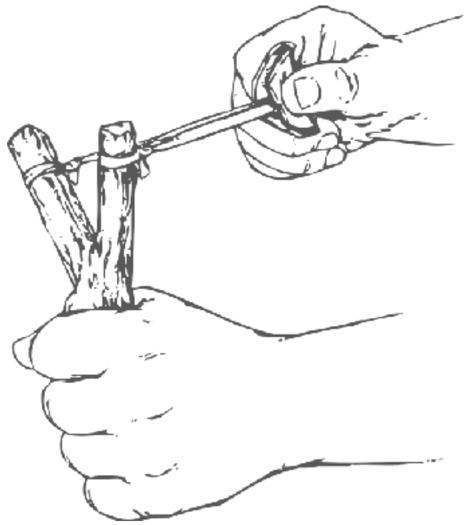
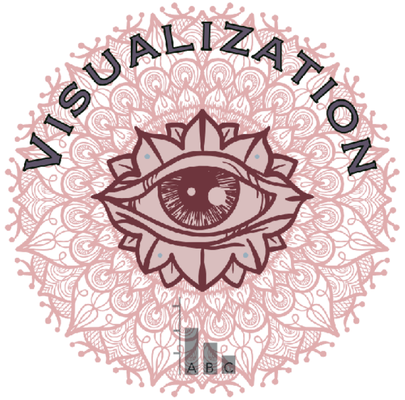
DATA ANALYSIS

DATA VISUALIZATION

LEARNING GOALS



- obtain a basic understanding of better/worse plotting
  - understand the idea of hypothesis-driven visualization
- develop a basic understanding of the 'grammar of graphs'
- get familiar with frequent visualization strategies
  - barplots, densities, violins, error bars etc.
- be able to fine-tune graphs for better visualization



Motivation

WHY VISUALIZE

- a picture can be worth a million words (and numbers)
- every data analysis should start with a ‘getting to know the data’ phase
  - visualization of different aspects of data is key to get intimate with the data
- data visualization as a means of communication (with others)
  - hypothesis-driven visualization: obtain visual (suggestive) evidence regarding a research question of relevance

WHY VISUALIZE

- a picture can be worth a million words (and numbers)
  - summary statistics can be misleading (because of information loss)
- every data analysis should start with a ‘getting to know the data’ phase
  - use extensive visualization to get intimate with the data
- data visualization as a means of communication (with others / with yourself)
  - hypothesis-driven visualization: obtain visual (suggestive) evidence regarding a research question of relevance

BEYOND SUMMARY STATISTIC

Motivating example: Anscombe's quartet

- famous data set, ships with core R

```
glimpse(anscombe %>% as_tibble)
```

```
## Observations: 11
## Variables: 8
## $ x1 <dbl> 10, 8, 13, 9, 11, 14, 6, 4, 12, 7, 5
## $ x2 <dbl> 10, 8, 13, 9, 11, 14, 6, 4, 12, 7, 5
## $ x3 <dbl> 10, 8, 13, 9, 11, 14, 6, 4, 12, 7, 5
## $ x4 <dbl> 8, 8, 8, 8, 8, 8, 8, 19, 8, 8, 8
## $ y1 <dbl> 8.04, 6.95, 7.58, 8.81, 8.33, 9.96,
## $ y2 <dbl> 9.14, 8.14, 8.74, 8.77, 9.26, 8.10,
## $ y3 <dbl> 7.46, 6.77, 12.74, 7.11, 7.81, 8.84,
## $ y4 <dbl> 6.58, 5.76, 7.71, 8.84, 8.47, 7.04,
```

messy start

```
tidy_anscombe <- anscombe %>% as_tibble %>%
  pivot_longer(
    ## we want o pivot every column
    everything(),
    ## use reg-exps to capture 1st and 2nd character
    names_pattern = "(.)(.)",
    ## assign names to new cols, using 1st part of
    ##  what reg-exp captures as new column names
    names_to = c(".value", "grp")
  ) %>%
  mutate(grp = paste0("Group ", grp))
tidy_anscombe
```

tidy up

```
## # A tibble: 44 x 3
##    grp         x     y
##    <chr>   <dbl> <dbl>
##  1 Group 1    10  8.04
##  2 Group 2    10  9.14
##  3 Group 3    10  7.46
##  4 Group 4     8  6.58
##  5 Group 1     8  6.95
##  6 Group 2     8  8.14
##  7 Group 3     8  6.77
##  8 Group 4     8  5.76
##  9 Group 1    13  7.58
## 10 Group 2    13  8.74
## # ... with 34 more rows
```

nice!

Motivating example: Anscombe's quartet

```
## # A tibble: 44 x 3
##    grp          x     y
##    <chr>    <dbl> <dbl>
##  1 Group 1     10  8.04
##  2 Group 2     10  9.14
##  3 Group 3     10  7.46
##  4 Group 4      8  6.58
##  5 Group 1      8  6.95
##  6 Group 2      8  8.14
##  7 Group 3      8  6.77
##  8 Group 4      8  5.76
##  9 Group 1     13  7.58
## 10 Group 2     13  8.74
## # ... with 34 more rows
```

input data

```
tidy_anscombe %>%
  group_by(grp) %>%
  summarise(
    mean_x    = mean(x),
    mean_y    = mean(y),
    min_x     = min(x),
    min_y     = min(y),
    max_x     = max(x),
    max_y     = max(y),
    crrltn    = cor(x,y)
  )
```

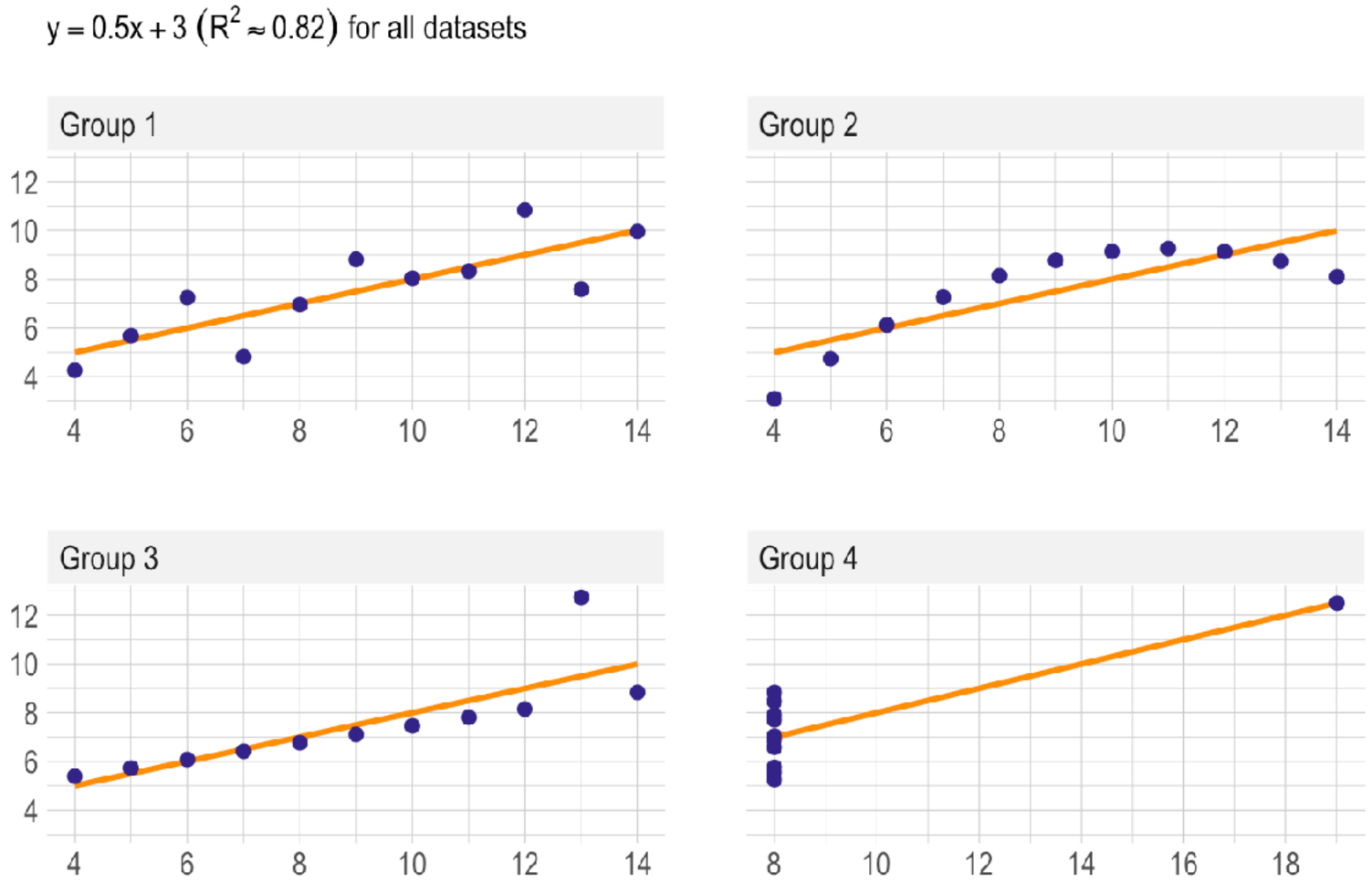
summarise

```
## # A tibble: 4 x 8
##   grp     mean_x mean_y min_x min_y max_x max_y crrltn
##   <chr>    <dbl>  <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
## 1 Group 1      9   7.50     4  4.26    14 10.8   0.816
## 2 Group 2      9   7.50     4  3.1     14  9.26  0.816
## 3 Group 3      9   7.5      4  5.39    14 12.7   0.816
## 4 Group 4      9   7.50     8  5.25    19 12.5   0.817
```

all four groups look very similar!

Motivating example: Anscombe's quartet

- quite different patterns despite similar correlation



The good, the bad and the info-graphic

PRINCIPLE OF GOOD VISUALIZATION

- maximize data-ink ratio (Tufte 1983)
  - maximize information, minimize ink
  - eliminate chart junk
  - ink vs. processing effort
- analogy to language
  - information flow
  - ease of processing
  - bound by conventional rules
- hypothesis-driven visualization
  - relevance of information

The vague & defeasible rule of thump of good data visualization (according to the author).

"Communicate a maximal degree of relevant true information in a way that minimizes the recipient's effort of retrieving this information."

How to Maximize the Data-ink Ratio?

To maximize the data-ink ratio, Edward Tufte suggested two principles to erase redundant elements from data visualization.

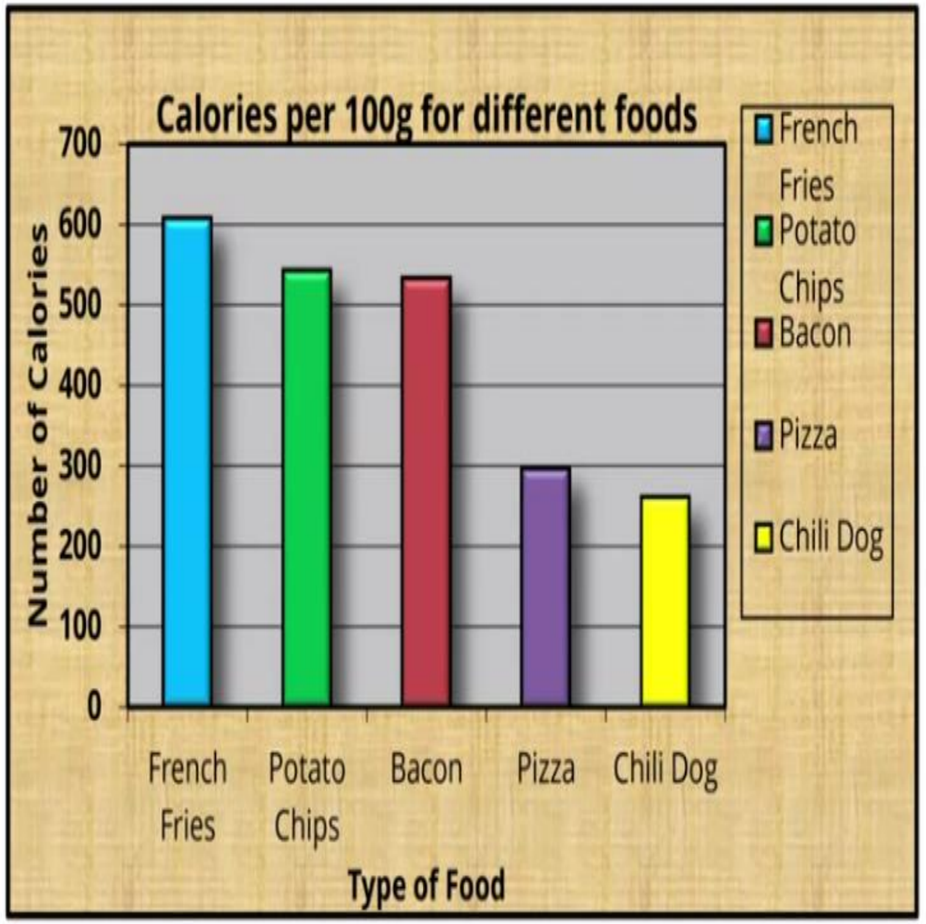
- **Erase non-data ink within reason**: Elements like 3-D effects, grids, annotations, colors, and borders that don't add any information should be deleted from the visualization.
- **Erase redundant data ink within reason**: In a chart, there can be different elements that convey the same information. In such a case, we can remove redundant elements that don't add any unique information to the visualization. The elements that often fall in this category are legends, labels, and information unrelated to the visualization. For example, you can add labels to a bar chart and legends to the chart simultaneously. In such a case, the legends become redundant. It has been explained in the example in the next section.

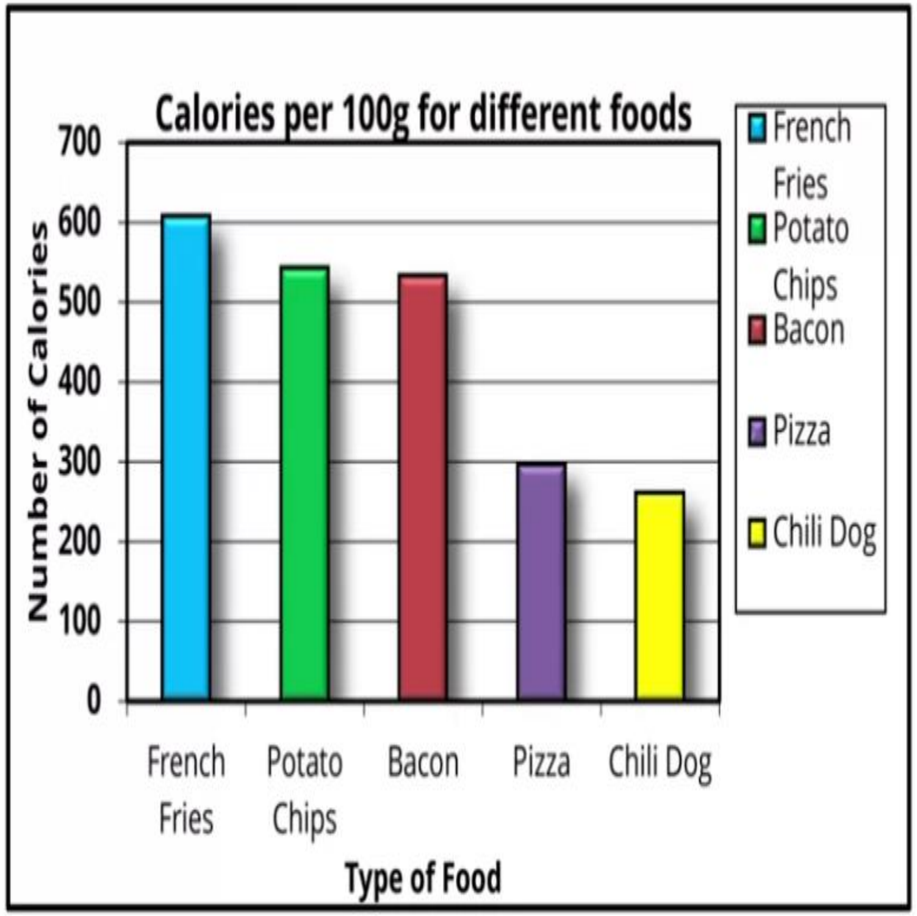
Five Laws of Data Ink

Edward Tufte has stated five laws of data ink for representing data in visualization as given below.

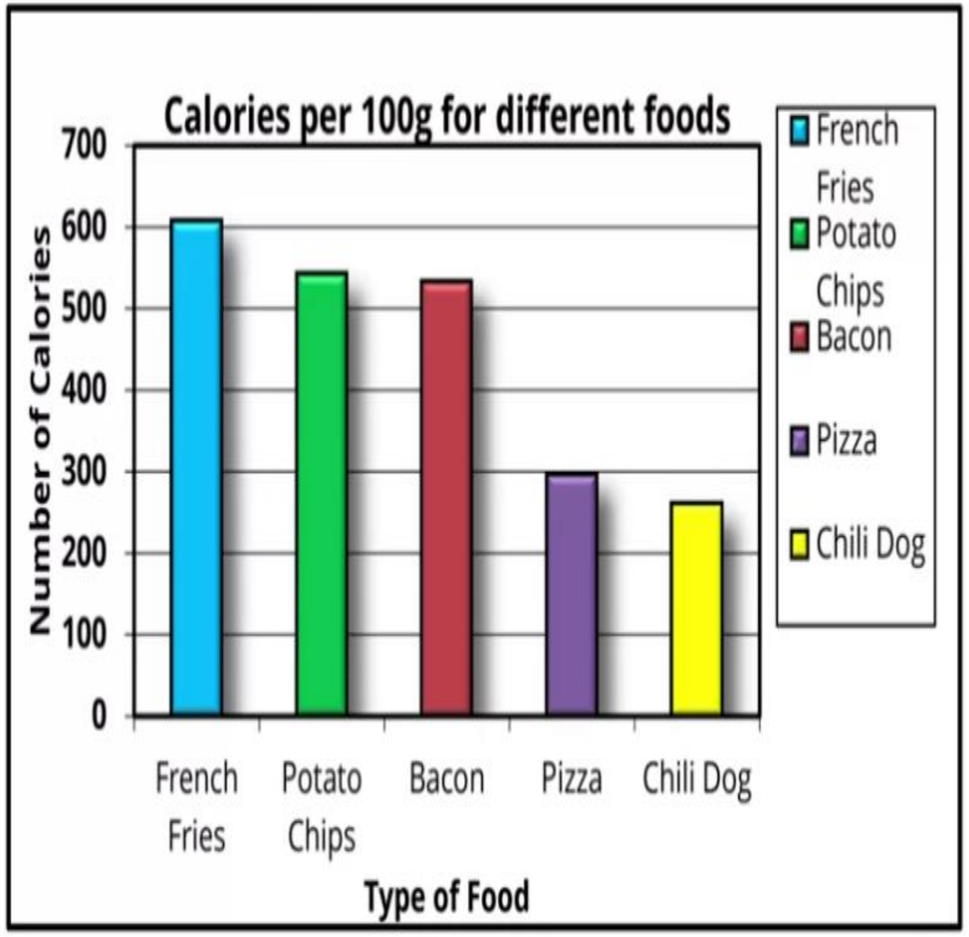
1. **Above all else, show the data**: Keep in mind that we need to show the data to the viewer. Hence, we should show all the relevant data in the chart. The data should be the number one priority.
2. **Maximize the data-ink ratio**: While presenting the data, we should focus on maximizing the data-ink ratio.
3. **Erase non-data ink**: To increase the data-ink ratio, we should erase all the elements of the visualization that don't contribute any information.
4. **Erase redundant data ink**: We should also delete the elements that show redundant data from the visualization.
5. **Revise and edit**: While creating any visualization, we should critically evaluate it and make sure that we have proper elements in the visualization and that there is no redundancy.

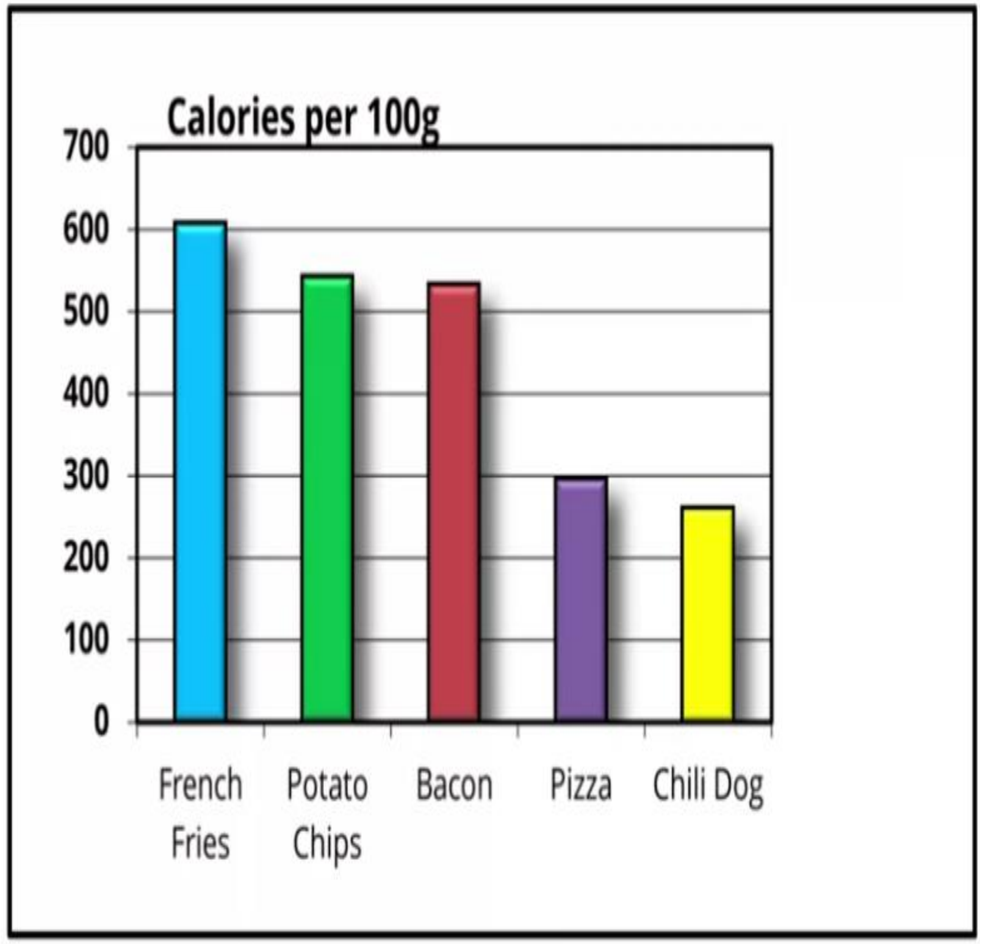
Data ink Ratio Maximization Example



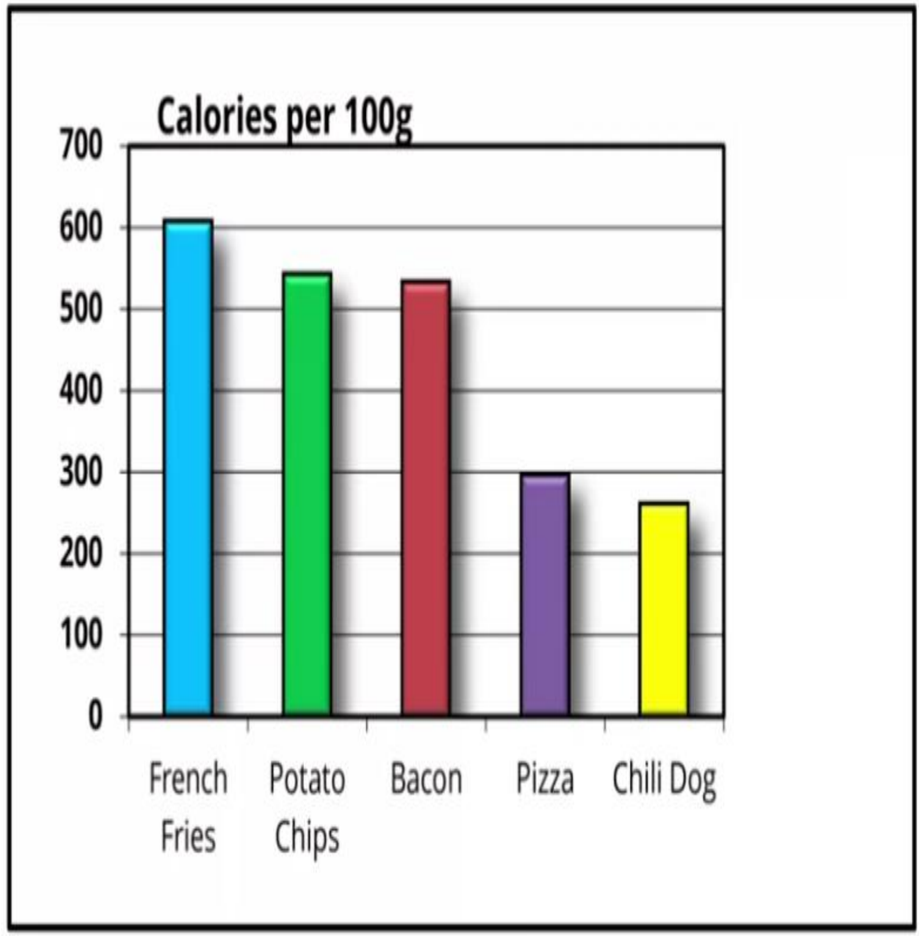


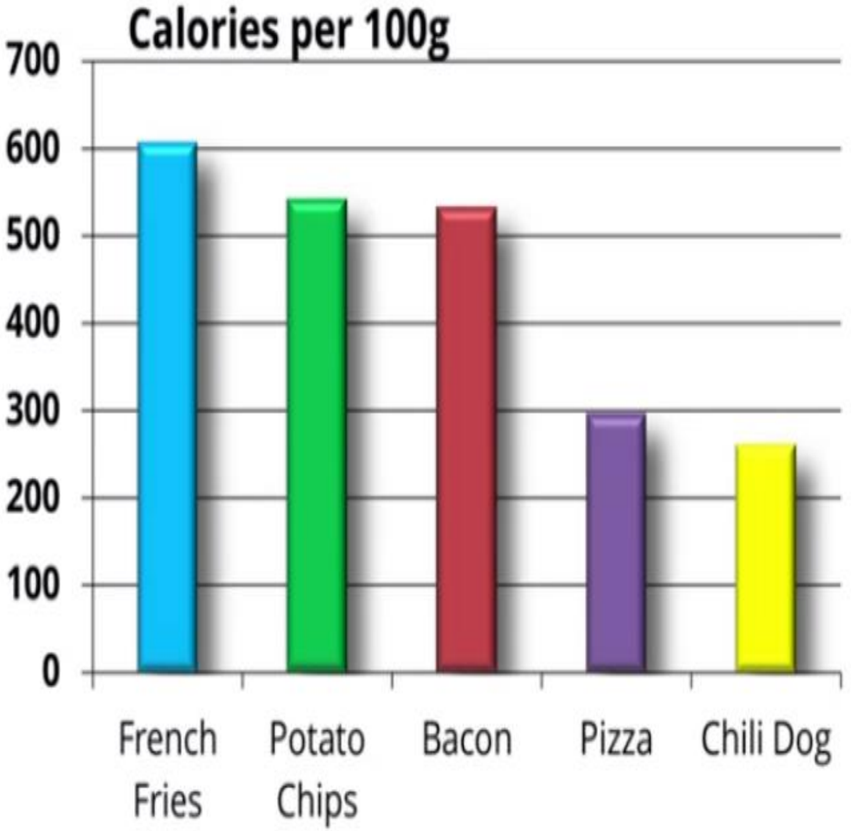
Data ink Ratio Maximization Example



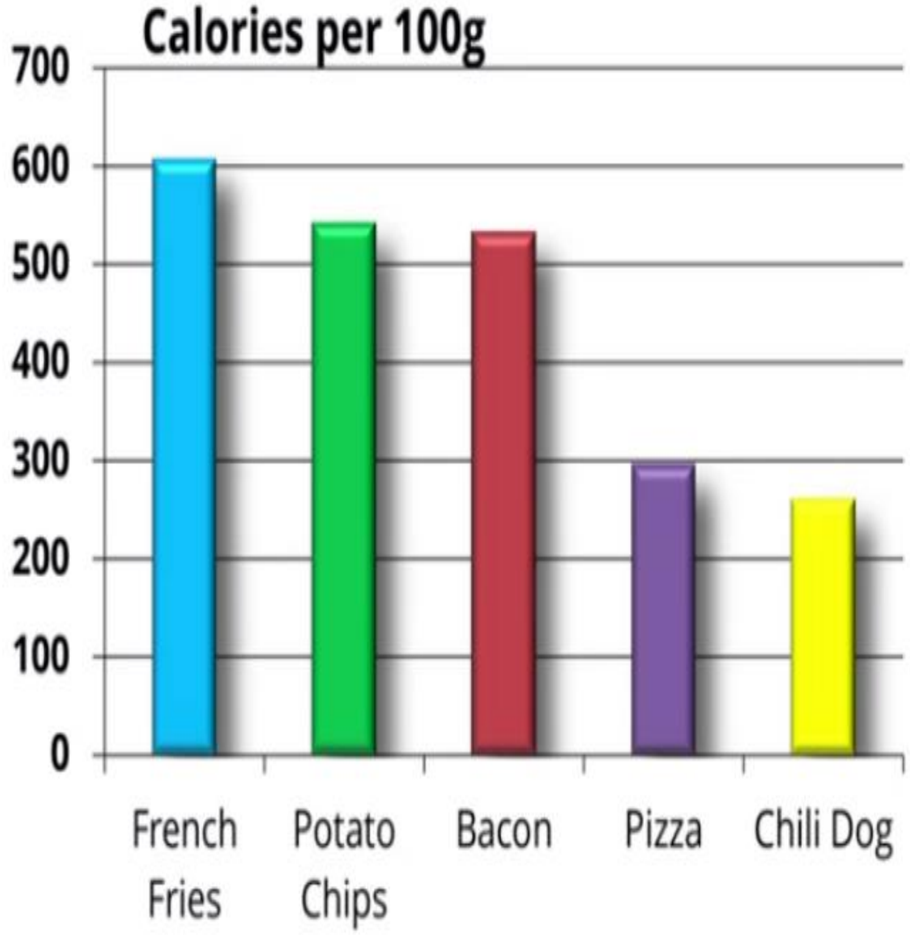


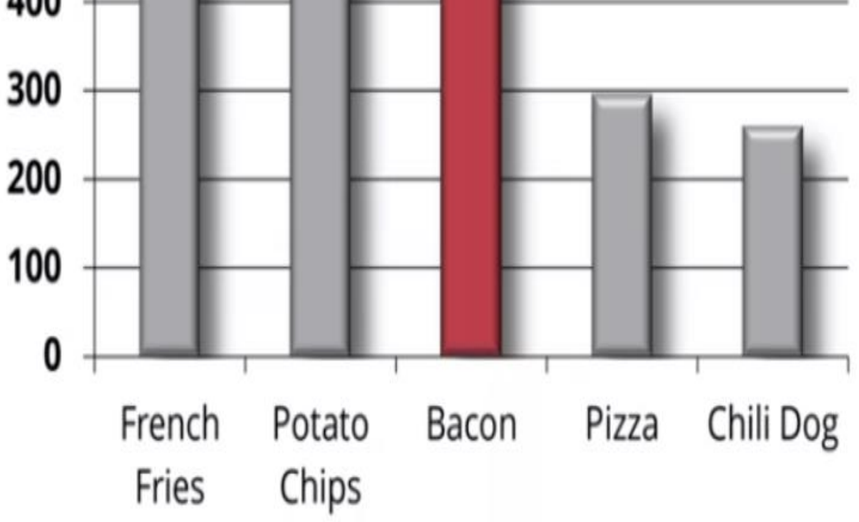
Data ink Ratio Maximization Example



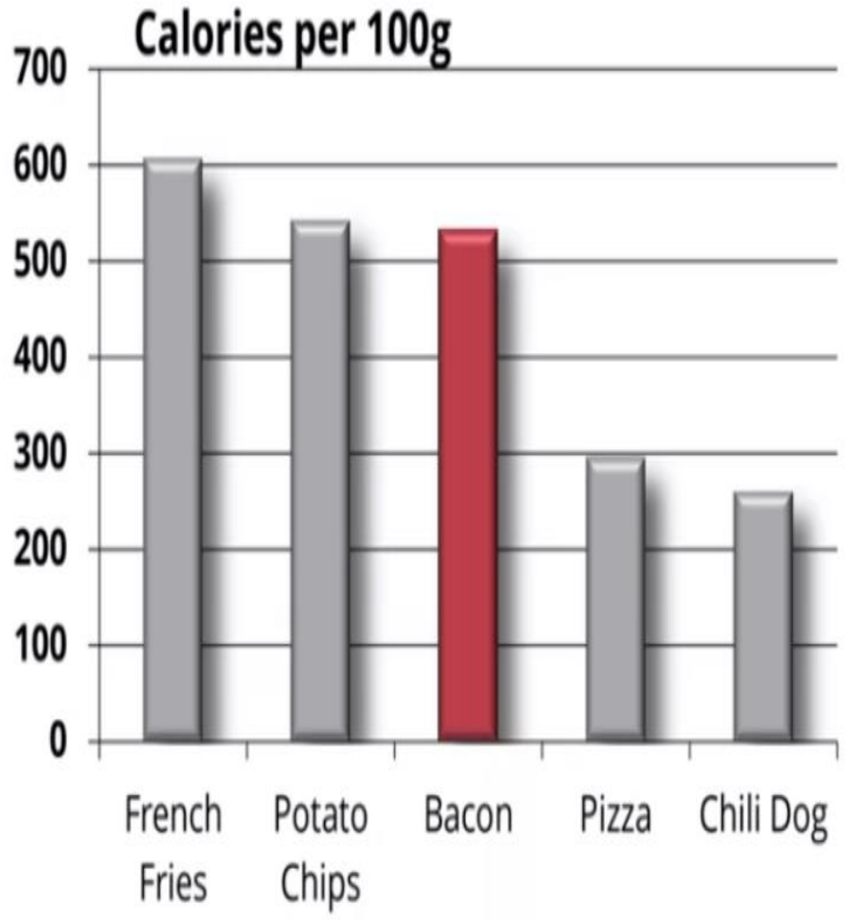


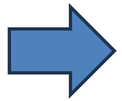
Data ink Ratio Maximization Example

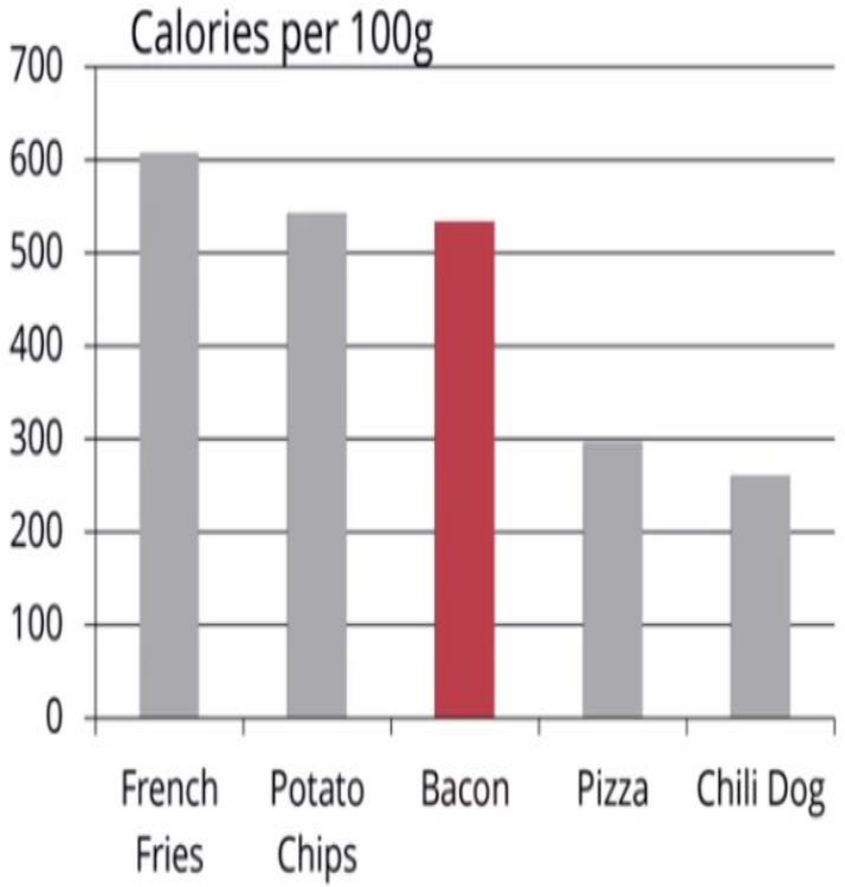




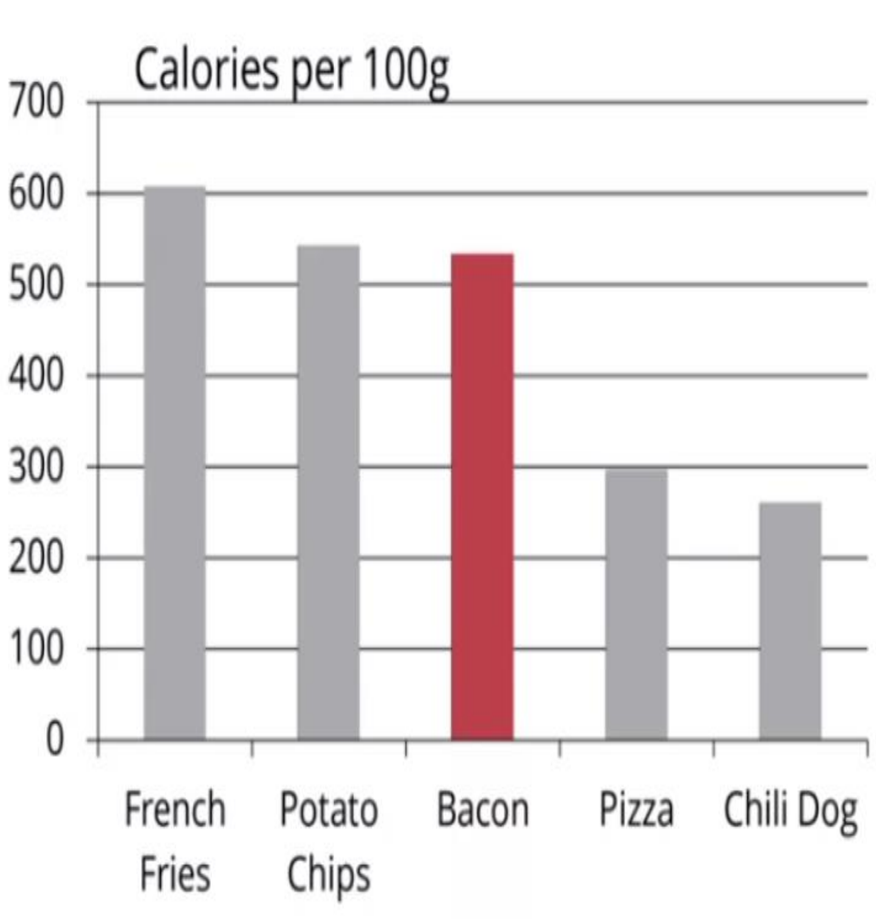
Data ink Ratio Maximization Example

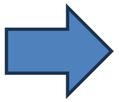


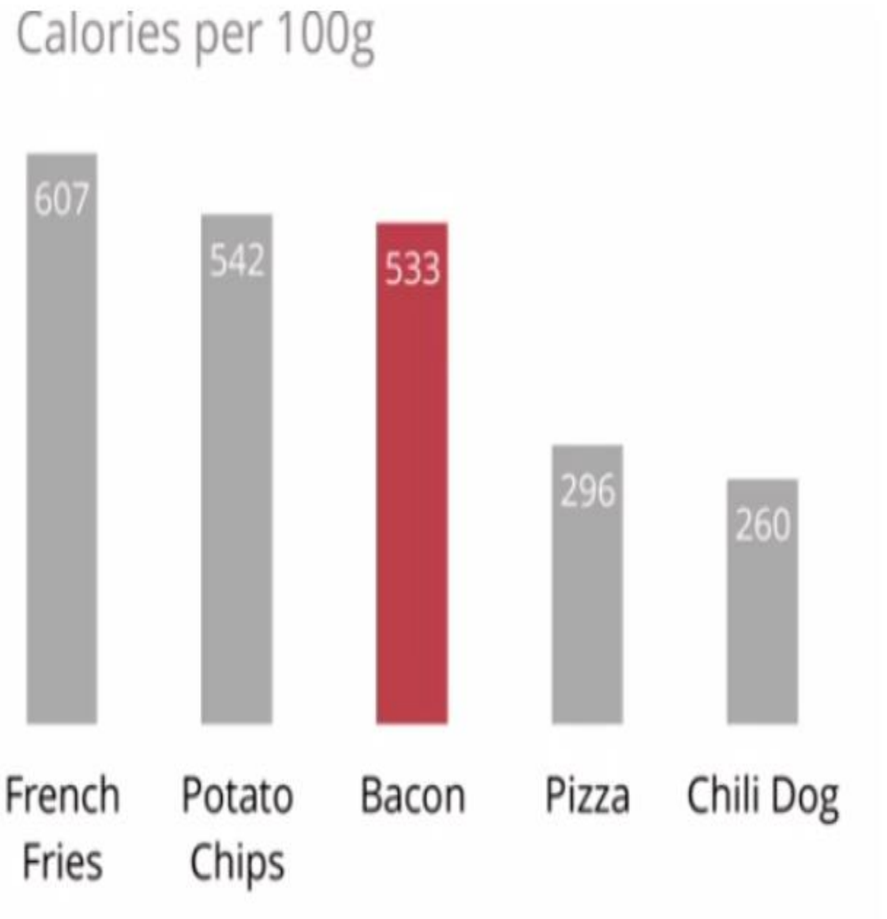




Data ink Ratio Maximization Example

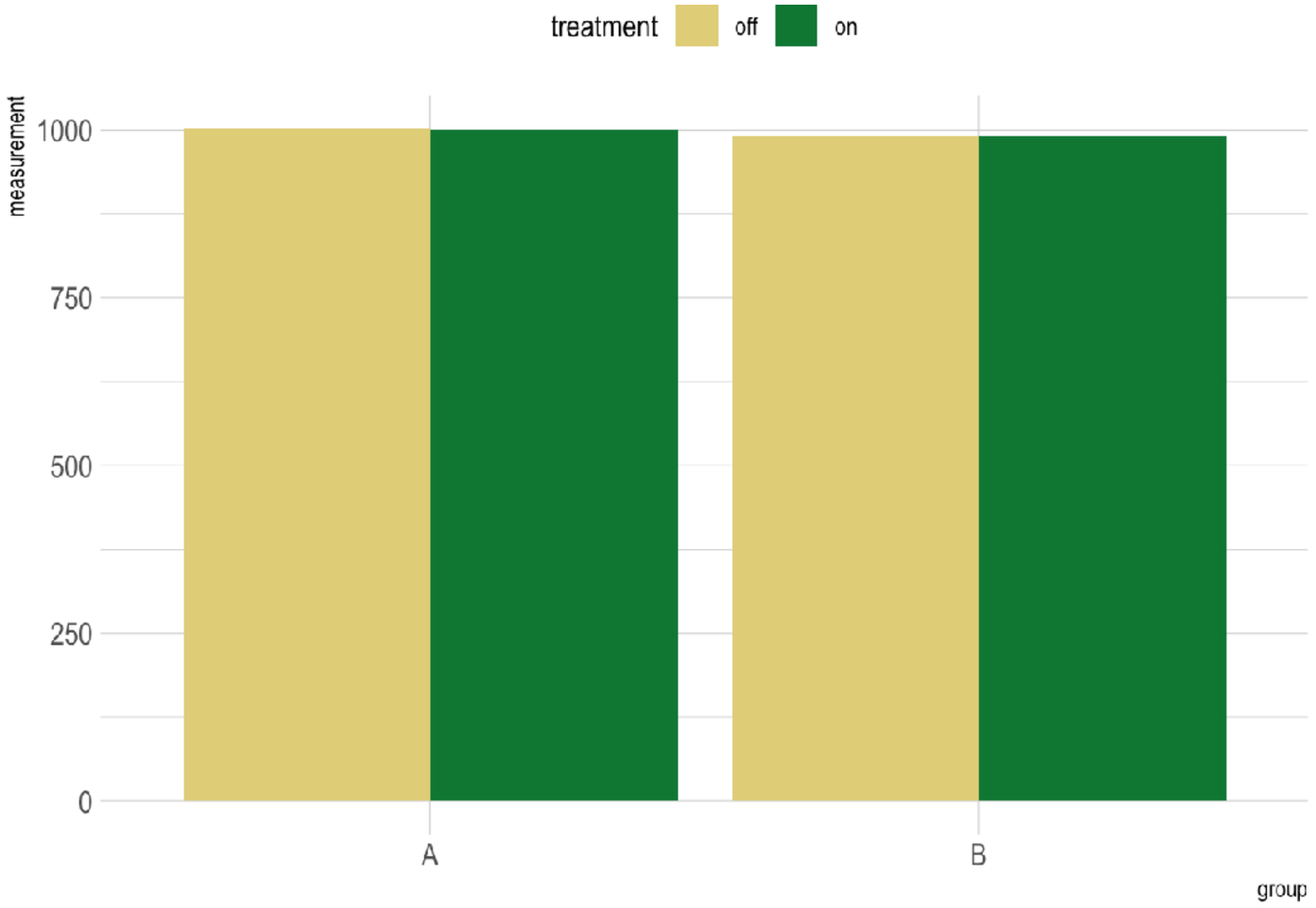






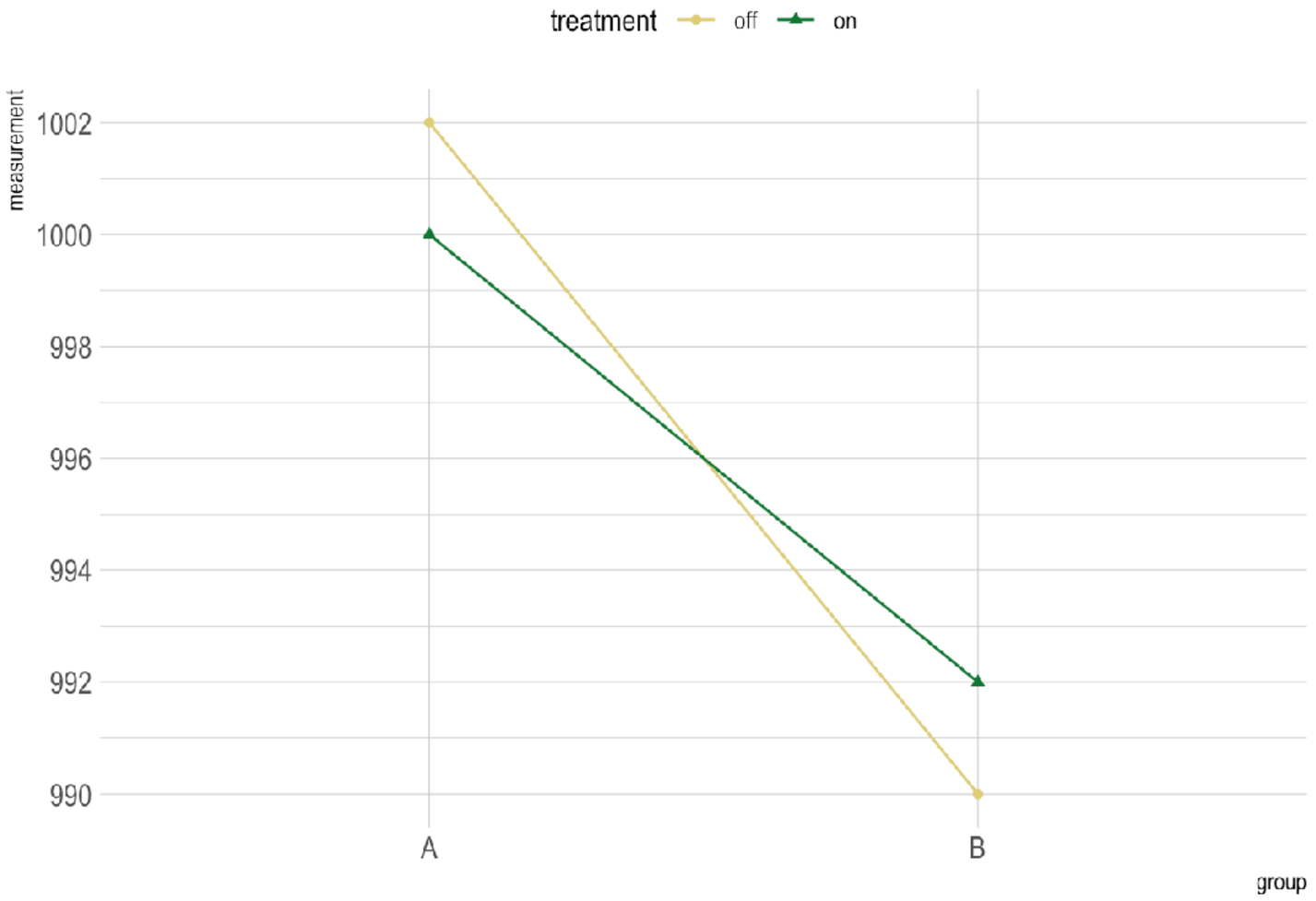
EXAMPLE OF UNINFORMATIVE PLOTTING

```
large_contrast_data <- tribble(
  ~group, ~treatment, ~measurement,
  "A",    "on",       1000,
  "A",    "off",      1002,
  "B",    "on",       992,
  "B",    "off",      990
)
```



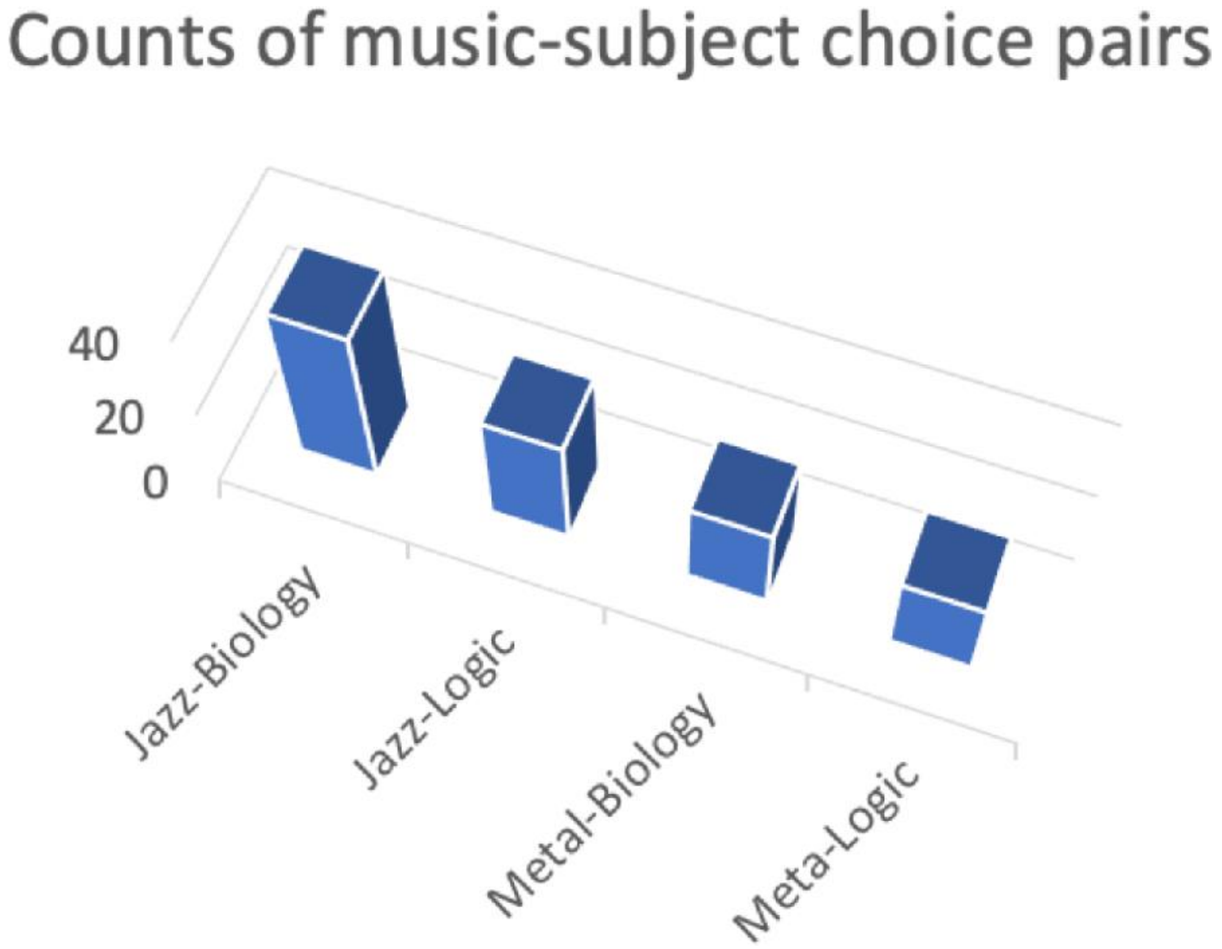
EXAMPLE OF INFORMATIVE HYPOTHESIS-DRIVEN PLOTTING

```
large_contrast_data <- tribble(
  ~group, ~treatment, ~measurement,
  "A",    "on",       1000,
  "A",    "off",      1002,
  "B",    "on",       992,
  "B",    "off",      990
)
```



EXAMPLE OF UNINFORMATIVE PLOTTING

```
## # A tibble: 4 x 3
##   JM    LB          n
##   <chr> <chr>   <int>
## 1 Jazz  Biology    38
## 2 Jazz  Logic      26
## 3 Metal Biology    20
## 4 Metal Logic      18
```



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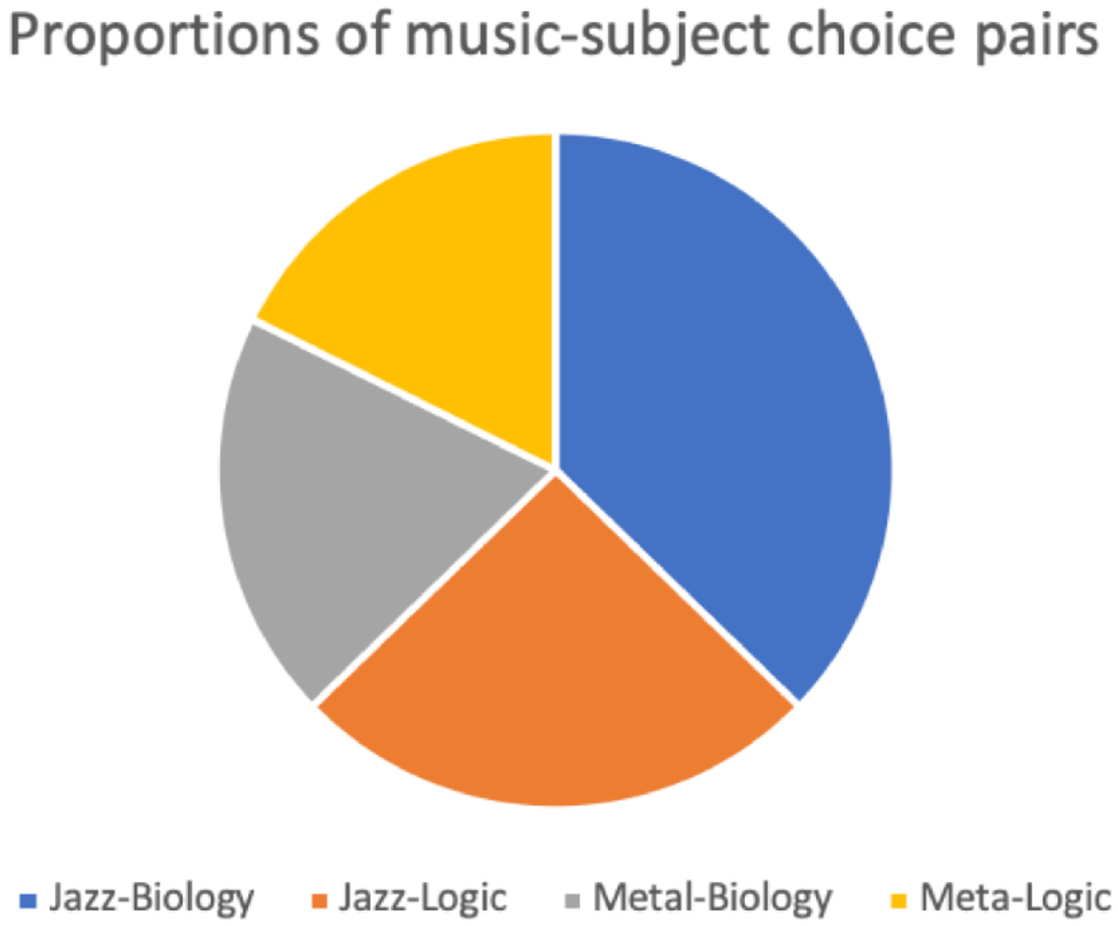

EXAMPLE OF INFORMATIVE HYPOTHESIS-DRIVEN PLOTTING

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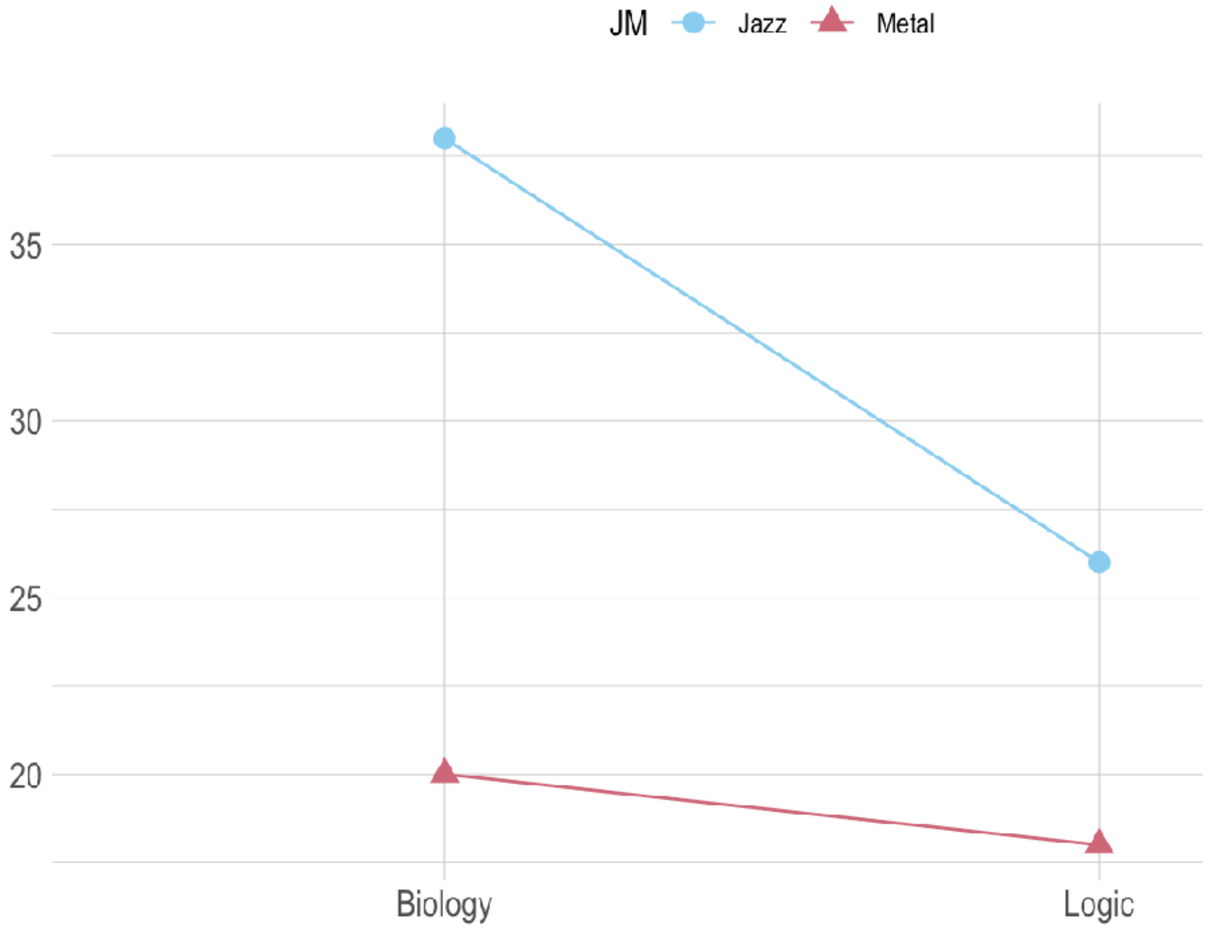
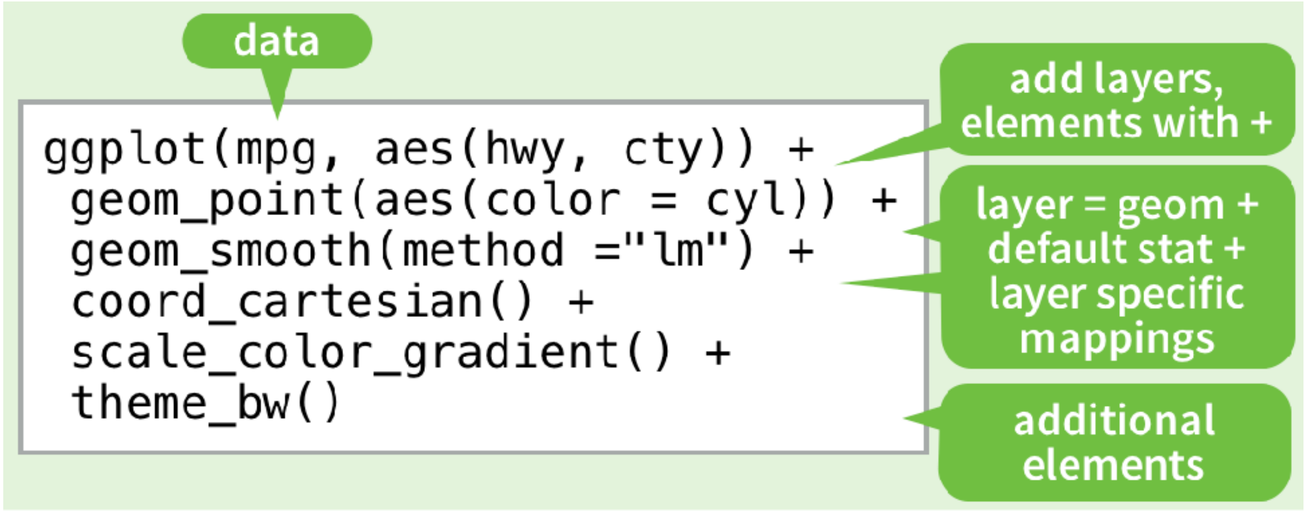
```



Basics of ggplot

BASICS OF GGPLOT

- "**grammar of layered graphs**"
  - incremental composition
  - layers
  - system of rich convenience functions & defaults
  - grouping
  - multiple ways of customization



INCREMENTAL COMPOSITION

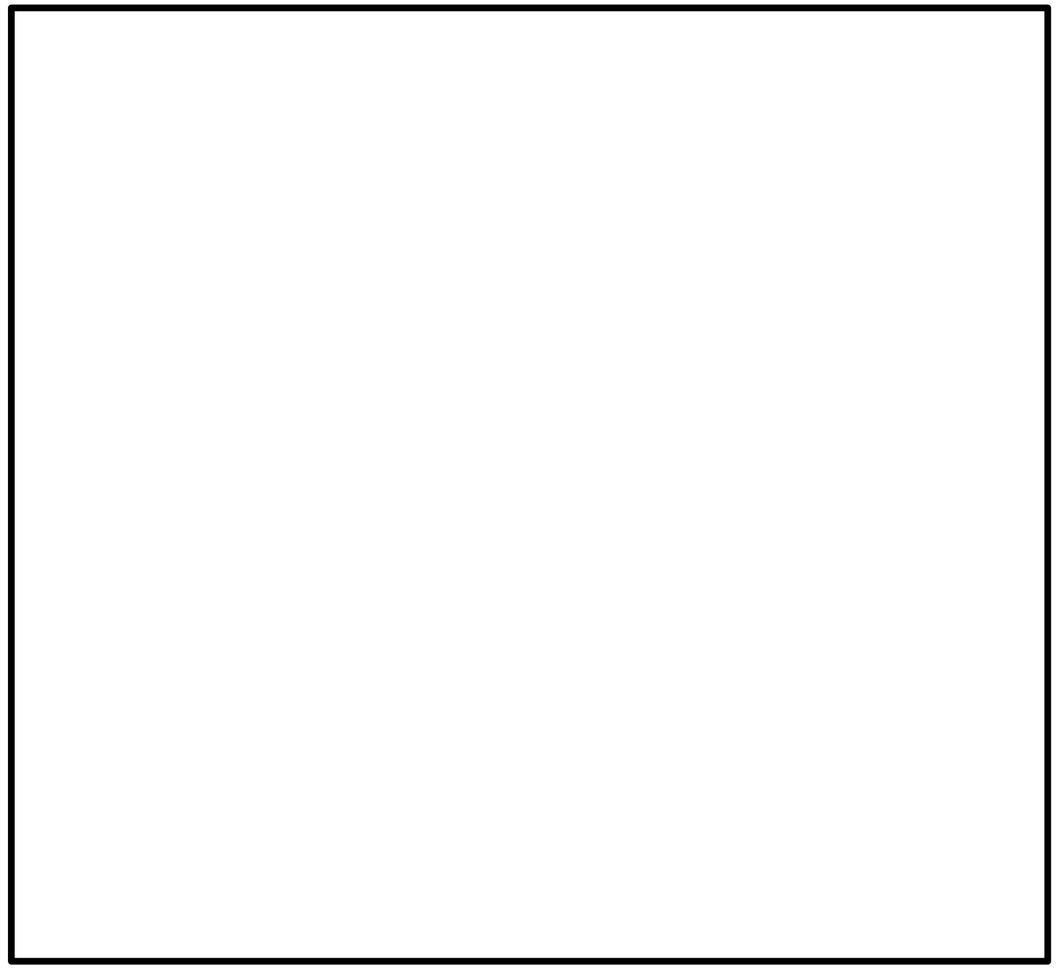
create a plot

```
incrementally_built_plot <- ggplot()
```

display the plot

```
incrementally_built_plot
```

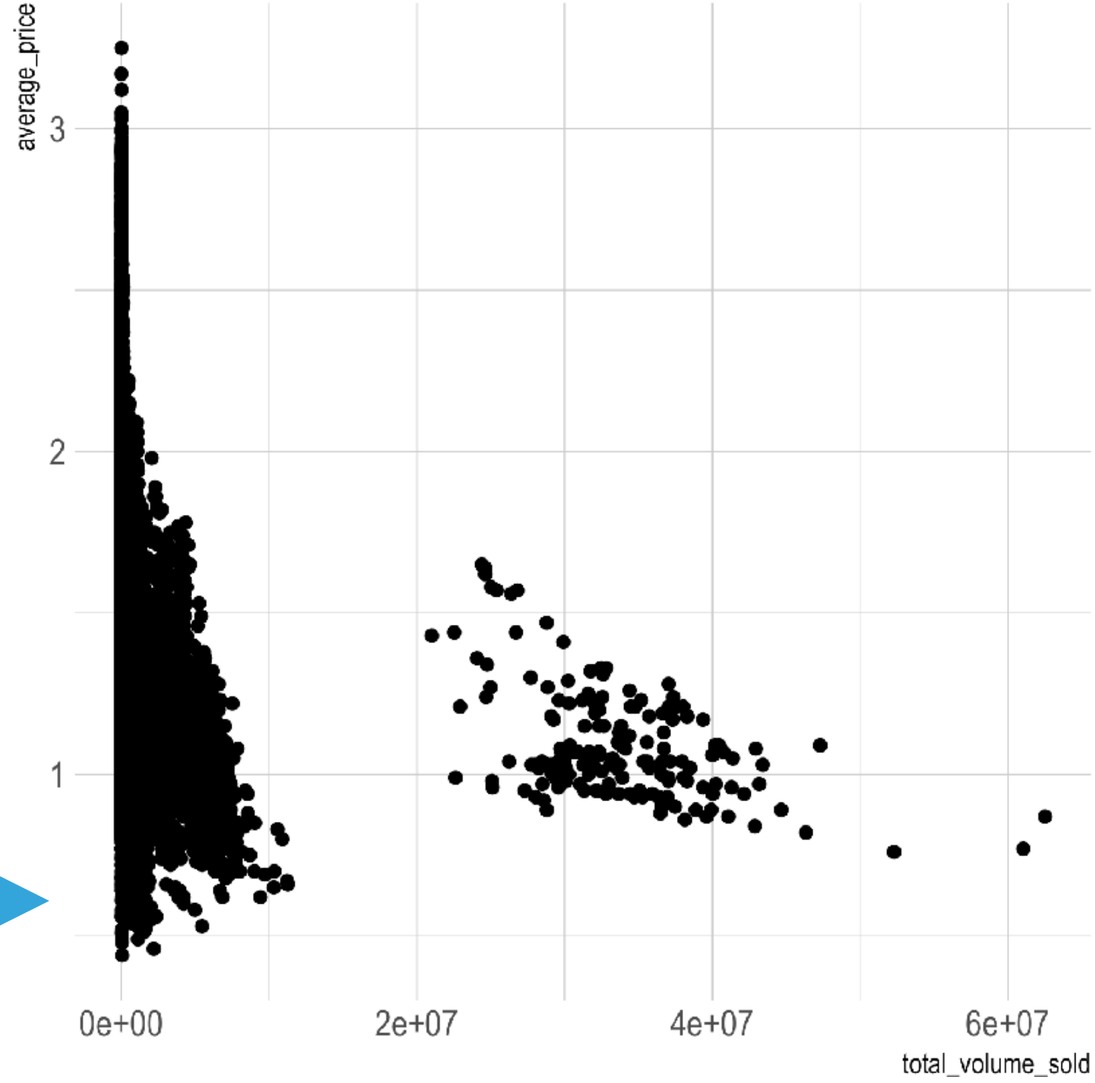
output 😉



INCREMENTAL COMPOSITION

```
incrementally_built_plot +
  # add a geom of type `point` (=> scatter plot)
  geom_point(
    # what data to use
    data = avocado_data,
    # supply a mapping (in the form of an 'aesthetic' (see below))
    mapping = aes(
      # which variable to map onto the x-axis
      x = total_volume_sold,
      # which variable to map onto the y-axis
      y = average_price
      )
  )
```

output

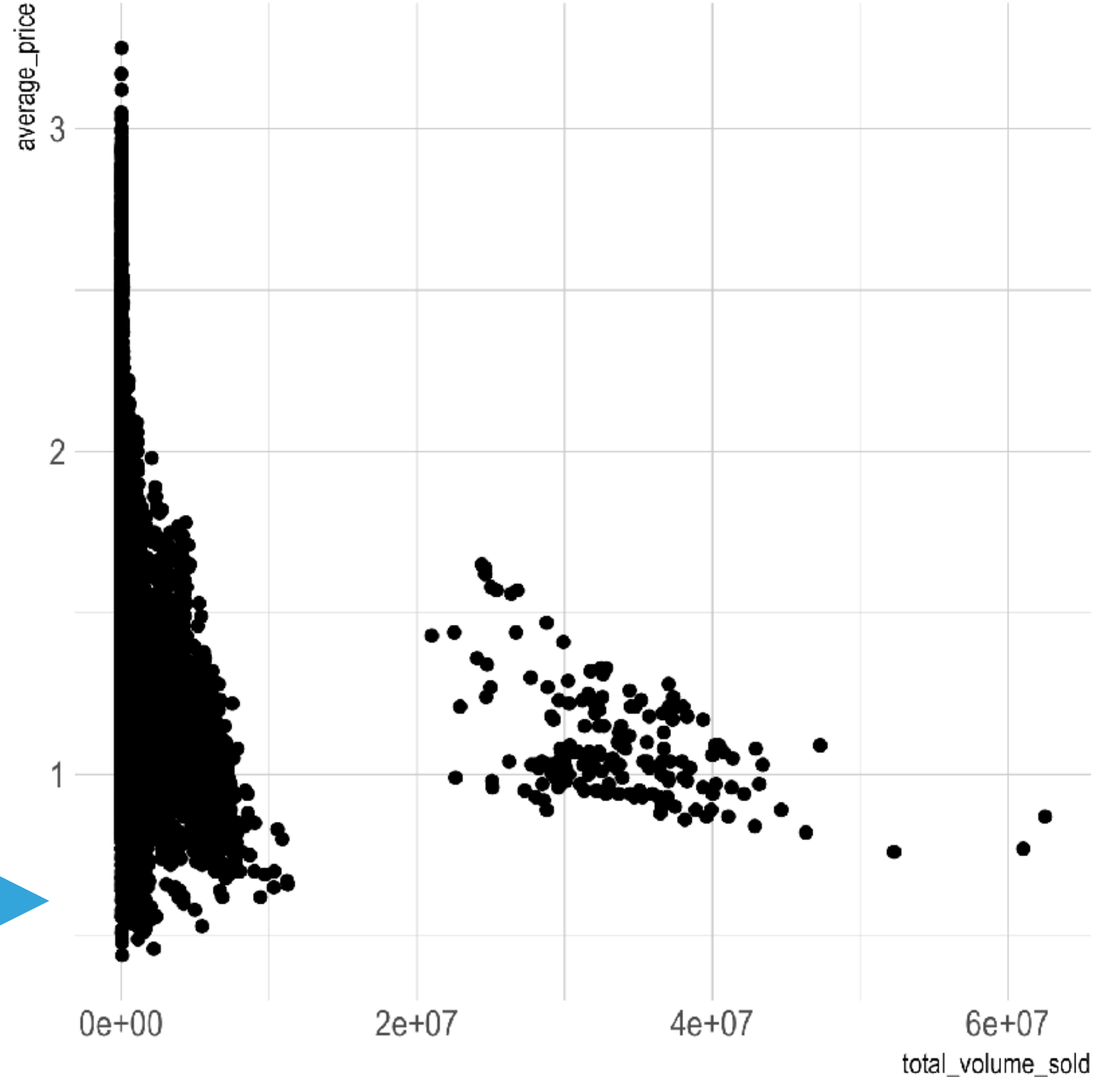


INCREMENTAL COMPOSITION

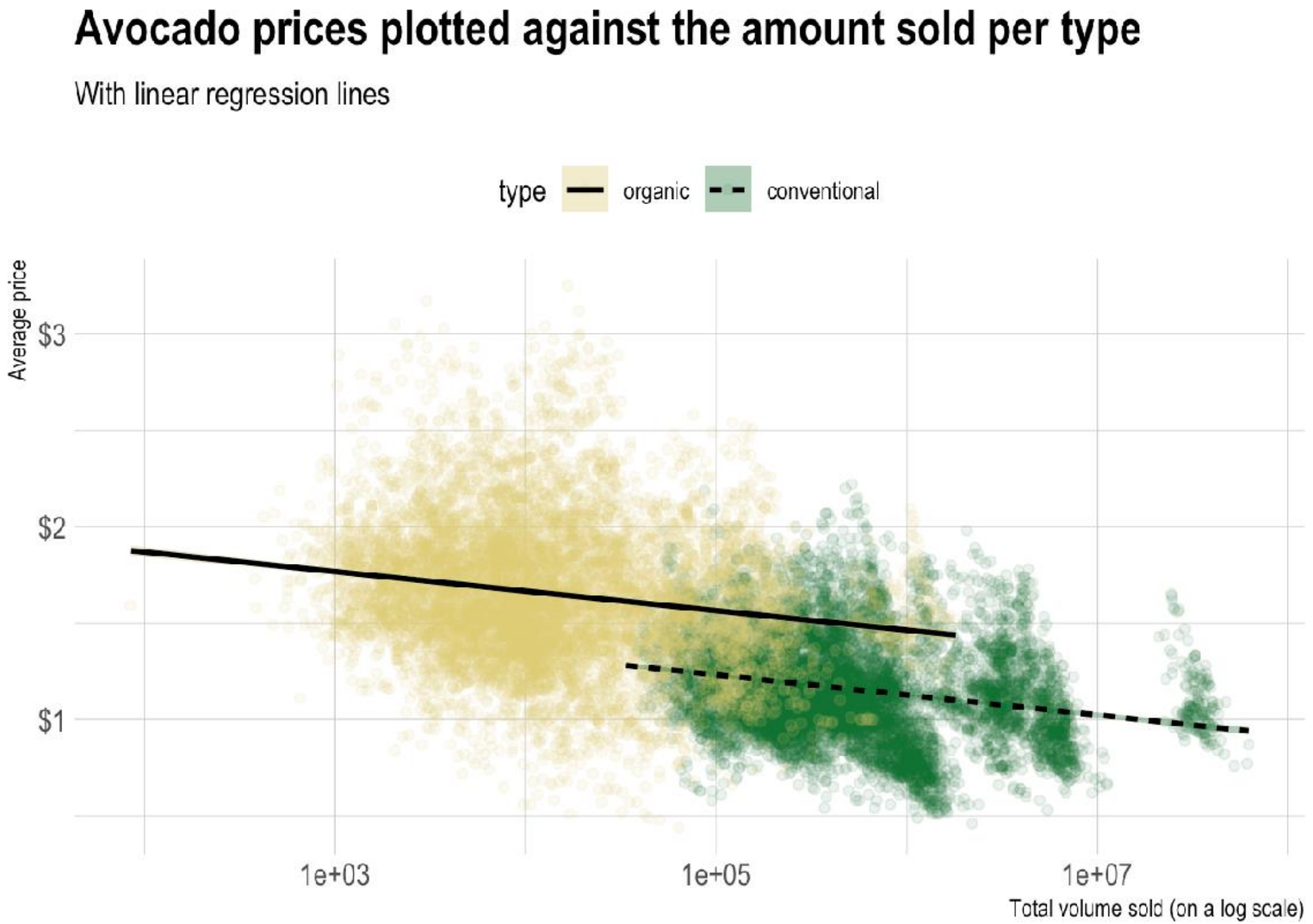
- piping data into 1st argument slot
- declaring mapping globally for all subsequent calls to `geom_` functions

```
avocado_data %>%
  ggplot(aes(x = total_volume_sold, y = average_price)) +
  geom_point()
```

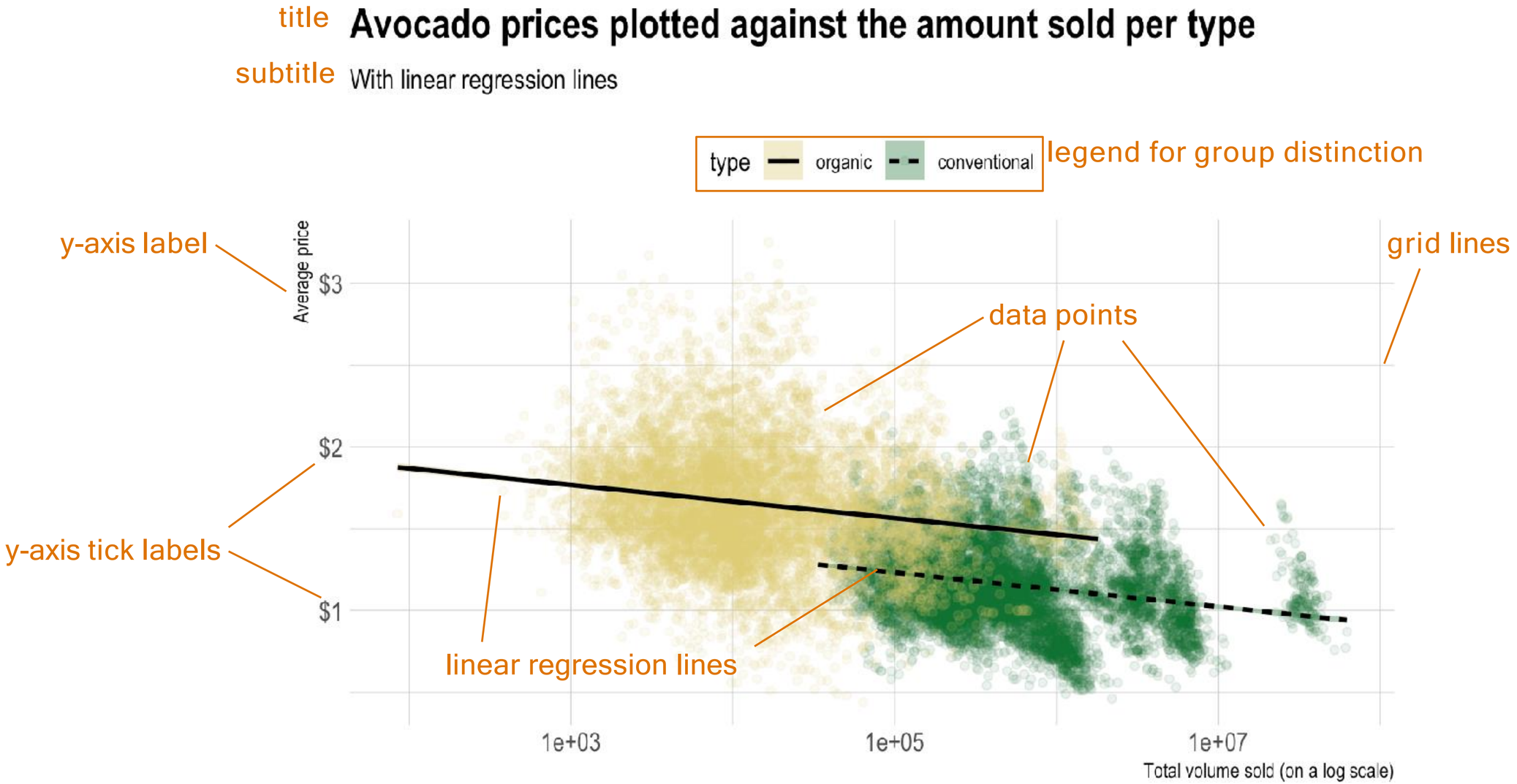
output



FULL EXAMPLE



FULL EXAMPLE



FULL EXAMPLE:: CODE

```
avocado_data %>%
  # reverse factor level so that horizontal legend entries align with
  # the majority of observations of each group in the plot
  mutate(
    type = fct_rev(type)
  ) %>%
  # initivalize the plot
  ggplot(
    # defined mapping
    mapping = aes(
      # which variable goes on the x-axis
      x = total_volume_sold,
      # which variable goes on the y-axis
      y = average_price,
      # which groups of variables to distinguish
      group = type,
      # color and fill to change by grouping variable
      fill = type,
      linetype = type,
      color = type
    )
  ) +
```

```
# declare that we want a scatter plot
geom_point(
  # set low opacity for each point
  alpha = 0.1
) +
# add a linear model fit (for each group)
geom_smooth(
  color = "black",
  method = "lm"
) +
# change the default (normal) of x-axis to log-scale
scale_x_log10() +
# add dollar signs to y-axis labels
scale_y_continuous(labels = scales::dollar) +
# change axis labels and plot title & subtitle
labs(
  x = 'Total volume sold (on a log scale)',
  y = 'Average price',
  title = "Avocado prices plotted against the amount sold per type",
  subtitle = "With linear regression lines"
)
```

LAYERED GRAMMAR OF GRAPH

> data -> statistical transformation ->
> geom. object -> aesthetics

- `geom_` functions are wrappers
- default stat. transform, position, axis type etc.
- defaults can be overwritten

```
avocado_data %>%
  ggplot(aes(x = total_volume_sold, y = average_price)) +
  geom_point()
```

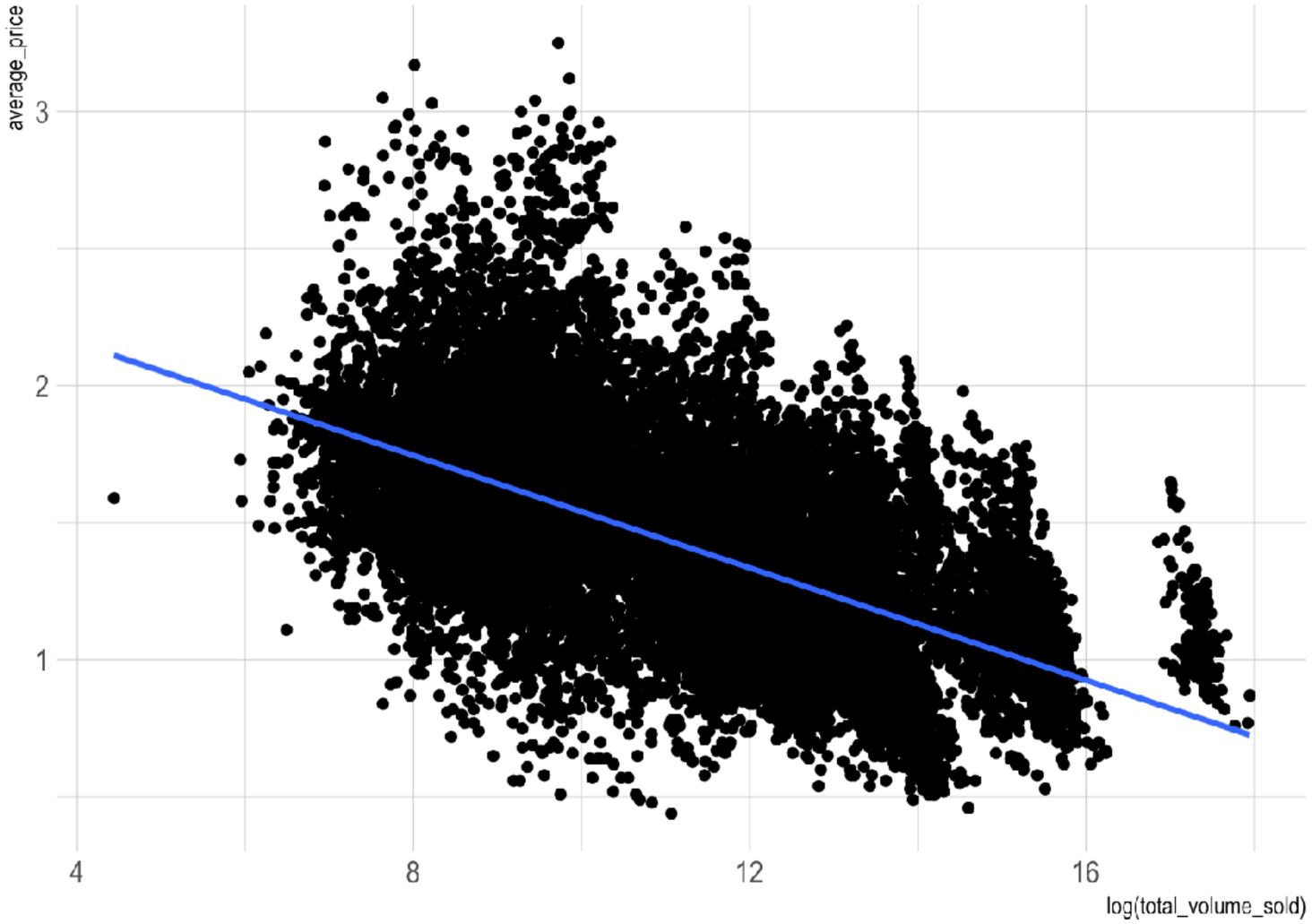
output equivalent

```
ggplot() +
  layer(
    data = avocado_data,
    mapping = aes(x = total_volume_sold, y = average_price),
    geom = "point",
    stat = "identity",
    position = "identity"
  ) +
  scale_x_continuous() +
  scale_y_continuous() +
  coord_cartesian()
```

Layers

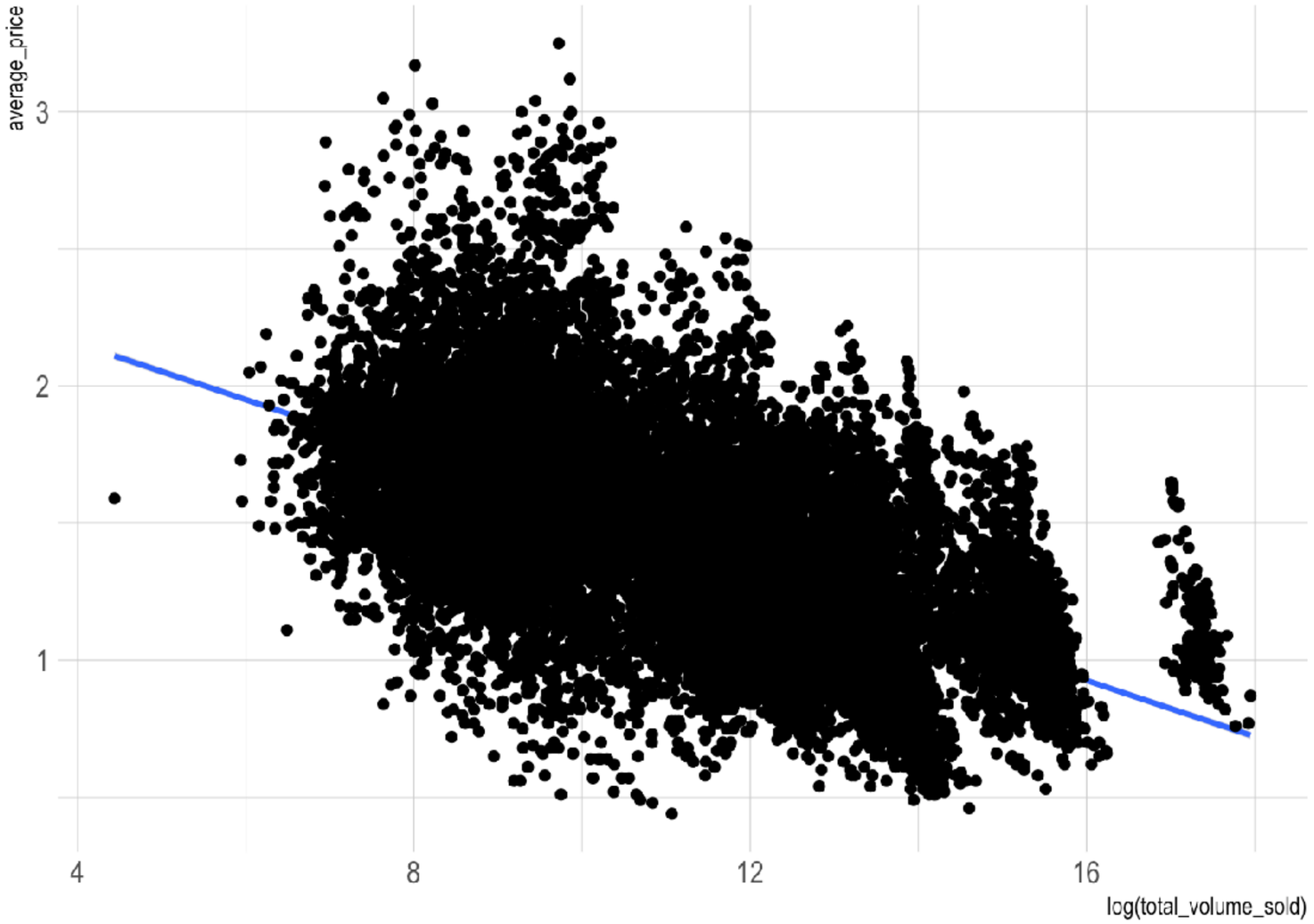
LAYERS

```
avocado_data %>%
  ggplot(
    mapping = aes(
      x = log(total_volume_sold),
      y = average_price
    )
  ) +
  # add a scatter plot
  geom_point() +
  # add a linear regression line
  geom_smooth(method = "lm")
```



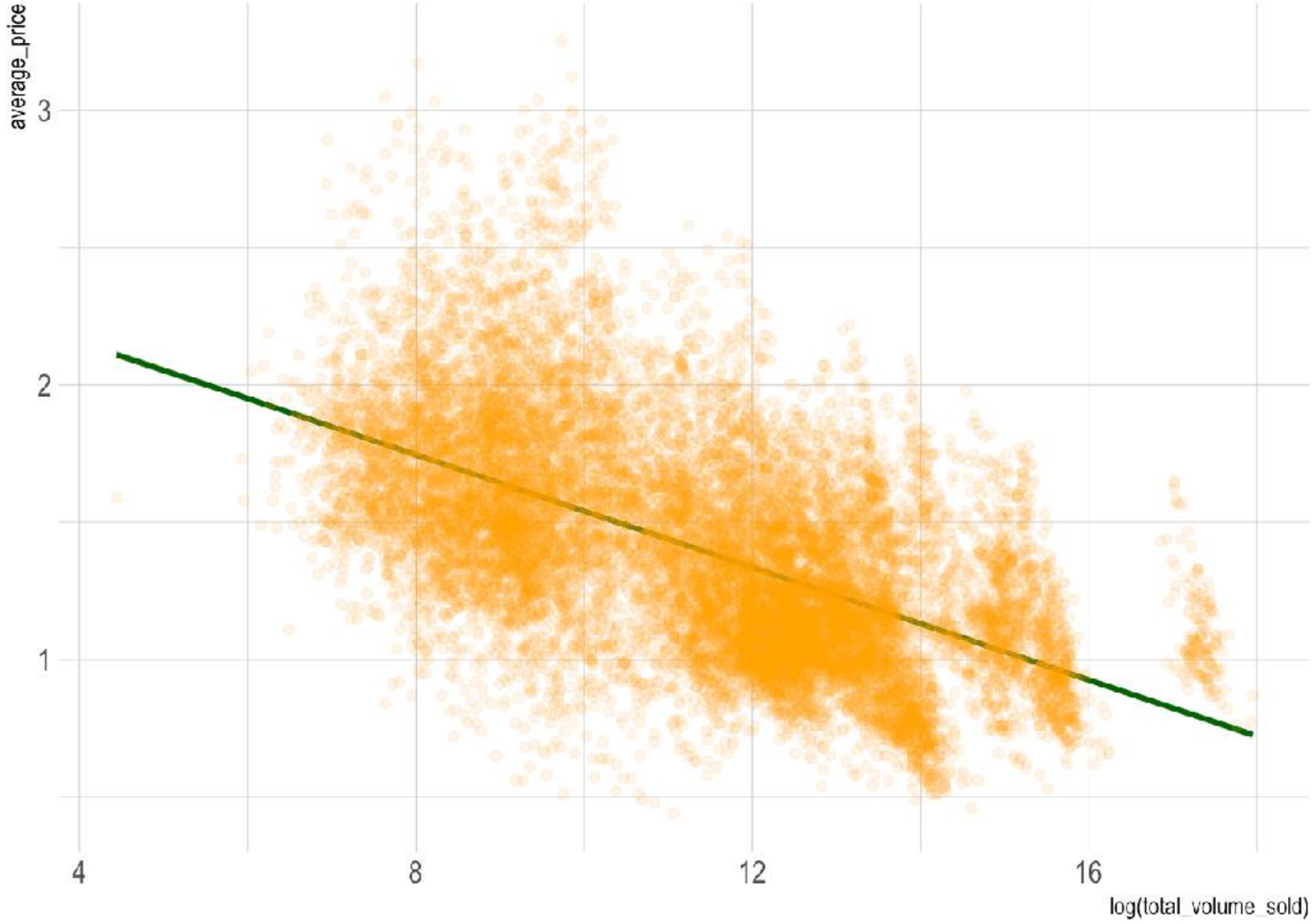
LAYER ORDER

```
avocado_data %>%
  ggplot(
    mapping = aes(
      x = log(total_volume_sold),
      y = average_price
    )
  ) +
 # FIRST: add a linear regression line
 geom_smooth(method = "lm") +
 # THEN: add a scatter plot
 geom_point()
```



OPACITY

```
avocado_data %>%
  ggplot(
    mapping = aes(
      x = log(total_volume_sold),
      y = average_price
    )
  ) +
 # FIRST: add a linear regression line
 geom_smooth(method = "lm", color = "darkgreen") +
 # THEN: add a scatter plot
 geom_point(alpha = 0.1, color = "orange")
```

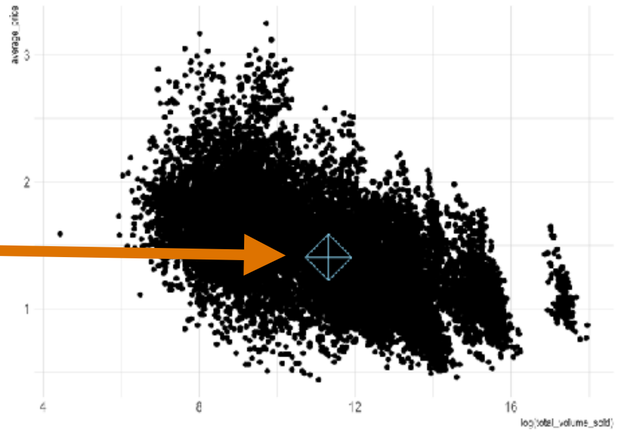


DIFFERENT DATA FOR DIFFERENT LAYERS

```
# create a small tibble with the means of both
#   variables of interest
avocado_data_means <-
  avocado_data %>%
  summarize(
    mean_volume = mean(log(total_volume_sold)),
    mean_price  = mean(average_price)
  )
avocado_data_means
```

```
## # A tibble: 1 x 2
##   mean_volume mean_price
##         <dbl>      <dbl>
## 1        11.3       1.41
```

```
avocado_data %>%
  ggplot(
    aes(x = log(total_volume_sold),
        y = average_price)
  ) +
  # first layer uses globally declared data & mapping
  geom_point() +
  # second layer uses different data set & mapping
  geom_point(
    data = avocado_data_means,
    mapping = aes(
      x = mean_volume,
      y = mean_price
    ),
    # change shape of element to display (see below)
    shape = 9,
    # change size of element to display
    size = 12,
    color = "skyblue"
  )
```

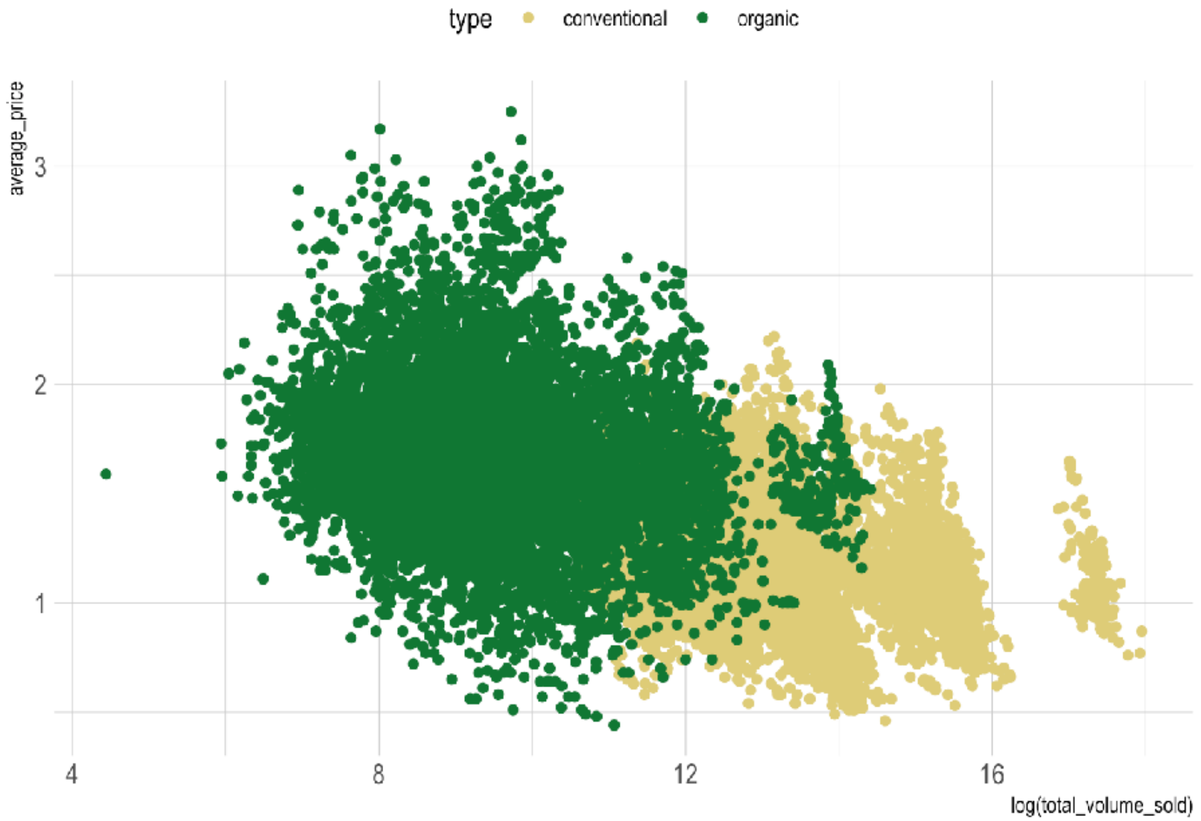


Grouping

GROUPING

- group information for uniform display in terms of color, shape, etc.

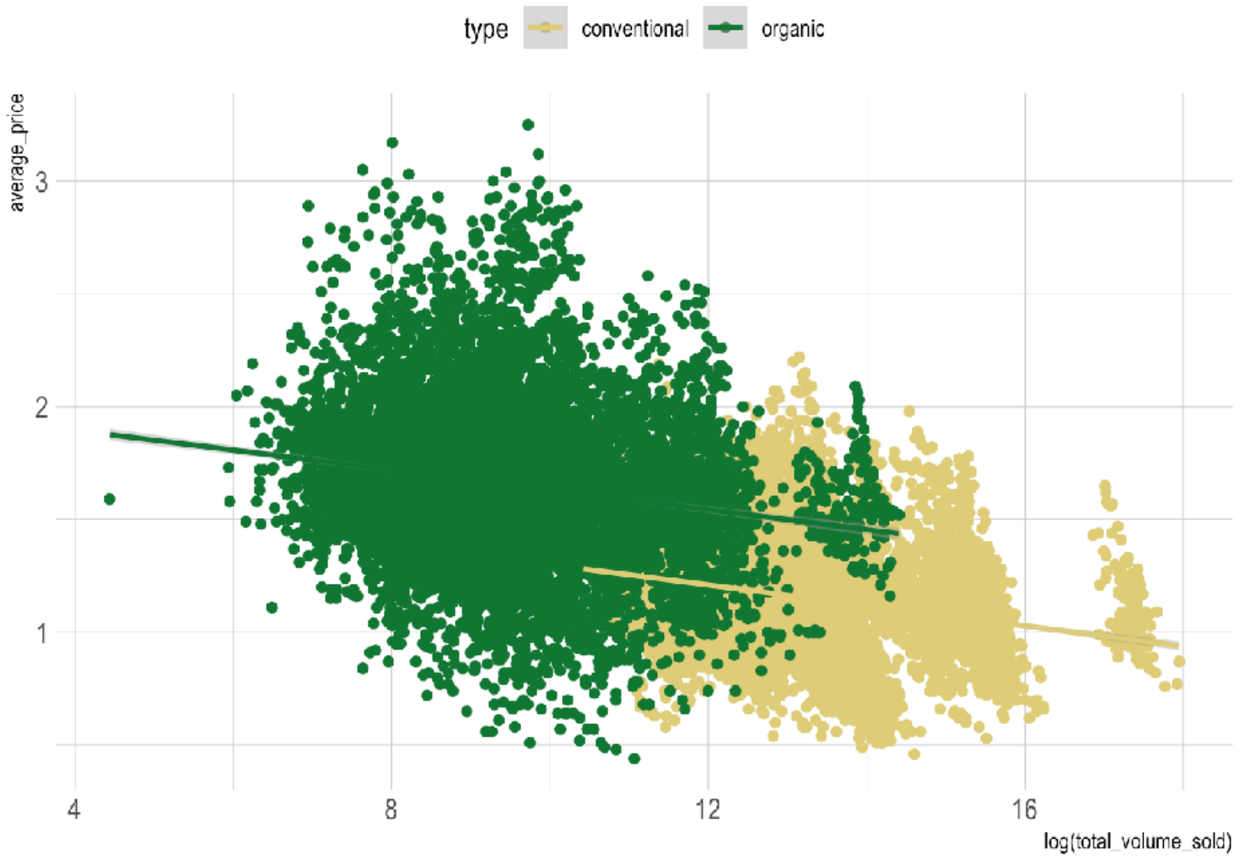
```
avocado_data %>%
  ggplot(
    aes(
      x = log(total_volume_sold),
      y = average_price,
      # use a different color for each type of avocado
      color = type
    )
  ) +
  geom_point(aes(color = type))
```



GLOBAL GROUPING

- global grouping applies to all subsequent layers

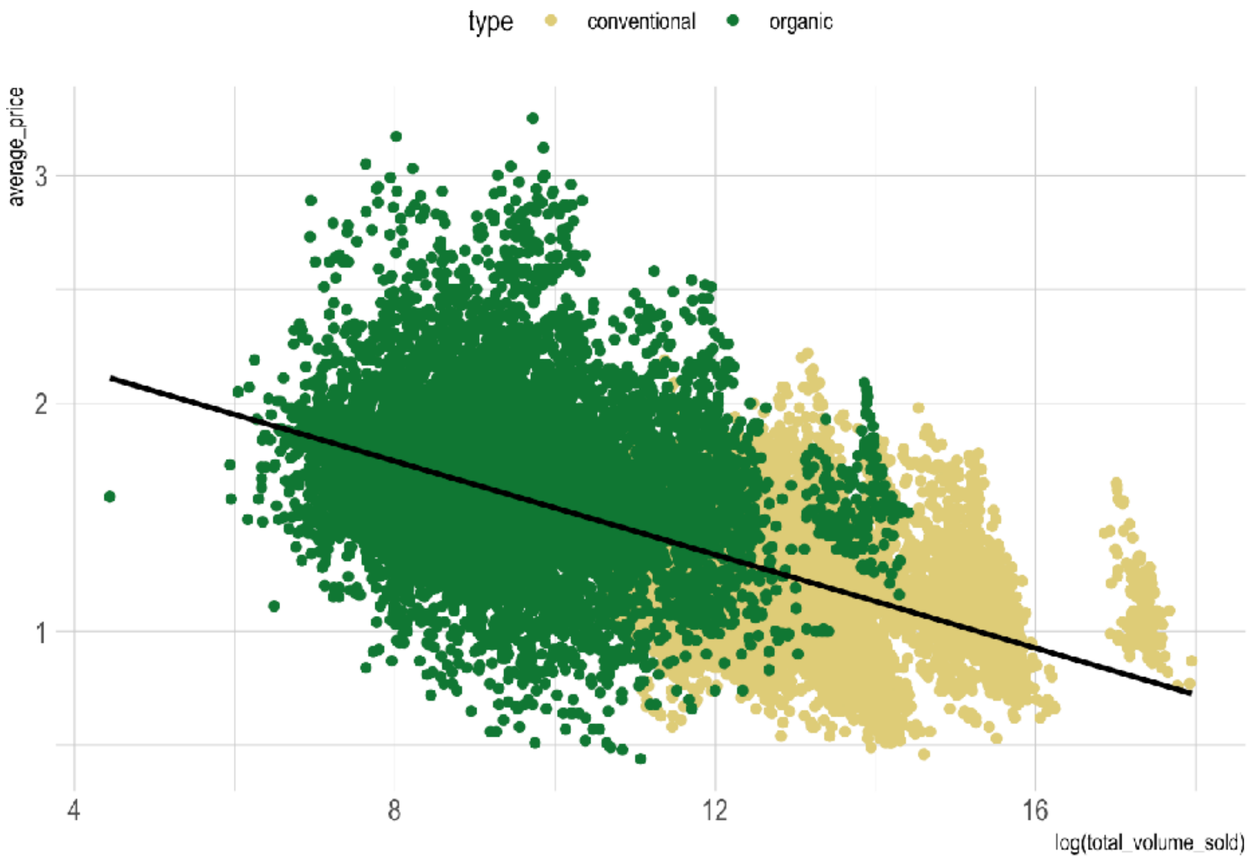
```
avocado_data %>%
  ggplot(
    aes(
      x = log(total_volume_sold),
      y = average_price,
      # use a different color for each type of avocado
      color = type
    )
  ) +
  geom_point(aes(color = type))  +
  geom_smooth(method = "lm")
```



OVERWRITING GROUPING INFORMATION

- overwriting grouping information locally

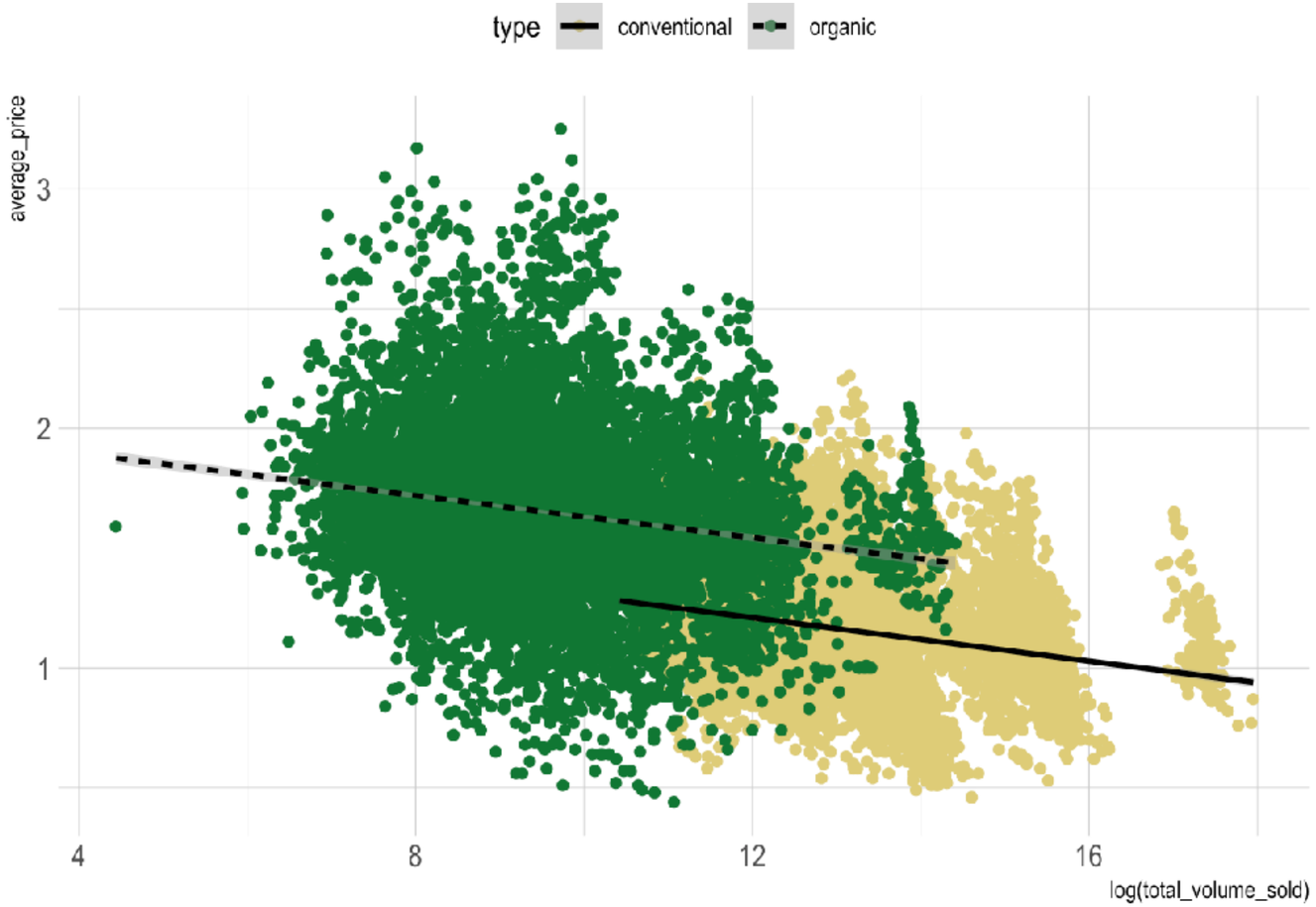
```
avocado_data %>%
  ggplot(
    aes(
      x = log(total_volume_sold),
      y = average_price,
      # use a different color for each type of avocado
      color = type
    )
  ) +
  geom_point(aes(color = type))  +
  geom_smooth(method = "lm", color = "black")
```



DIFFERENT GROUPING IN DIFFERENT LAYERS

- each layer has its own grouping information

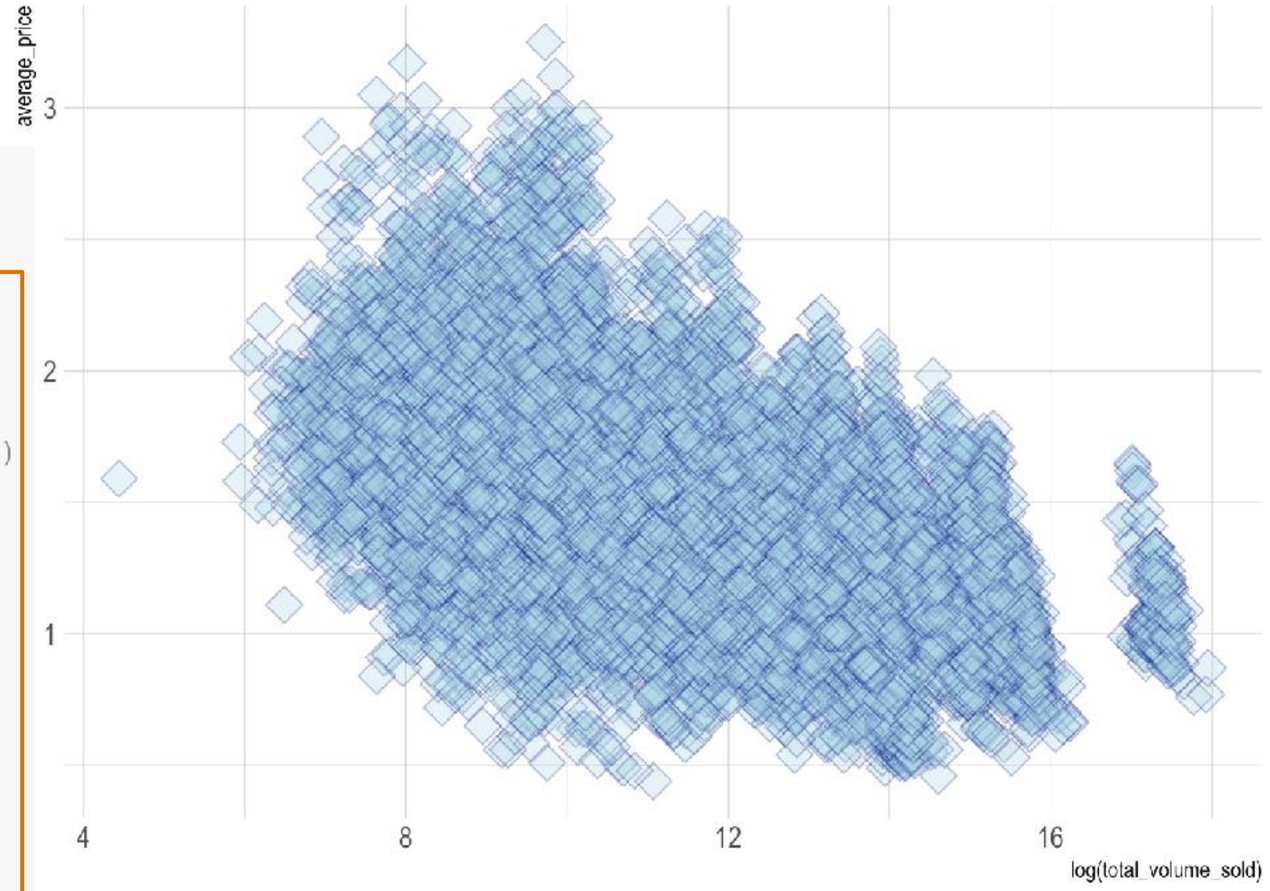
```
avocado_data %>%
  ggplot(
    aes(
      x = log(total_volume_sold),
      y = average_price,
      # use a different color for each type of avocado
      color = type
    )
  ) +
  geom_point(aes(color = type))  +
  geom_smooth(
    # tell the smoother to deal with avocados types separately
    aes(group = type, linetype = type),
    method = "lm",
    color = "black"
  )
```



Geoms & plot types

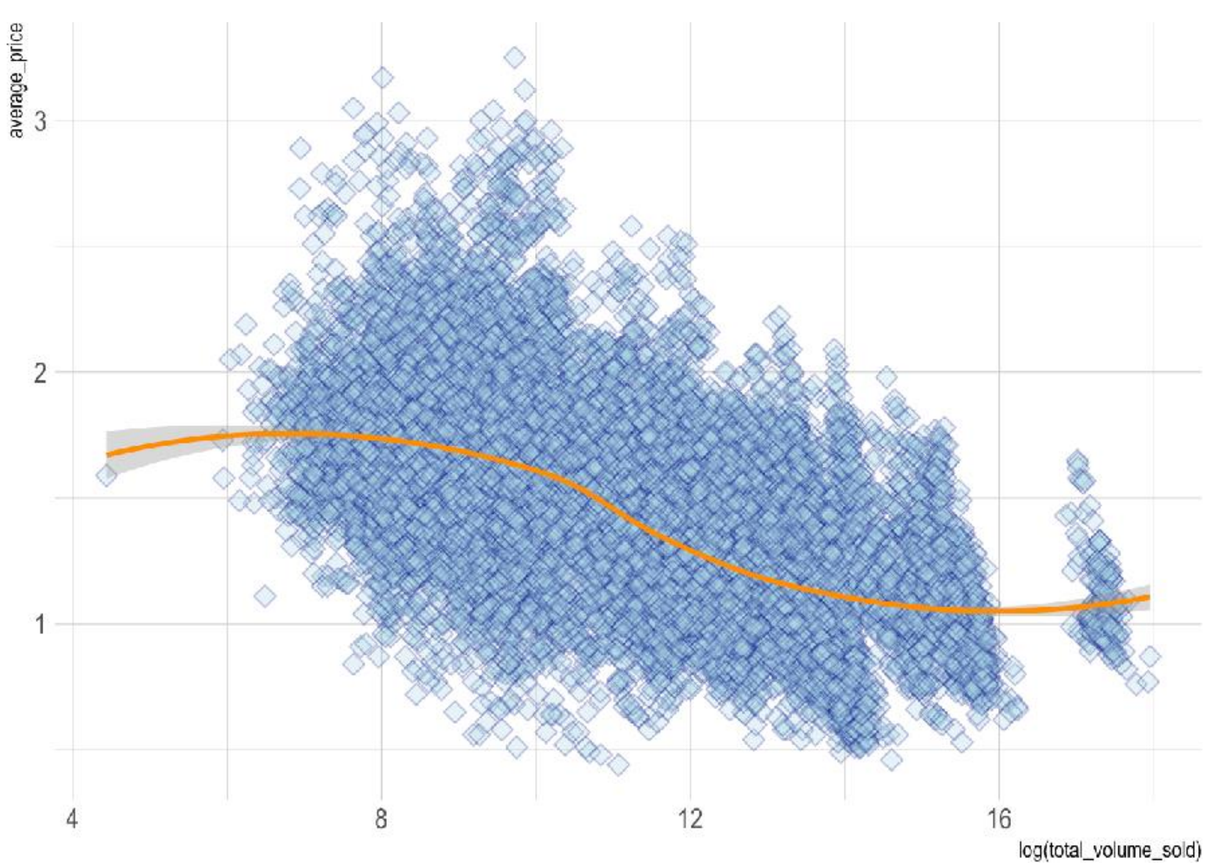
SCATTER PLOTS

```
avocado_data %>%
  ggplot(aes(x = log(total_volume_sold), y = average_price)) +
  geom_point(
    # shape to display is number 23 (tilted rectangle, see below)
    shape = 23,
    # color of the surrounding line of the shape (for shapes 21-24)
    color = "darkblue",
    # color of the interior of each shape
    fill = "lightblue",
    # size of each shape (default is 1)
    size = 5,
    # level of opacity for each shape
    alpha = 0.3
  )
```



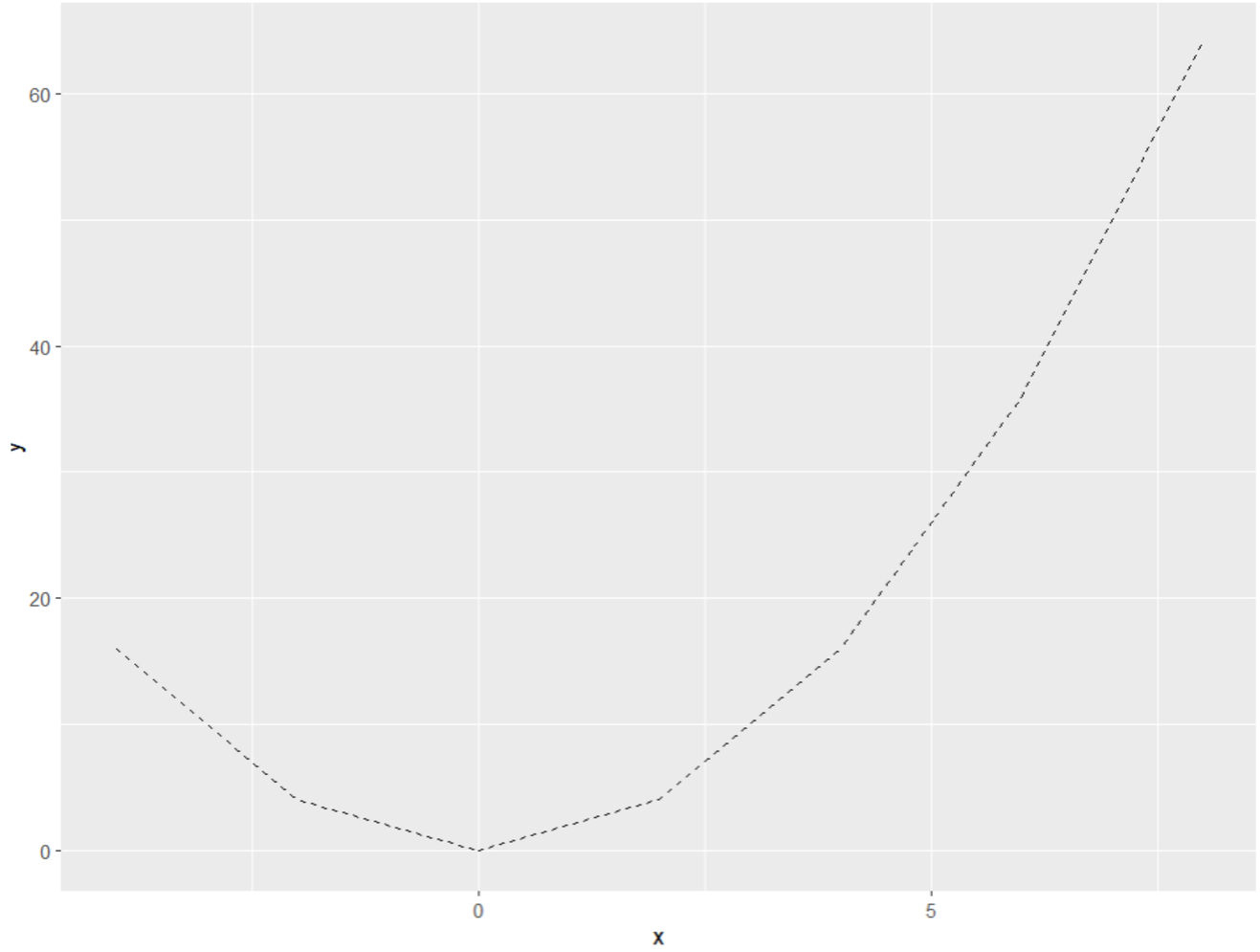
CURVE AND LINE FITS

```
avocado_data %>%
  ggplot(aes(x = log(total_volume_sold), y = average_price))
  geom_point(
    shape = 23,
    color = "darkblue",
    fill = "lightblue",
    size = 3,
    alpha = 0.3
  ) +
  geom_smooth(
    # fitting a smoothed curve to the data
    method = "loess",
    # display standard error around smoothing curve
    se = T,
    color = "darkorange"
    )
```



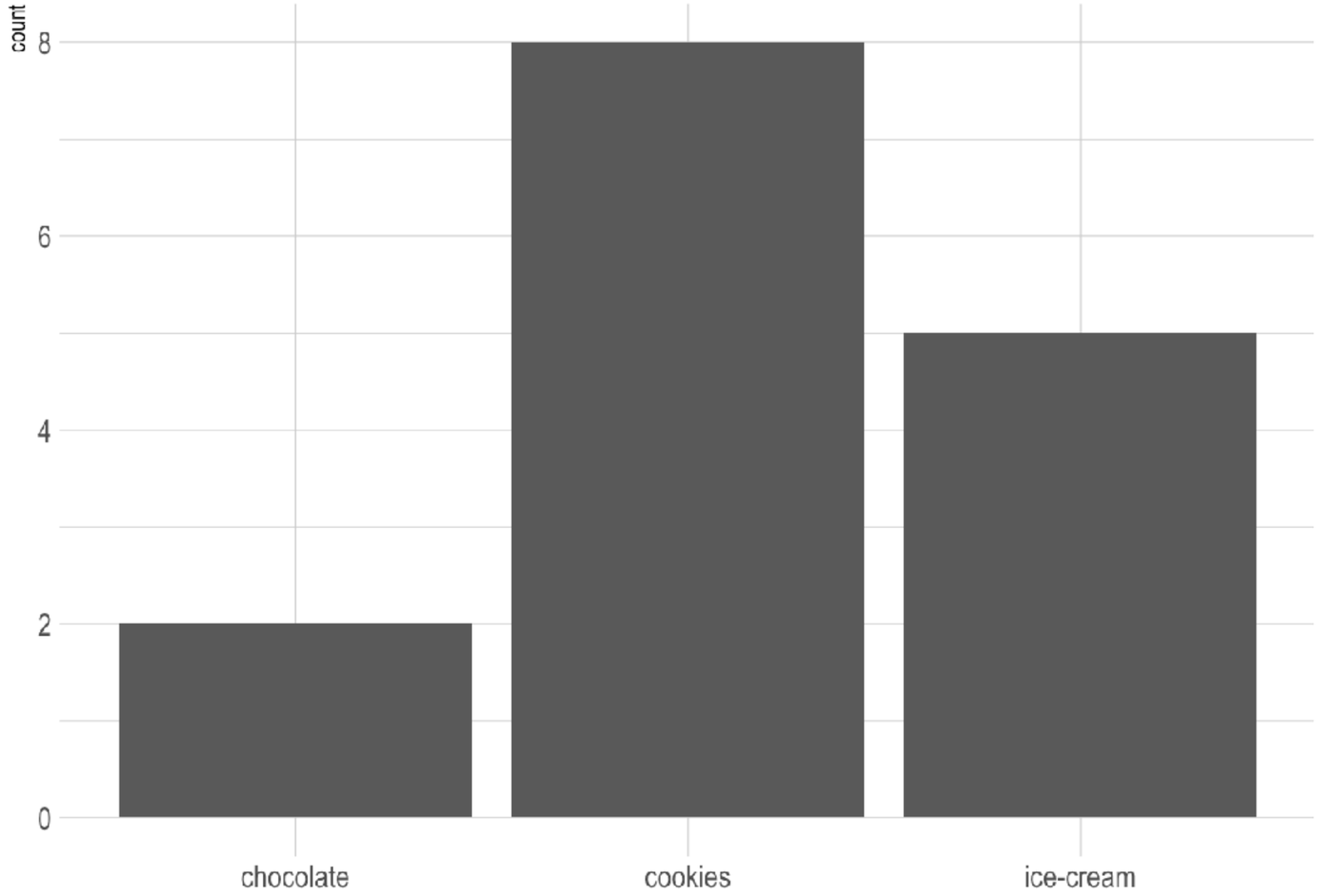
LINE PLOTS

```
tibble(
  x = seq(-4, 8, by = 2),
  y = x^2
  ) %>%
  ggplot(aes(x, y)) +
  geom_line(
    linetype = "dashed"
  )
```



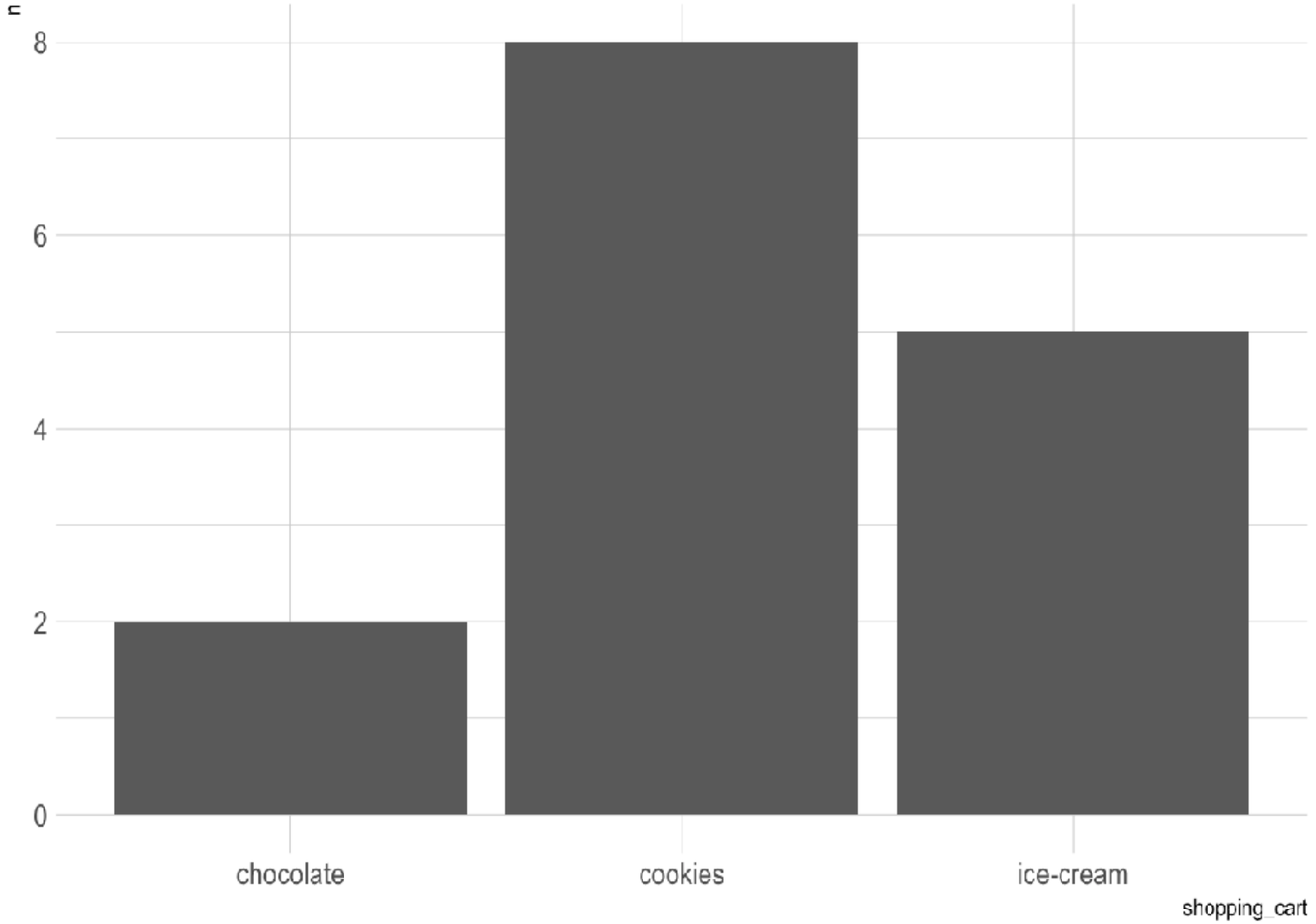
BAR PLOTS

```
tibble(
  shopping_cart = c(
    rep("chocolate", 2),
    rep("ice-cream", 5),
    rep("cookies",8)
  )
) %>%
  ggplot(aes(x = shopping_cart)) +
  geom_bar()
```



BAR PLOTS

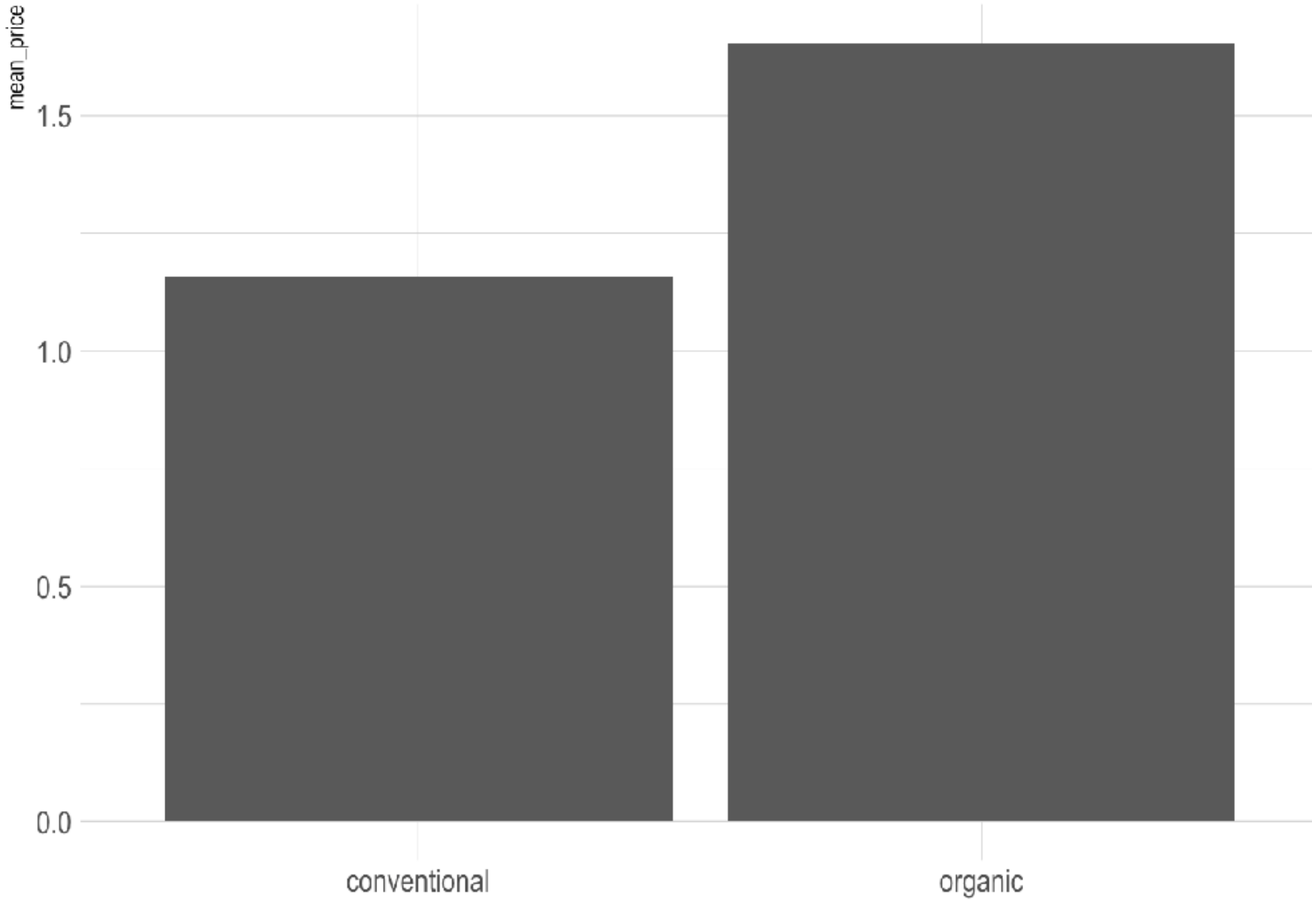
```
tibble(
  shopping_cart = c(
    rep("chocolate", 2),
    rep("ice-cream", 5),
    rep("cookies",8)
  )
) %>%
  dplyr::count(shopping_cart) %>%
    ggplot(aes (x = shopping_cart, y = n) ) +
    geom_col()
```



BAR PLOTS CAN BE UNDER INFORMATIVE

- suboptimal data-ink ratio
- lacks distributional information

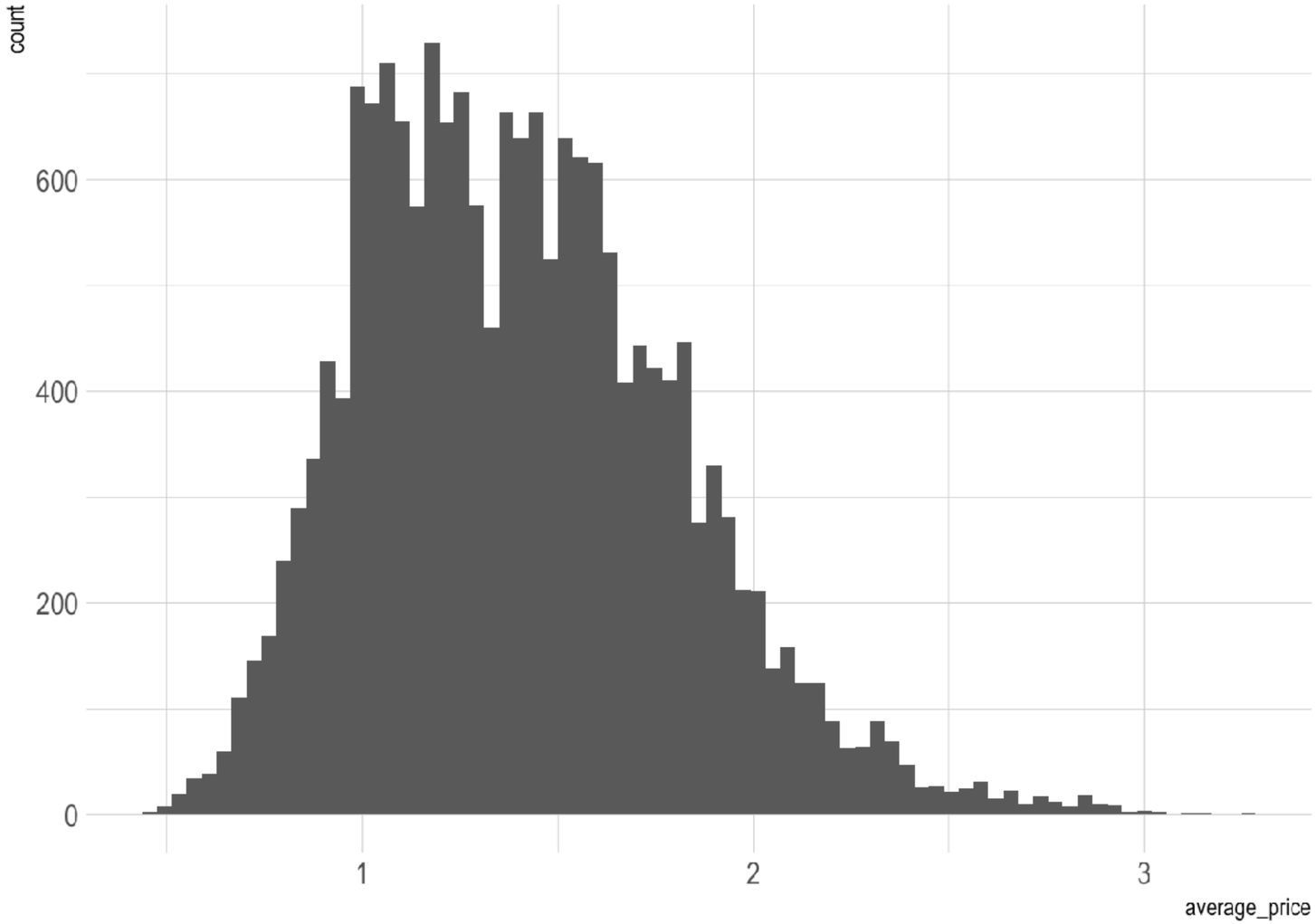
```
avocado_data %>%
  group_by(type) %>%
  summarise(
    mean_price = mean(average_price)
  ) %>%
  ggplot(aes(x = type, y = mean_price)) +
  geom_col()
```



HISTOGRAMS

- fix bins
- count number of data points in each bin
- plot as bar

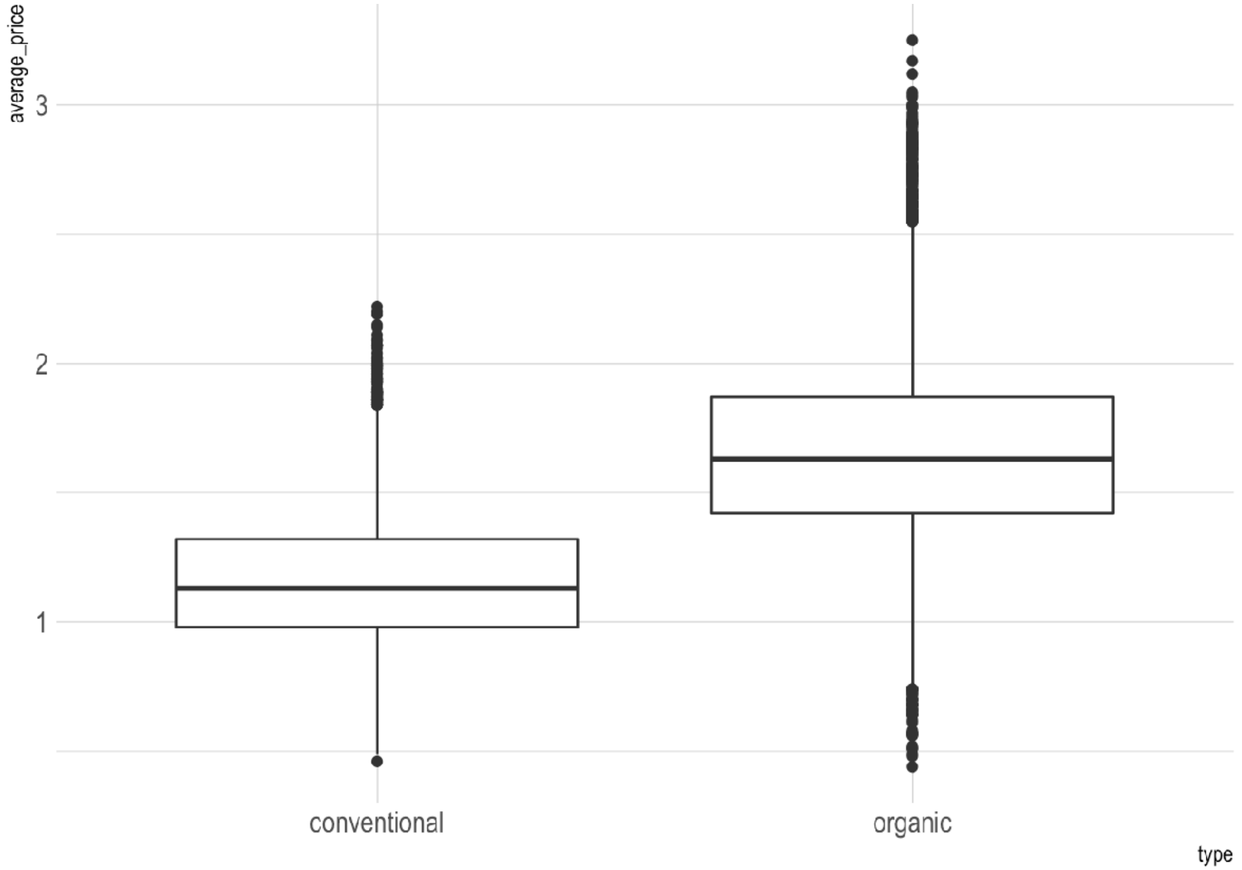
```
avocado_data %>%
  ggplot(aes(x = average_price)) +
  geom_histogram(bins = 75)
```



BOX PLOTS

- visualize common summary statistics
  - mean
  - 25% & 75% quantile
  - ...

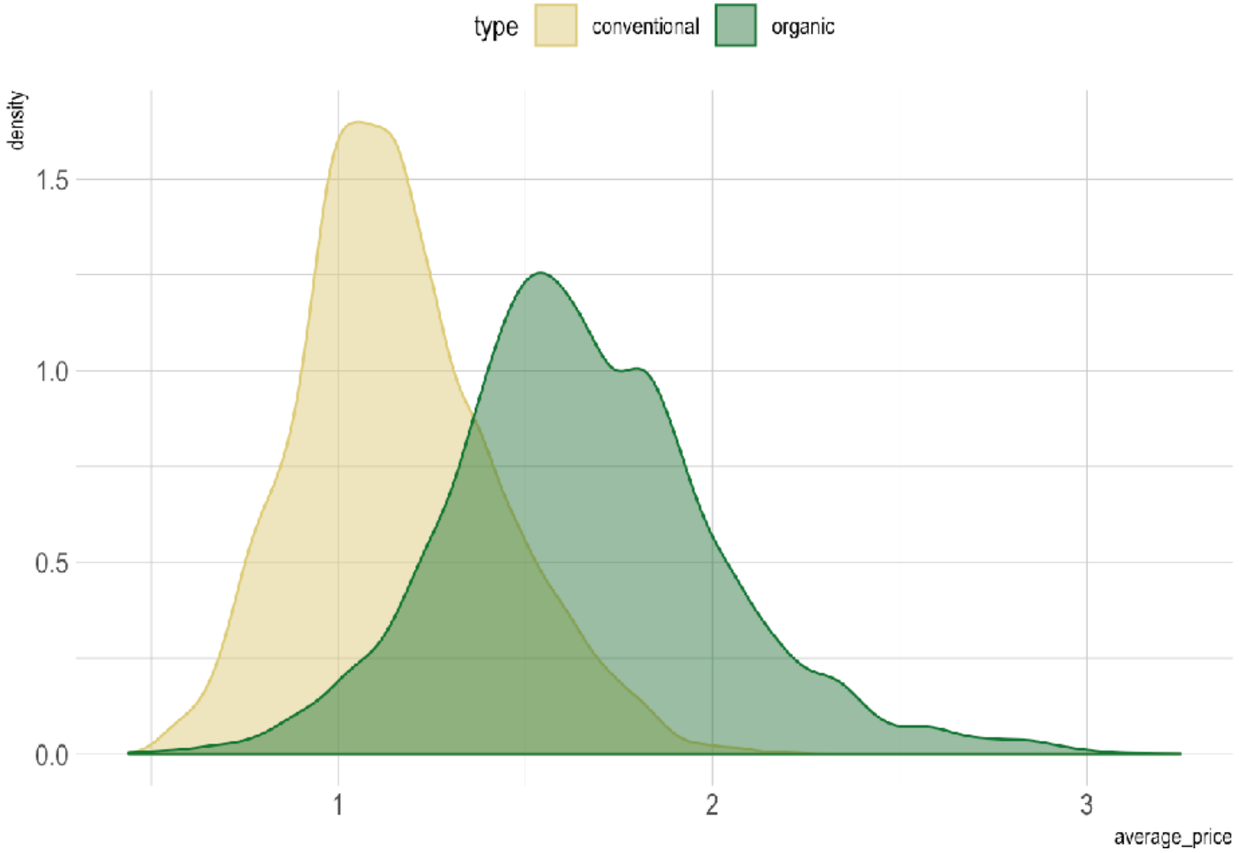
```
avocado_data %>%
  ggplot(aes(x = type , y = average_price)) +
  geom_boxplot()
```



DENSITY PLOTS

- “generalized histogram”
- uses kernel estimation to predict smoothed curves

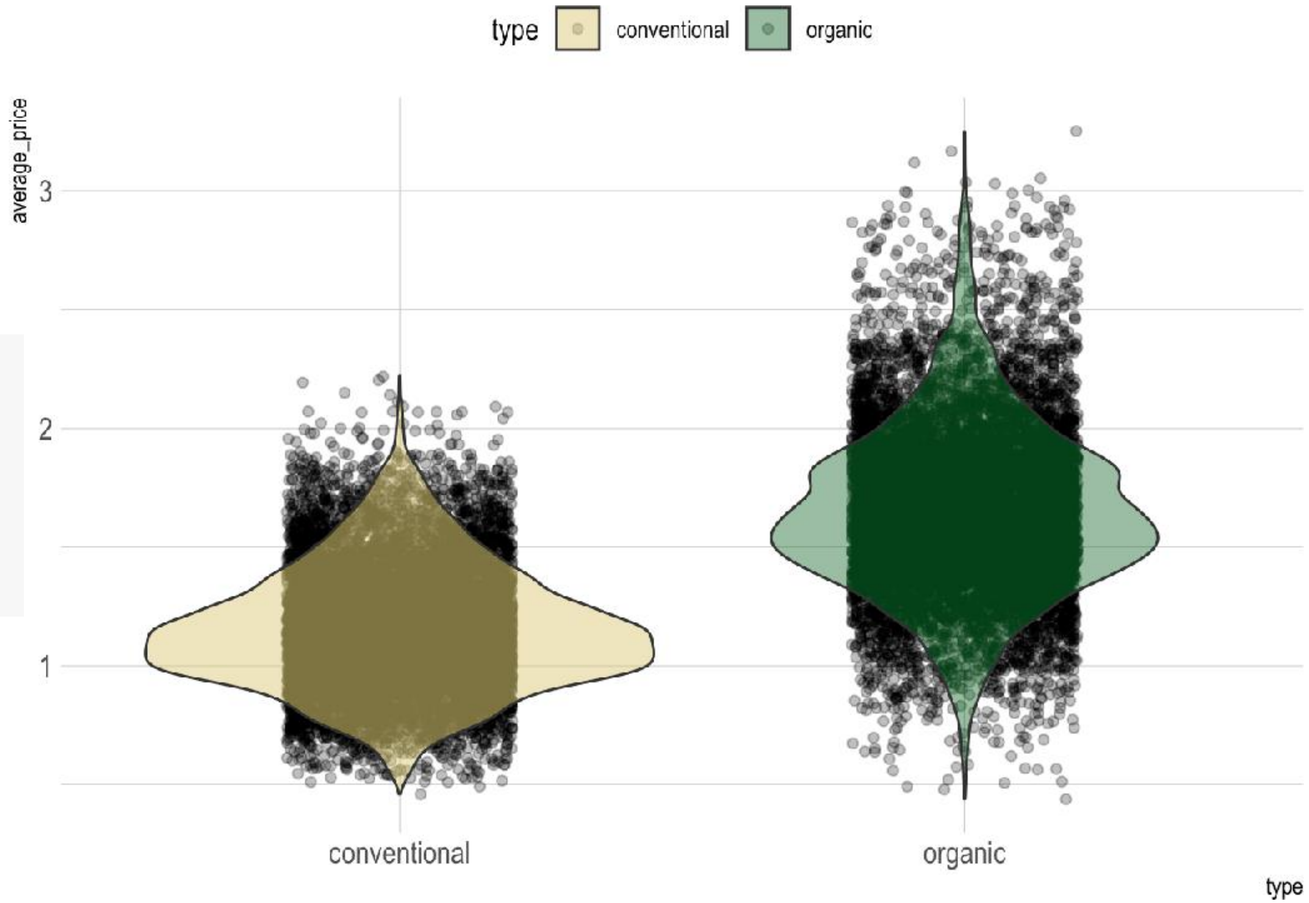
```
avocado_data %>%
  ggplot(aes(x = average_price, color = type, fill = type)) +
  geom_density(alpha = 0.5)
```



VIOLIN PLOTS

- “mirrored density plots”
- good for multi-group comparisons

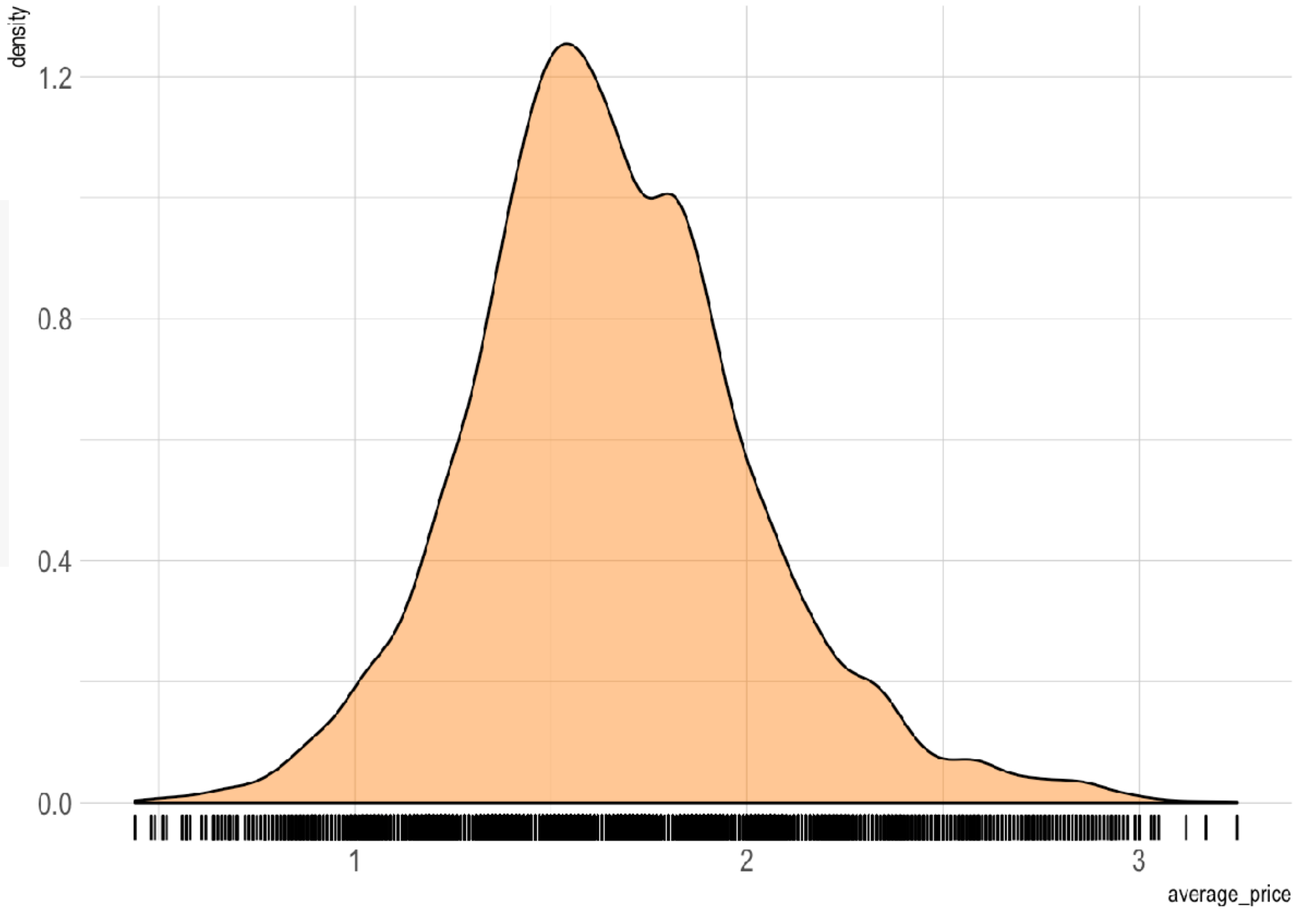
```
avocado_data %>%
  ggplot(aes(x = type, y= average_price, fill = type)) +
  geom_jitter(alpha = 0.3, width = 0.2) +
  geom_violin(alpha = 0.5)
```



RUG PLOTS

- show data points near axis

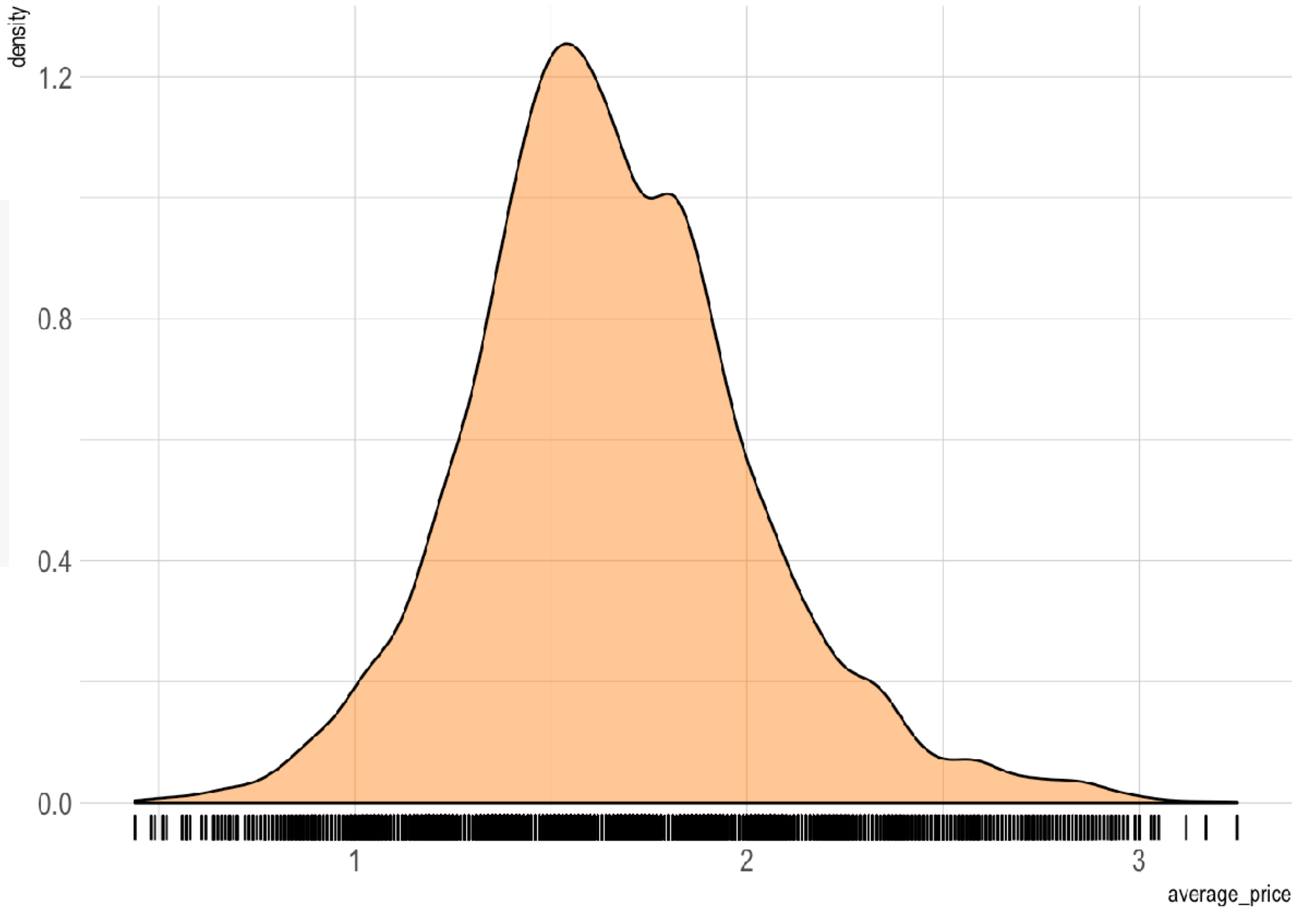
```
avocado_data %>%
  filter(type == "organic") %>%
  ggplot(aes(x = average_price)) +
  geom_density(fill = "darkorange", alpha = 0.5) +
  geom_rug()
```



RUG PLOTS

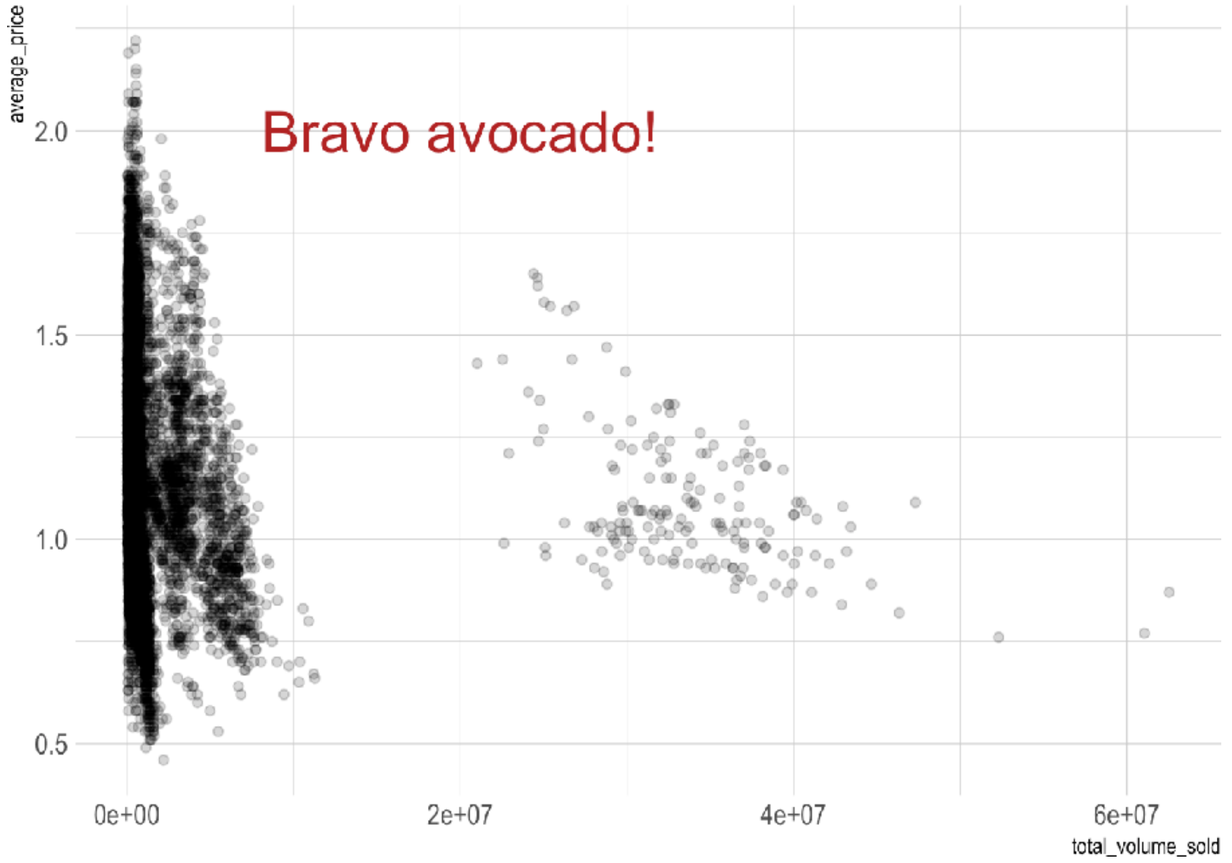
- show data points near axis

```
avocado_data %>%
  filter(type == "organic") %>%
  ggplot(aes(x = average_price)) +
  geom_density(fill = "darkorange", alpha = 0.5) +
  geom_rug()
```



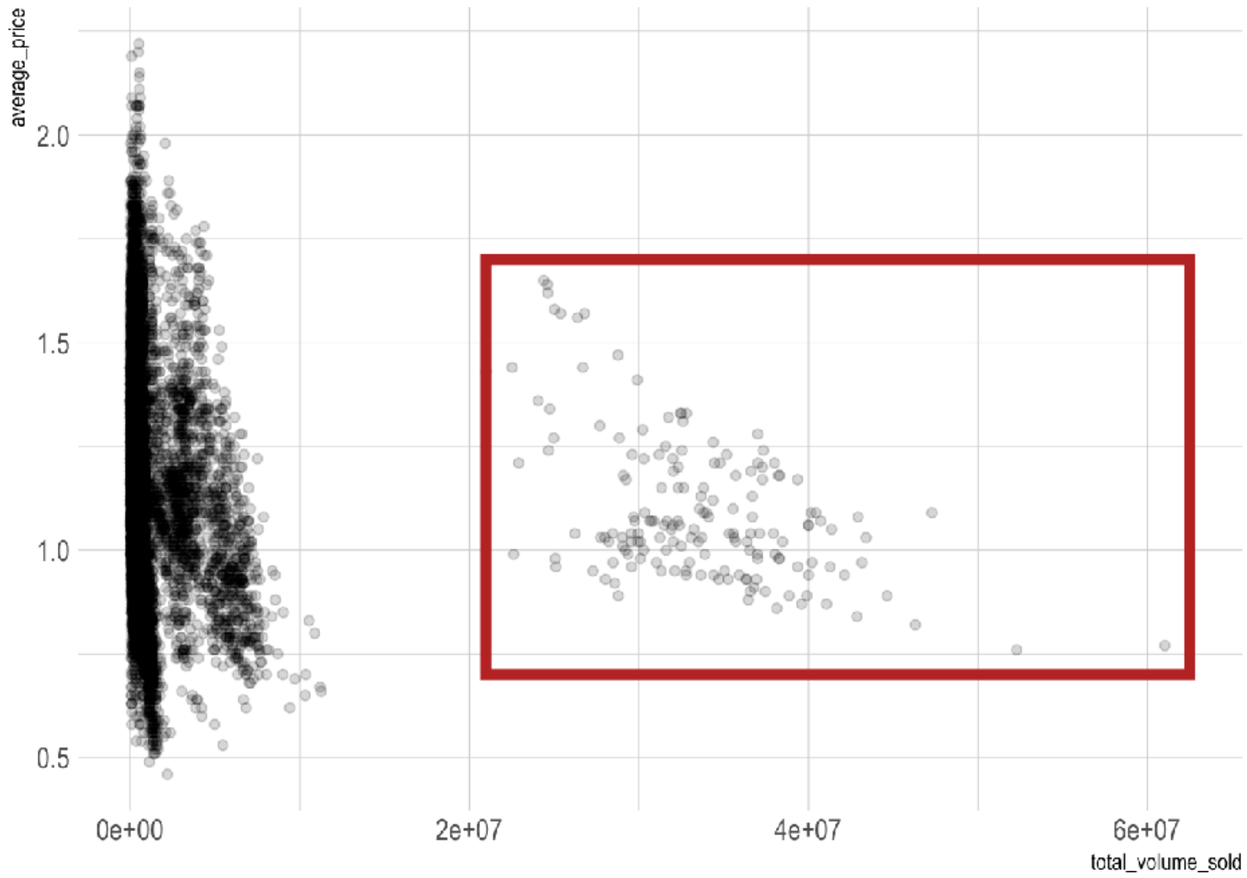
ANOTATION

```
avocado_data %>%
  filter(type == "conventional") %>%
  ggplot(aes(x = total_volume_sold, y = average_price)) +
  geom_point(alpha = 0.2) +
  annotate(
    geom = "text",
    # x and y coordinates for the text
    x = 2e7,
    y = 2,
    # text to be displayed
    label = "Bravo avocado!",
    color = "firebrick",
    size = 8
  )
```



ANOTATION

```
avocado_data %>%
  filter(type == "conventional") %>%
  ggplot(aes(x = total_volume_sold, y = average_price)) +
  geom_point(alpha = 0.2) +
  annotate(
    geom = "rect",
    # coordinates for the rectangle
    xmin = 2.1e7,
    xmax = max(avocado_data$total_volume_sold) + 100,
    ymin = 0.7,
    ymax = 1.7,
    color = "firebrick",
    fill = "transparent",
    size = 2
  )
```

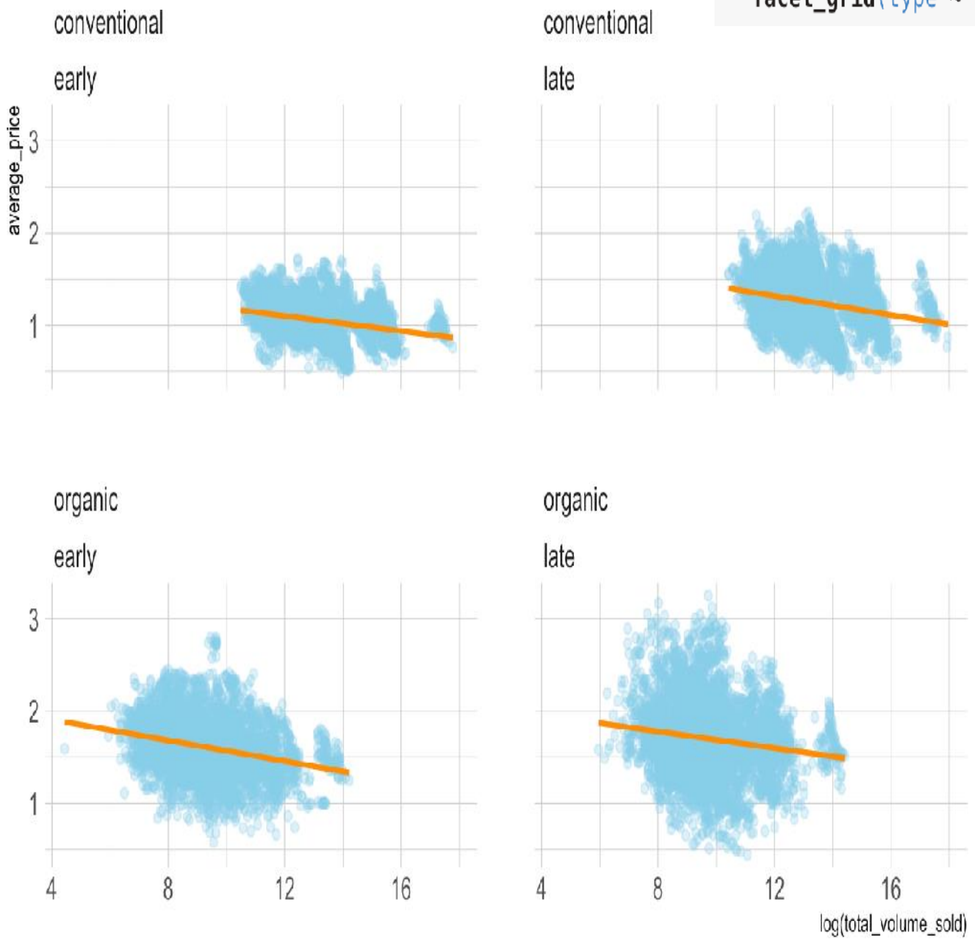


Faceting

FACET GRID

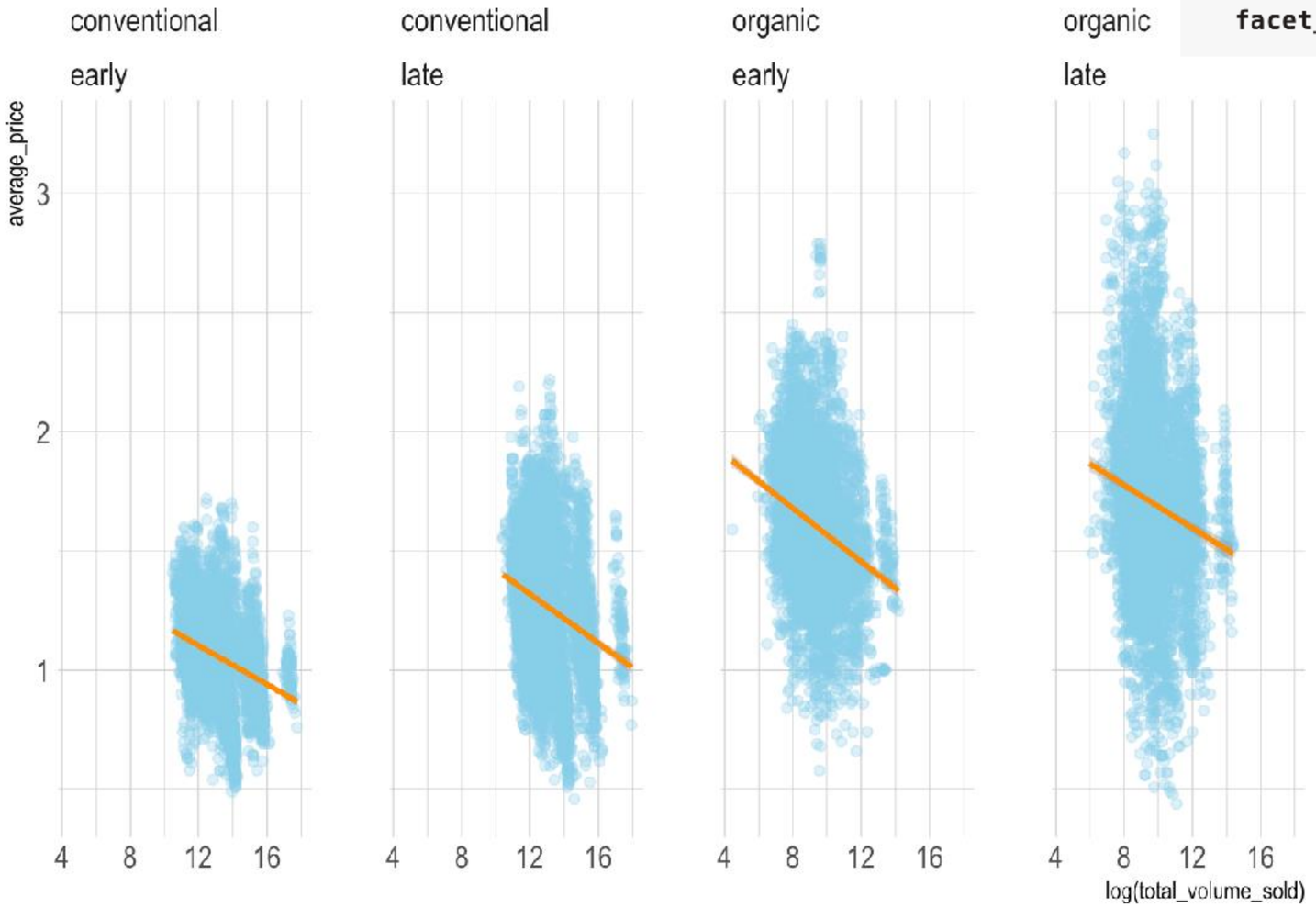
If we have grouping information, sometimes it can just get too much to put all of the information in a single plot, even if we use colors, shapes or line types for disambiguation. Facets are a great way to separately repeat the same kind of plot for different levels of relevant factors.

```
avocado_data_early_late %>%
  ggplot(aes(x = log(total_volume_sold), y = average_price)) +
  geom_point(alpha = 0.3, color = "skyblue") +
  geom_smooth(method = "lm", color = "darkorange") +
  facet_grid(type ~ early)
```



FACET WRAP

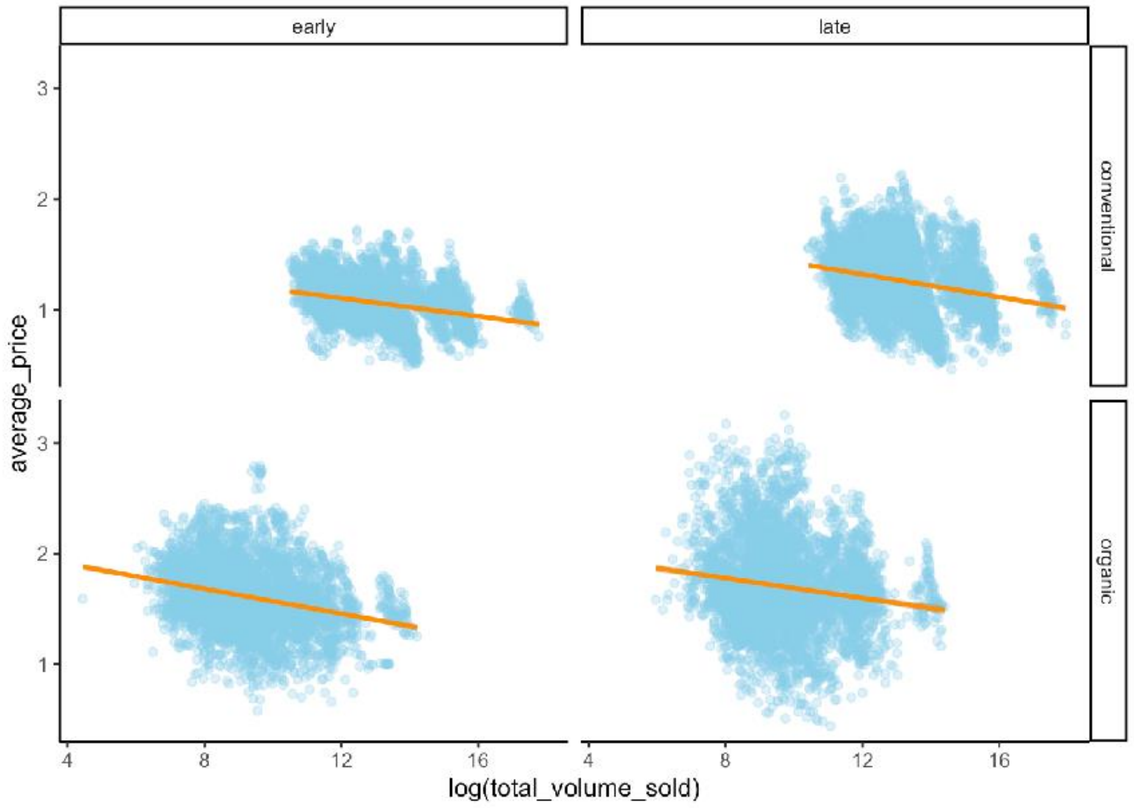
```r
avocado_data_early_late %>%
  ggplot(aes(x = log(total_volume_sold), y = average_price)) +
  geom_point(alpha = 0.3, color = "skyblue") +
  geom_smooth(method = "lm", color = "darkorange") +
  facet_wrap(type ~ early, nrow = 1)
```



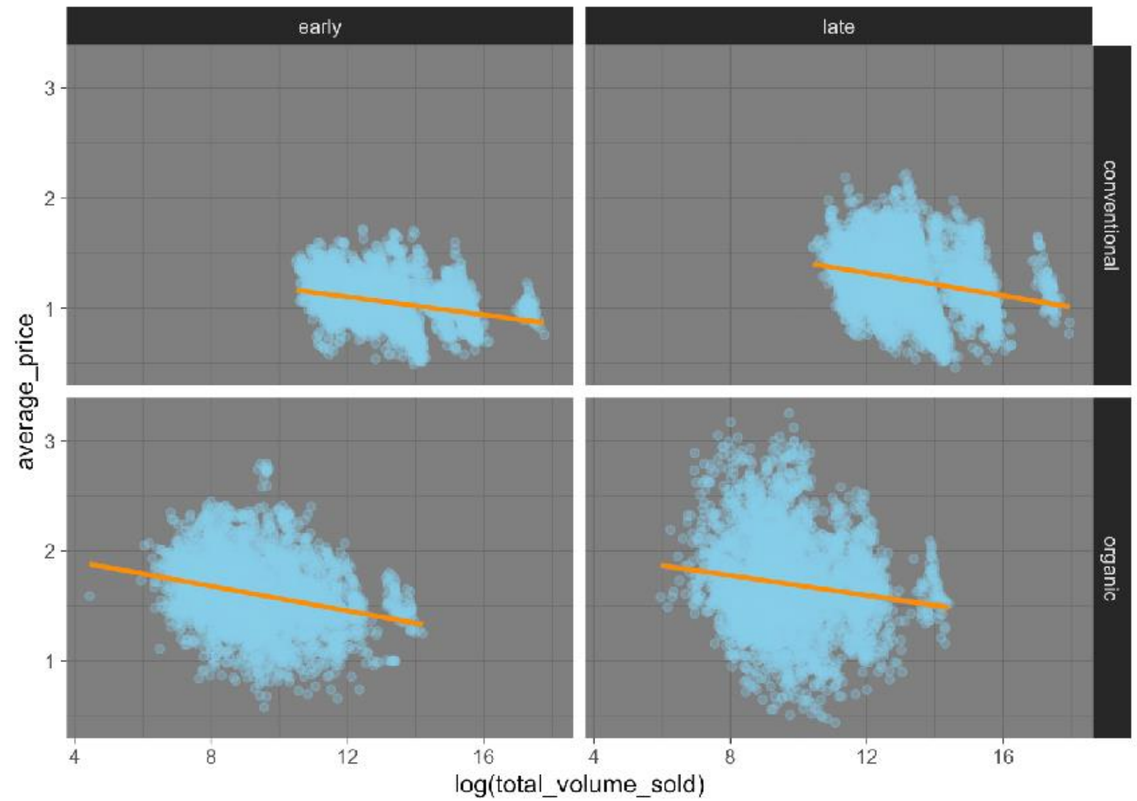
Bells & whistles

READY-MADE THEMES

```
avocado_grid_plot + theme_classic()
```

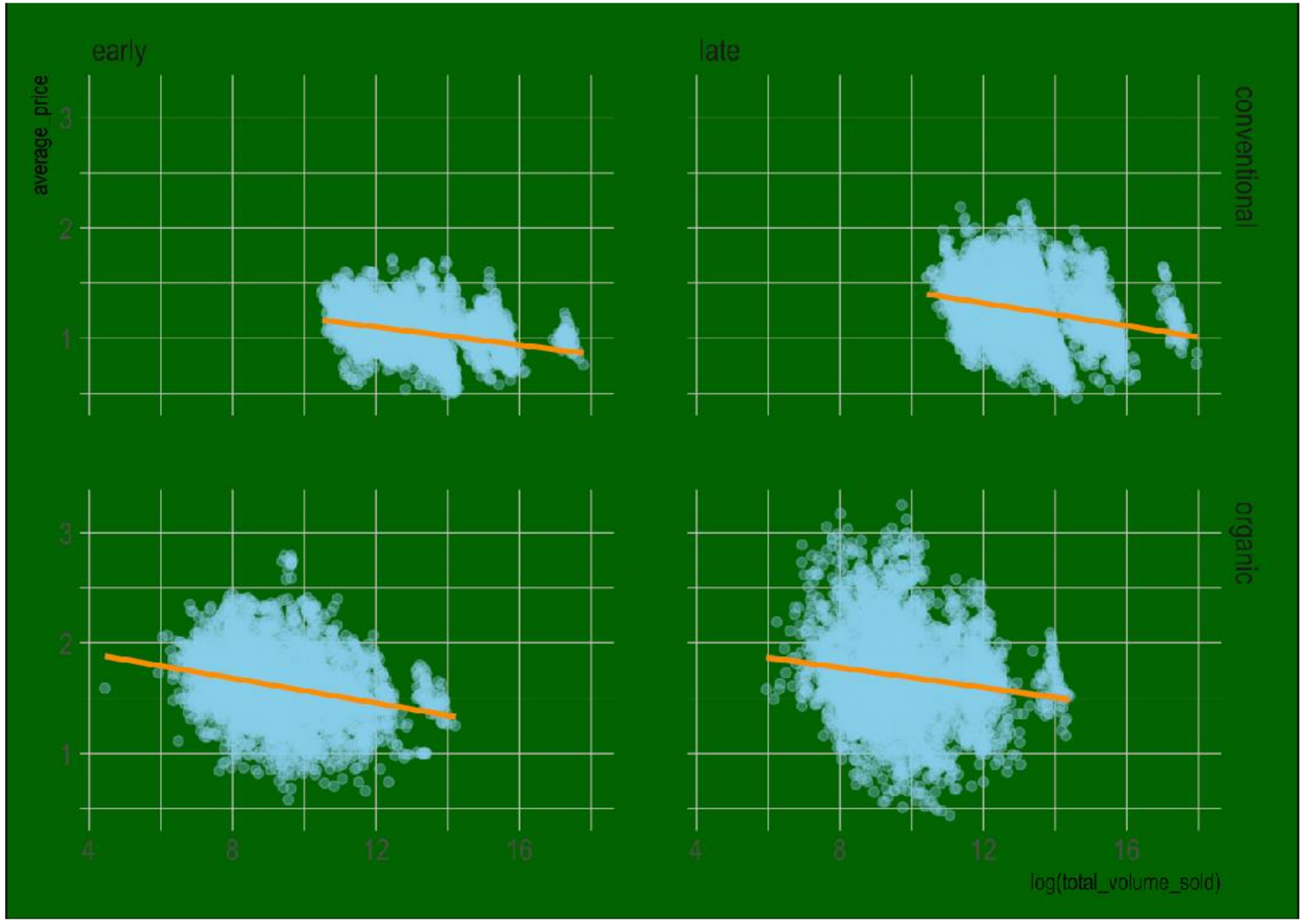



```
avocado_grid_plot + theme_dark()
```



TWEAKING AN EXISTING THEME

```
avocado_grid_plot + theme(plot.background = element_rect(fill = "darkgreen"))
```



Thank you for listening