Figure formats, interactivity and paired comparisons

Contents

Lecture learning goals

By the end of the lecture you will be able to:

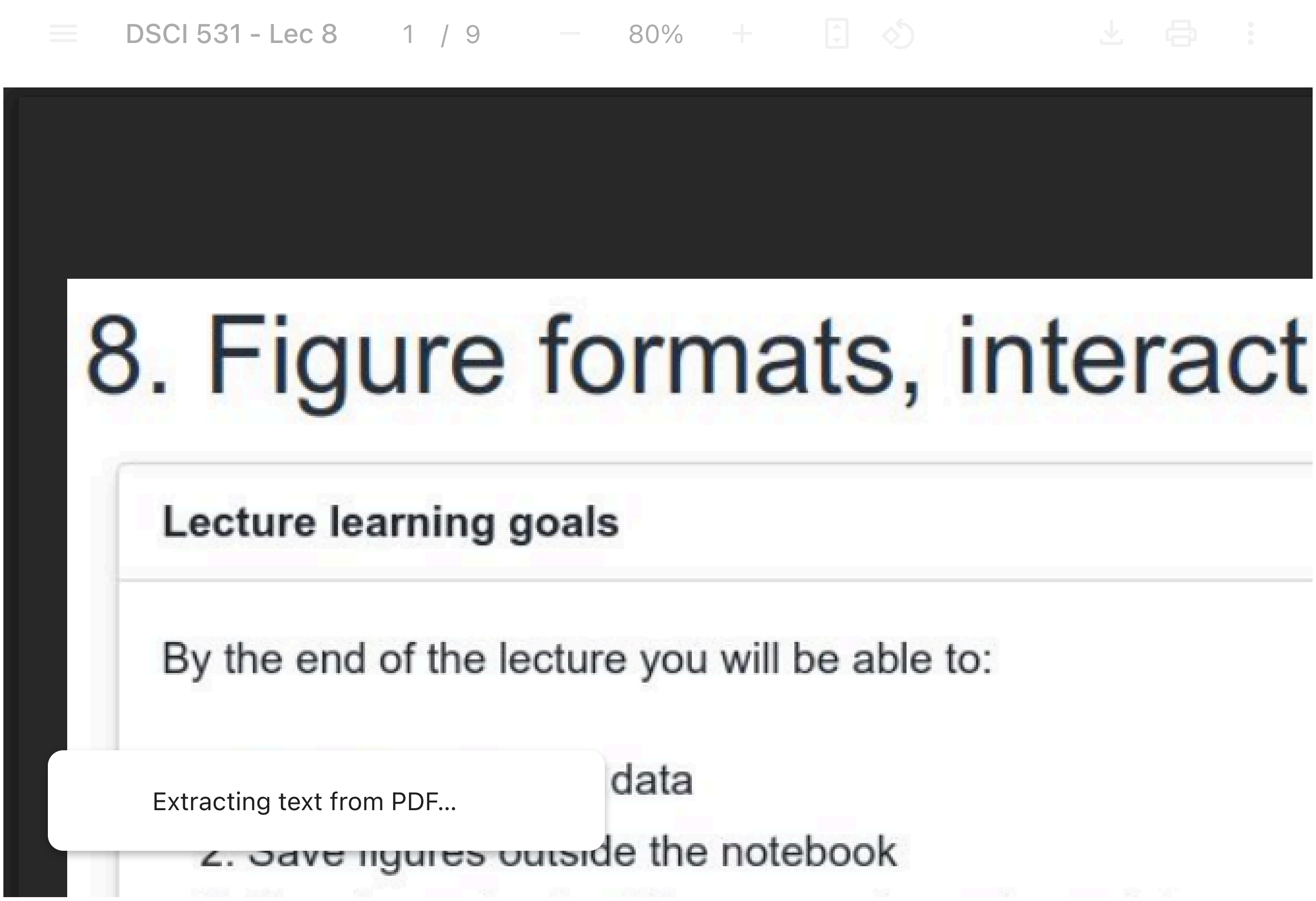
1. Telling a story with data
2. Save figures outside the notebook
3. Visualize pair-wise differences using a slope plot
4. Creat interactive ggplots charts via plotly (not on the quiz)
5. Create widget-based interactivity (not on the quiz)
6. Explain figure formats in the notebook (not on the quiz)

Required activities

After class:

- Review the lecture notes.
- Watch this 15 min video on paired comparisons
- Section 29 on how to tell a story with data. It is really important to read this chapter, it has some great details on how to tell a story with several examples.

Lecture slides



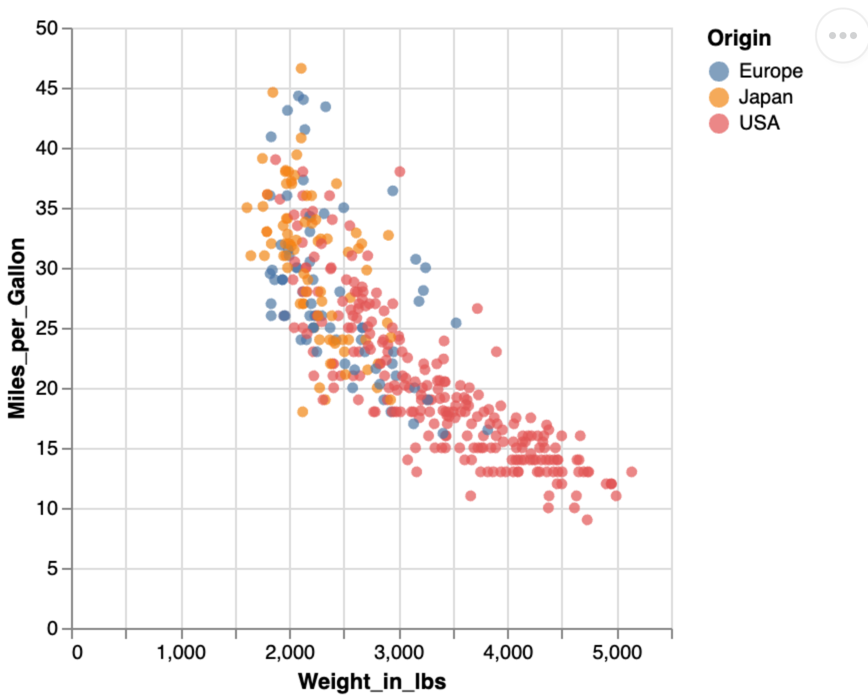
8.1. Saving figures

8.1.1. Py

In addition to exporting an entire notebook, how can we save individual figures via Altair and ggplot?

Saving as HTML ensures that any interactive features are still present in the saved file.

```
import altair as alt
from vega_datasets import data

cars = data.cars()

mpg_weight = alt.Chart(cars).mark_circle().encode(
    x='Weight_in_lbs',
    y='Miles_per_Gallon',
    color='Origin',
    tooltip=['Name', 'Origin', 'Horsepower', 'Miles_per_Gallon']
)
mpg_weight
```




```
mpg_weight.save('mpg_weight.html')
```

This means we could send this HTML file to anyone (e.g. as an email attachment) and they could open it on their computer and still have the interactive elements loaded in the browser, since they don't require a Python server running. You could also upload this file to a static web page generator such as GitHub pages and have it served online (rename the chart `index.html` if you want it to be displayed as the landing page on GitHub pages), e.g. as I have done here joelostblom/altair-demos (live at https://joelostblom.github.io/altair-demos/).

It is also possible to save as non-interactive formats such as png (raster) and svg (vector). Internally this relies on another packages called vl-convert, which we have installed in the 531 environment.

```
mpg_weight.save('mpg_weight.png')
```

The resolution/size of the saved image can be controlled via the `scale_factor` parameter.

```
mpg_weight.save('mpg_weight-hires.png', scale_factor=3)
```

You might have noticed that Altair charts do not show up on GitHub when you e.g. review a PR. This is the same for all interactive charting libraries and it is because GitHub does not load interactive features, and only displays static images. Altair can include a static image as a fallback for each chart you make, so that you still have the interactive chart in your JupyterLab or VS code, but in environments that can't display these (such as GitHub) and image will be used instead.

```
# Run the following line to enable the backup image that will make charts appe
# alt.renderers.enable('mimetype')
```

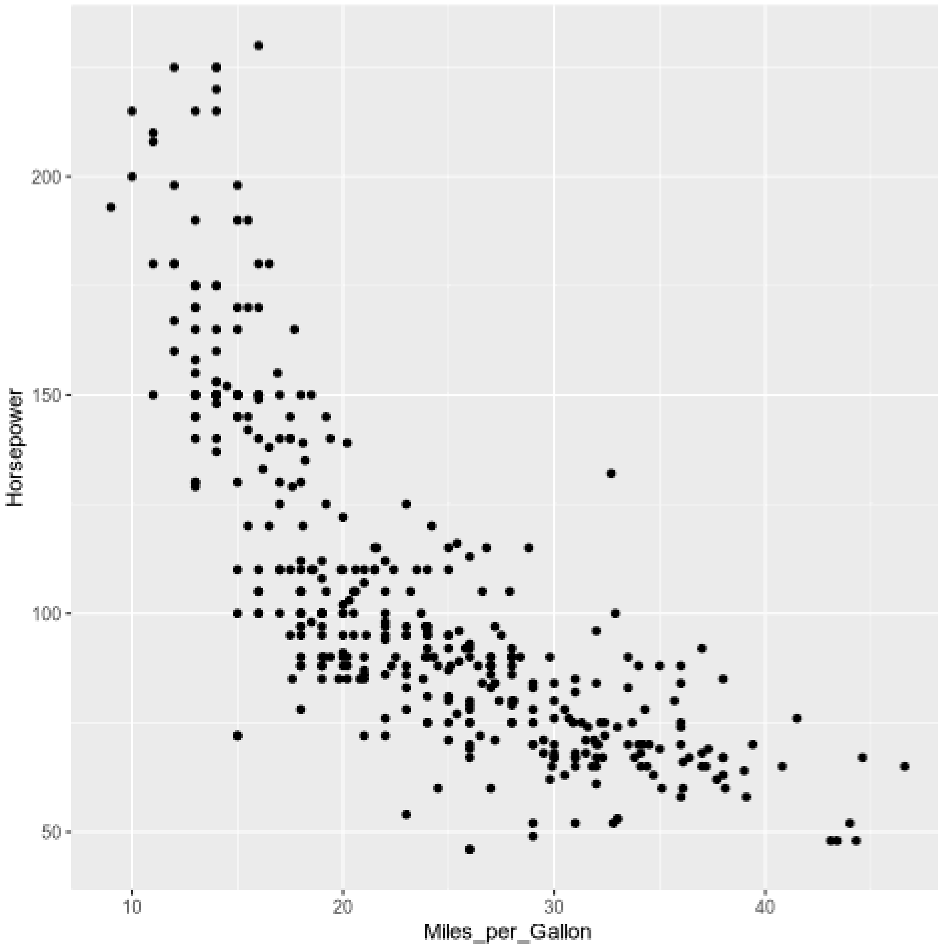
8.1.2. R

```
# Load the R cell magic
%load_ext rpy2.ipython
```

```
%%R -i cars
library(tidyverse)

mpg_weight <- ggplot(cars) +
    aes(Miles_per_Gallon, Horsepower) +
    geom_point()
mpg_weight
```

```
── Attaching core tidyverse packages ──────────────────────── tidyverse 2.0.0 -
✔ dplyr     1.1.4     ✔ readr     2.1.5
✔ forcats   1.0.0     ✔ stringr   1.5.1
✔ ggplot2   3.5.1     ✔ tibble    3.2.1
✔ lubridate 1.9.3     ✔ tidyr     1.3.1
✔ purrr     1.0.2
```

```
── Conflicts ──────────────────────────────────────── tidyverse_conflicts() ─
✖ dplyr::filter() masks stats::filter()
✖ dplyr::lag()    masks stats::lag()
ℹ Use the conflicted package (<http://conflicted.r-lib.org/>) to force all con
```



The `ggsave` functions saves the most recent plot to a file.

```
%%R
ggsave('mpg_weight-r.png')
```

```
Saving 6.67 x 6.67 in image
```

You can also specify which figure to save.

```
%%R
ggsave('mpg_weight-r.png', mpg_weight)
```

```
Saving 6.67 x 6.67 in image
```

Setting the dpi controls the resolution of the saved figure.

```
%%R
ggsave('mpg_weight-hires-r.png', dpi=96)
```

```
Saving 6.67 x 6.67 in image
```

You can save to PDF and SVG as well. Note that saving to svg requires the `svglite` package.

```
%%R
ggsave('mpg_weight-r.pdf', mpg_weight)
```

```
Saving 6.67 x 6.67 in image
```

8.2. Pairwise comparisons

8.2.1. R

Let's start by looking at your results from the world health quiz we did in lab 1! Below, I read in the data and assign a label for whether each student had a positive or negative outlook of their own results compared to their estimation of the class average.

```
%%R -o scores_this_year
library(tidyverse)

theme_set(theme_grey(base_size=18))

scores_raw <- read_csv('data/students-gapminder.csv')
colnames(scores_raw) <- c('time', 'student_score', 'estimated_class_mean')
scores_this_year <- scores_raw |>
    mutate(
        diff = student_score - estimated_class_mean,
        self_belief = case_when(
            diff == 0 ~ 'neutral',
            diff < 0 ~ 'negative',
            diff > 0 ~ 'positive'
        ),
        year = time |> lubridate::parse_date_time(order='mdY HMS') |> lubridat
    ) |>
    # Only keep the scores from October which is when we run the survey in MDS
    filter((time |> lubridate::parse_date_time(order='mdY HMS') |> lubridate::
    filter(year == 2024) |>
    pivot_longer(
        !c(time, year, self_belief, diff),  # time is kept as a student ID
        values_to = 'score',
        names_to = 'score_type'
    ) |>
    mutate(score_type = factor(score_type, levels = c('student_score', 'estima
    arrange(desc(diff))
scores_this_year
```

```
Rows: 315 Columns: 3
```

```
── Column specification ──────────────────────────────────────────────────
Delimiter: ","
chr (1): Timestamp
dbl (2): Please enter how many questions you answered correctly on the test ..
```

```
ℹ Use `spec()` to retrieve the full column specification for this data.
ℹ Specify the column types or set `show_col_types = FALSE` to quiet this messa
```

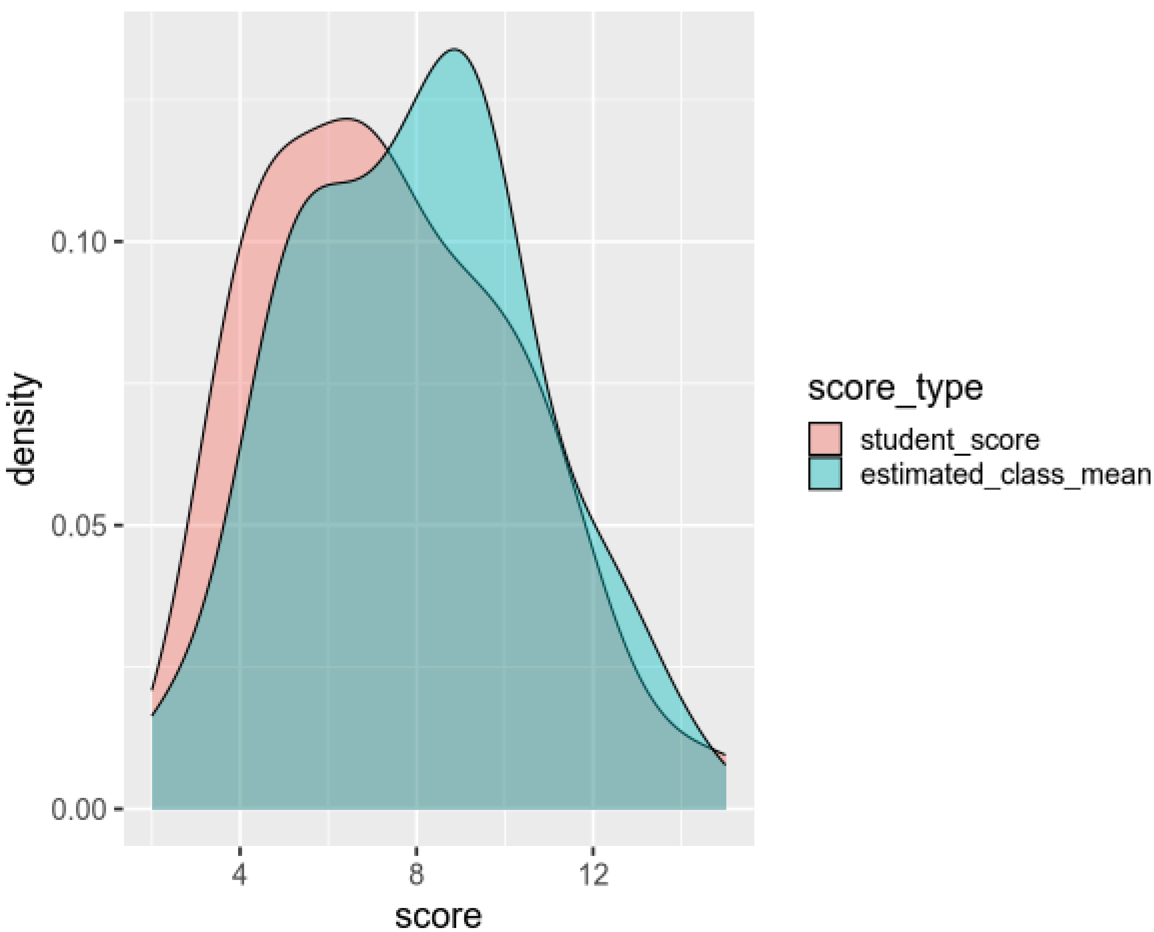
```
# A tibble: 92 × 6
```

```
   time                    diff self_belief  year score_type           score
```

```
   <chr>              <dbl> <chr>      <dbl> <fct>               <dbl>
 1 10/12/2024 0:04:22     5 positive    2024 student_score          15
 2 10/12/2024 0:04:22     5 positive    2024 estimated_class_mean   10
 3 10/8/2024 20:19:17     3 positive    2024 student_score           9
 4 10/8/2024 20:19:17     3 positive    2024 estimated_class_mean    6
 5 10/7/2024 14:28:51     2 positive    2024 student_score           7
 6 10/7/2024 14:28:51     2 positive    2024 estimated_class_mean    5
 7 10/7/2024 14:37:58     2 positive    2024 student_score           6
 8 10/7/2024 14:37:58     2 positive    2024 estimated_class_mean    4
 9 10/8/2024 10:38:58     2 positive    2024 student_score           5
10 10/8/2024 10:38:58     2 positive    2024 estimated_class_mean    3
# ℹ 82 more rows
# ℹ Use `print(n = ...)` to see more rows
```

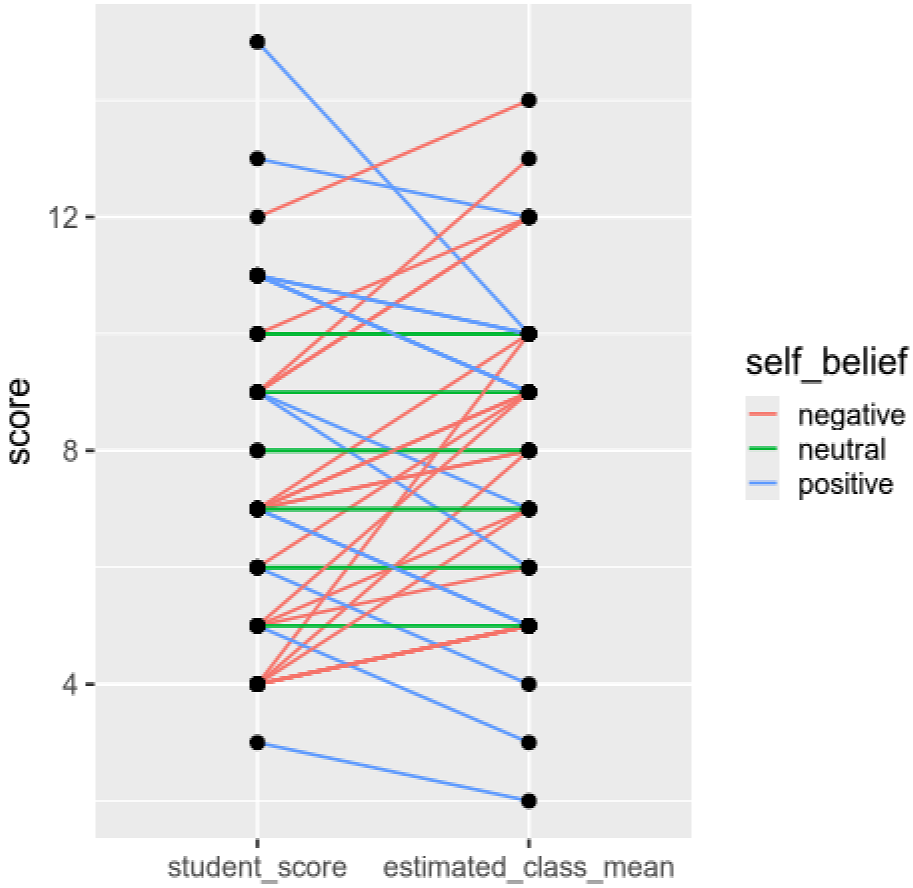
We could make a distribution plot, such as a KDE for the students score and estimated class score. From this plot we can see that on average students seemed to believe their classmates scored better, but we don’t know if this is because all students thought this, or some thought their classmates scored much better while others thought it was about the same.

```
%%R -w 600
ggplot(scores_this_year) +
    aes(x = score,
       fill = score_type) +
    geom_density(alpha=0.4)
```



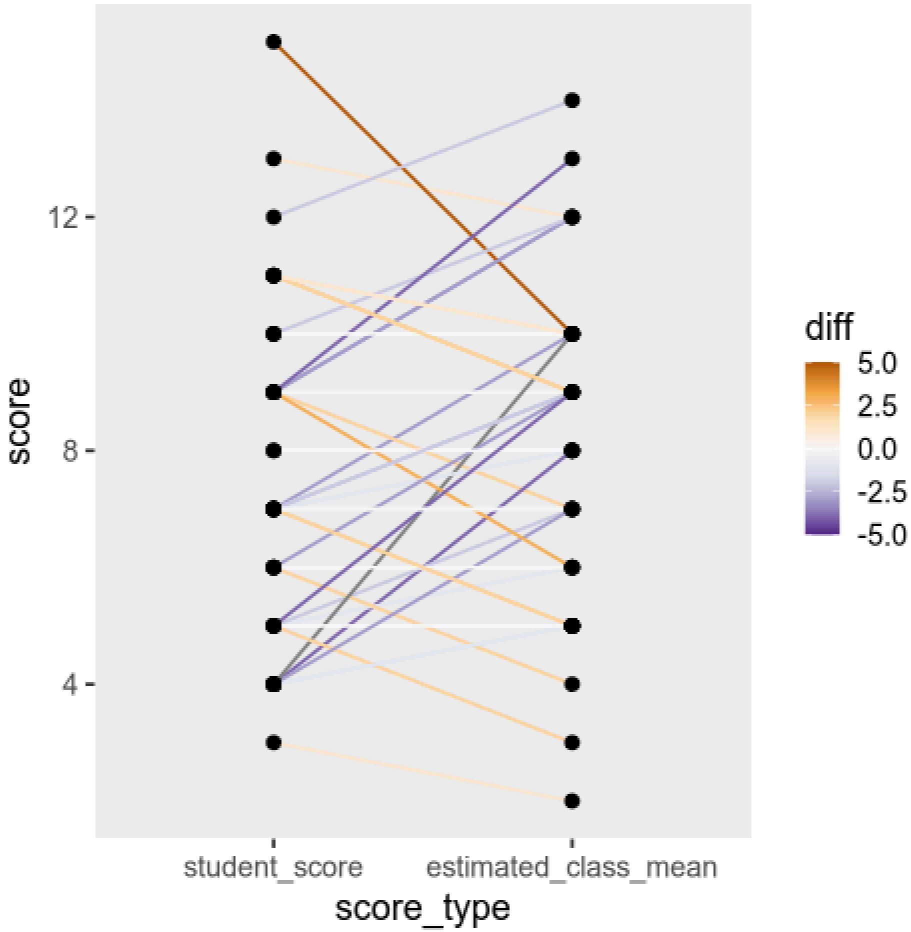
Drawing out each students score and estimated score, and then connecting them with a line allows us to easily see the trends in how many students thought their score was better or worse than the class (this is sometimes called a “slope plot”).

```
%%R
ggplot(scores_this_year) +
    aes(x = score_type,
        y = score,
       group = time) +
    geom_line(aes(color = self_belief), size = 0.8) +
    geom_point(size=3) + labs(x='')
```



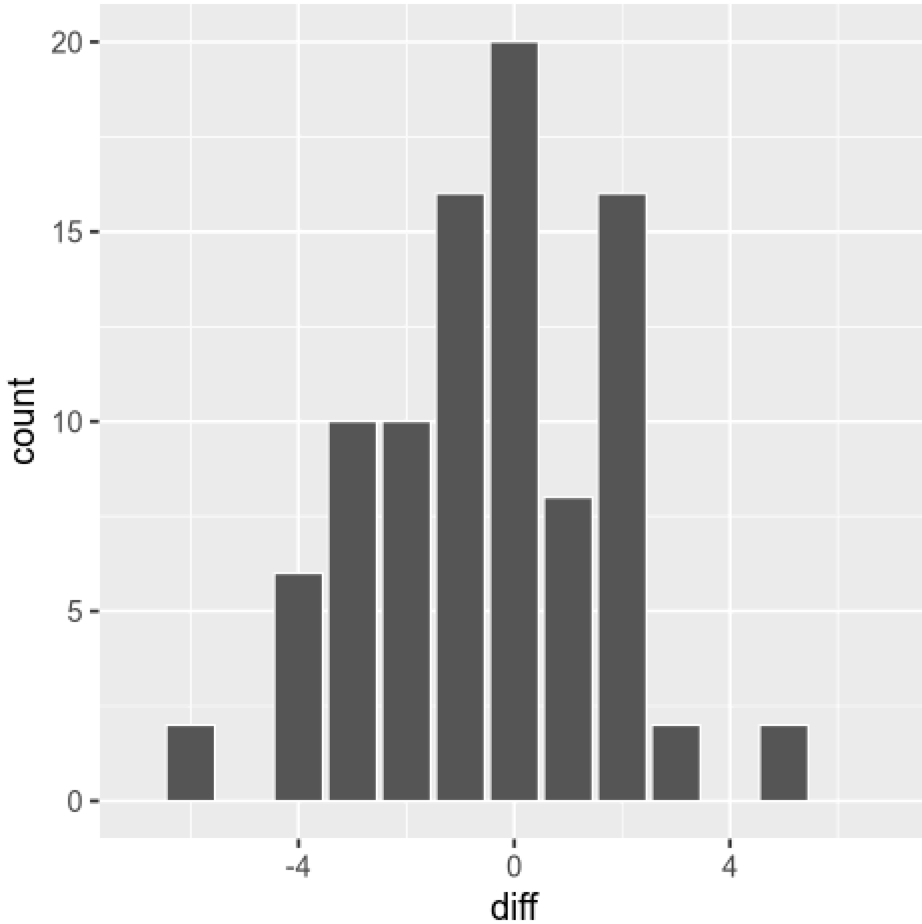
To make it easier to see how much better or worse each student score is compared to the class estimate, we can color the lines by the difference and set a diverging colormap. However, this can become quite noisy and it is not as easy to pick up the high level patterns as in the simpler visualization above (and the white lines are hard to see).

```
%%R
ggplot(scores_this_year) +
    aes(x = score_type,
        y = score,
       group = time) +
    geom_line(aes(color = diff), size = 0.8) +
    geom_point(size=3) +
    scale_color_distiller(palette = 'PuOr', limits = c(-5, 5)) +
    theme(panel.grid.major = element_blank(),
          panel.grid.minor = element_blank())
```



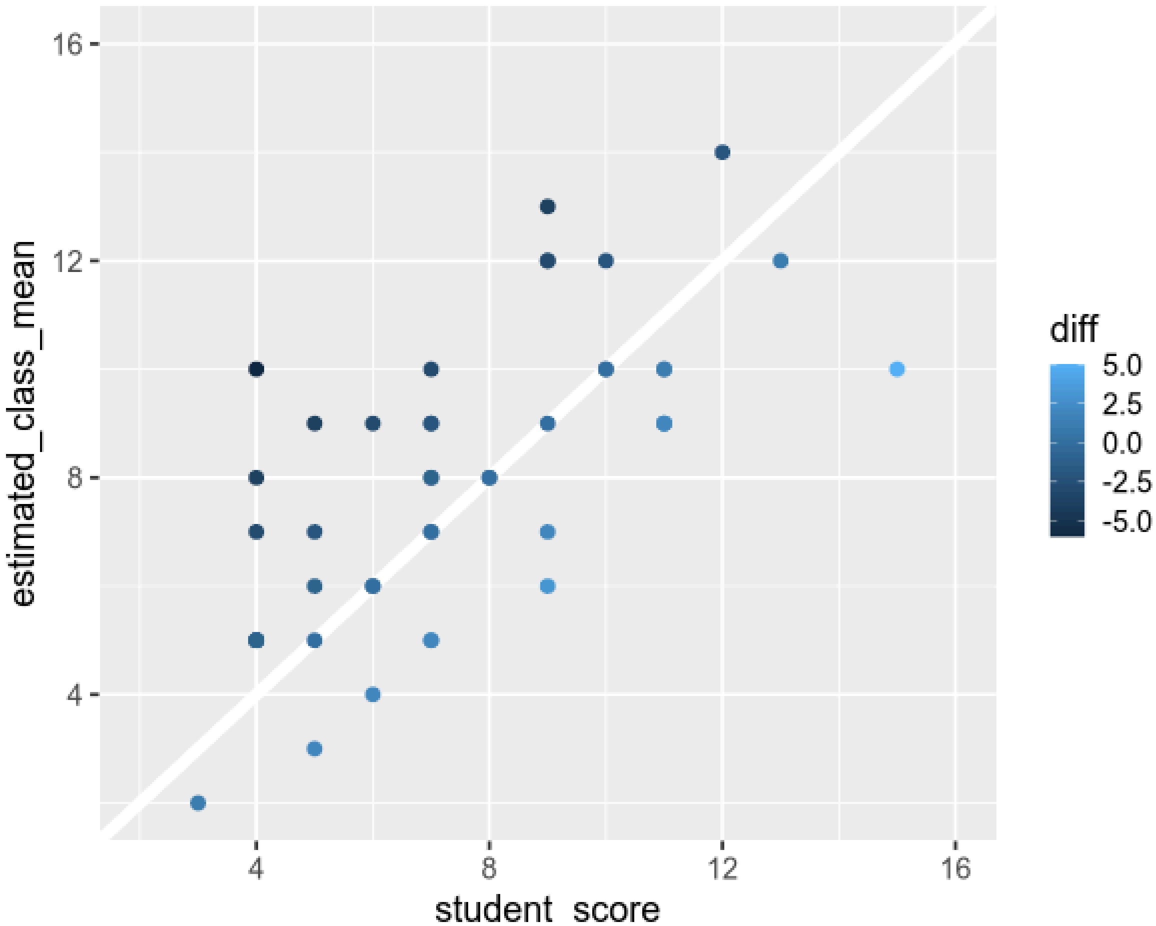
Another way we could have visualized these differences would have been as a bar plot of the differences, but we would not know the students' score, just the difference.

```
%%R
ggplot(scores_this_year) +
    aes(x = diff) +
    geom_bar(color='white') +
    scale_x_continuous(limits=c(-7, 7))  # center around 0
```



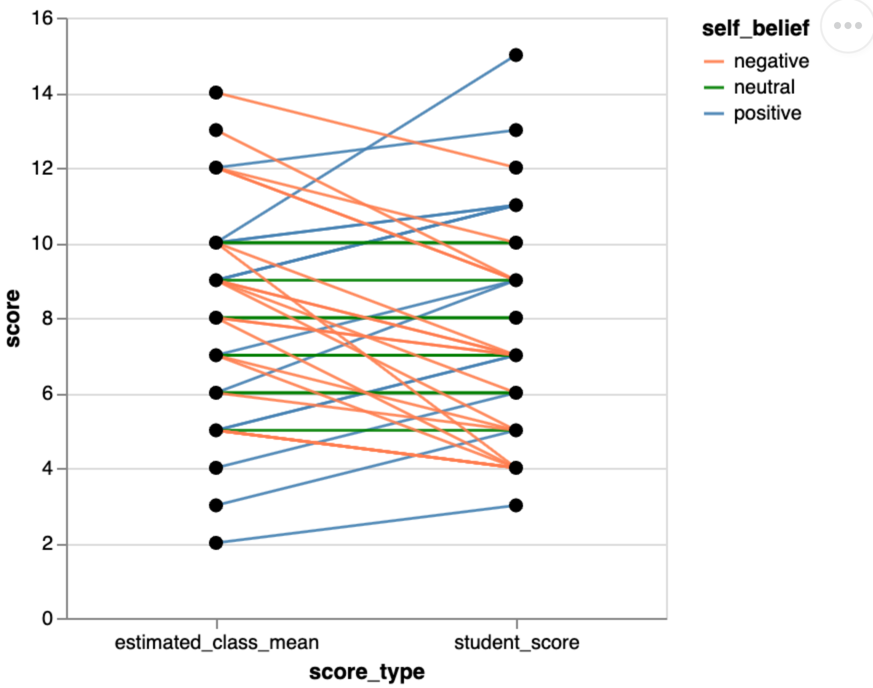
A scatter plot could also work for this comparison, ideally with a diagonal line at zero difference.

```
%%R -w 600
p <- ggplot(scores_this_year |> pivot_wider(names_from = score_type, values_fr
    aes(x = student_score,
        y = estimated_class_mean,
       color = diff) +
    geom_abline(slope = 1, intercept = 0, color = 'white', size = 3) +
    geom_point(size = 3) +
    # Compare over square plot with same axis extents makes it easier to judge
    scale_x_continuous(limits=c(2, 16)) +
    scale_y_continuous(limits=c(2, 16))
p
```

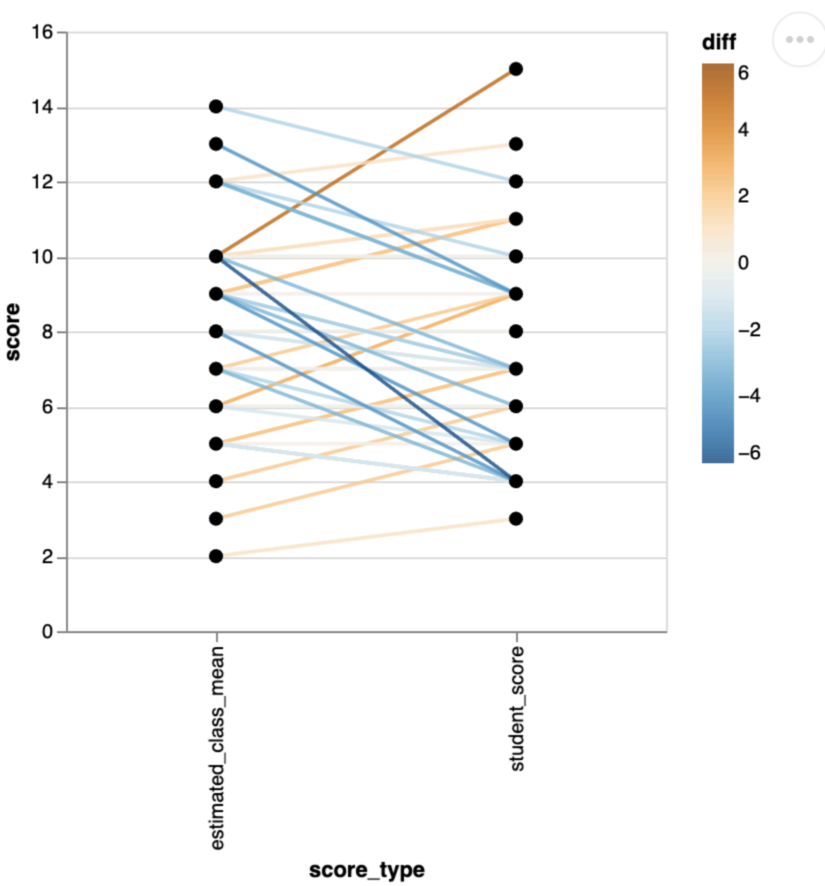


8.2.2. Py

```
points = alt.Chart(scores_this_year).mark_circle(size=50, color='black', opaci
    alt.X('score_type').axis(labelAngle=0),
    alt.Y('score'),
    alt.Detail('time')
).properties(
    width=300
)
(points.mark_line(size=1.4, opacity=0.9).encode(alt.Color('self_belief').scale
```




```
points = alt.Chart(scores_this_year).mark_circle(size=50, color='black', opaci
    alt.X('score_type'),
    alt.Y('score'),
    alt.Detail('time')).properties(width=300)
points.mark_line(size=1.8, opacity=0.8).encode(alt.Color('diff', scale=alt.Sca
```



8.3. Interactivity with plotly in R (not on the quiz)

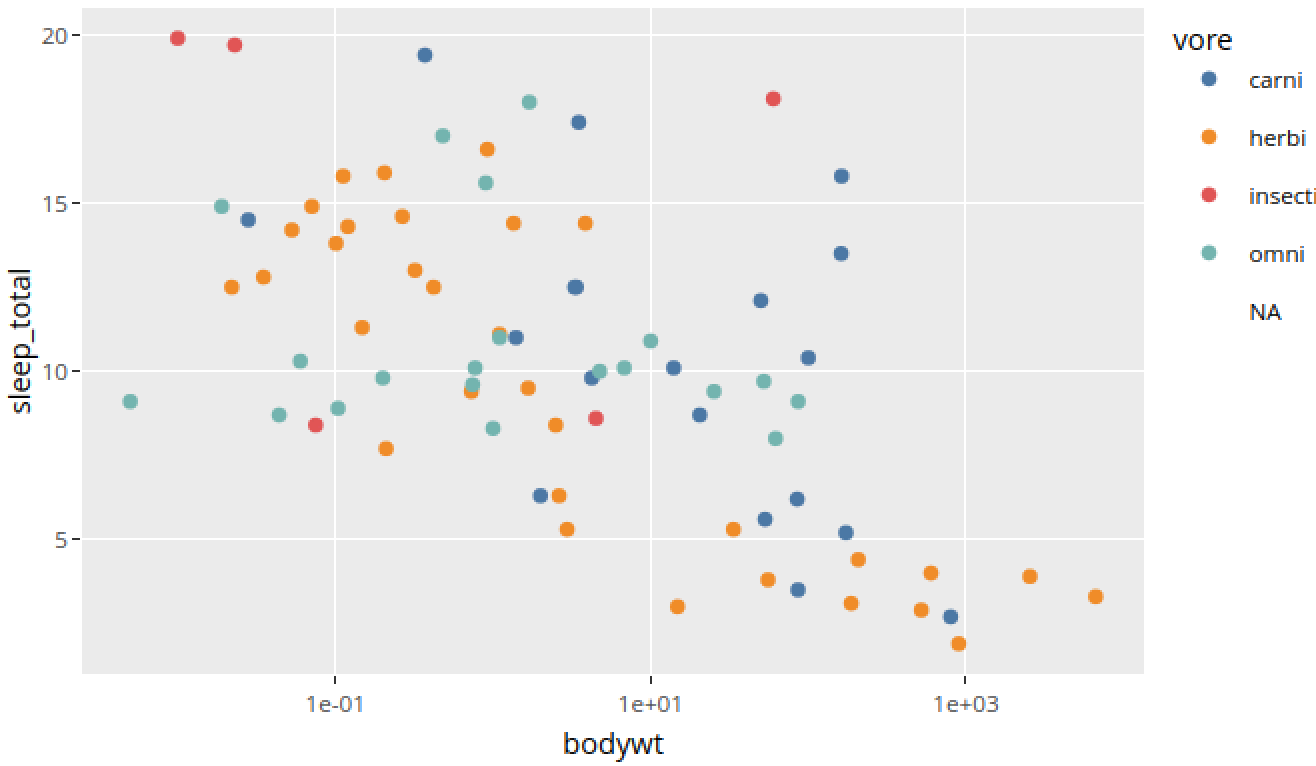
Everything from here and onwards will not be on the quiz, but is included in case your're interesting in learning more about the powerful interactive visualization we can build. You can find even more examples of interactive elements such as search boxes and checkboxes in the interactive secction of the Altair docs.

8.3.1. Making ggplot interactive with `ggplotly()`

Plotly is a separate library that can be used to convert ggplot charts into interactive versions. Plotly does not have an easily composable interaction grammar, but instead makes a few specific functions available for us to use. One of these lets us create animations, which is very cool! Plotly interactions work out of the box in RStudio (via the Htmlwidgets library), and will work in the knitted notebooks. They should also work in JupyterLab if you first install the JupyterLab plotly extensions. They will not work in these lecture notes however, so you will need to use one of the approaches above to try it out.

To make a basic interactive version of a chart, giving it a tooltip on hover, a clickable legend, and the ability to zoom, we can wrap our ggplot chart in the function `ggplotly()`:

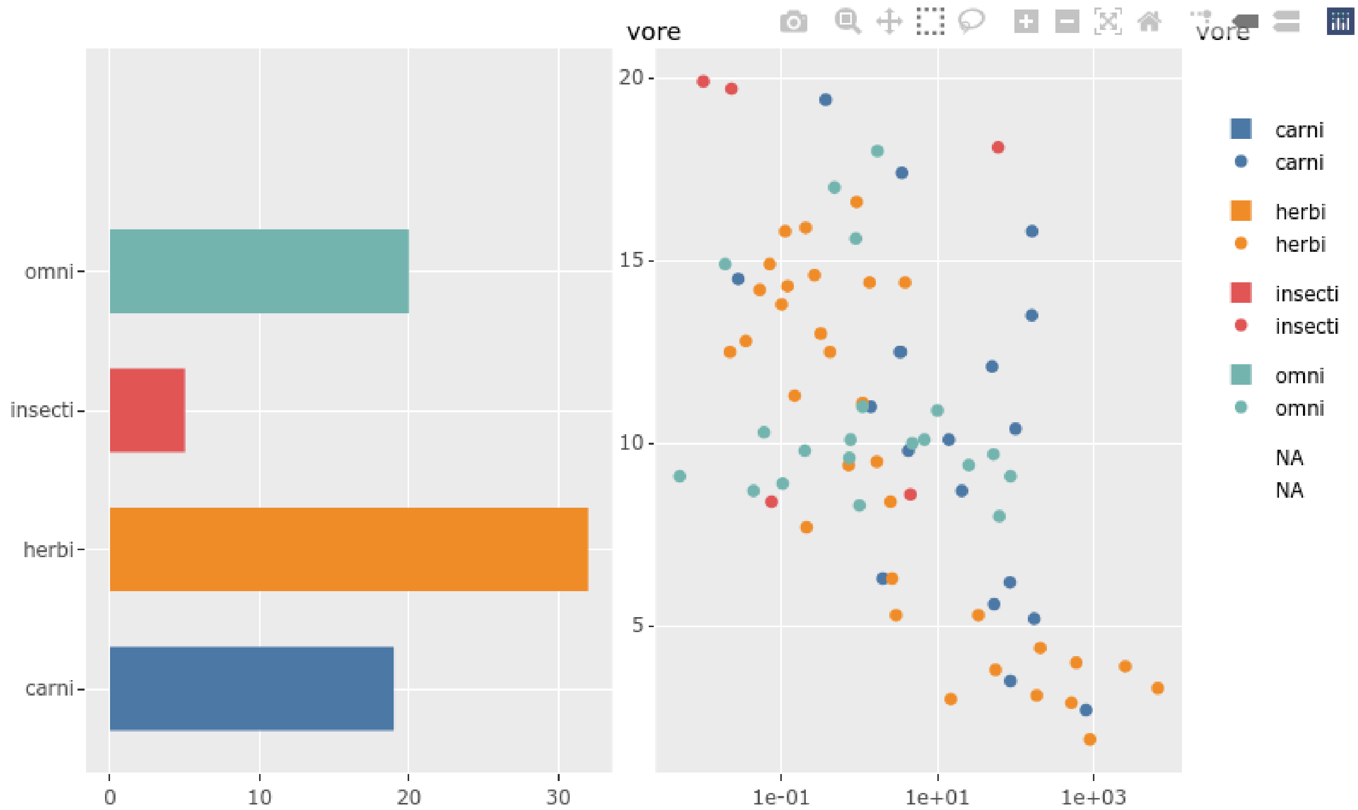
```
library(ggplot2)
library(plotly)
library(dplyr)

p <- ggplot(msleep) +
    aes(x = bodywt,
        y = sleep_total,
        color = vore,
        text = name) +
    geom_point() +
    scale_x_log10() +
    ggthemes::scale_color_tableau()

ggplotly(p)
```



8.3.2. Sharing legend interactivity

As we saw above, we get zooming and interactive legends by default in plotly. If we put two plots together in a plotly `subplot` layout they share an interactive legend (although with doubled glyphs in the legend). There is also a highlight function that can be used to drive non-legend based selection between two plots.

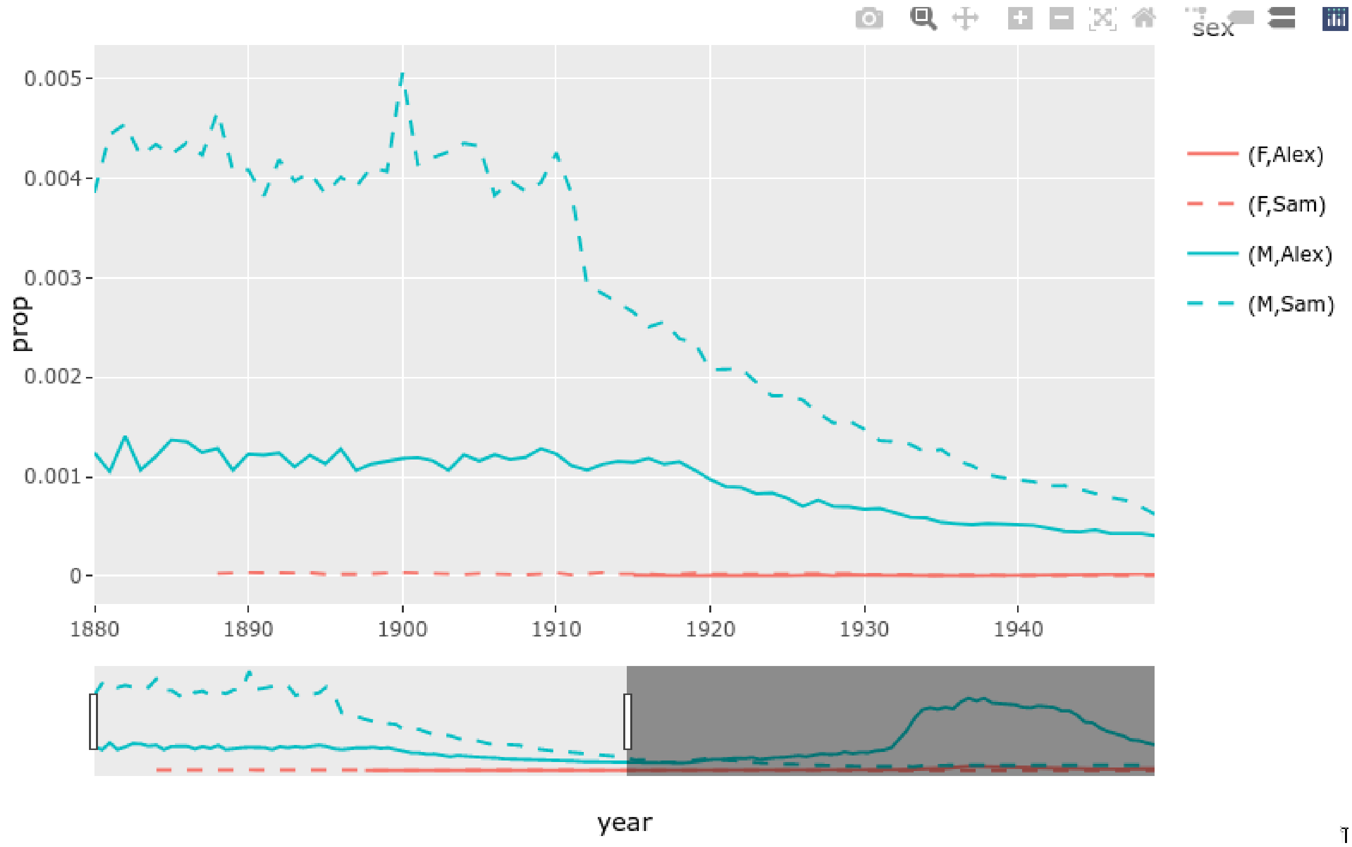
```
p <- ggplot(msleep) +
    aes(y = vore,
        fill = vore) +
    geom_bar(width = 0.6) +
    ggthemes::scale_fill_tableau()
p1 <- ggplotly(p, tooltip = 'text') %>% layout(dragmode = 'select')

p <- ggplot(msleep) +
    aes(x = bodywt,
        y = sleep_total,
        color = vore,
        text = name) +
    geom_point() +
    scale_x_log10() +
    ggthemes::scale_color_tableau()
p2 <- ggplotly(p, tooltip = 'text') %>% layout(dragmode = 'select')

subplot(p1, p2)
```



8.3.3. Rangeslider

There is a built-in function for creating a small plot (a rangeslider) that can be used as a zoom widget of the bigger plot.

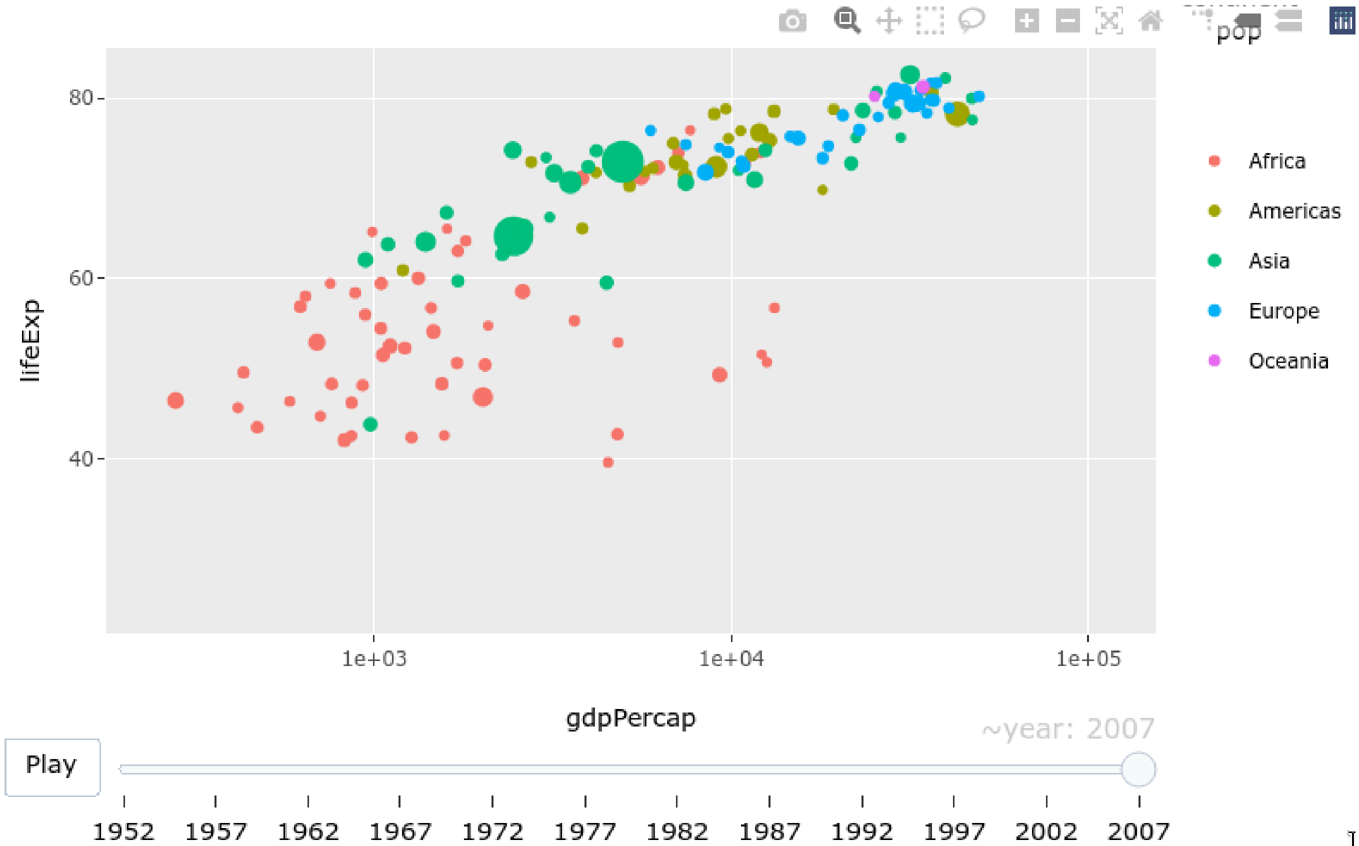
```
library(babynames)

nms <- filter(babynames, name %in% c("Sam", "Alex"))
range_p <- ggplot(nms) +
    geom_line(aes(year, prop, color = sex, linetype = name))

ggplotly(range_p, dynamicTicks = TRUE) %>%
    rangeslider() %>%
    layout(hovermode = "x")
```



8.3.4. Animations!

Animations are easily created by passing a column to the `frame` aesthetic in ggplot.

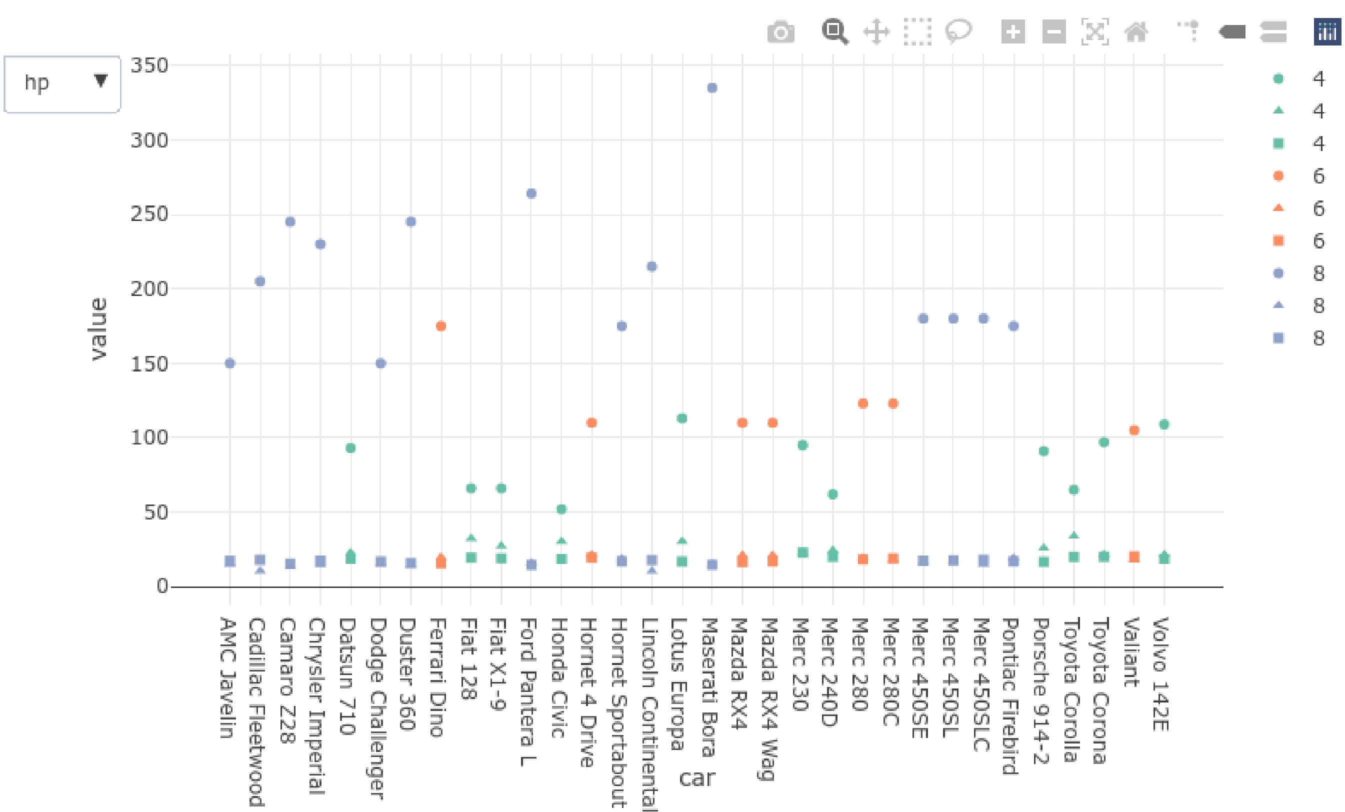
```
library(gapminder)

gap_p <- ggplot(gapminder, aes(gdpPercap, lifeExp, color = continent)) +
  geom_point(aes(size = pop, frame = year, ids = country)) +
  scale_x_log10()

ggplotly(gap_p)
```



8.3.5. Dropdowns

Dropdowns are a bit verbose to use with plotly and they cannot be used with ggpltoly to dynamically query and filter the data as we saw with the Altair plots. They could be used to control properties of the plot aesthetics such as marker color or which column's plot is shown, the same goes for sliders) here is an example of the latter with ggplotly:

```
dat <- mtcars
dat$cyl <- factor(dat$cyl)
dat$car <- rownames(mtcars)

dat %>%
  tidyr::pivot_longer(c(mpg, hp, qsec)) %>%
  plot_ly(x = ~car, y = ~value, color = ~cyl, symbol = ~name) %>%
  add_trace(type='scatter', mode='markers', name = ~cyl) %>%
  layout(
    updatemenus = list(
      list(
        type = "list",
        label = 'Category',
        buttons = list(
          list(method = "restyle",
               args = list('visible', c(TRUE, FALSE, FALSE)),
               label = "hp"),
          list(method = "restyle",
               args = list('visible', c(FALSE, TRUE, FALSE)),
               label = "mpg"),
          list(method = "restyle",
               args = list('visible', c(FALSE, FALSE, TRUE)),
               label = "qsec")
        )
      )
    )
  )
```



8.4. Bindings different elements to selection events in Altair (not on the quiz)

8.4.1. Reading in data

```
import altair as alt
import pandas as pd
from vega_datasets import data

# Simplify working with large datasets in Altair
alt.data_transformers.enable('vegafusion')

# Load the R cell magic
%load_ext rpy2.ipython
```

```
The rpy2.ipython extension is already loaded. To reload it, use:
  %reload_ext rpy2.ipython
```

```
movies = (
    data.movies()
    .drop(columns=['US_DVD_Sales', 'Director', 'Source', 'Creative_Type'])
    .dropna(subset=['Running_Time_min', 'Major_Genre', 'Rotten_Tomatoes_Rating
    .assign(
        Release_Year=lambda df: pd.to_datetime(df['Release_Date']).dt.year,
        Title=lambda df: df['Title'].astype(str)
    )
    .reset_index(drop=True))
movies
```

	Title	US_Gross	Worldwide_Gross	Production_Budget	Release_Da
0	Broken Arrow	70645997.0	148345997.0	65000000.0	Feb 09 19
1	Brazil	9929135.0	9929135.0	15000000.0	Dec 18 19
2	The Cable Guy	60240295.0	102825796.0	47000000.0	Jun 14 19
3	Chain Reaction	21226204.0	60209334.0	55000000.0	Aug 02 19
4	City Hall	20278055.0	20278055.0	40000000.0	Feb 16 19
...	...	...	...	...	
973	Zoolander	45172250.0	60780981.0	28000000.0	Sep 28 20
974	Zombieland	75590286.0	98690286.0	23600000.0	Oct 02 20
975	Zack and Miri Make a Porno	31452765.0	36851125.0	24000000.0	Oct 31 20
976	The Legend of Zorro	45575336.0	141475336.0	80000000.0	Oct 28 20
977	The Mask of Zorro	93828745.0	233700000.0	65000000.0	Jul 17 19

978 rows × 13 columns

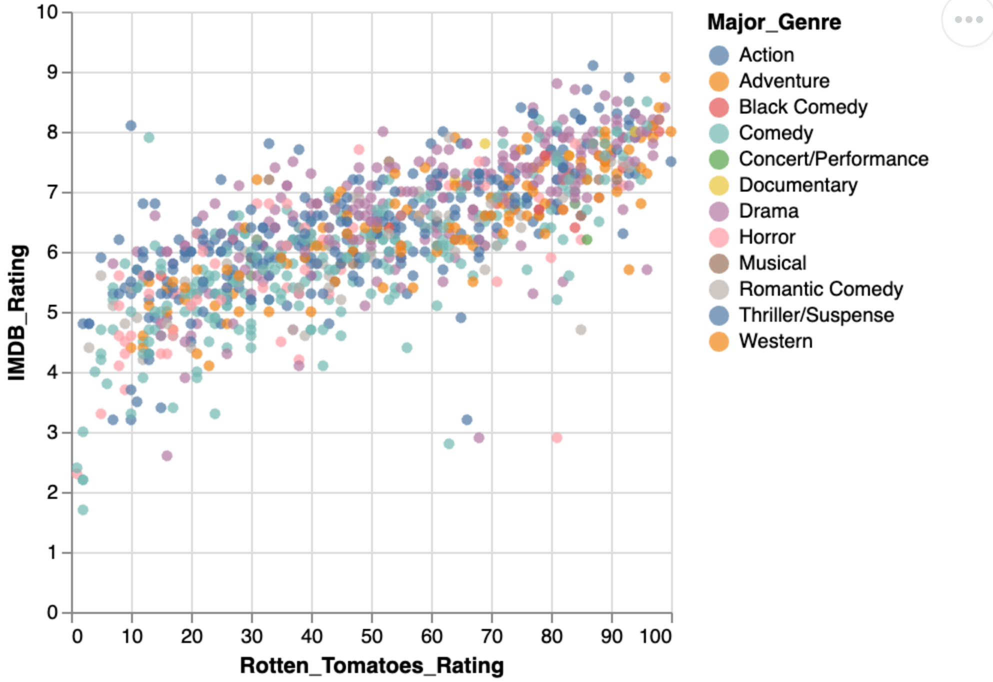
```
movies.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 978 entries, 0 to 977
Data columns (total 13 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   Title                   978 non-null    object 
 1   US_Gross                978 non-null    float64
 2   Worldwide_Gross         978 non-null    float64
 3   Production_Budget       977 non-null    float64
 4   Release_Date            978 non-null    object 
 5   MPAA_Rating             978 non-null    object 
 6   Running_Time_min        978 non-null    float64
 7   Distributor             977 non-null    object 
 8   Major_Genre             978 non-null    object 
 9   Rotten_Tomatoes_Rating  978 non-null    float64
 10  IMDB_Rating             978 non-null    float64
 11  IMDB_Votes              978 non-null    float64
 12  Release_Year            978 non-null    int32  
dtypes: float64(7), int32(1), object(5)
memory usage: 95.6+ KB
```

8.4.2. Legends

We saw before how we could use the `bind` parameter of an altair selection to link it to the legend of the plot.

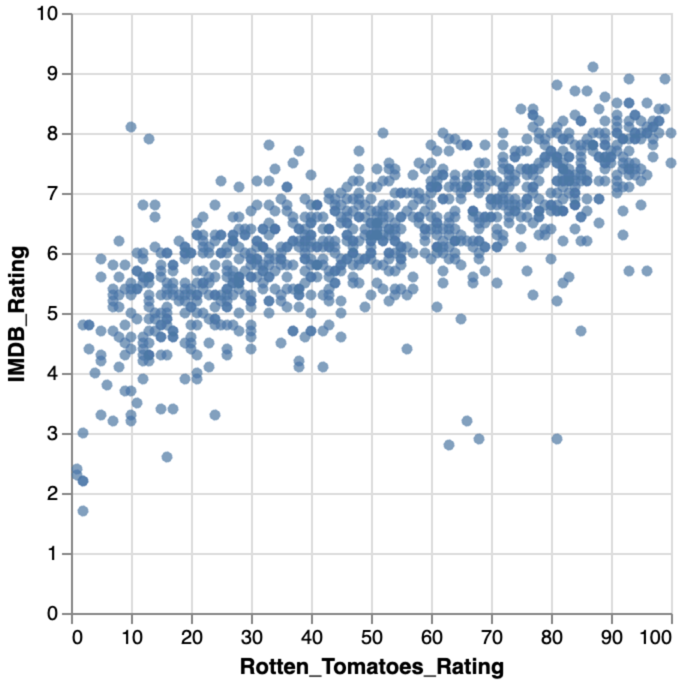
```python
select_genre = alt.selection_point(
    fields=['Major_Genre'], # limit selection to the Major_Genre field
    bind='legend'
)

alt.Chart(movies).mark_circle().encode(
    x='Rotten_Tomatoes_Rating',
    y='IMDB_Rating',
    tooltip='Title',
    color='Major_Genre',
    opacity=alt.condition(select_genre, alt.value(0.7), alt.value(0.1))
).add_params(
    select_genre
)
```



8.4.3. Dropdowns

Binding to the legend doesn't work that well in this case since there are so many colors that the plot looks a bit messy. Instead, we could create a dropdown selection widget directly in Altair (`alt.binding_select`) to let us choose categories without coloring the points. Instead of binding `alt.selection_point` to the legend we can pass along the dropdown we just created.

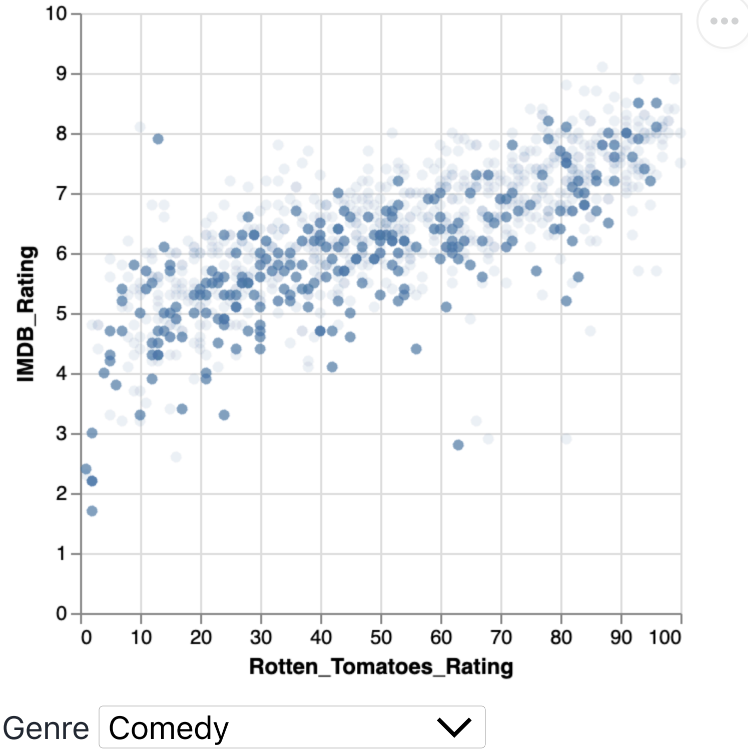
```
# The drop down requires an array of options, here we sort the genres alphabei
genres = sorted(movies['Major_Genre'].unique())
dropdown = alt.binding_select(options=genres)

select_genre = alt.selection_point(
    fields=['Major_Genre'],
    bind=dropdown
)

alt.Chart(movies).mark_circle().encode(
    x='Rotten_Tomatoes_Rating',
    y='IMDB_Rating',
    tooltip='Title',
    opacity=alt.condition(select_genre, alt.value(0.7), alt.value(0.1))
).add_params(
    select_genre
)
```



param_2_Major_Genre Action

Let's give our dropdown a better name and set the default value for the selection.

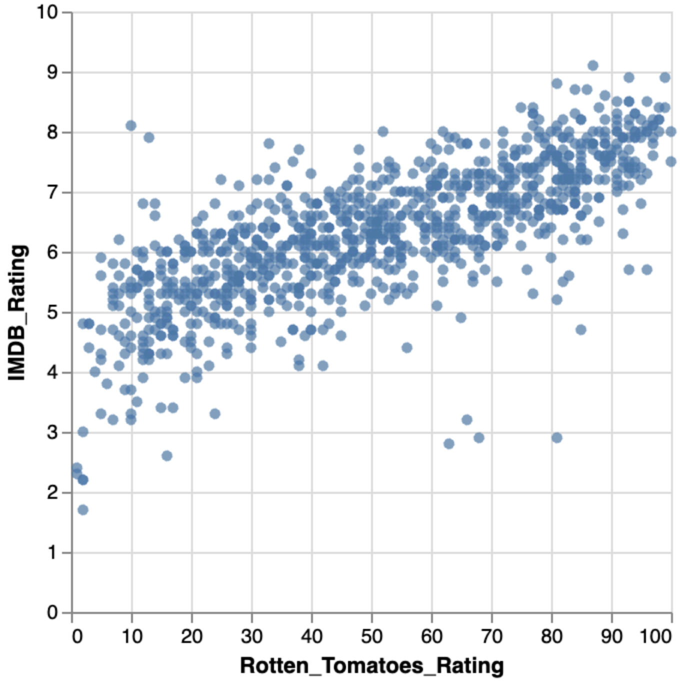
```
# The drop down requires an array of options, here we sort the genres alphabei
genres = sorted(movies['Major_Genre'].unique())
dropdown = alt.binding_select(name='Genre ', options=genres)

select_genre = alt.selection_point(
    fields=['Major_Genre'],
    bind=dropdown,
    value=[{'Major_Genre': 'Comedy'}])

alt.Chart(movies).mark_circle().encode(
    x='Rotten_Tomatoes_Rating',
    y='IMDB_Rating',
    tooltip='Title',
    opacity=alt.condition(select_genre, alt.value(0.7), alt.value(0.1))
).add_params(
    select_genre
)
```



8.4.4. Dropdown and radio buttons

We could also add multiple widgets together, by binding them to different fields in the selection. Here we're adding a radio button for the MPAA rating to the plot above.

```
# The drop down requires an array of options, here we sort the genres alphabet
genres = sorted(movies['Major_Genre'].unique())
dropdown_genre = alt.binding_select(name='Genre ', options=genres)

mpaa_rating = sorted(movies['MPAA_Rating'].unique())
dropdown_mpaa = alt.binding_radio(name='MPAA Rating ', options=mpaa_rating)

select_genre_and_mpaa = alt.selection_point(
    fields=['Major_Genre', 'MPAA_Rating'],
    bind={'Major_Genre': dropdown_genre, 'MPAA_Rating': dropdown_mpaa}
)

alt.Chart(movies).mark_circle().encode(
    x='Rotten_Tomatoes_Rating',
    y='IMDB_Rating',
    tooltip='Title',
    opacity=alt.condition(select_genre_and_mpaa, alt.value(0.7), alt.value(0.1
).add_params(
    select_genre_and_mpaa
)
```



MPAA Rating ◯G◯Not Rated◯PG◯PG-13◯R

Genre Action

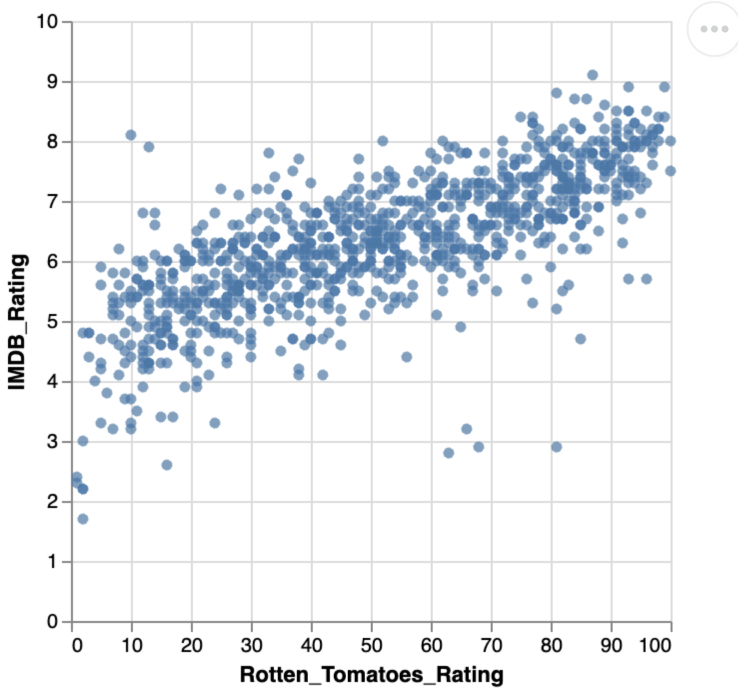
Here it would makes sense to sort the ratings according to their natural order instead of alphabetically, but they are roughly the same.

8.4.5. Slider

In addition to dropdowns and add radio buttons we can add sliders, and checkboxes, but there are no multiselection dropdown or range sliders. For multiple selections, we can instead use `selection_multi` on other plots or legends, and for range sliders, we can use the `selection_interval` on another plot.

Let's explore the slider.

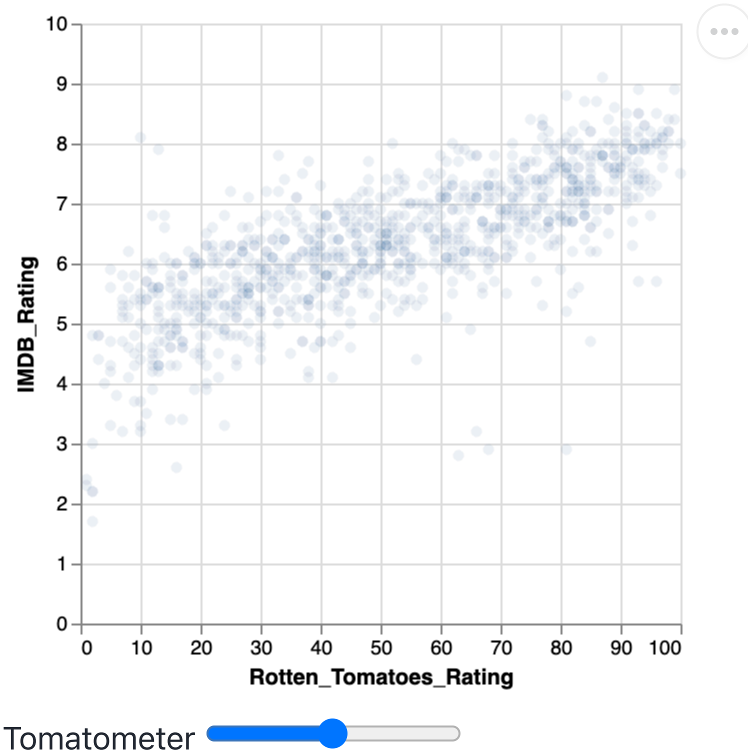
```python
slider = alt.binding_range(name='Tomatometer ')
select_rating = alt.selection_point(
    fields=['Rotten_Tomatoes_Rating'],
    bind=slider
)

alt.Chart(movies).mark_circle().encode(
    x='Rotten_Tomatoes_Rating',
    y='IMDB_Rating',
    tooltip='Title',
    opacity=alt.condition(select_rating, alt.value(0.7), alt.value(0.1))
).add_params(
    select_rating
)
```



Tomatometer

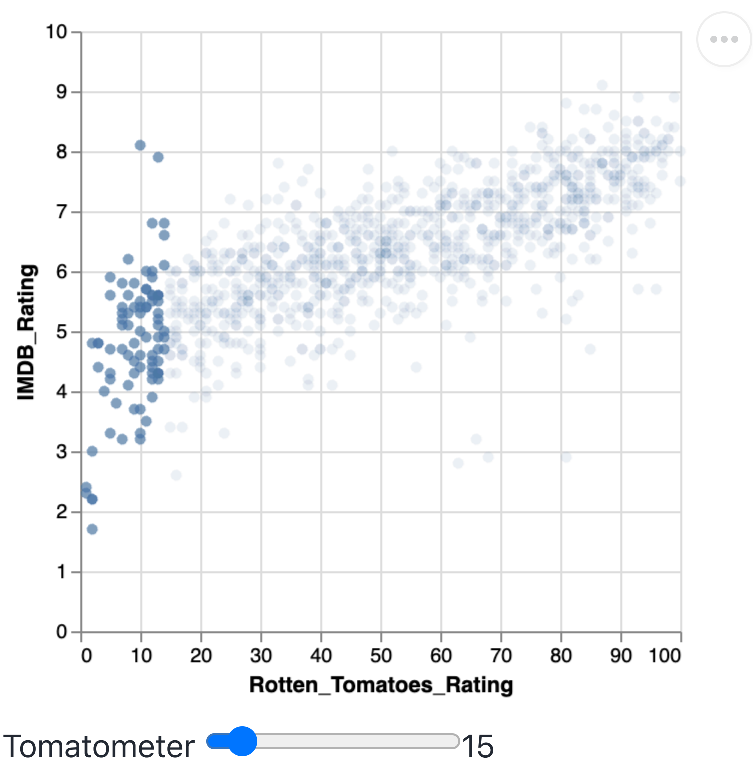
The default behavior is to only filter points that are the exact values of the slider. This is useful for selection widgets like the dropdown, but for the slider we want to make comparisons such as bigger and smaller than. We can use `alt.datum` for this, which let's us use columns from the data inside comparisons and more complex expression in Altair, where it is not possible to write the column name only (this makes it clear that is the the column name and not just a string of the same name that is referenced in the expression).

```
slider = alt.binding_range(name='Tomatometer ')
select_rating = alt.selection_point(
    fields=['Rotten_Tomatoes_Rating'],
    bind=slider
)

alt.Chart(movies).mark_circle().encode(
    x='Rotten_Tomatoes_Rating',
    y='IMDB_Rating',
    tooltip='Title',
    opacity=alt.condition(
        alt.datum.Rotten_Tomatoes_Rating < select_rating.Rotten_Tomatoes_Ratin
        alt.value(0.7), alt.value(0.1))
).add_params(
    select_rating
)
```



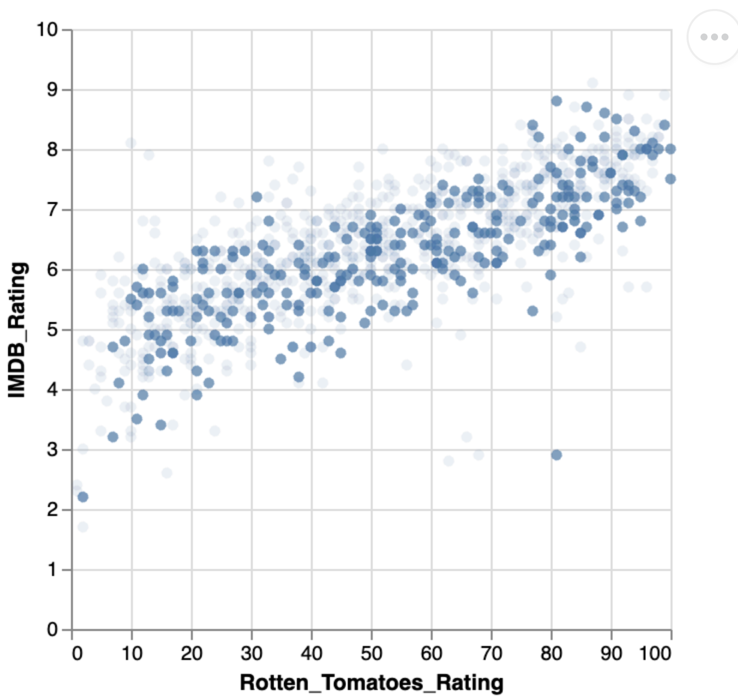
We can set an explicit start value to avoid that all points appear unselected at the start, as well as define the range and step size for the slider.

```
slider = alt.binding_range(name='Tomatometer ', min=10, max=60, step=5)
select_rating = alt.selection_point(
    fields=['Rotten_Tomatoes_Rating'],
    bind=slider,
    value=[{'Rotten_Tomatoes_Rating': 15}]
)

alt.Chart(movies).mark_circle().encode(
    x='Rotten_Tomatoes_Rating',
    y='IMDB_Rating',
    tooltip='Title',
    opacity=alt.condition(
        alt.datum.Rotten_Tomatoes_Rating < select_rating.Rotten_Tomatoes_Ratin
        alt.value(0.7), alt.value(0.1))
).add_params(
    select_rating
)
```



A more useful function of our slider would be to filter for the year.

```
slider = alt.binding_range(
    name='Year ', step=1,
    min=movies['Release_Year'].min(), max=movies['Release_Year'].max())
select_rating = alt.selection_point(
    fields=['Release_Year'],
    bind=slider,
    value=[{'Release_Year': 2000}]
)

alt.Chart(movies).mark_circle().encode(
    x='Rotten_Tomatoes_Rating',
    y='IMDB_Rating',
    tooltip='Title',
    opacity=alt.condition(
        alt.datum.Release_Year < select_rating.Release_Year,
        alt.value(0.7), alt.value(0.1))
).add_params(
    select_rating
)
```



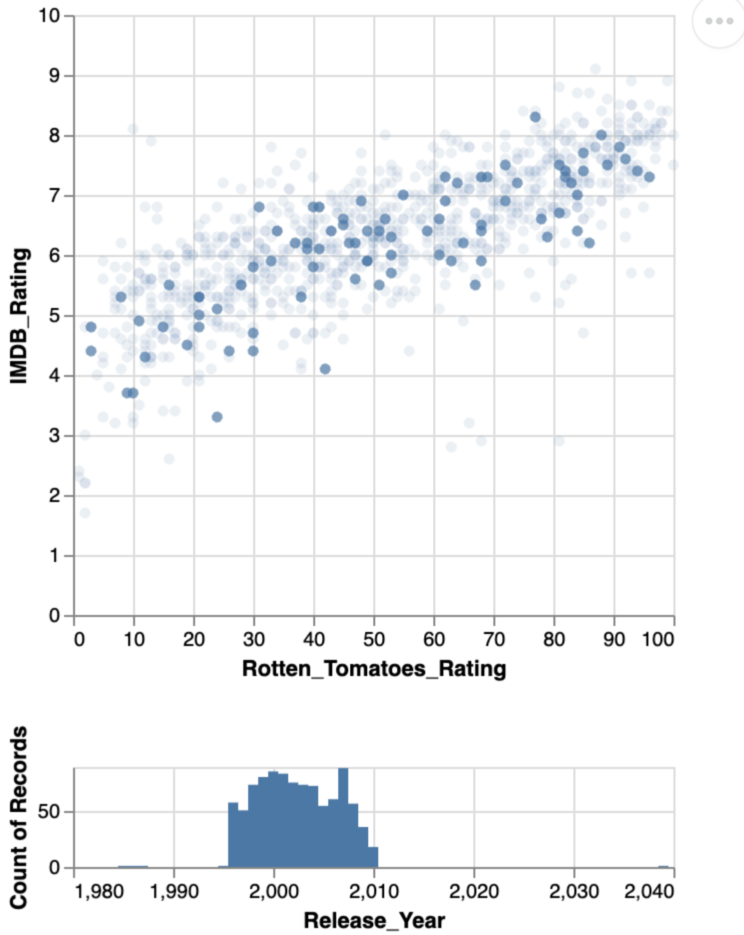
Year 2000

8.4.6. Driving slider-like selections from another plot instead

The plot above has several problems. Since there is no range slider, we would have to add a second slider to filter a range of values. And it is a bit unclear why the max is 2040, I guess there is a mislabeled movie, but can't be sure. I also don't get any information about which years have the most releases.

Due to Altair's consistent interaction grammar, we can bind a similar selection event to a bar chart (or any chart type we want) instead of the slider, and change it to an interval to be able to select a range of points.

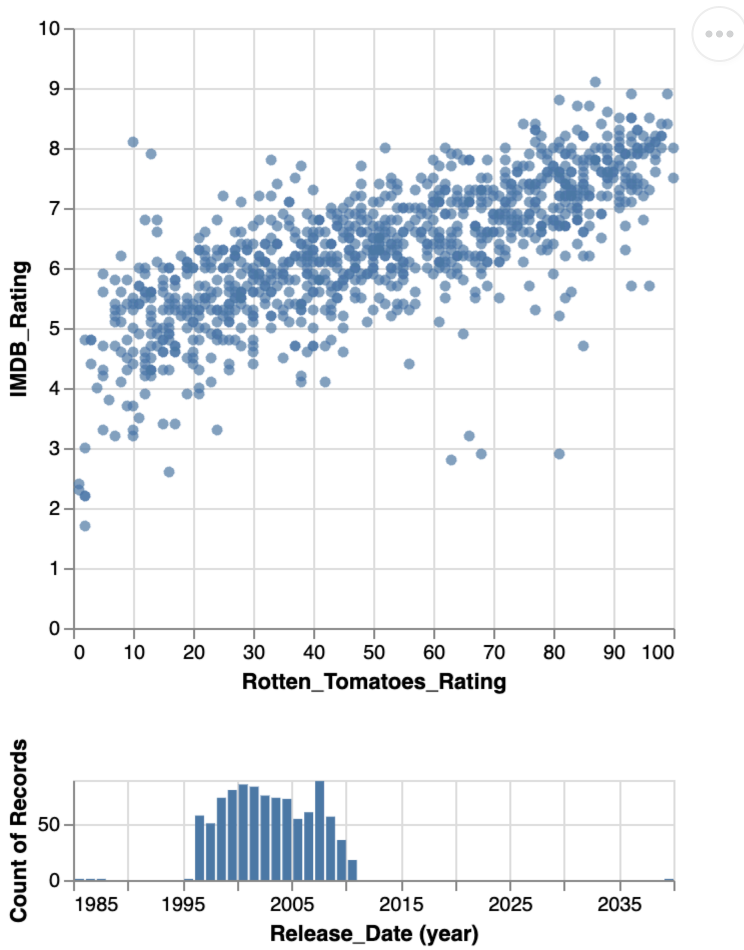
```
select_year = alt.selection_point(
    fields=['Release_Year'],
    value=[{'Release_Year': 2000}]
)

bar_slider = alt.Chart(movies).mark_bar().encode(
    x='Release_Year',
    y='count()').properties(height=50).add_params(select_year)

scatter_plot = alt.Chart(movies).mark_circle().encode(
    x='Rotten_Tomatoes_Rating',
    y='IMDB_Rating',
    tooltip='Title',
    opacity=alt.condition(
        select_year,
        alt.value(0.7), alt.value(0.1)
    )
)

scatter_plot & bar_slider
```



It is great to be able to see where most movies are along the year axis! This bar plot is a much more informative driver of the selection event compared to the slider.

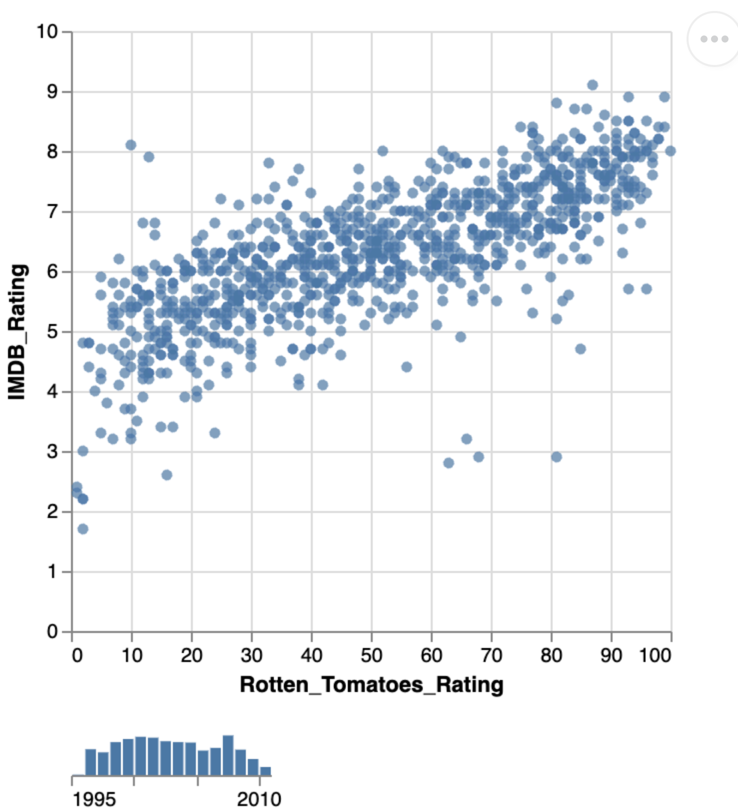
Now let's switch it over an interval selection, I will change from `fields` to `encodings` here, to indicate that we only want to drag the interval along the x-axis and use whatever column is on that axis. I will also fix the formatting of the x-axis to display years properly by using the `year()` function on the date column directly (similar to how we have used `sum()`, `mean()` etc before).

```
select_year = alt.selection_interval(encodings=['x'])

bar_slider = alt.Chart(movies).mark_bar().encode(
    x='year(Release_Date)',
    y='count()').properties(height=50).add_params(select_year)

scatter_plot = alt.Chart(movies).mark_circle().encode(
    x='Rotten_Tomatoes_Rating',
    y='IMDB_Rating',
    tooltip='Title',
    opacity=alt.condition(
        select_year,
        alt.value(0.7), alt.value(0.1)
    )
)

scatter_plot & bar_slider
```



Now let's ask ourselves "What is a widget?". Is there any distinct difference between this small plot and the slider that disqualifies it from being called a widget? At this point, I think is mostly comes down to looks, so let's make our bar selector appear more "widgety".

```python
select_year = alt.selection_interval(encodings=['x'])

# Filter out a few of the extreme value to make it look better
movies_fewer_years = movies.query('1994 < Release_Year < 2030')
bar_slider = alt.Chart(movies_fewer_years).mark_bar().encode(
    alt.X('year(Release_Date)', title='', axis=alt.Axis(grid=False)),
    alt.Y('count()', title='', axis=None)
).properties(
    height=20,
    width=100
).add_params(
    select_year
)

scatter_plot = alt.Chart(movies_fewer_years).mark_circle().encode(
    x='Rotten_Tomatoes_Rating',
    y='IMDB_Rating',
    tooltip='Title',
    opacity=alt.condition(
        select_year,
        alt.value(0.7), alt.value(0.1)
    )
)

(scatter_plot & bar_slider).configure_view(strokeWidth=0)
```

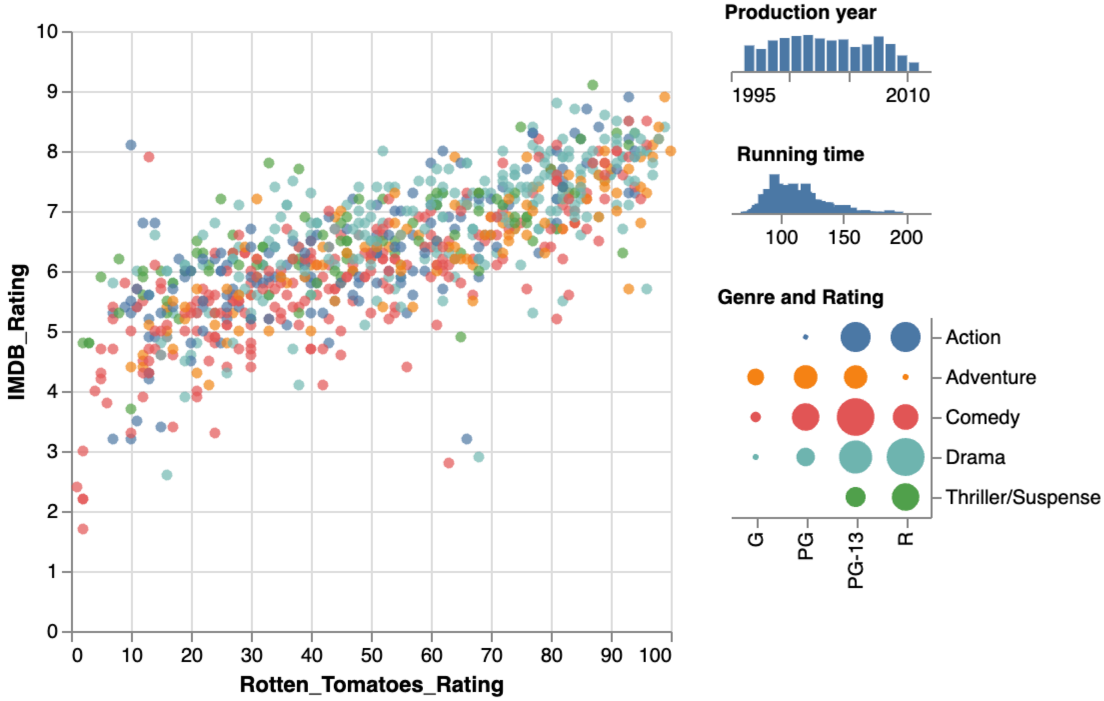


[If it looks like a duck...](#) then it is a widget to me!

8.4.7. Multi-dimensional legends

Realizing the mutual properties between what we traditionally refer to as plots and legends, means that it is almost only your imagination that sets the limits. For example, legends are usually one-dimensional, but it doesn't have to be that way! Let's make a three dimensional legend and link two of those dimensions to a selection. We will use the [Altair composition operator](#) `&` for triggering the condition only at the intersection of all selections.

```
# To make the final result  bit more elegant, I am filtering out a few low cou
top_genres = movies_fewer_years['Major_Genre'].value_counts()[:5].index
mpaa_rating_clean = [rate for rate in mpaa_rating if rate != 'Not Rated']
movies_clean = movies_fewer_years.query('Major_Genre in @top_genres and MPAA_R

select_genre_and_mpaa = alt.selection_point(
    fields=['Major_Genre', 'MPAA_Rating'],
    empty=True,
    nearest=True)

multidim_legend = alt.Chart(movies_clean, title=alt.TitleParams(text='Genre an
    alt.X('MPAA_Rating', title=''),
    alt.Y('Major_Genre', title='', axis=alt.Axis(orient='right')),
    alt.Size('count()', legend=None),
    alt.Color('Major_Genre', legend=None),
    opacity=alt.condition(select_genre_and_mpaa, alt.value(1), alt.value(0.2))
#     alt.Shape('MPAA_Rating', legend=None)
).add_params(select_genre_and_mpaa).properties(width=100)


select_year = alt.selection_interval(empty=True, encodings=['x'])

# Filter out a few of the extreme value to make it look better
bar_slider = (
    alt.Chart(movies_clean, title=alt.TitleParams(text='Production year', font
    alt.X('year(Release_Date)', title='', axis=alt.Axis(grid=False),
          scale=alt.Scale(domain=[1995, 2012])),
    alt.Y('count()', title='', axis=None))
    .properties(height=20, width=100)
    .add_params(select_year))

select_time = alt.selection_interval(empty=True, encodings=['x'])

# Filter out a few of the extreme value to make it look better
bar_slider_time = (
    alt.Chart(movies_clean, title=alt.TitleParams(text='Running time', fontSiz
    alt.X('Running_Time_min', title='', axis=alt.Axis(grid=False)),
    alt.Y('count()', title='', axis=None))
    .properties(height=20, width=100)
    .add_params(select_time))

scatter_plot = alt.Chart(movies_clean).mark_circle().encode(
    x='Rotten_Tomatoes_Rating',
    y='IMDB_Rating',
    color='Major_Genre',
    tooltip='Title',
    opacity=alt.condition(
        select_year & select_genre_and_mpaa & select_time,
        alt.value(0.7), alt.value(0.1)))

(scatter_plot | (bar_slider & bar_slider_time & multidim_legend)).configure_vi
```




```
(scatter_plot | (bar_slider & bar_slider_time & multidim_legend)).configure_vi
```

Building advanced layouts like this is not the most common use case for notebook interactivity when it is focused on exploration. However, it can be nice to know how to implement these features when creating a more polished notebook to share with someone.