Data Visualization

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DATA 2010—Tools and Techniques for Data Science

Lecture Objectives

- Identify the main types of data visualization
- Contrast their strengths and weaknesses

Motivation

- Summary statistics are useful in doing quick comparisons.
    - Or even statistical inference
- Data visualizations are an effective way of sharing *a lot* of information about a dataset.
- In this slide deck, we'll focus on the main types of data visualizations; in the next one, we'll discuss important principles for **effective** visualization.

Main principles

Why would we want to visualize data?

- Quality control
- Identify outliers
- Find patterns of interest (EDA)
- *Communicate results*

Histogram i

- A **histogram** represents the frequency of observations occurring in certain bins.
  - Most software will choose default bins, but you can always change them.
- It is useful for displaying continuous data, and comparing its distribution across subgroups.

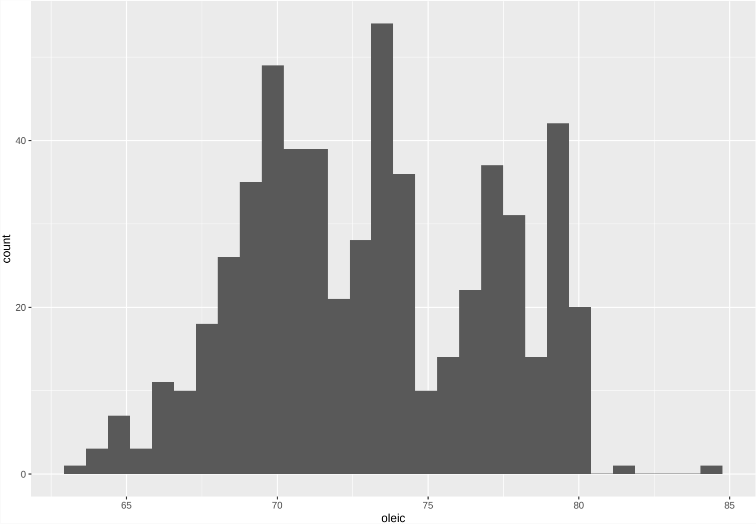
```
library(tidyverse)
library(dslabs)

dim(olive)
```

Histogram ii

```
## [1] 572  10
```

```
# Create histogram for oleic acid
ggplot(olive,
       aes(x = oleic)) +
  geom_histogram()
```

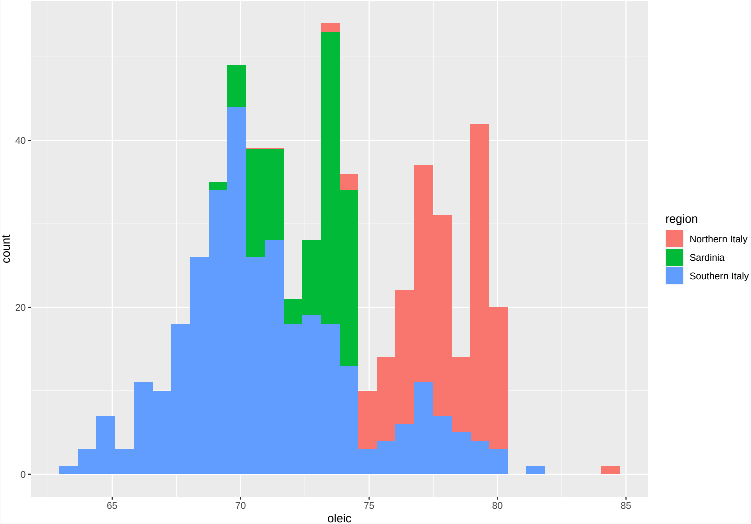
Histogram iii



Histogram iv

```
# Look at distribution by region
ggplot(olive,
       aes(x = oleic, fill = region)) +
  geom_histogram()
```

Histogram v

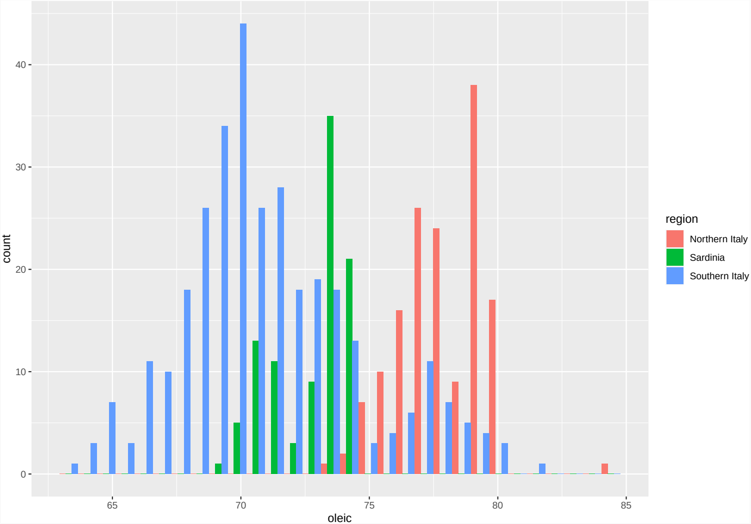


count
40
20
0
65
70
75
80
85
oleic
region
Northern Italy
Sardinia
Southern Italy

Histogram vi

```r
# Dodge instead of stack
ggplot(olive,
       aes(x = oleic, fill = region)) +
  geom_histogram(position = "dodge")
```

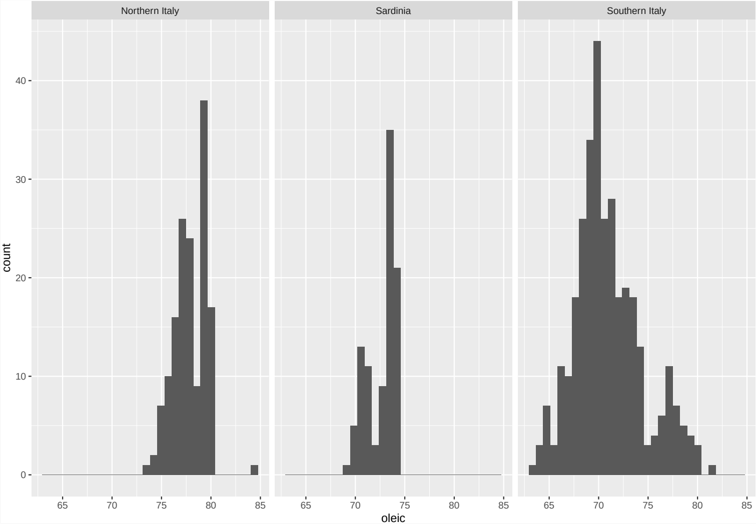
Histogram vii



Histogram viii

```r
# Or with facets
ggplot(olive,
       aes(x = oleic)) +
  geom_histogram() +
  facet_grid( ~ region)
```

Histogram ix



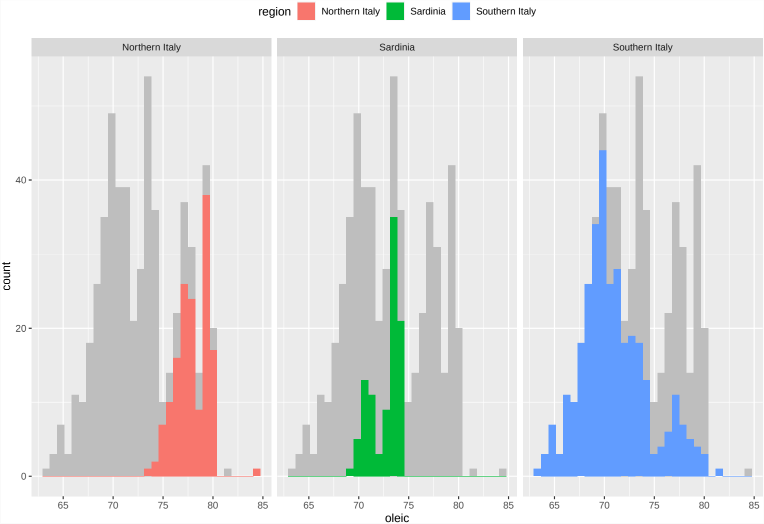
Histogram—Summary

- **Histograms** help visualize the distribution of a single variable.
  - It bins data and displays the counts in each bin
  - But large bins can hide important features, while small bins can create artifacts.
- `ggplot` takes a `data.frame` as input and maps variables to different features of the graph.
  - `oleic` is mapped to the `x`-axis
  - `region` is mapped to the `fill` colour.
  - **Important**: This mapping happens inside the function `aes`.
- `ggplot2` automatically takes care of choosing the colour, drawing the limits, and printing a legend.
- `facet_grid` can be used to display multiple plots together, one per value of the variable.

A more complex histogram i

```r
# Create a copy of the data to serve as background
olive_bg <- select(olive, -region)
ggplot(olive, aes(x = oleic)) +
  # Start with grey background
  geom_histogram(data = olive_bg,
                 fill = 'grey') +
  # Add colour on top
  geom_histogram(aes(fill = region)) +
  facet_grid( ~ region) +
  # Move legend to top
  theme(legend.position = 'top')
```

A more complex histogram ii



A more complex histogram iii

- Note: The order in which you add the layers (e.g. the two `geom_histogram`) is important!
- Try swapping the two `geom_histogram` calls and see what happens.

Exercise

Use the dataset `nba_players_19` from the package `openintro` to plot a histogram of the heights of basketball players.

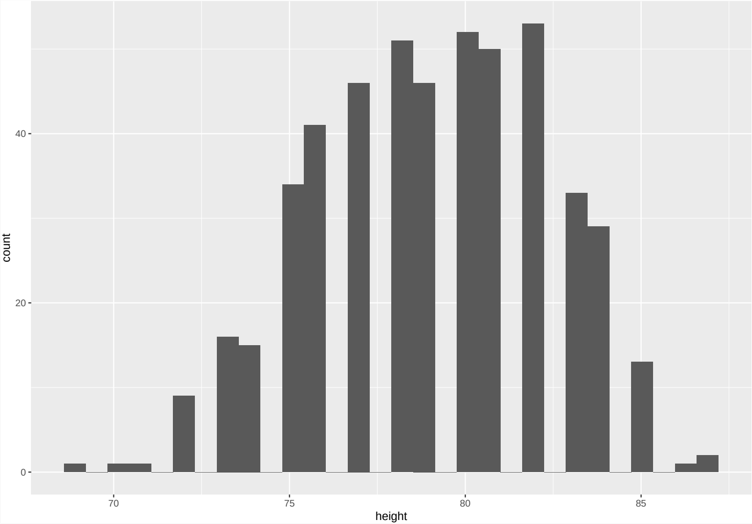
Next, use histograms to compare the height distribution of guards vs centers.

Solution i

- First, we plot the overall histogram.

```r
library(tidyverse)
library(openintro)

ggplot(nba_players_19, aes(height)) +
  geom_histogram()
```

Solution ii

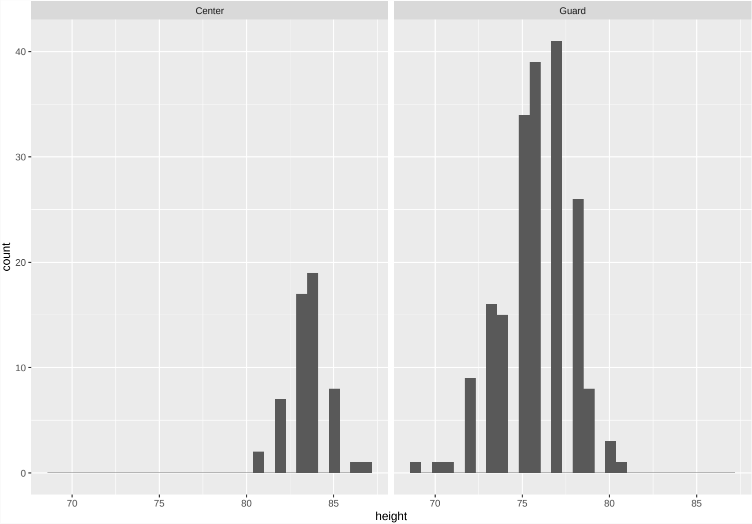


Solution iii

- Next, we need to figure out which variable encodes the position of each player.
    - You can look at the help page `?nba_players_19`.
    - You can look at `str(nba_players_19)`.
- Then we can filter using `position`.

```
nba_players_19 %>%
  filter(position %in% c("Center", "Guard")) %>%
  ggplot(aes(height)) +
  geom_histogram() +
  facet_grid(~position)
```

Solution iv

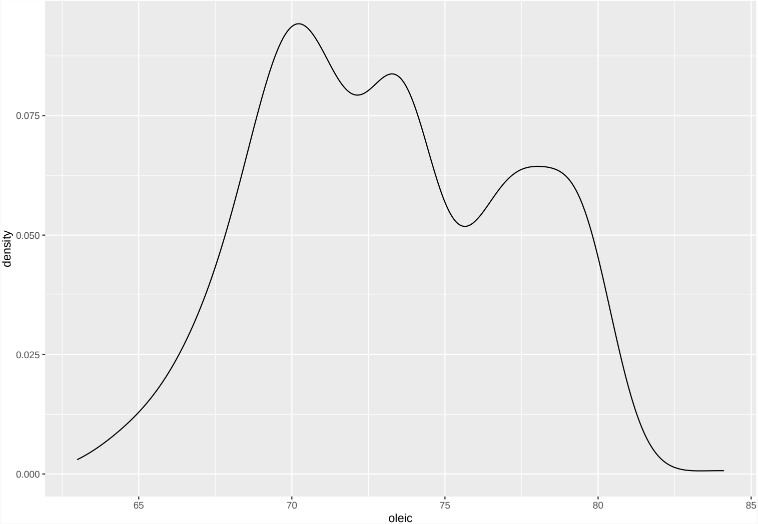


Density plot i

- **Density plots** can be thought of as *smoothed* histograms.
    - Their mathematical definition is much more involved and beyond the scope of this course.
- They can be used interchangeably with histograms.

```
ggplot(olive, aes(x = oleic)) +
  geom_density()
```

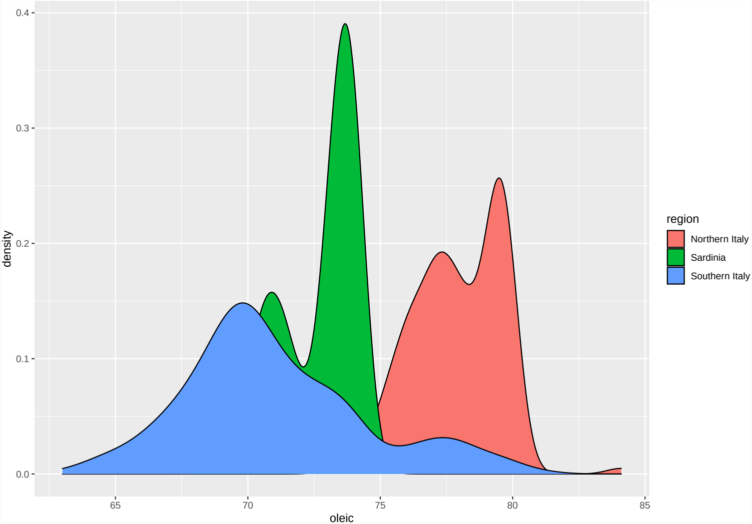
Density plot ii



Density plot iii

```r
# Split by region
ggplot(olive, aes(x = oleic,
                  fill = region)) +
  geom_density()
```

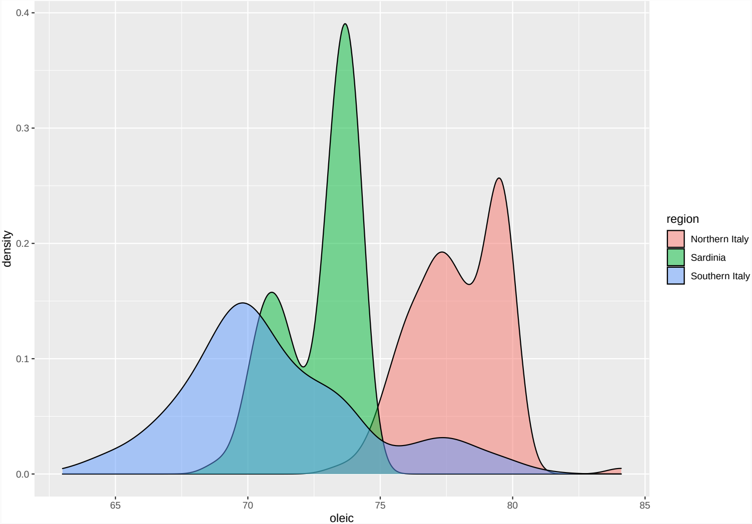
Density plot iv



Density plot v

```r
# Add transparency
ggplot(olive, aes(x = oleic,
                  fill = region)) +
  geom_density(alpha = 0.5)
```

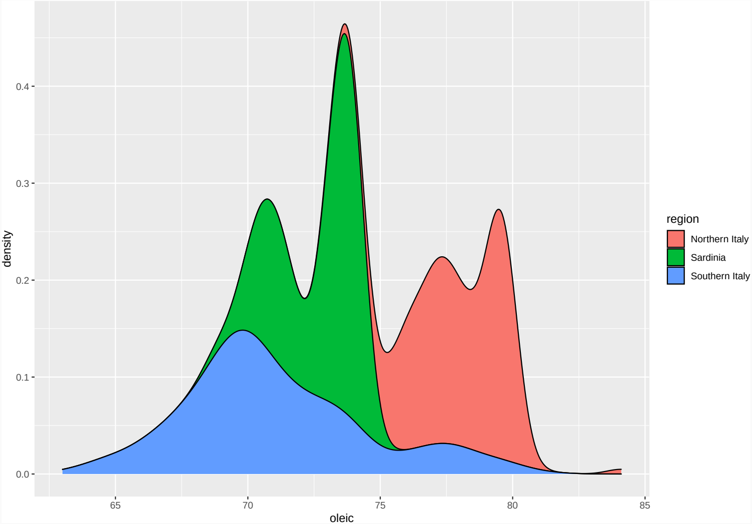
Density plot vi



Density plot vii

```
# Alternative: stacked density plots
ggplot(olive, aes(x = oleic,
                  fill = region)) +
  geom_density(position = "stack")
```

Density plot viii



Density plot—Summary

- **Density plots** can be thought of as *smoothed* histograms.
    - There is a parameter (`adjust`) controlling the level of smoothness: too large and it will hide important features; too small and it may create artifacts.
- We used a different *geom* to create the plot.
    - `geom_density` as opposed to `geom_histogram`.
- The attribute `alpha` can be used to control transparency.
    - `alpha = 0` is completely transparent
    - `alpha = 1` is completely opaque.

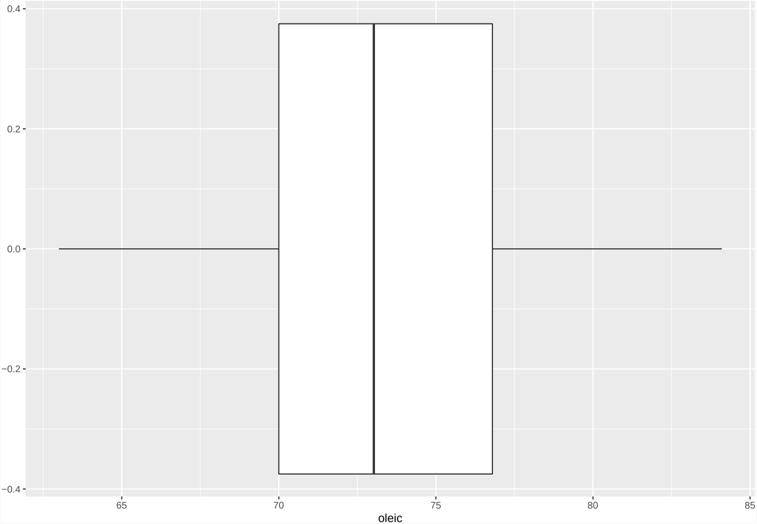
Boxplot i

- Box plots are a simple way to display important quantiles and identify outliers
- Components (per Tukey):
    - A box delimiting the first and third quartile;
    - A line indicating the median;
    - Whiskers corresponding to the lowest datum still within 1.5 IQR of the lower quartile, and the highest datum still within 1.5 IQR of the upper quartile;
    - Any datum that falls outside the whiskers is considered a (potential) outlier.

Boxplot ii

```
ggplot(olive, aes(x = oleic)) +
  geom_boxplot()
```

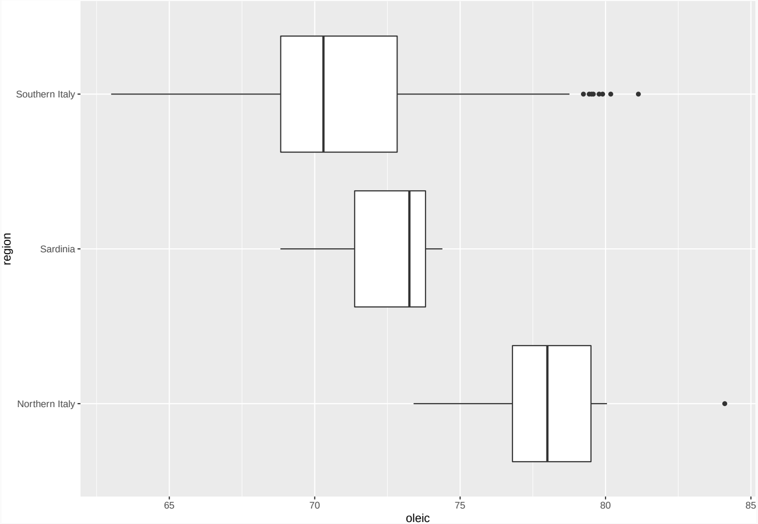
Boxplot iii



Boxplot iv

```r
# Map region to y-axis
ggplot(olive, aes(x = oleic,
                  y = region)) +
  geom_boxplot()
```

Boxplot v

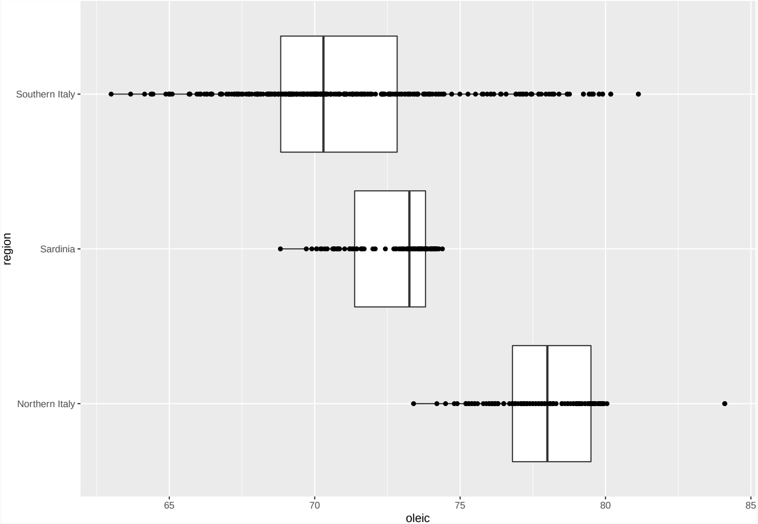


Southern Italy
Sardinia
Northern Italy
region
65
70
75
80
85
oleic

Boxplot vi

```r
# Add all points on top of boxplots
ggplot(olive, aes(x = oleic,
                  y = region)) +
  geom_boxplot() +
  geom_point()
```

Boxplot vii

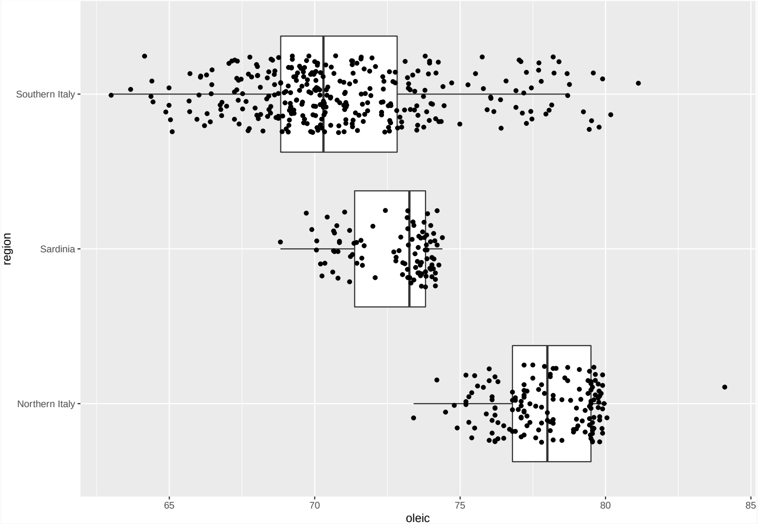


Southern Italy
Sardinia
Northern Italy
region
65
70
75
80
85
oleic

Boxplot viii

```r
# Add vertical noise to the points to reduce overlap
# Note: need to remove outliers or you will get
#       duplicates
ggplot(olive, aes(x = oleic,
                  y = region)) +
  geom_boxplot(outlier.colour = NA) +
  geom_jitter(height = 0.25, width = 0)
```

Boxplot ix

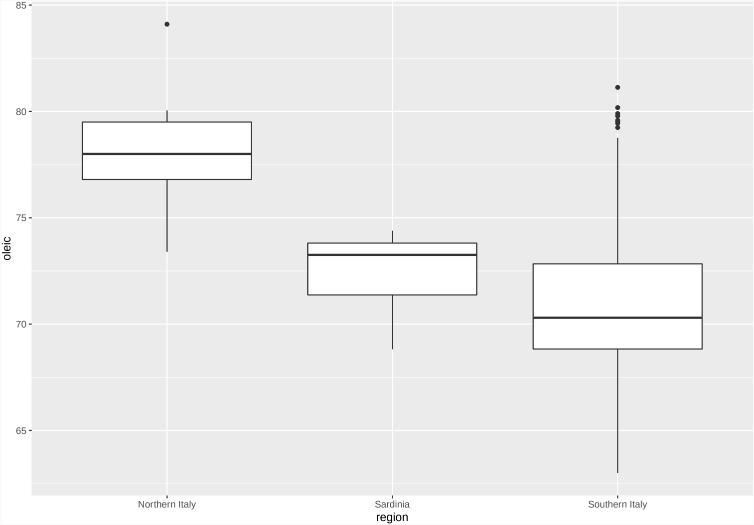


Southern Italy
Sardinia
Northern Italy
region
65
70
75
80
85
oleic

Boxplot x

```r
# Flip boxplots by switching the axes
ggplot(olive, aes(x = region,
                  y = oleic)) +
  geom_boxplot()
```

Boxplot xi


85
80
75
70
65
oleic
Northern Italy
Sardinia
Southern Italy
region

Boxplot—Summary

- **Boxplots** are a mixture between a data visualization and a summary statistics.
    - It is essentially a graphical depiction of the five-number summary.
- Widely different datasets can give rise to the same boxplot.
    - I recommend to overlay the actual data (potentially jittered).

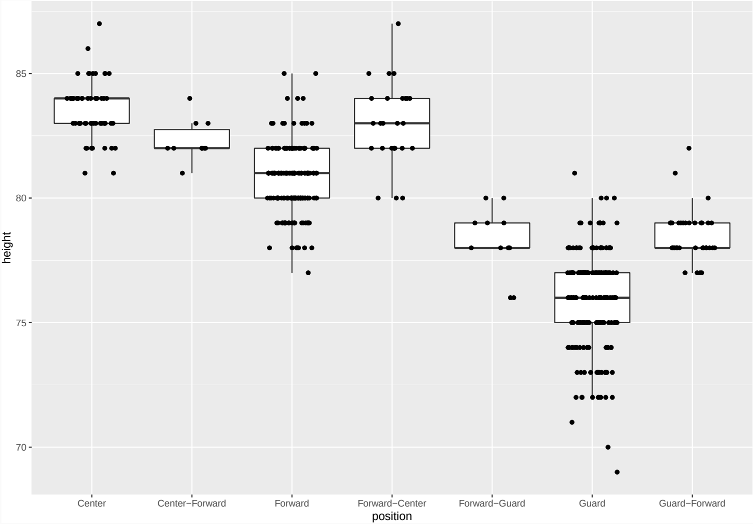
Exercise

Using the dataset `nba_players_19` from the package `openintro`, compare the distribution of heights across all positions.

Solution i

```r
ggplot(nba_players_19, aes(x = position,
                           y = height)) +
  geom_boxplot(outlier.colour = NA) +
  geom_jitter(height = 0, width = 0.25)
```

Solution ii



85
80
75
70
height
Center
Center−Forward
Forward
Forward−Center
Forward−Guard
Guard
Guard−Forward
position

Single-variable visualization

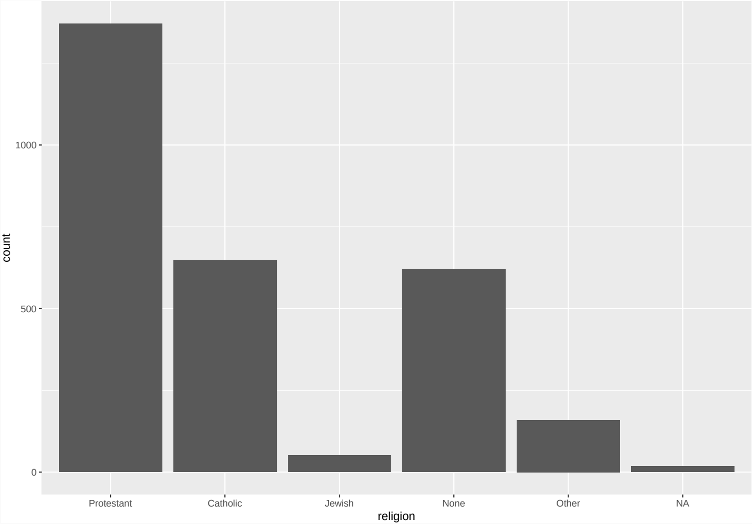
- All three data visualizations above focused on a single continuous variable.
- But you can draw one such visualization for the same variable, but in different subgroups.
    - E.g. GPA for math, biology and psychology majors.
- In this way, they can all be used to investigate the relationships between *one continuous and one categorical variable*.

Bar plots i

- **Bar plots** are a very efficient way of displaying counts or percentages for different levels of a categorical variable.
  - Much, much better than pie charts
- When displaying summary statistics, they are also known as **dynamite plots**.
  - I **don't** recommend the use of dynamite plots.

```
library(socviz)

ggplot(gss_sm, aes(x = religion)) +
  geom_bar()
```

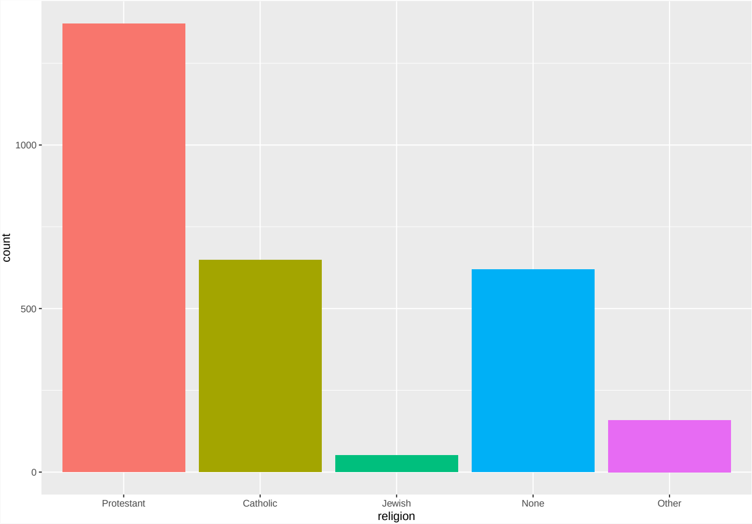
Bar plots ii


1000
500
0
count
Protestant
Catholic
Jewish
None
Other
NA
religion

Bar plots iii

```r
# Remove NA and add fill colour
gss_sm |>
  filter(!is.na(religion)) |>
  ggplot(aes(x = religion)) +
  geom_bar(aes(fill = religion),
           show.legend = FALSE)
```

Bar plots iv

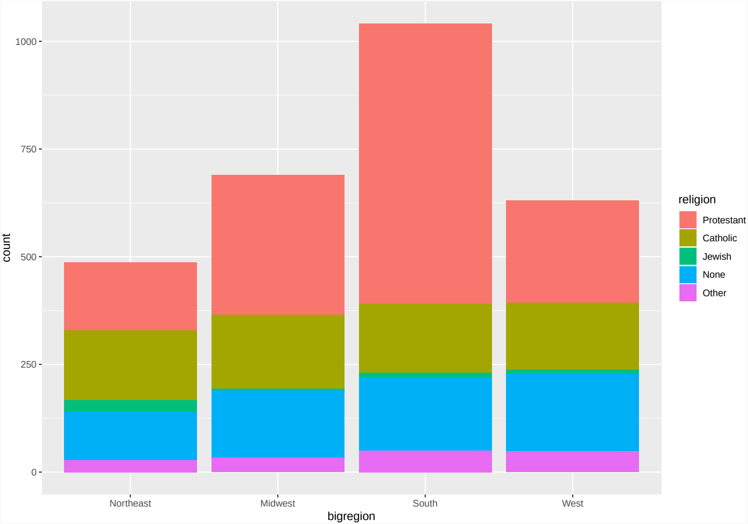


count
1000
500
0
Protestant
Catholic
Jewish
None
Other
religion

Bar plots v

```r
# Across two categorical variables
gss_sm |>
  filter(!is.na(religion)) |>
  ggplot(aes(x = bigregion)) +
  geom_bar(aes(fill = religion))
```

Bar plots vi

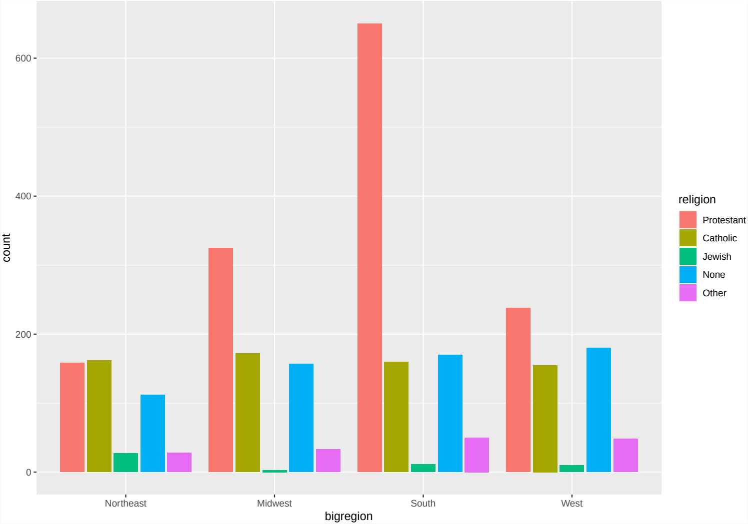


count
1000
750
500
250
0
Northeast
Midwest
South
West
bigregion
religion
Protestant
Catholic
Jewish
None
Other

Bar plots vii

```
# Use dodge instead of stack
gss_sm |>
  filter(!is.na(religion)) |>
  ggplot(aes(x = bigregion)) +
  geom_bar(aes(fill = religion),
           position = "dodge2") # Adds some white space
```

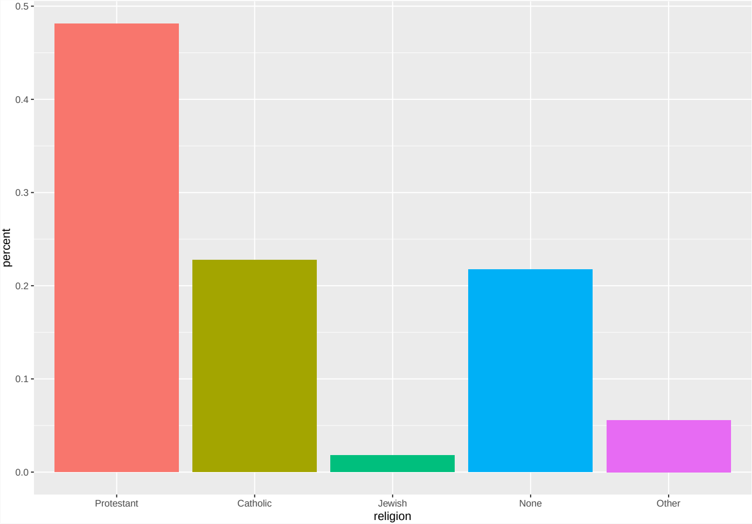
Bar plots viii



Bar plots ix

```
# For %, summarize first
gss_sm |>
  filter(!is.na(religion)) |>
  count(religion) |>
  mutate(percent = n/sum(n)) |>
  ggplot(aes(x = religion, y = percent)) +
  geom_col(aes(fill = religion),
           show.legend = FALSE)
```

Bar plots x

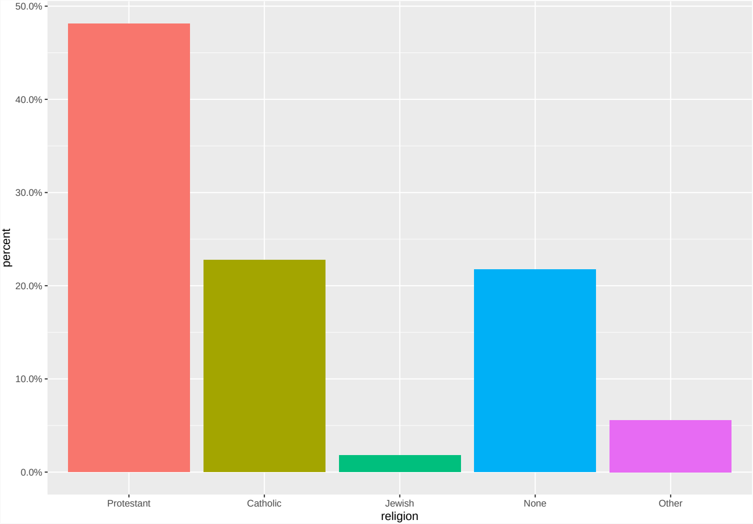


0.5
0.4
0.3
0.2
0.1
0.0
percent
Protestant
Catholic
Jewish
None
Other
religion

Bar plots xi

```r
# Turn into % by changing y scale
gss_sm |>
  filter(!is.na(religion)) |>
  count(religion) |>
  mutate(percent = n/sum(n)) |>
  ggplot(aes(x = religion, y = percent)) +
  geom_col(aes(fill = religion),
           show.legend = FALSE) +
  scale_y_continuous(labels = scales::percent)
```

Bar plots xii



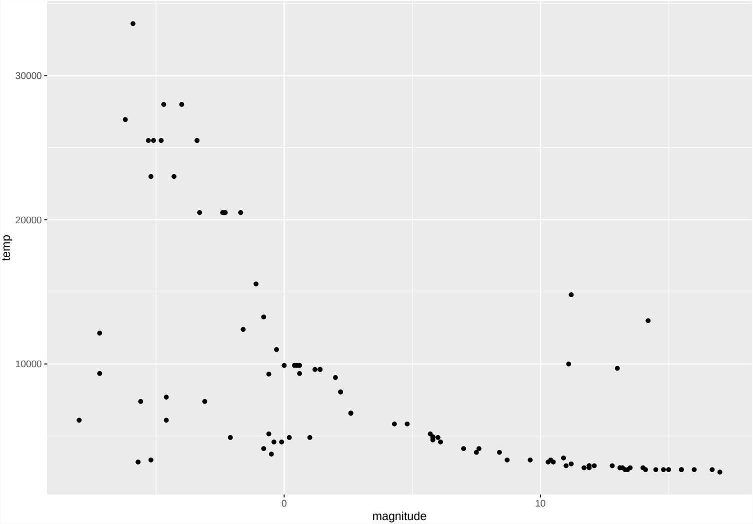
Bivariate plots

Scatter plot i

- The simplest way to represent the relationship between two continuous variables is a **scatter plot**.
    - Not really suitable with categorical variables.
- Technically still possible with three variables, but typically more difficult to read.

```
ggplot(stars, aes(x = magnitude,
                  y = temp)) +
  geom_point()
```

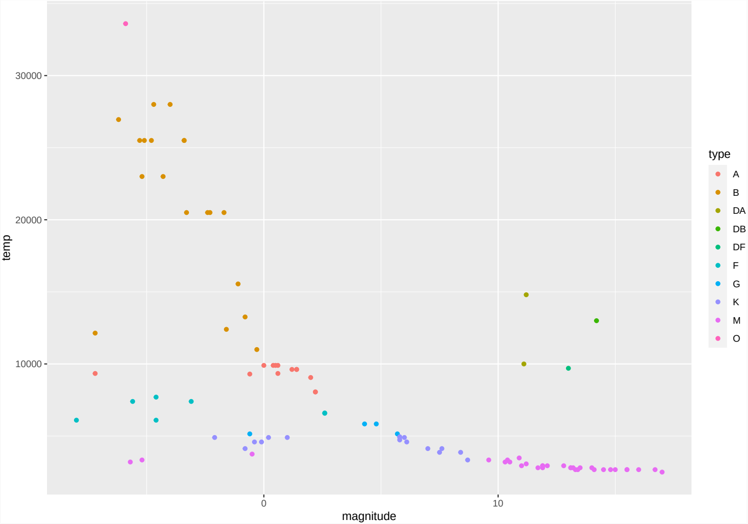
Scatter plot ii



Scatter plot iii

```r
# Add colour for type of stars
ggplot(stars, aes(x = magnitude,
                  y = temp,
                  colour = type)) +
  geom_point()
```

Scatter plot iv



Exercise

Use the dataset `babies_crawl` from the package `openintro` to plot the average crawling age against the average outdoor temperature at 6 months.

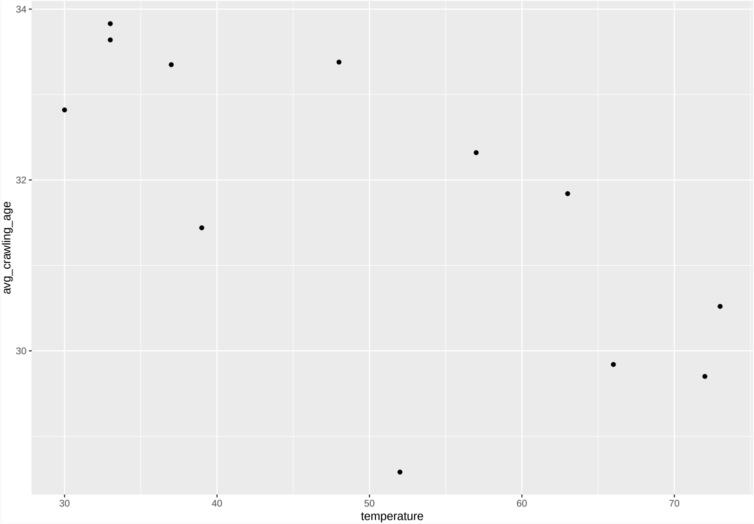
Solution i

- First, we need to figure out the name of the variables we need to plot.
    - You can look at the help page `?babies_crawl`.
    - You can look at `str(babies_crawl)`.
- Our two variables are `temperature` and `avg_crawling_age`

Solution ii

```r
library(tidyverse)
library(openintro)

ggplot(babies_crawl, aes(x = temperature,
                         y = avg_crawling_age)) +
  geom_point()
```

Solution iii

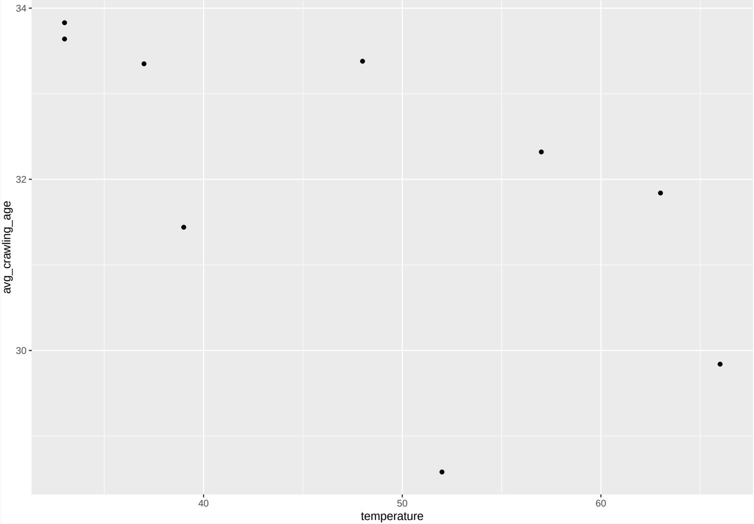


Solution iv

- What if we want to restrict the range of temperatures?

```
# First option
# Restrict the data before plotting
babies_crawl %>%
    filter(temperature > 30, temperature < 70) %>%
    ggplot(aes(x = temperature,
               y = avg_crawling_age)) +
    geom_point()
```

Solution v

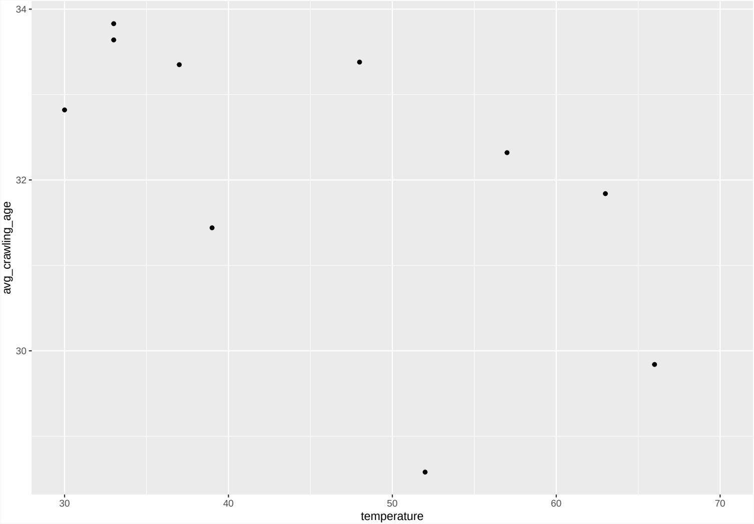


Solution vi

```r
# Second option
# xlim removes the points from the plot
ggplot(babies_crawl, aes(x = temperature,
                         y = avg_crawling_age)) +
    geom_point() +
    xlim(c(30, 70))
```

```
## Warning: Removed 2 rows containing missing values (ge
```

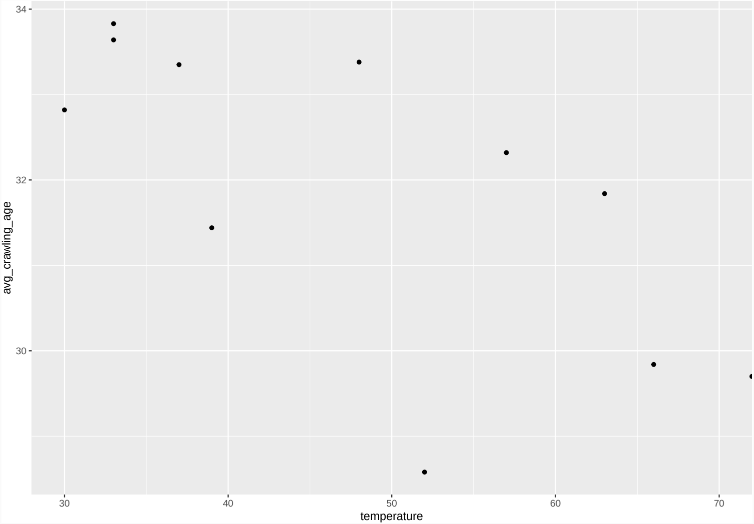
Solution vii



Solution viii

```
# Third option
# coord_cartesian zooms in/out
ggplot(babies_crawl, aes(x = temperature,
                         y = avg_crawling_age)) +
    geom_point() +
    coord_cartesian(xlim = c(30, 70))
```

Solution ix



Beyond two variables

Limitations

- Three-dimensional scatter plots are possible, but hard to interpret.
- Density plots can technically be constructed for any dimension
    - But as the dimension increases, its performance *decreases* rapidly
- **Solution**: We can look at each variable one at a time and at each pairwise comparison.

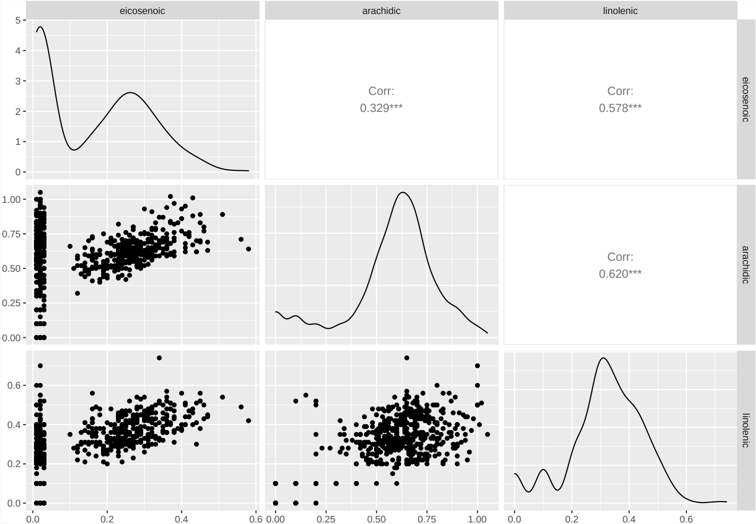
Pairs plot i

- A pairs plot arranges these univariate summaries and pairwise comparisons along a matrix.
- Each variable corresponds to both a row and a column
- Univariate summaries appear on the diagonal, and pairwise comparisons off the diagonal.
- Because of symmetry, we often see a different summary of the comparison above and below the diagonal.

Pairs plot ii

```r
library(GGally)

# Select three variables
olive_sub <- olive %>%
  select(eicosenoic, arachidic, linolenic)

ggpairs(olive_sub)
```

Pairs plot iii



Pairs plot iv

- As we can see, `GGally` displays the following:
    - Scatter plots below the diagonal
    - Density plots on the diagonal
    - Pearson correlations above the diagonal
- These can all be changed—see the documentation for more information.