# Confidence intervals, figure layouts, and interactivity

## **Contents**

- 7.1. Confidence intervals
- 7.2. Figure composition
- 7.3. Interactivity between plots using Altair

#### Lecture learning goals

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

- Create and understand how to interpret confidence intervals and confidence bands.
- 2. Layout plots in panels of a figure grid.
- 3. Create selections within a plot in Altair
- 4. Link selections between plots to highlight and select data.

#### **Required activities**

#### After class:

- Review the lecture notes.
- This 30 min video on confidence intervals and figure layouts (it starts a bit abruptly).
- Section 16 on visualizing uncertainty (some of this will be repetition from 552).

#### **Lecture slides**

· Review the lecture notes.

 Section 16 on visualizing uncert of this will be repetition from 552

DSCI 531 - Le... 1 / 25 88% 7. Confidence intervals, figure layouts, and interactivity Required activities Lecture learning goals By the end of the lecture you will be able to: Before class: 1. Create and understand how to interpret This 30 min video on confidence confidence intervals and confidence bands. and figure layouts (it starts a bit 2. Layout plots in panels of a figure grid. After class: 3. Create selections within a plot in Altair

## 7.1. Confidence intervals

and select data.

4. Link selections between plots to highlight

## 7.1.1. Py

To show the confidence interval of the points as a band, we can use mark\_errorband. By default this mark show the standard deviation of the points, but we can change the extent to use bootstrapping on the sample data to construct the 95% confidence interval of the mean.

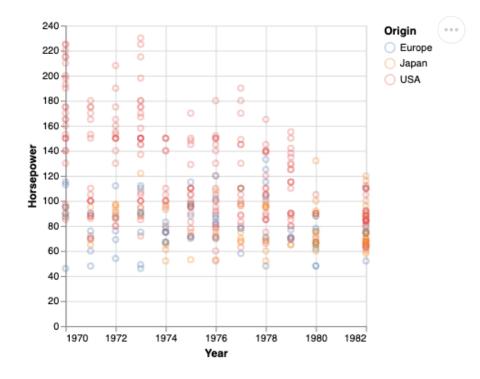
```
import altair as alt
import pandas as pd
from vega_datasets import data

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

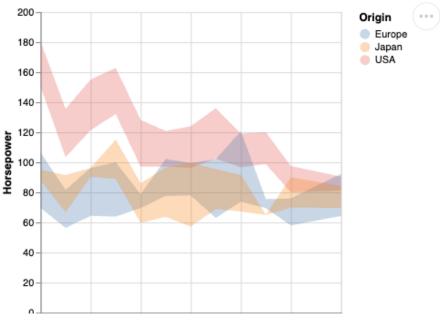
# Load the R cell magic
```

```
cars = data.cars()

points = alt.Chart(cars).mark_point(opacity=0.3).encode(
    alt.X('Year'),
    alt.Y('Horsepower'),
    alt.Color('Origin')
)
points
```



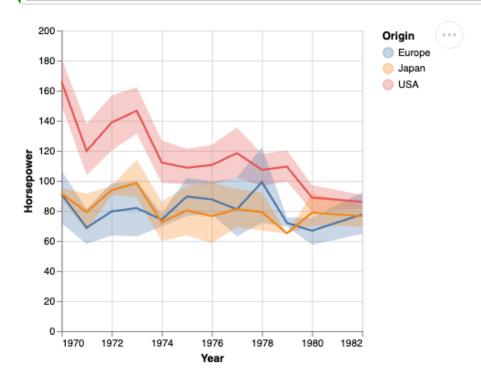




Skip to main content

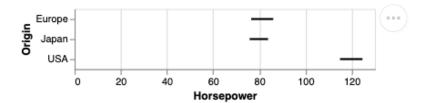
We can add in the mean line.

```
points.mark_errorband(extent='ci') + points.encode(y='mean(Horsepower)').mark_
```



We can use mark\_errorbar to show the standard deviation or confidence interval around a single point.

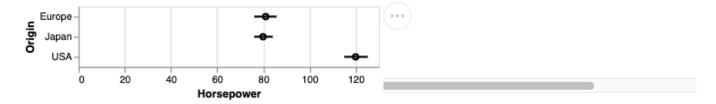
```
alt.Chart(cars).mark_errorbar(extent='ci', rule=alt.LineConfig(size=2)).encode
    x='Horsepower',
    y='Origin'
)
```



Also here, it is helpful to include an indication of the mean.

```
err_bars = alt.Chart(cars).mark_errorbar(extent='ci', rule=alt.LineConfig(size:
x='Horsepower',
y='Origin'
```

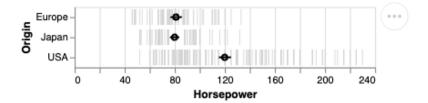
```
err_bars + err_bars.mark_point(color='black').encode(x='mean(Horsepower)')
```



An particularly usful visualization is to combine the above with an indication of the distribution of the data, e.g. as a faded violinplot in the background or as faded marks for all observations. This gives the reader a chance to study the raw data in addition to seeing the mean and its certainty.

```
err_bars = alt.Chart(cars).mark_errorbar(extent='ci', rule=alt.LineConfig(size:
    x='Horsepower',
    y='Origin'
)

(err_bars.mark_tick(color='lightgrey')
    + err_bars
    + err_bars.mark_point(color='black').encode(x='mean(Horsepower)'))
```



### 7.1.2. R

In ggplot, we can create confidence bands via <code>geom\_ribbon</code>. Previously we have passed specific statistic summary functions to the <code>fun</code> parameter, but here we will use <code>fun.data</code> because we need both the lower and upper bond of where to plot the ribbon. Whereas <code>fun</code> only allows functions that return a single value which decides where to draw the point on the y-axis (such as <code>mean</code>), <code>fun.data</code> allows functions to return three values (the min, middle, and max y-value). The <code>mean\_cl\_boot</code> function is especially helpful here, since it returns the upper and lower bound of the bootstrapped CI (and also the mean value, but that is not used by <code>geom\_ribbon</code>).

You need the Hmisc package installed in order to use mean\_cl\_boot, if you don't nothing will show up but you wont get an error, so it can be tricky to realize what is wrong.

```
%%R -i cars
library(tidyverse)
ggplot(cars) +
    aes(x = Year,
        y = Horsepower,
        color = Origin) +
    geom_point() +
    geom_line(stat = 'summary', fun = 'mean')
— Attaching packages —
                                                               - tidyverse 1.3.2 -

✓ ggplot2 3.4.2

                     ✓ purrr
                               1.0.1

✓ tibble 3.2.1

                               1.1.2

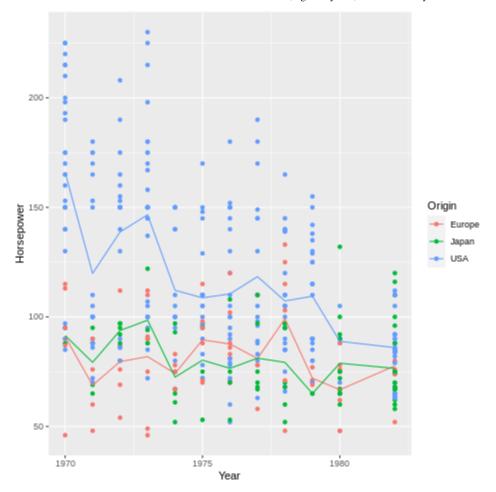
✓ dplyr

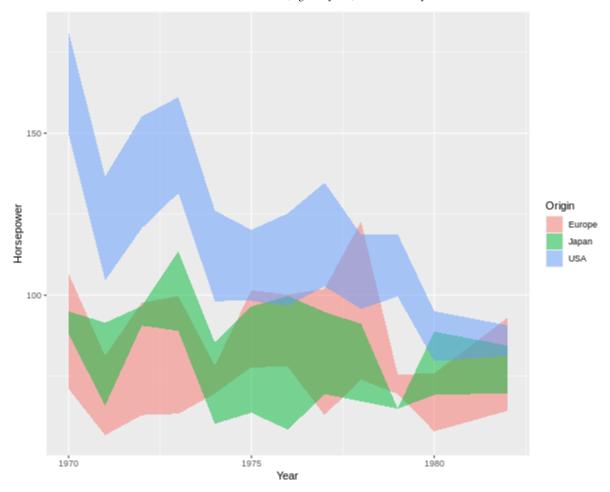
✓ tidyr

          1.3.0

✓ stringr 1.5.0

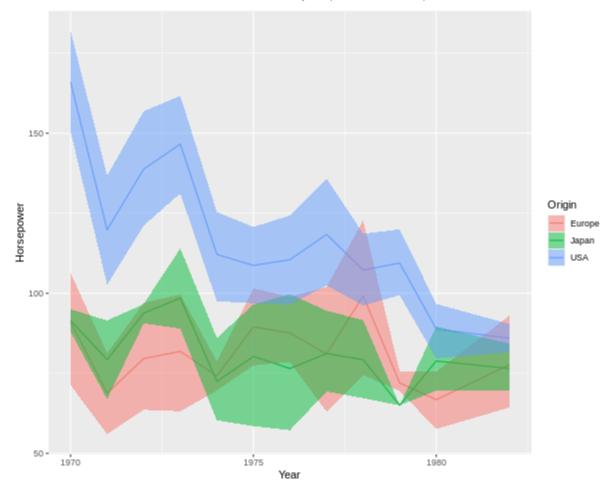
✓ readr
          2.1.4
                    ✓ forcats 1.0.0
— Conflicts -
                                                         - tidyverse_conflicts() -
* dplyr::filter() masks stats::filter()
* dplyr::lag()
                  masks stats::lag()
```





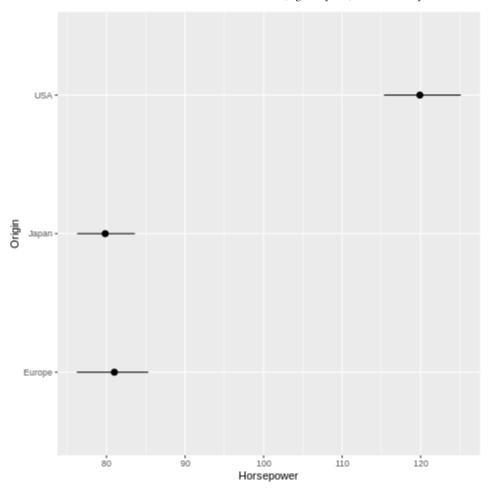
We can add a line for the mean here as well.

```
%R -w 600
ggplot(cars) +
  aes(x = Year,
        y = Horsepower,
        color = Origin,
        fill = Origin) +
      geom_line(stat = 'summary', fun = mean) +
      geom_ribbon(stat = 'summary', fun.data = mean_cl_boot, alpha=0.5, color = I
```



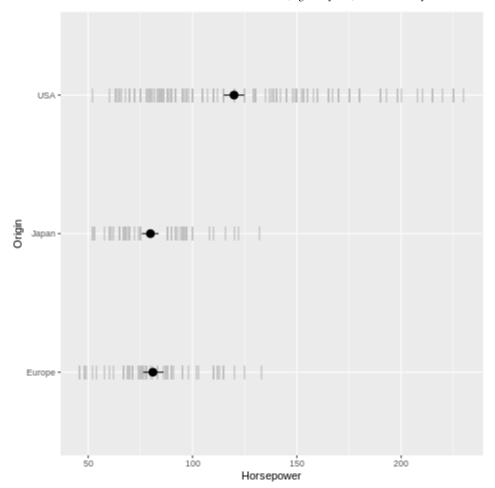
To plot the confidence interval around a single point, we can use geom\_pointrange, which also plots the mean (so it uses all three values return from mean\_cl\_boot).

```
%R
ggplot(cars) +
  aes(x = Horsepower,
      y = Origin) +
  geom_pointrange(stat = 'summary', fun.data = mean_cl_boot)
```

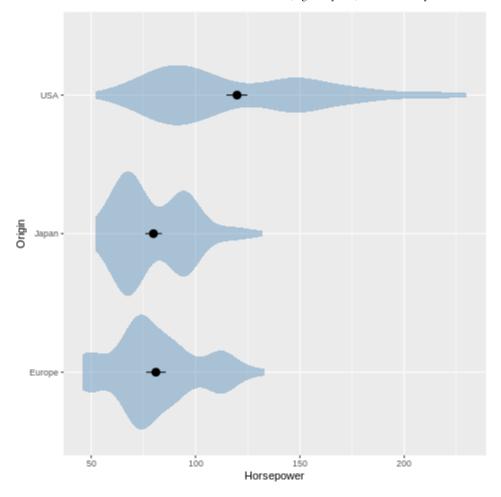


And finally we can plot the observations in the backgound here.

```
%R
ggplot(cars) +
  aes(x = Horsepower,
      y = Origin) +
  geom_point(shape = '|', color='grey', size=5) +
  geom_pointrange(stat = 'summary', fun.data = mean_cl_boot, size = 0.7)
```



```
%R
ggplot(cars) +
  aes(x = Horsepower,
        y = Origin) +
  geom_violin(color = NA, fill = 'steelblue', alpha = 0.4) +
  geom_pointrange(stat = 'summary', fun.data = mean_cl_boot, size = 0.7)
```



## 7.2. Figure composition

## 7.2.1. Py

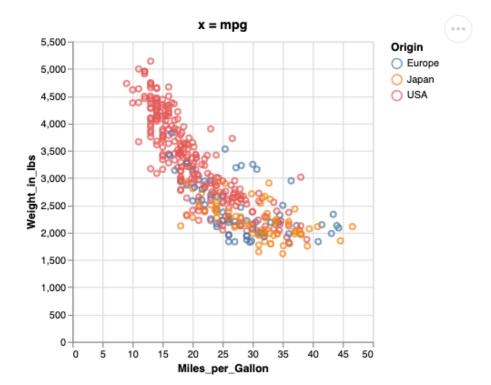
Let's create two figures to layout together. The titles here are a bit redundant, they're just mean to facilitate spotting which figure goes where in the multi-panel figure.

```
import altair as alt
from vega_datasets import data

cars = data.cars()
```

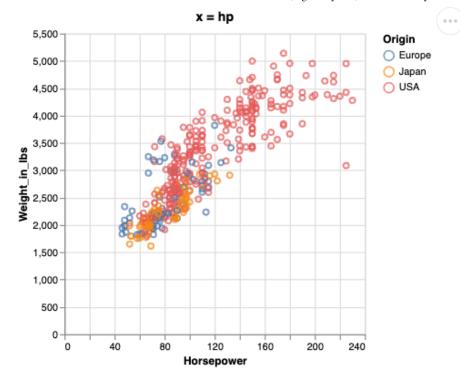
```
mpg_weight = alt.Chart(cars, title='x = mpg').mark_point().encode(
    x=alt.X('Miles_per_Gallon'),
    y=alt.Y('Weight_in_lbs'),
    color='Origin'
```

```
mpg_weight
```



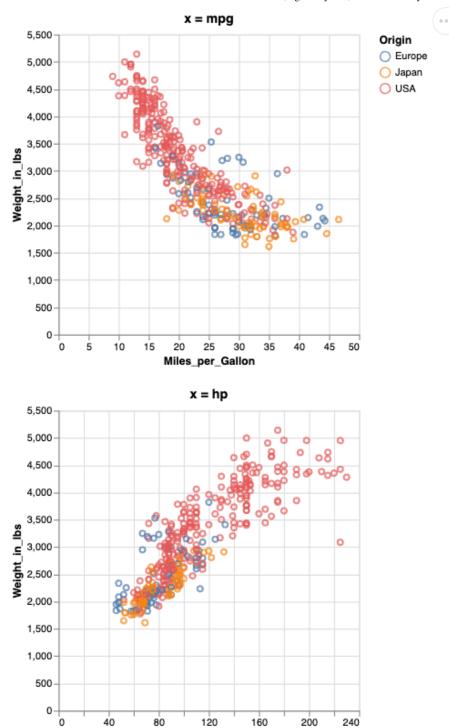
If a variable is shared between two figures, it is a good idea to have it on the same axis. This makes it easier to compare the relationship with the previous plot.

```
hp_weight = alt.Chart(cars, title='x = hp').mark_point().encode(
    x=alt.X('Horsepower'),
    y=alt.Y('Weight_in_lbs'),
    color='Origin'
)
hp_weight
```



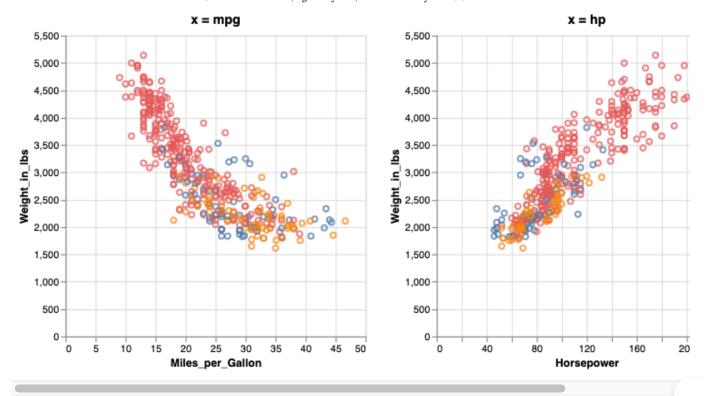
To concatenate plots vertically, we can use the ampersand operator.

mpg\_weight & hp\_weight



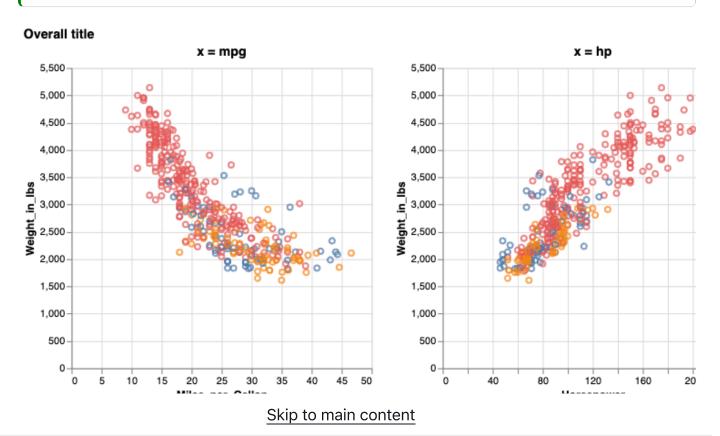
To concatenate horizontally, we use the pipe operator.

Horsepower



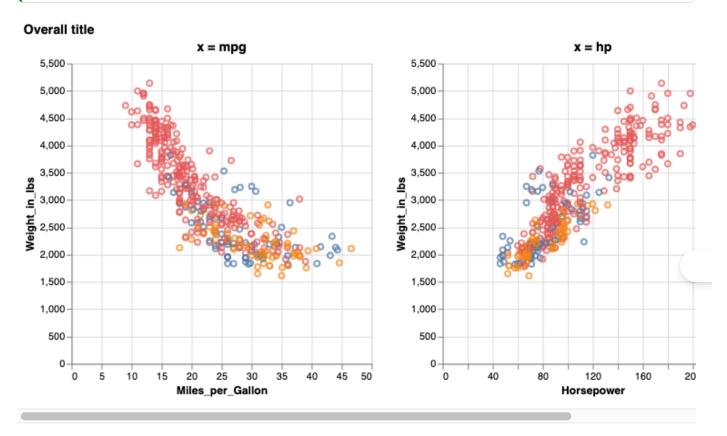
To add an overall title to the figure, we can use the properties method. We need to
surround the plots with a parentheis to show that we are using properties of the composed
figures rather than just hp\_weight one.

(mpg\_weight | hp\_weight).properties(title='Overall title')



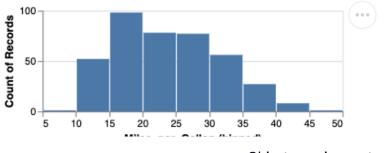
In addition to & and ||, we could use the functions vconcat and hconcat. You can use what you find the most convenient, this is how to add a title with one of those functions.

```
alt.hconcat(mpg_weight, hp_weight, title='Overall title')
```



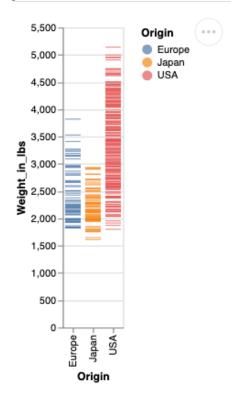
We can also build up a figure with varying sizes for the different panels, e.g. adding marginal distribution plots to a scatter plot.

```
mpg_hist = alt.Chart(cars).mark_bar().encode(
    alt.X('Miles_per_Gallon').bin(),
    y='count()'
).properties(
    height=100
)
mpg_hist
```

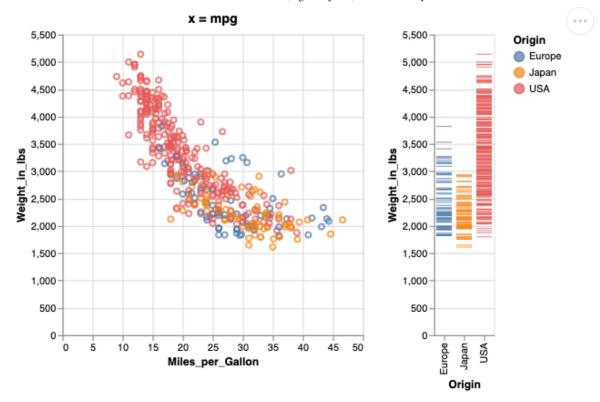


Skip to main content

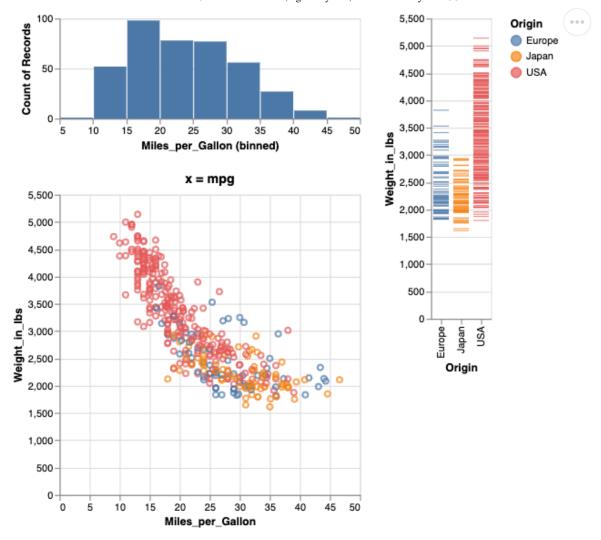
```
weight_ticks = alt.Chart(cars).mark_tick().encode(
    x='Origin',
    y='Weight_in_lbs',
    color='Origin'
)
weight_ticks
```



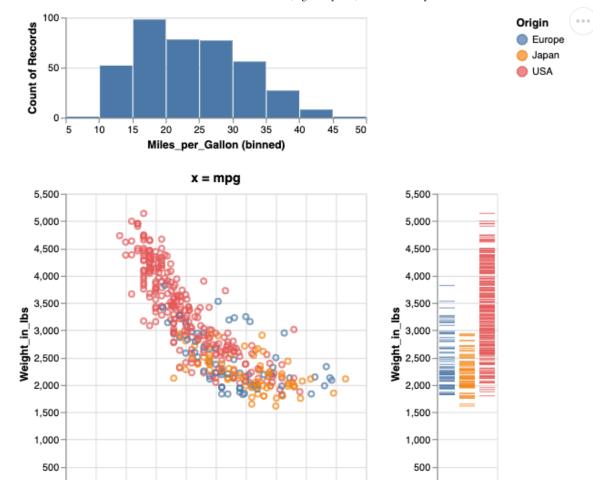
```
mpg_weight | weight_ticks
```



Just adding operations after each other can lead to the wrong grouping of the panels in the figure.



Adding parenthesis can indicate how to group the different panels.



## 7.2.2. R

o

10

15

20

25

Miles\_per\_Gallon

35

30

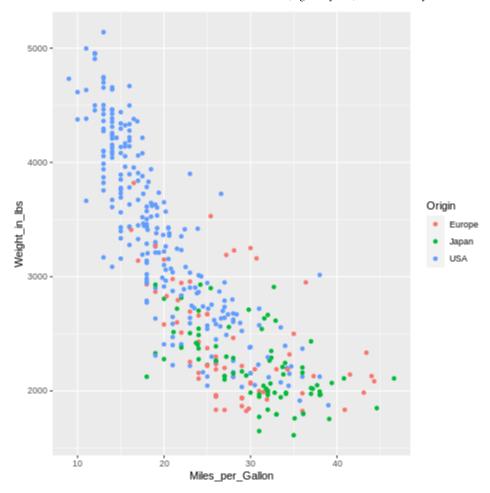
40

45

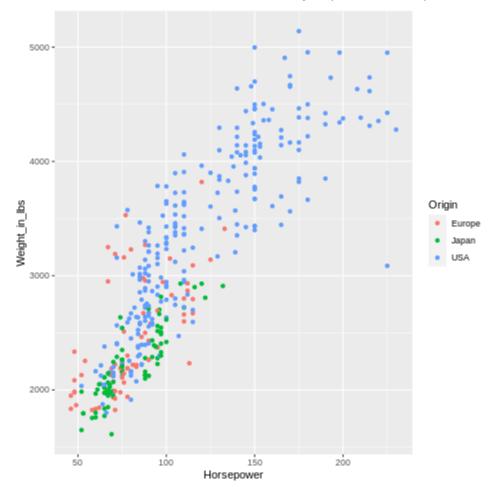
Origin

```
%%R
library(tidyverse)
```

```
%R -i cars
mpg_weight <- ggplot(cars) +
   aes(x = Miles_per_Gallon,
        y = Weight_in_lbs,
        color = Origin) +
      geom_point()
mpg_weight</pre>
```



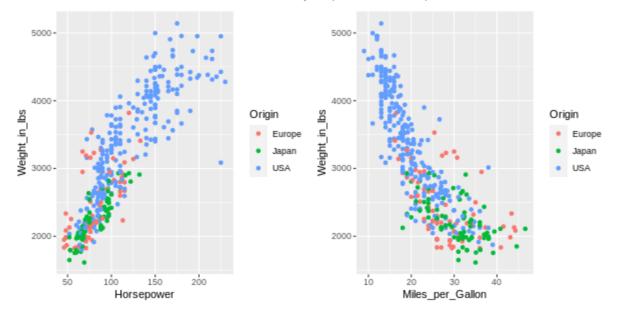
```
%R -i cars
hp_weight <- ggplot(cars) +
   aes(x = Horsepower,
        y = Weight_in_lbs,
        color = Origin) +
      geom_point()
hp_weight</pre>
```



Laying out figures is not built into ggplot, but the functionality is added in separate packages.

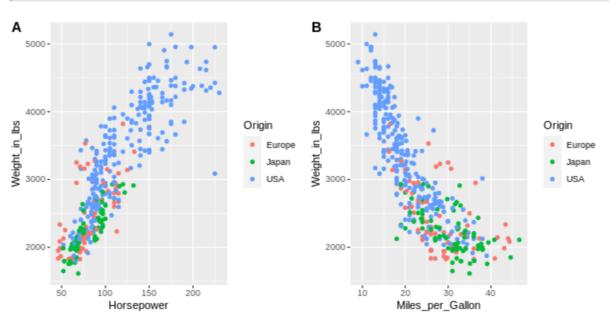
patchwork is similar to the operator-syntax we used with Altair, and cowplot works similar to the concatenation functions in Altair. Here I will be showing the latter, but you're free to use either ("cow" are the author's initials, Claus O Wilke, the same person who wrote Fundamentals of Data Visualization).

```
%%R -w 600 -h 300
library(cowplot)
plot_grid(hp_weight, mpg_weight)
```



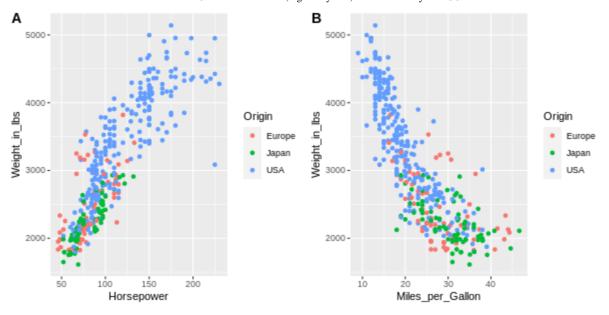
Panels can easily be labeled.

```
%%R -w 600 -h 300 plot_grid(hp_weight, mpg_weight, labels=c('A', 'B'))
```



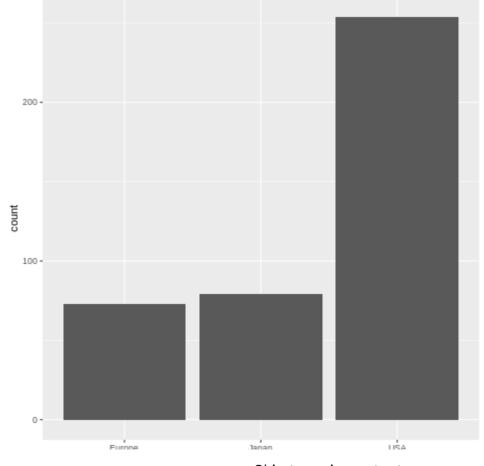
And this can even be automated.

```
%%R -w 600 -h 300
plot_grid(hp_weight, mpg_weight, labels='AUTO')
```



Let's create a composite figure with marginal distribution plots.

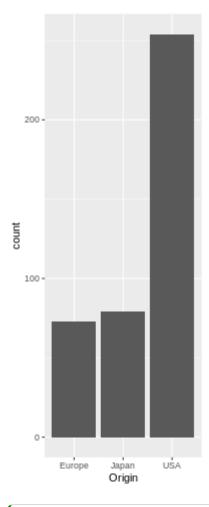
```
%%R
ggplot(cars) +
aes(x = Origin) +
geom_bar()
```



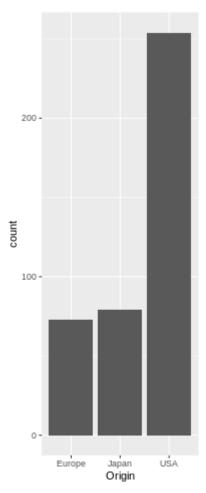
Skip to main content

If we were to present this barplot as a communication firgure, the bars should not be that wide. It is more visually appealing with narrower bars.

```
%%R -w 200
ggplot(cars) +
aes(x = Origin) +
geom_bar()
```

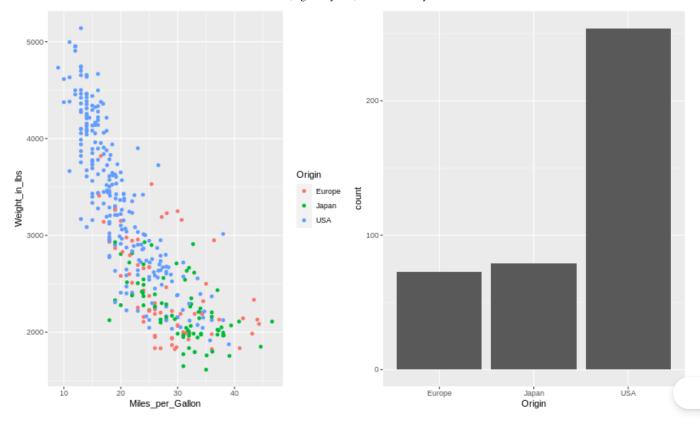


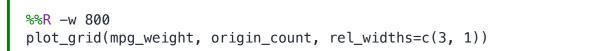
```
%%R -w 200
origin_count <- ggplot(cars) +
   aes(x = Origin) +
   geom_bar()
origin_count
```

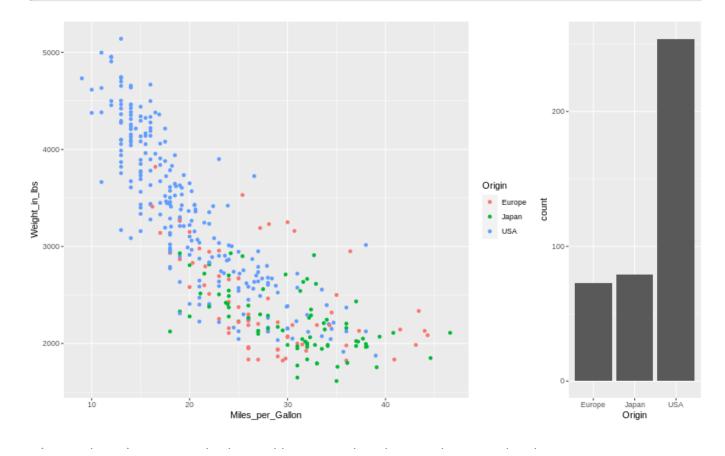


To set the widths of figures in the composition plot, we can use rel\_widths.

```
%%R -w 800
plot_grid(mpg_weight, origin_count)
```

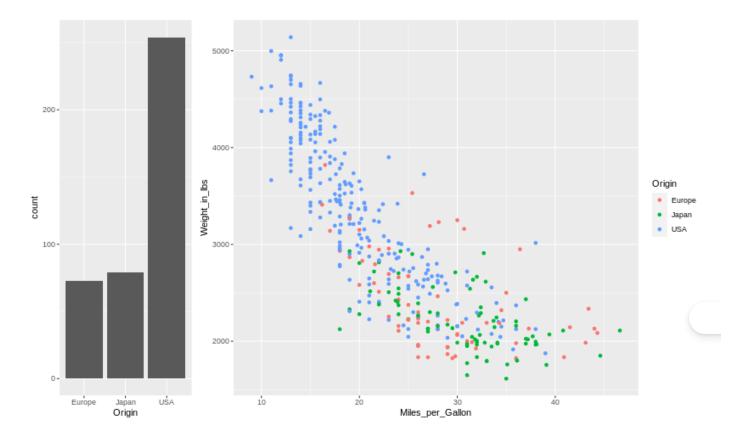






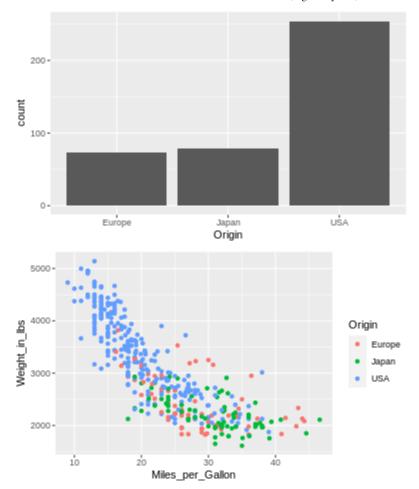
Skip to main content

```
%%R -w 800 plot_grid(origin_count, mpg_weight, rel_widths=c(1, 3))
```



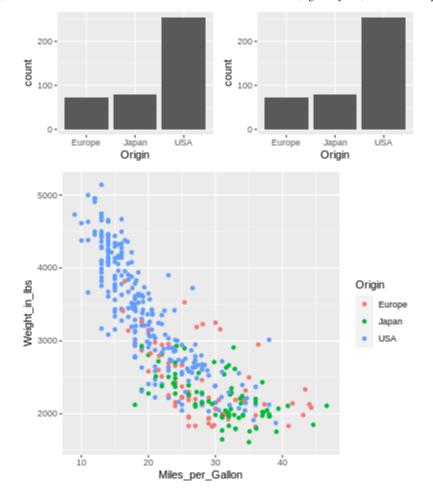
To concatenate vertically, we set the number of columns to 1.

```
%%R -w 400
plot_grid(origin_count, mpg_weight, ncol=1)
```



Finally, we can nest plot grids within each other.

```
%%R -w 400
top_row <- plot_grid(origin_count, origin_count)
plot_grid(top_row, mpg_weight, ncol=1, rel_heights=c(1,2))
```



There are <u>some more tricks in the readme</u>, including how to add a common title for the figures via <u>ggdraw</u>.

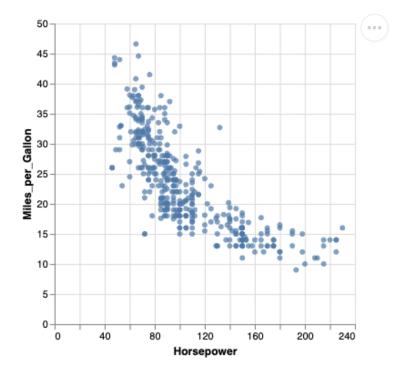
## 7.3. Interactivity between plots using Altair

One of the unique features of Altair is that it does not only define a grammar of graphics, but also a grammar of interactivity, which makes it intuitive to add many of the plot-to-plot interactions. This can be beneficial both for exploring data ourselves and for letting others explore our figures in a richer context. This interactivity is specified in the Altair/Vega-lite spec, so when you export your plot to HTML files, the interactivity is still there in the HTML and JS code, even after you shut down your Python/JupyterLab. This is called client side interactivity and is great for emailing someone an interactive chart. In contrast, building dashboards as we will learn about in viz 2 often requires an active Python server running for interactivity to work.

## 7.3.1. Tooltips

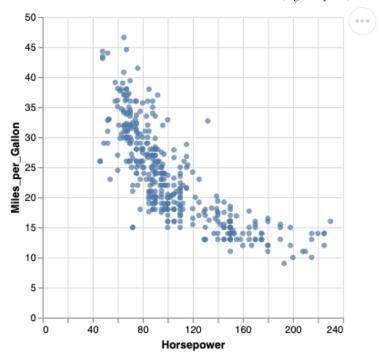
Hover over the points to see the information in a tooltip.

```
alt.Chart(cars).mark_circle().encode(
    x='Horsepower',
    y='Miles_per_Gallon',
    tooltip='Name'
)
```



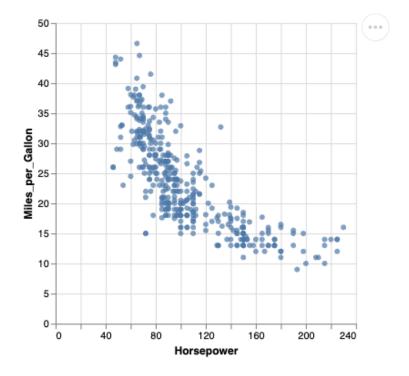
Multiple fields can be included as a list to a tooltip.

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



## 7.3.2. Panning and zooming

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

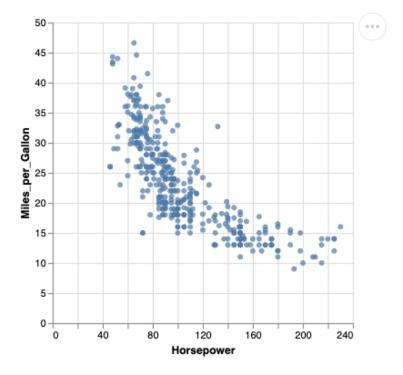


## 7.3.3. Interval selections

Let's add a selection that lets us drag and drop with the mouse to create an interval of selected points. An interval selection is often called a "brush" and connecting two plots is often referred to as "linked brushing".

```
brush = alt.selection_interval()

alt.Chart(cars).mark_circle().encode(
    x='Horsepower',
    y='Miles_per_Gallon'
).add_params(
    brush
)
```

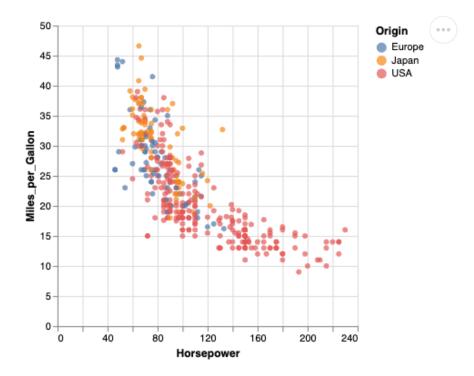


## 7.3.4. Highlighting points with selections

It would be nice if the points were highlighted when selected. Altair has a built in if/else function called condition that checks if an event is present (such as selection) and then lets us define what to do if it is True and if it is False.

```
alt.condition(check-this, if-true-do-this, if-false-do-this)
```

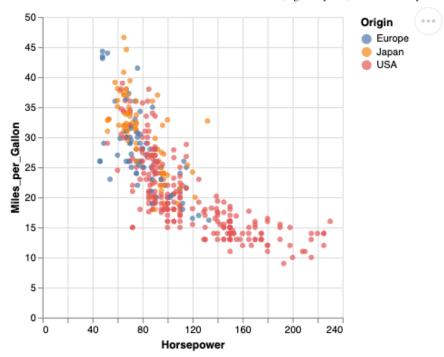
```
alt.Chart(cars).mark_circle().encode(
    x='Horsepower',
    y='Miles_per_Gallon',
    color=alt.condition(brush, 'Origin', alt.value('lightgray'))
).add_params(
    brush
)
```



We could change along which dimensions the selection is active. By default is is both x and y for scatter plots.

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

alt.Chart(cars).mark_circle().encode(
    x='Horsepower',
    y='Miles_per_Gallon',
    color=alt.condition(brush, 'Origin', alt.value('lightgray'))
).add_params(
    brush
)
```



## 7.3.5. Linking selections across plots

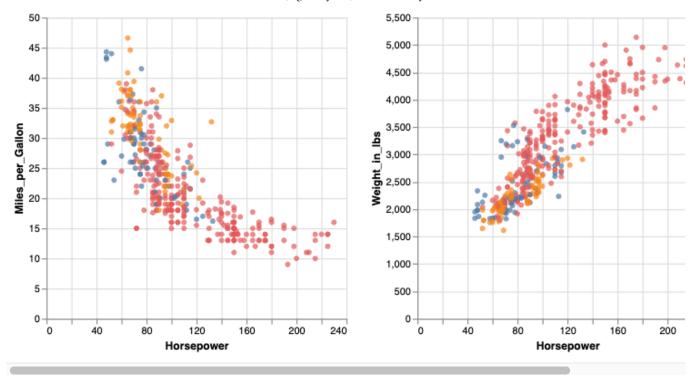
Selections are automatically linked between plots. This is great for comparing the same observations across multiple dimensions.

```
brush = alt.selection_interval()

points = alt.Chart(cars).mark_circle().encode(
    x='Horsepower',
    y='Miles_per_Gallon',
    color=alt.condition(brush, 'Origin', alt.value('lightgray'))
).add_params(
    brush
)

points | points.encode(y='Weight_in_lbs')
```

resolve='union'.

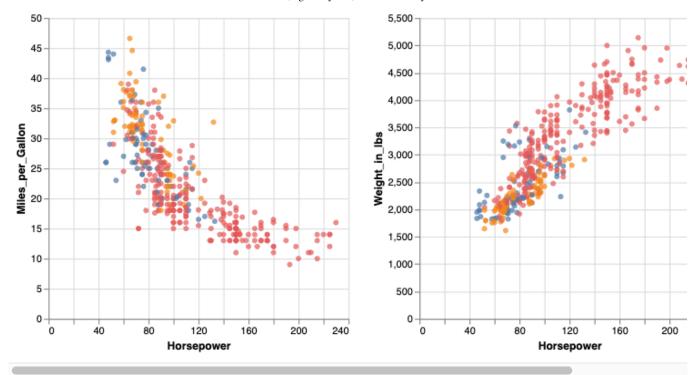


There is only one interval selection above, if I start dragging in another plot, the first selection disappears. I can modify this behavior and change it so that each subplot gets its own selection and that points within any section are highlighted within all plots by setting

```
brush = alt.selection_interval(resolve='union') # The default is 'global'

points = alt.Chart(cars).mark_circle().encode(
    x='Horsepower',
    y='Miles_per_Gallon',
    color=alt.condition(brush, 'Origin', alt.value('lightgray'))
).add_params(
    brush
)

points | points.encode(y='Weight_in_lbs')
```

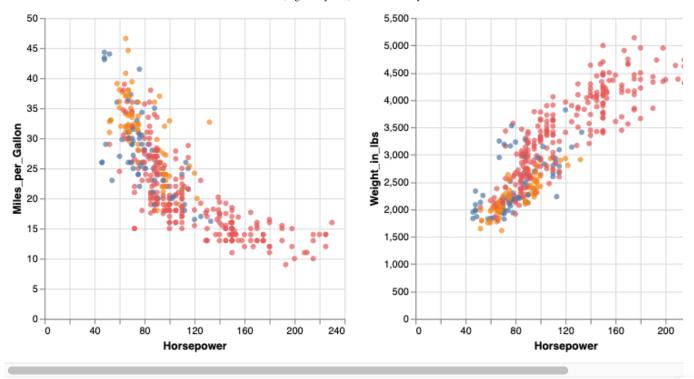


I could modify this behavior so that only points that fall within the intersection of *all* the selections are highlighted.

```
brush = alt.selection_interval(resolve='intersect')

points = alt.Chart(cars).mark_circle().encode(
    x='Horsepower',
    y='Miles_per_Gallon',
    color=alt.condition(brush, 'Origin', alt.value('lightgray'))
).add_params(
    brush
)

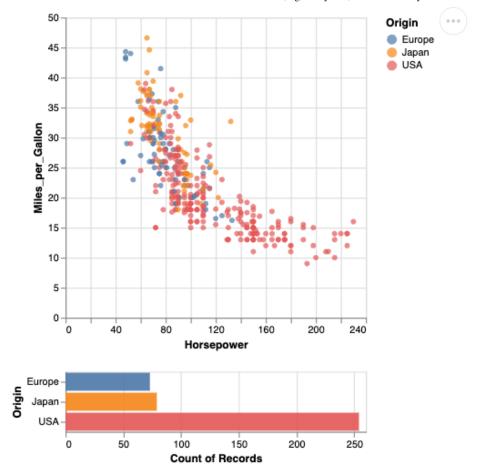
points | points.encode(y='Weight_in_lbs')
```



## 7.3.6. Click selections

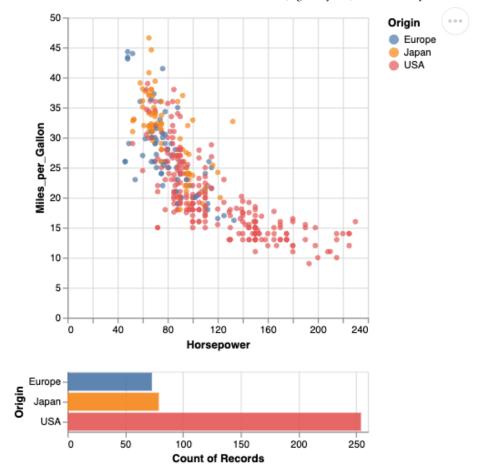
In addition to interval/drag interactivity, there is also interactivity via clicking. Let's add add a bar chart that changes the opacity of bars when not clicked. You can hold shift to select multiple.

```
brush = alt.selection_interval()
click = alt.selection point(fields=['Origin'])
points = alt.Chart(cars).mark_circle().encode(
    x='Horsepower',
    y='Miles_per_Gallon',
    color=alt.condition(brush, 'Origin', alt.value('lightgray'))
).add_params(
    brush
bars = alt.Chart(cars).mark bar().encode(
    x='count()',
    y='0rigin',
    color='Origin',
    opacity=alt.condition(click, alt.value(0.9), alt.value(0.2))
).add params(
    click
noints & hars
```



We can change the interaction that controls the clicks by setting on='mouseover'. Now the bars are selected while just hovering, no clicking needed.

```
brush = alt.selection interval()
click = alt.selection_point(on='mouseover', fields=['Origin'])
points = alt.Chart(cars).mark_circle().encode(
    x='Horsepower',
    y='Miles per Gallon',
    color=alt.condition(brush, 'Origin', alt.value('lightgray'))
).add_params(
    brush
bars = alt.Chart(cars).mark_bar().encode(
    x='count()',
    y='0rigin',
    color='Origin',
    opacity=alt.condition(click, alt.value(0.9), alt.value(0.2))
).add_params(
    click
points & bars
```

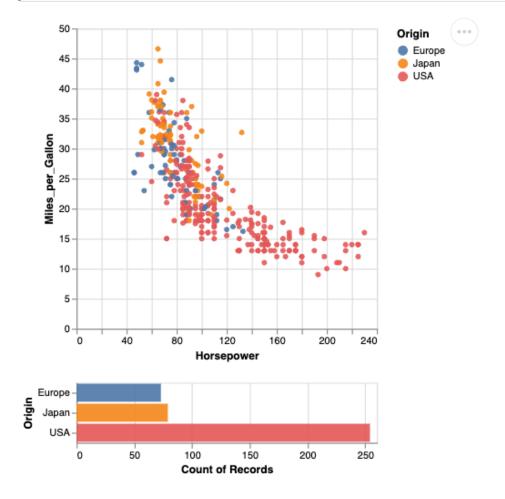


## 7.3.7. Linking selection on charts with different encodings

It would be cool if selection in one chart was reflected in the other one... Let's link the charts together! For the bar chart selector, we need to specify which field/column we should be selecting on since the x and y axis are not the same between the two plots so Altair can't link them automatically like the two scatters with the same axes.

```
bars = alt.Chart(cars).mark_bar().encode(
    x='count()',
    y='0rigin',
    color='0rigin',
    opacity=alt.condition(click, alt.value(0.9), alt.value(0.2))
).add_params(
    click
)

points & bars
```



## 7.3.8. Legend selections

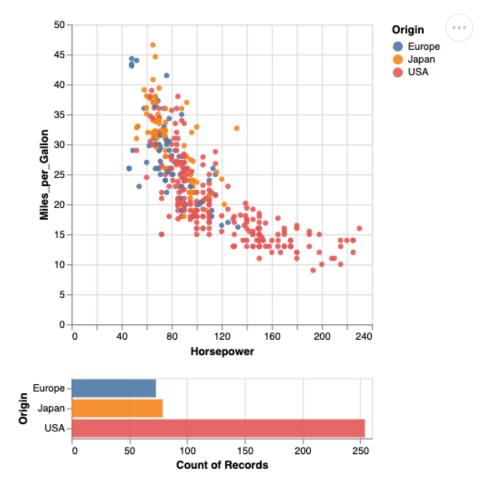
It is often nice to include legend interactivity in scatter plots. For this we could use the same technique as above and specify that we want to bind it to the legend. We also need to add the selection to the combined chart instead of to the bar chart since the legend belongs to both of them.

```
brush = alt.selection_interval()
click = alt selection_noint(fields=['Origin'] hind='legend')
```

```
x='Horsepower',
y='Miles_per_Gallon',
color=alt.condition(brush, 'Origin', alt.value('lightgray')),
opacity=alt.condition(click, alt.value(0.9), alt.value(0.2))
).add_params(
brush
)

bars = alt.Chart(cars).mark_bar().encode(
x='count()',
y='Origin',
color='Origin',
opacity=alt.condition(click, alt.value(0.9), alt.value(0.2))
)

(points & bars).add_params(click)
```

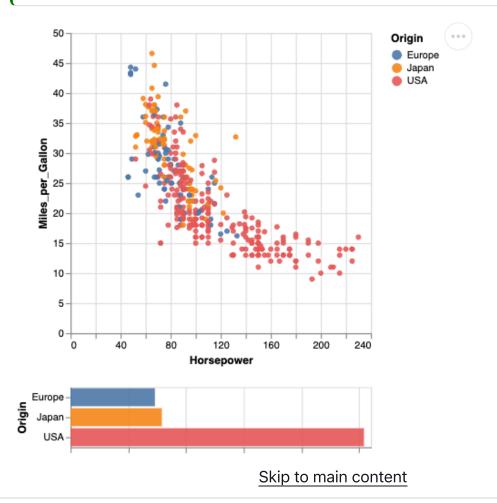


## 7.3.9. Filtering data based on a selection

Another useful type of interactivity is to actually filter the data based on a selection, rather than just styling the graphical elements differently as we have done so far. We can do this by

so they are best used for operations like this where we can't use pandas. This type of interaction is sometimes called a dynamic query.

```
brush = alt.selection interval()
click = alt.selection_point(fields=['Origin'], bind='legend')
points = alt.Chart(cars).mark circle().encode(
    x='Horsepower',
    y='Miles_per_Gallon',
    color=alt.condition(brush, 'Origin', alt.value('lightgray')),
    opacity=alt.condition(click, alt.value(0.9), alt.value(0.2))
) add_params(
    brush
bars = alt.Chart(cars).mark_bar().encode(
    x='count()',
    y='0rigin',
    color='Origin',
    opacity=alt.condition(click, alt.value(0.9), alt.value(0.2))
).transform_filter(
    brush
(points & bars).add_params(click)
```



## 7.3.10. Binding selection to other chart attributes

We can also bind the selection to other attributes of our plot. For example, a selection could bound to the domain of the scale which sets the axis range. This way one chart could be used as a minimap to navigate another chart.

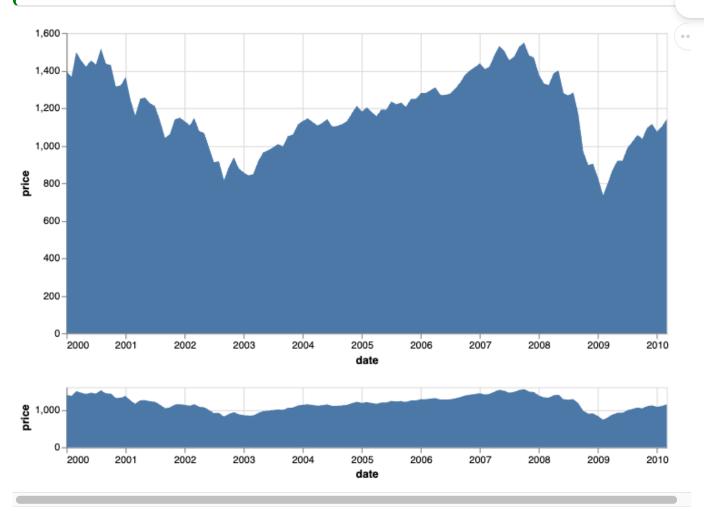
```
source = data.sp500.url

base = alt.Chart(source, width=600).mark_area().encode(
    x = 'date:T',
    y = 'price:Q')

brush = alt.selection_interval(encodings=['x'])
lower = base.properties(height=60).add_params(brush)

upper = base.encode(alt.X('date:T').scale(domain=brush))

upper & lower
```



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