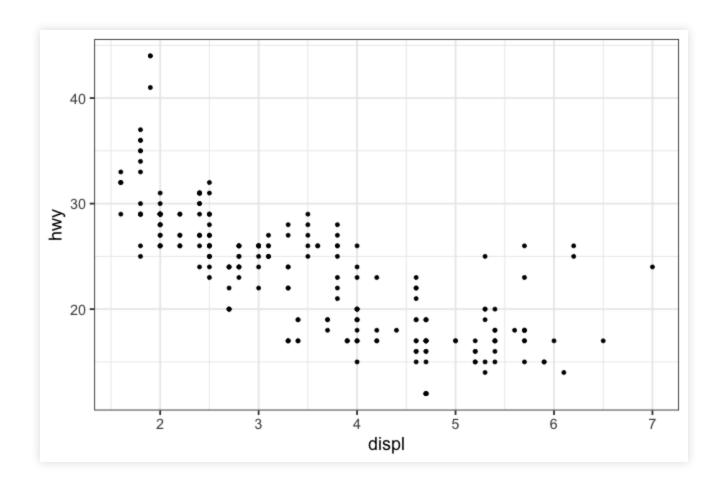
Scatter plots

Here are several rows of a data frame about cars. Every row is a car. Every column is a feature describing the car.

```
# A tibble: 6 x 12
 manufacturer model displ year
                                    cyl trans drv
                                                       cty
                                                             hwy fl
                                                                        class
               <chr> <dbl> <int> <int> <chr> <int> <int> <int> <chr>
  <chr>
1 ford
               f150...
                        4.6 1999
                                      8 manu... 4
                                                        13
                                                              16 r
                                                                        pick...
2 toyota
                       2.4 2008
                                                        22
               camr...
                                      4 auto... f
                                                              31 r
                                                                        comp...
                       5.4 1999
                                      8 auto... r
                                                              17 r
3 ford
               expe...
                                                                        suv
                                                              24 r
              tibu...
                       2.7 2008
                                      6 manu... f
                                                        16
4 hyundai
                                                                        subc...
                       3.3 1999
5 nissan
               path...
                                                        15
                                                              17 r
                                      6 manu... 4
                                                                        suv
                        6.2 2008
6 chevrolet
               corv...
                                      8 manu... r
                                                        16
                                                              26 p
                                                                        2sea...
# ... with 1 more variable: orig.id <chr>
```

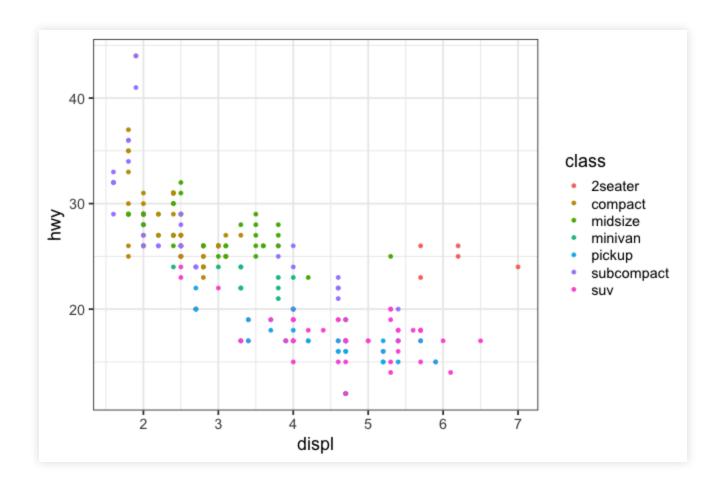
Scatter plots

For numerical data, our workhorse is the humble scatter plot.



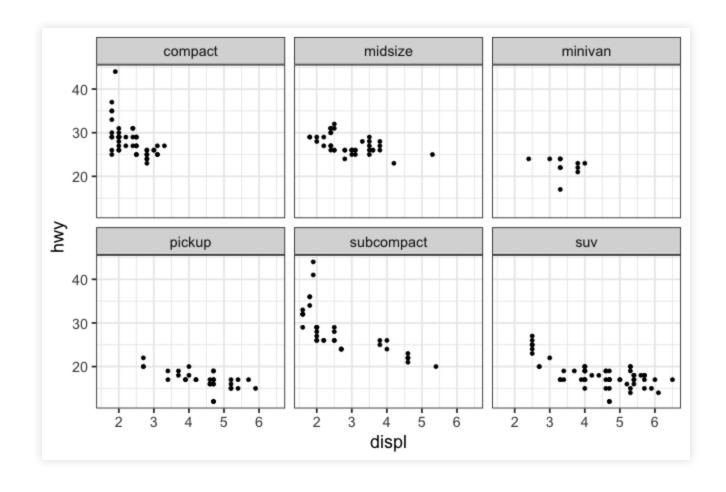
Scatter plots

There are lots of strategies for enriching a scatter plot with additional information. We can color points according to a key...



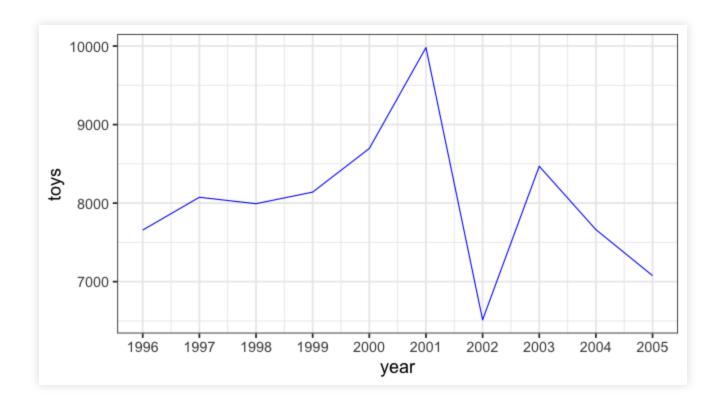
Scatter plots: faceting

Or facet on a third variable...



Line graphs

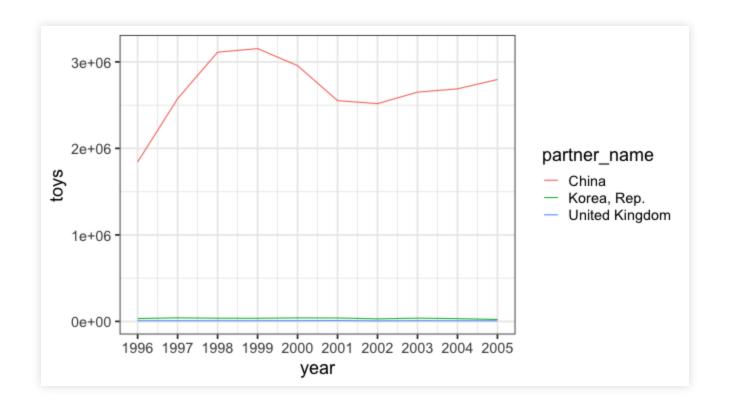
When it's important to emphasize continuity of a set of points (e.g. over time), use a line graph.



Total value of toy imports from the United Kingdom over time (thousands USD). Q: what might account for the big spikes?

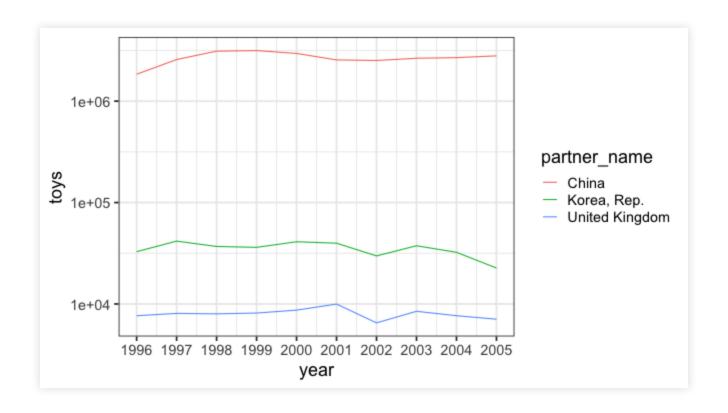
Line graphs

Actually, all those Harry Potter toys come from China...



Line graphs

This is what logarthimic scales were invented for :-)



Note: OK not to start this y axis at 0, because we don't use height to judge relative size on a log scale.

Here are the first several rows of a data frame about passengers on the Titanic. Every row is a passenger. Every column is a feature describing the passenger.

```
age passengerClass
                             name survived
                                              sex
                                       yes female 29.0000
  Allen, Miss. Elisabeth Walton
                                                                     1st
 Allison, Master. Hudson Trevor
                                             male 0.9167
                                                                     1st
    Allison, Miss. Helen Loraine
                                      no female 2.0000
                                                                     1st
4 Allison, Mr. Hudson Joshua Crei
                                             male 30.0000
                                                                     1st
5 Allison, Mrs. Hudson J C (Bessi
                                       no female 25.0000
                                                                     1st
                                            male 48.0000
             Anderson, Mr. Harry
                                                                     1st
                                       yes
```

We see both categorical (sex, passengerClass, survived) and numerical (age) variables.

A natural thing might be to cross-tabulate survival by passenger class:

```
passengerClass
survived 1st 2nd 3rd
no 123 158 528
yes 200 119 181
```

We're literally just counting how many passengers have each combination of features. (If you know Excel: this is like a pivot table.)

An aside: piping

A really useful operation is piping. Example:

```
a = log(3)
b = exp(a)
c = sqrt(b)
c
[1] 1.732051
```

versus:

```
a = log(3)
a %>% exp() %>% sqrt()
[1] 1.732051
```

We can pipe our table to prop.table to standardize along the columns (margin=2):

Now you can compare survival proportions by passenger class.

Seven decimal places seems overkill – let's round to third decimal place by piping the the result to round:

```
xtabs(~survived + passengerClass, data=TitanicSurvival) %>%
  prop.table(margin=2) %>%
  round(3)

    passengerClass
survived 1st 2nd 3rd
  no 0.381 0.570 0.745
  yes 0.619 0.430 0.255
```

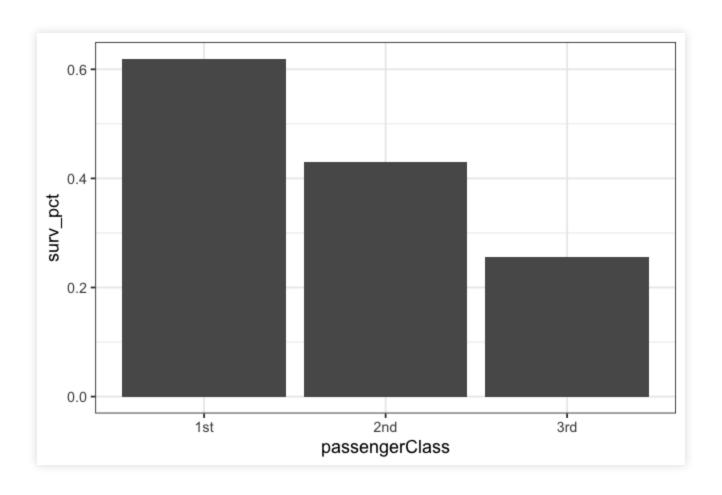
If you pipe the result to kable, you'll get a prettier table (formatted in Markdown):

```
library(knitr)
xtabs(~survived + passengerClass, data=TitanicSurvival) %>%
  prop.table(margin=2) %>%
  round(3) %>%
  kable()
```

	lst	2nd	3rd
no	0.381	0.57	0.745
yes	0.619	0.43	0.255

Bar plots

We can also turn this information into a bar plot.



Remember to start your y-axis at 0!

Another good use of tables is to display summary statistics of numerical variables. For example, here's how we'd use pipes to compute the average age by passenger class:

Use group_by to group cases according to the passengerClass variable. Then compute a summary statistic by averaging age. (na.rm = TRUE tells R to ignore missing values.)

Now with two variables defining the groups:

```
TitanicSurvival %>%
 group by(passengerClass, survived) %>%
 summarize(mean age = mean(age, na.rm=TRUE))
# A tibble: 6 x 3
# Groups: passengerClass [3]
 passengerClass survived mean age
 <fct>
              <fct>
                         <dbl>
1 1st no 2 1st yes
                         43.2
                        36.8
3 2nd
                         33.2
              no
4 2nd
            yes
no
                          24.9
5 3rd
                          26.0
              no
                          21.5
6 3rd
              yes
```

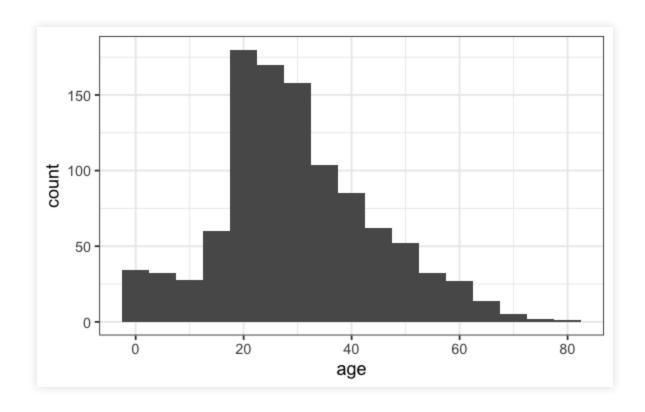
This gives us a "flat" table.

If you want to un-flatten the table, use spread:

spread says to spread out the levels of the survived variables along the columns of the table and put the mean_age variable in each entry.

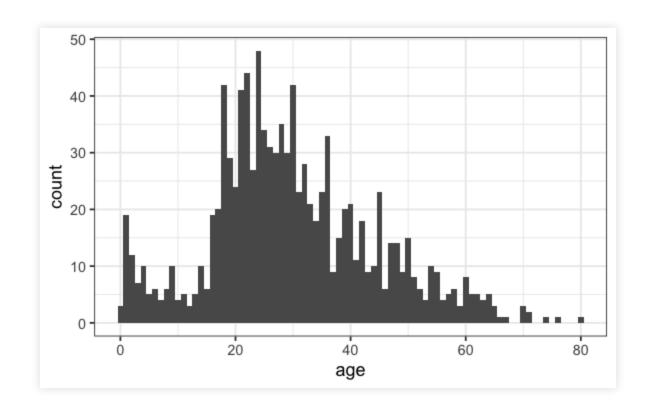
You can compute lots of summary statistics this way:

Now let's say we wanted to look at the *full* distribution of ages on the Titanic (i.e. not just a summary like the average).

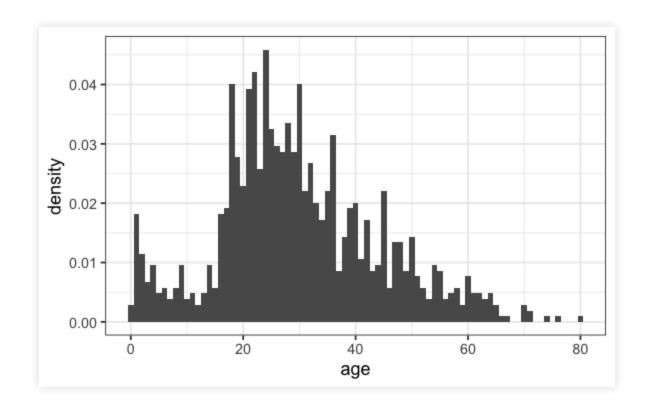


Our workhorse for this kind of thing is a histogram.

We can change the bin width on a histogram (here I, versus 5):



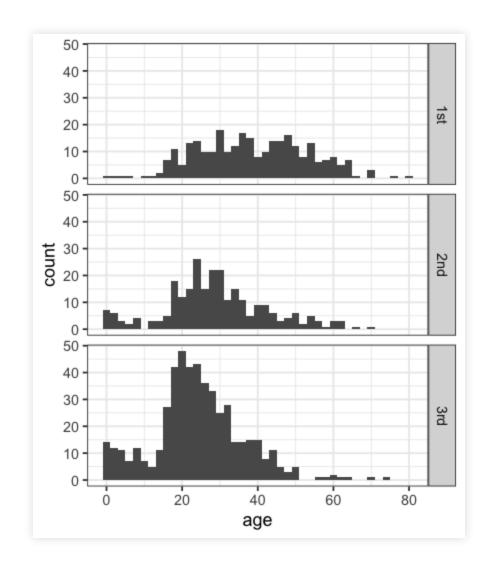
We can also normalize the total area to sum to 1:



This is called a density histogram. It's like an estimated probability density.

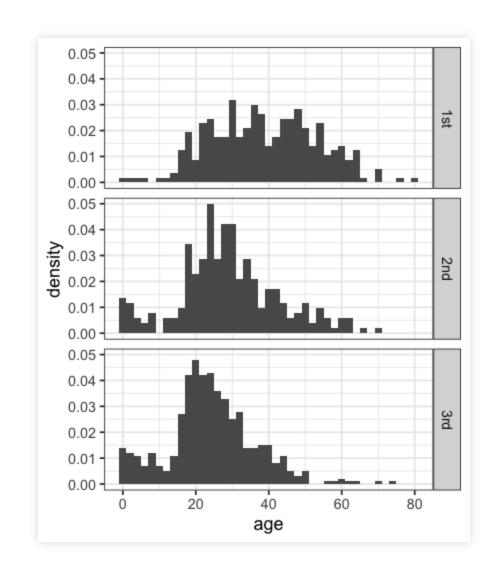
We can also compare histograms across different levels of a categorical variable (recall this is *faceting*).

With raw counts, each histogram has a different total area.



In density form.

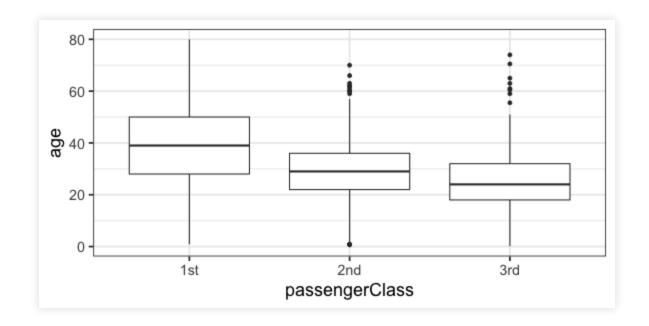
Notice that now, each panel has total area 1.



Boxplots

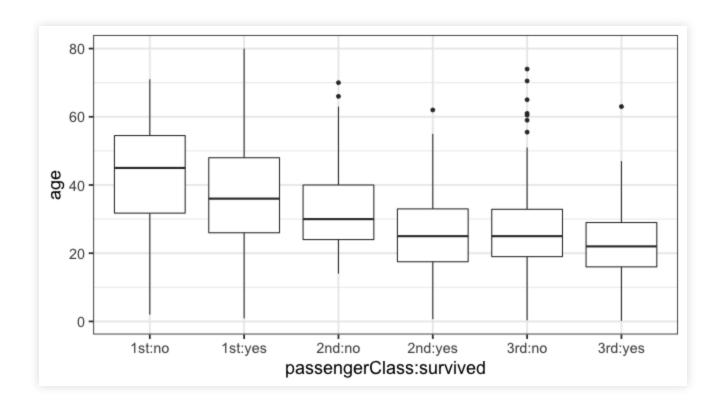
Another way to compare data across categories is with a boxplot.

- Each box shows the median and first/third quartiles.
- By default, the whiskers extend 1.5 times the inter-quartile range. Points outside these are shown individually.



Boxplots

Boxplots are preferred when there are lots of categories, because individual histograms can look cluttered.



Violin plots

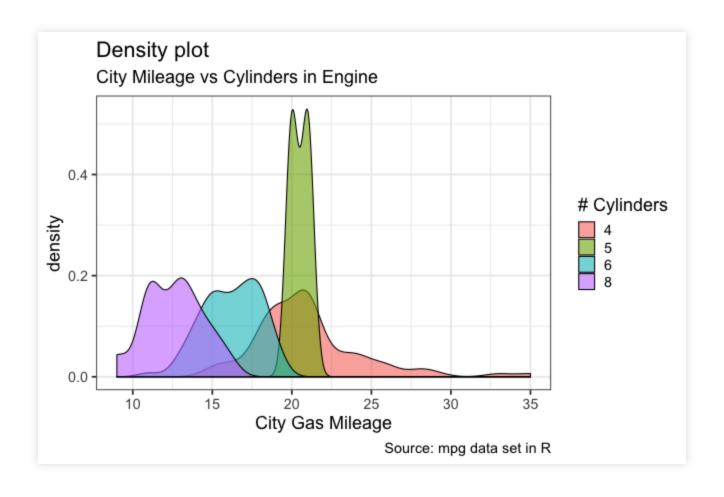
A violin plot is a variant; it attempts to show a bit more of the shape of each distribution.



The width of the violin is kind of like the height of the histogram.

Density plots

Another variant is the density plot, which is like a smooth version of a histogram:



Take-home skills

We've covered:

- data types (categorica/ordinal/numerical)
- cross tabulation and contingency tables
- some basic plots (bar charts, scatter plots, line graphs, histograms and their variations)
- basics of data workflow (pipe/group/summarize)

To the code!

Let's look at the code examples in:

- mpg.R
- titanic.R
- toyimports_linegraph.R