Data 550: Data Visualization I

Lecture 7: Trendlines and visualizing uncertainty

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https://github.com/ubco-mds-2022/Data-550

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Overview

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

- Visualize pair-wise differences using a slope plot.
- Visualize trends using regression and loess lines.
- Create and understand how to interpret confidence intervals and confidence bands.

Suggested readings from Fundamentals of Data Visualization.

- Section 14 - 14.2 on visualizing trends.
- Section 16 on visualizing uncertainty

https://github.com/ubco-mds-2022/Data-550

Trendlines

https://github.com/ubco-mds-2022/Data-550

Introduction

- It is often the case that we are interested in the overarching trend of the data (rather than the specific values).
- Trends are usually visualized by a straight or curved line.
- These can be layered on top of or instead of the actual data points to help the reader identify key features in the data.
- Once established, we can look at deviations from the trend, or explore separating the data into multiple components

Trendlines

- Trendlines[1] highlight general trends in the data that can be hard to elucidate by looking at the raw data points.
- This can happen if there are many data points or many groups inside the data.
- Two fundamental approaches to determining a trend are:
  1. smoothing (e.g. moving average)
  2. fitting a curve with a functional form (e.g. regression)

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1. also sometimes called “lines of best fit”, or “fitted lines”

Cars data

```python
from vega_datasets import data

cars = data.cars()
cars
```

	Name	Miles_per_Gallon	Cylinders	Displacement	Horsepower	Weight_in_lbs	Acceleration	Year	Origin
0	chevrolet chevelle malibu	18.0	8	307.0	130.0	3504	12.0	1970-01-01	USA
1	buick skylark 320	15.0	8	350.0	165.0	3693	11.5	1970-01-01	USA
2	plymouth satellite	18.0	8	318.0	150.0	3436	11.0	1970-01-01	USA
3	amc rebel sst	16.0	8	304.0	150.0	3433	12.0	1970-01-01	USA
4	ford torino	17.0	8	302.0	140.0	3449	10.5	1970-01-01	USA
...	...	...	...	...	...	...	...	...	...
401	ford mustang gl	27.0	4	140.0	86.0	2790	15.6	1982-01-01	USA
402	vw pickup	44.0	4	97.0	52.0	2130	24.6	1982-01-01	Europe
403	dodge rampage	32.0	4	135.0	84.0	2295	11.6	1982-01-01	USA
404	ford ranger	28.0	4	120.0	79.0	2625	18.6	1982-01-01	USA
405	chevy s-10	31.0	4	119.0	82.0	2720	19.4	1982-01-01	USA

406 rows × 9 columns

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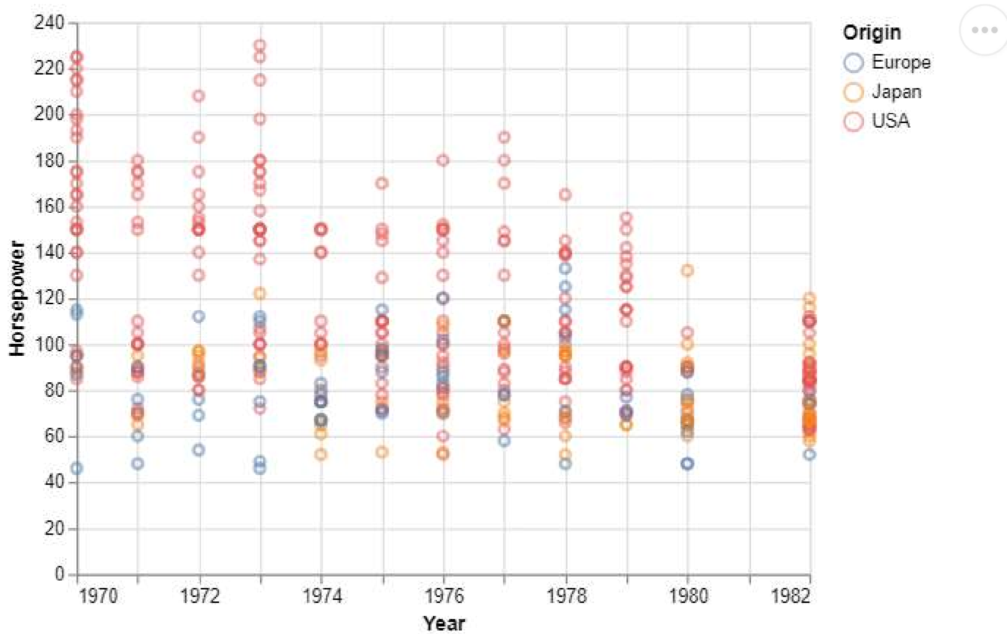
Scatter plot

▶ Code



We might be interested in studying the general trend of horsepower over time for European, Japanese and US cars.

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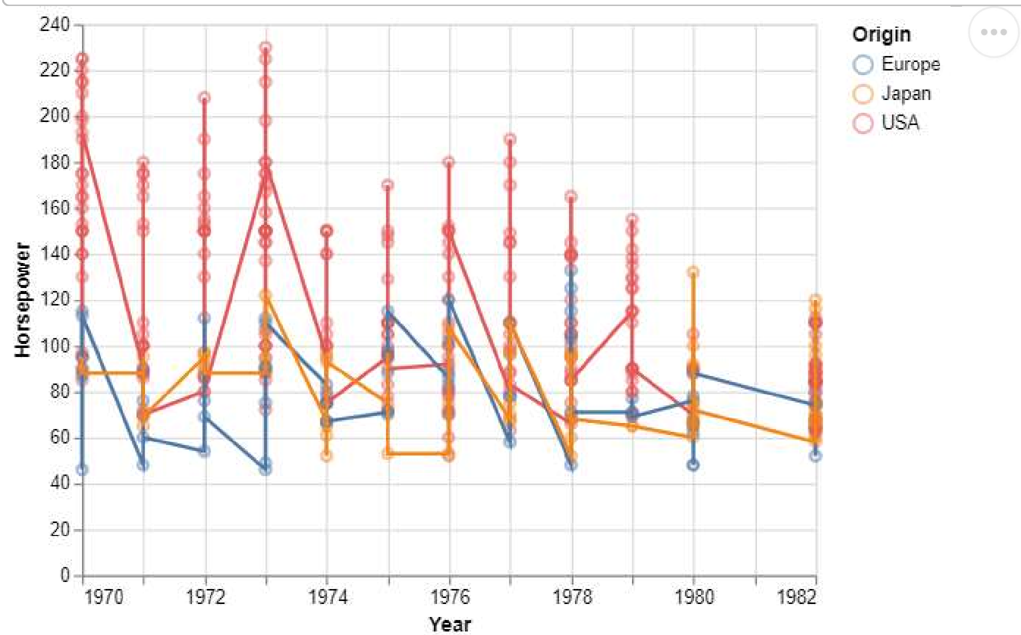
Line chart

```
points + points.mark_line()
```



A not so effective way to visualize the trend in this data is to connect all data points with a line.

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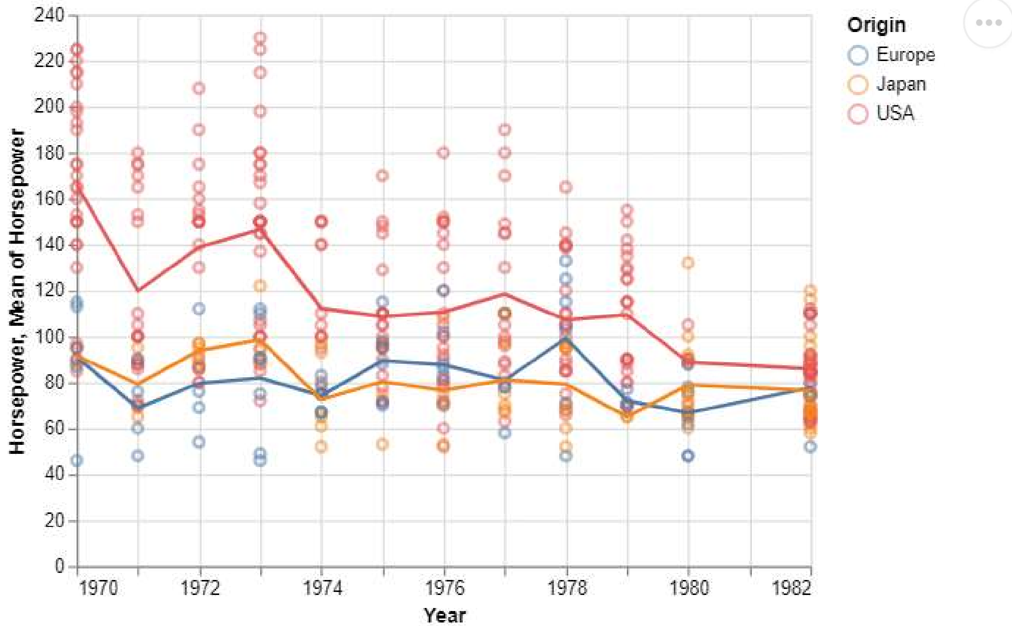
Mean y-value

```
points + points.encode(y='mean(Horsepower)').mark_line()
```



A simple trend line can be found by averaging the mean y-value at each x …

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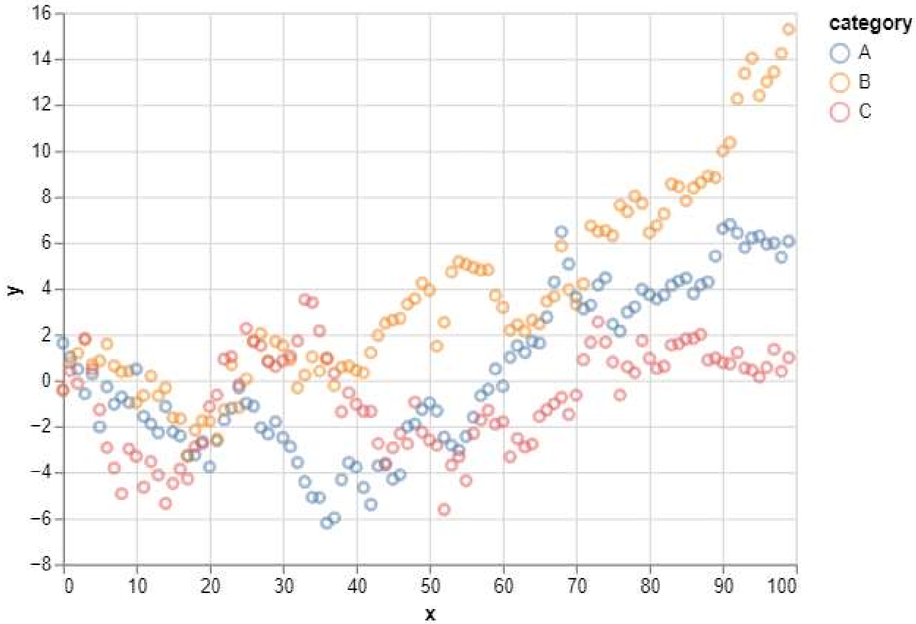
Continuous x

▶ Code



The strategy on the previous slide works for the cars data, but with a continuous x-values, we would need to bin the x-axis before taking the mean y-value.

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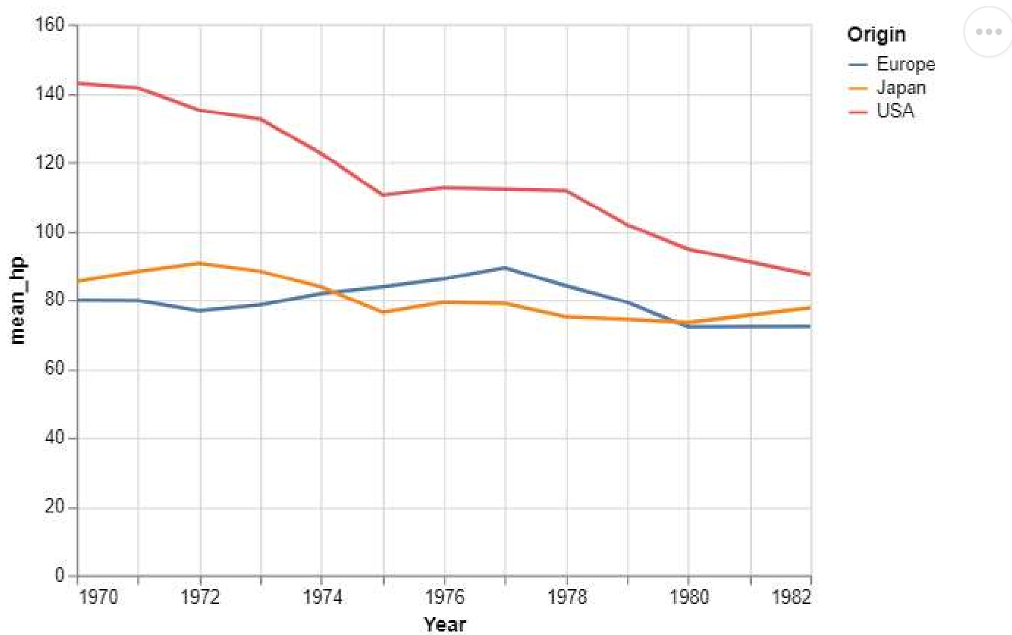
Moving Average

▶ Show the code (*this will not be on the quiz*)



An alternative to binning continuous data is to use a moving/rolling average, that takes the mean of the last n observations.

Altair documentation for transform window.

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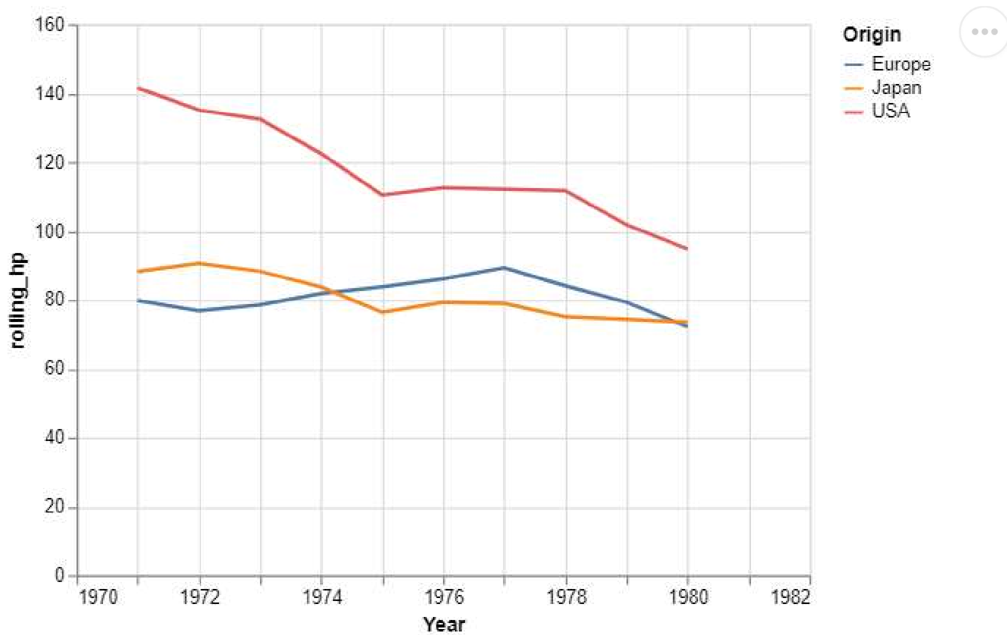
Rolling method

▶ Show the code (*this will not be on the quiz*)



We can also use the rolling method in pandas for this calculation, but it handles the edges a bit differently.

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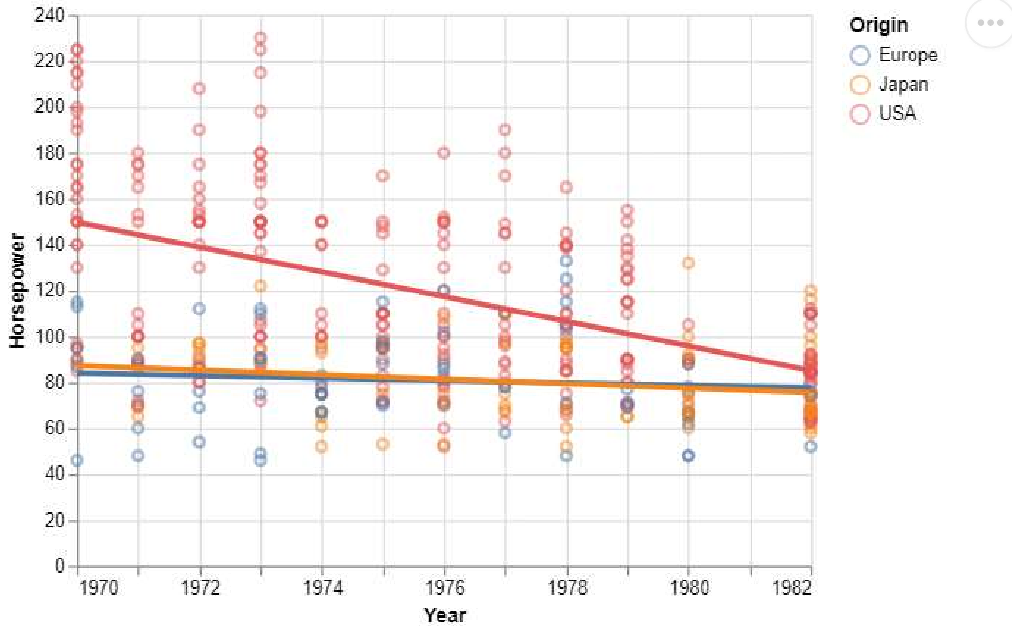
Regression

```
points +  points.transform_regression(
    'Year', 'Horsepower', # The field names of the x and y values, resp
    groupby=['Origin']).mark_line(size=3)
```



Another way of showing a trend in the data is via regression transform[1]

This uses ordinary least squares to fit a linear (`linear`) model with the functional form:

$$y = a + b * x$$

1. this can be used for smoothing and prediction

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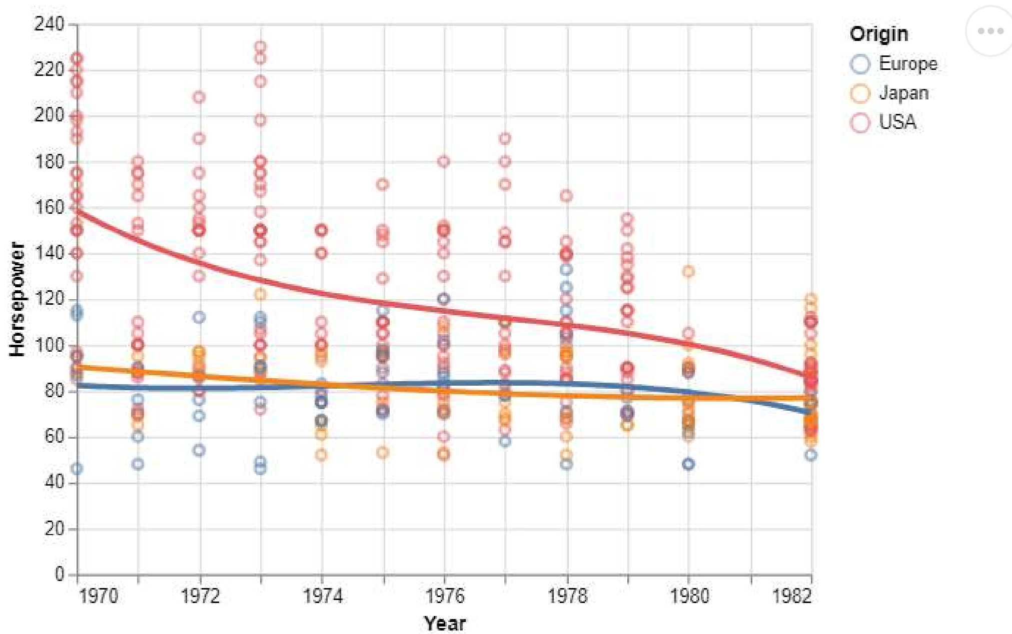
Nonlinear

You are not limited to fitting linear lines; other fits that are:



logarithmic (`log`): $y = a + b * log(x)$

exponential (`exp`): $y = a + eb * x$

power (`pow`): $y = a * xb$

quadratic (`quad`): $y = a + b * x + c * x2$

polynomial (`poly`): $y = a + b * x + \ldots + k * xorder$

```
points +  points.transform_regression(
    'Year', 'Horsepower', # The field names of the input x and y values.
    groupby=['Origin'], method='poly'
).mark_line(size=3)
```

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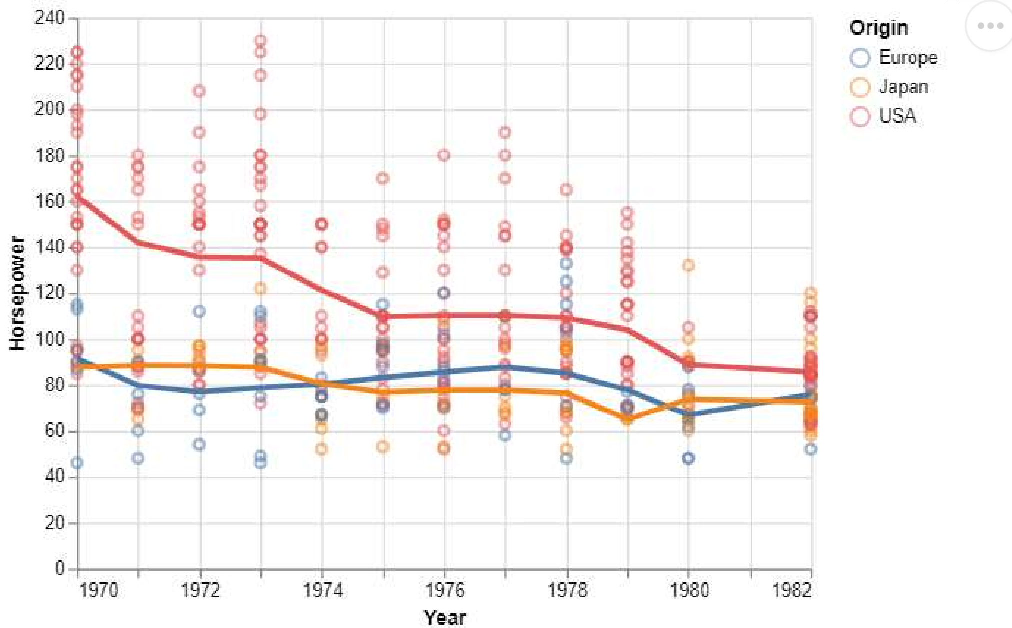
Loess

```
points +  points.transform_loess(
    'Year', 'Horsepower', groupby=['Origin']).mark_line(size=3)
```



The LOESS transform[1] fits low-degree polynomials to subsets of the data such that points in the center are weighted more heavily than points at the boundaries.

see complete list of tranform loess options here

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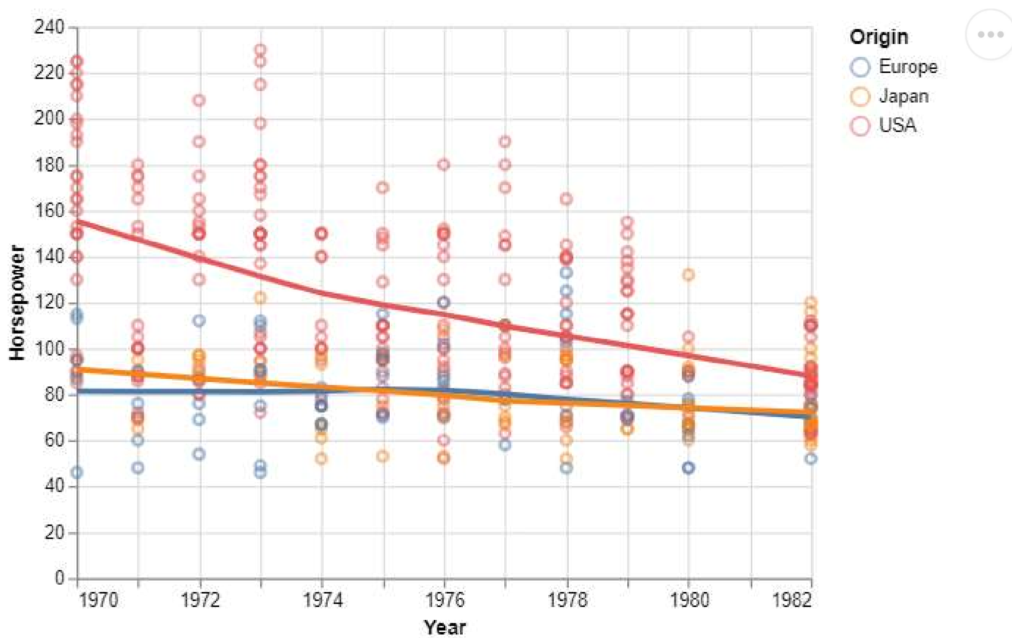
Bandwidth

▶ Code



The `bandwidth` parameter controls how much the loess fit should be influenced by local variation in the data

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When to choose which trendline?

- The most straightforward trendlines when communicating data to a general audience rolling mean. Choose this if it is important that the line has values that are easy to interpret.
- loess works with very little assumptions and tends to produce “natural” results that look right to the human eye
- N.B. loess requires the fitting of many separate regression models, making it slow for large datasets, even on modern computing equipment.

When to choose which trendline?

- Smoothing models can produce widely different results (particularly near the boundaries of the data).
- Furthermore smoothers do not provide parameter estimates that have a meaningful interpretation.
- Therefore, whenever possible, it is preferable to fit a curve with a specific functional form that is appropriate for the data and that uses parameters with clear meaning.

Visualizing Uncertainty

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Visualizing Uncertainty

- When we see a data point drawn in a specific location, we tend to interpret it as a precise representation of the true data value.
- Whether and how we choose to represent this uncertainty can make a major difference in how accurately our audience perceives the meaning of the data.
- Two commonly used approaches to indicate uncertainty are error bars (`mark_errorbar`) and confidence bands (`mark_errorbar`).

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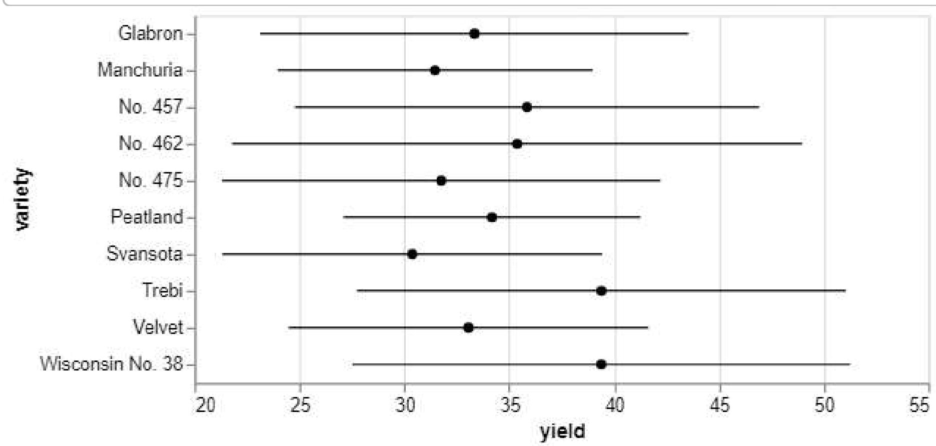
Error bars

This example shows error bars surrounding the average crop yield of different types of barley in the 1930s.

```
from vega_datasets import data
source = data.barley()
```



What do the bars represent?

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Comments

1. It is not obvious what the error bars represent. *Do they represent the standard deviation of the data, the standard error of the mean, a 95% confidence interval, or something else altogether? There is no commonly accepted standard.*
2. By representing each group by a single point (mean) and two error bars, we are losing a lot of information about the data.
3. symmetric error bars are misleading if there is any skew in the data

https://github.com/ubco-mds-2022/Data-550

Comments

1. It is not obvious what the error bars represent. *Do they represent the standard deviation of the data, the standard error of the mean, a 95% confidence interval, or something else altogether? There is no commonly accepted standard.*
2. It is not obvious what the circles represent (*mean/median*?).
3. By representing each group by a single point (mean) and two error bars, we are losing a lot of information about the data.
4. symmetric error bars are misleading for skewed data

https://github.com/ubco-mds-2022/Data-550

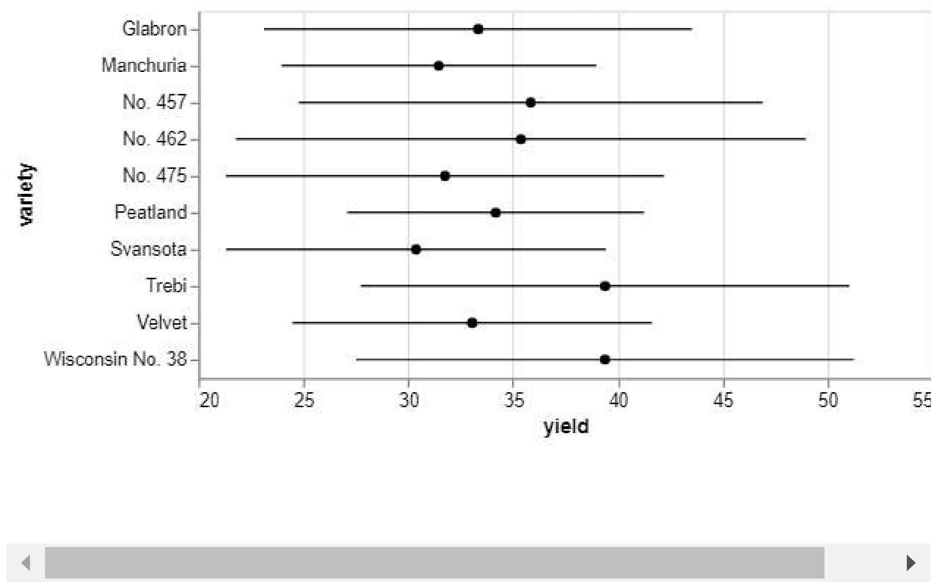
Error bars with Standard Deviation

The error bars in this chart represent standard deviation.

```
error_bars = (alt.Chart(source)
.mark_errorbar(extent='stdev')
.encode(
  alt.X('yield', scale=alt.Scale(z
  alt.Y('variety')))

mean_pts = (alt.Chart(source)
.mark_point(filled=True, color='bl
.encode(
  alt.X('yield', aggregate='mean')
  alt.Y('variety')))

error_bars + mean_pts
```



The `extend` argument of `mark_errorbar` tells Altair if you want to show the standard

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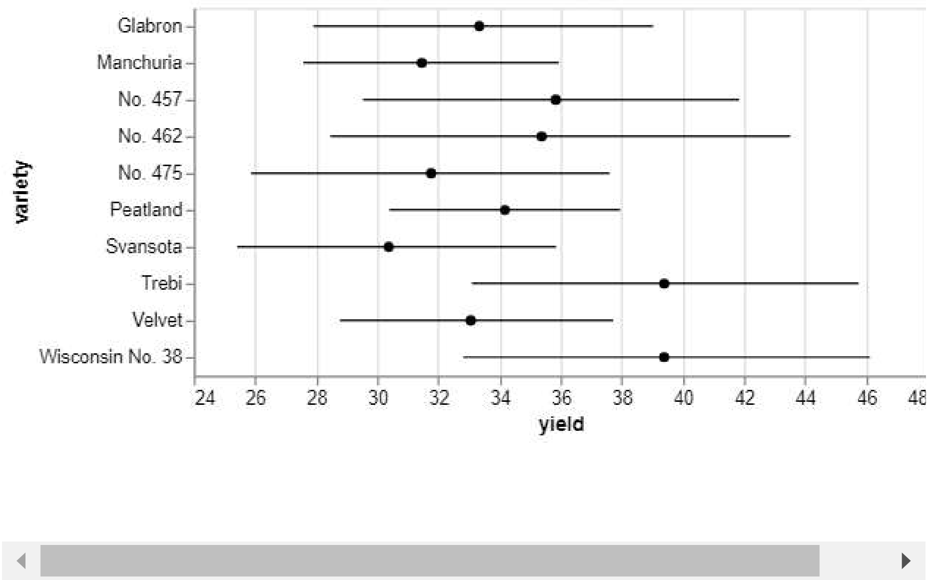
Error bars with Confidence Interval

These error bars represent a 95% confidence interval.

```
error_bars = (alt.Chart(source)
.mark_errorbar(extent='ci')
.encode(
  alt.X('yield', scale=alt.Scale(z
  alt.Y('variety')))

mean_pts = (alt.Chart(source)
.mark_point(filled=True, color='bl
.encode(
  alt.X('yield', aggregate='mean')
  alt.Y('variety')))

error_bars + mean_pts
```



The confidence intervals are computed internally in vega by a non-parametric bootstrap

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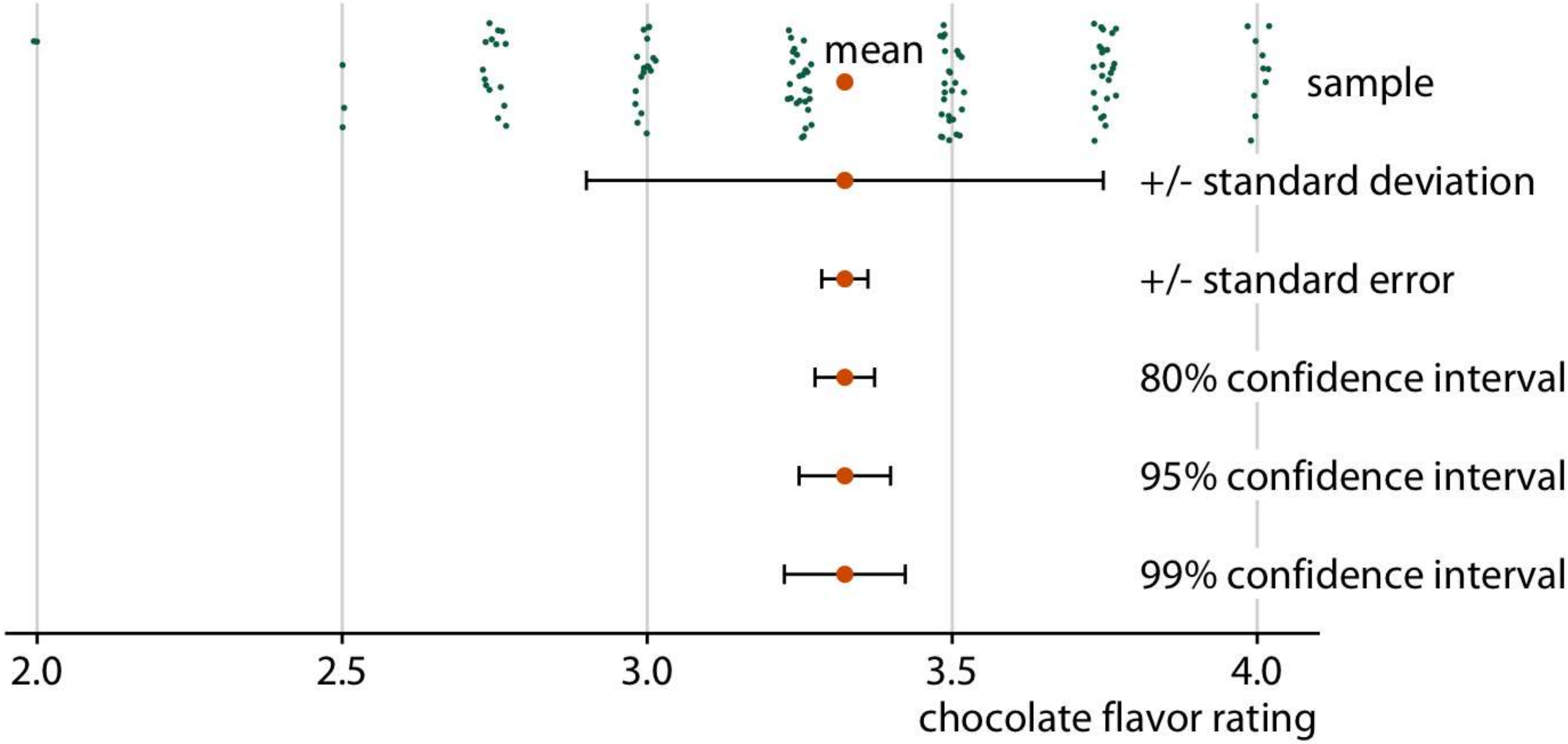
Error bar choices



Relationship between sample, sample mean, standard deviation, standard error, and confidence intervals, in an example of chocolate bar ratings. Wilkes Ch 16 Visualizing Uncertainty, Data source: Brady Brelinski, Manhattan Chocolate Society

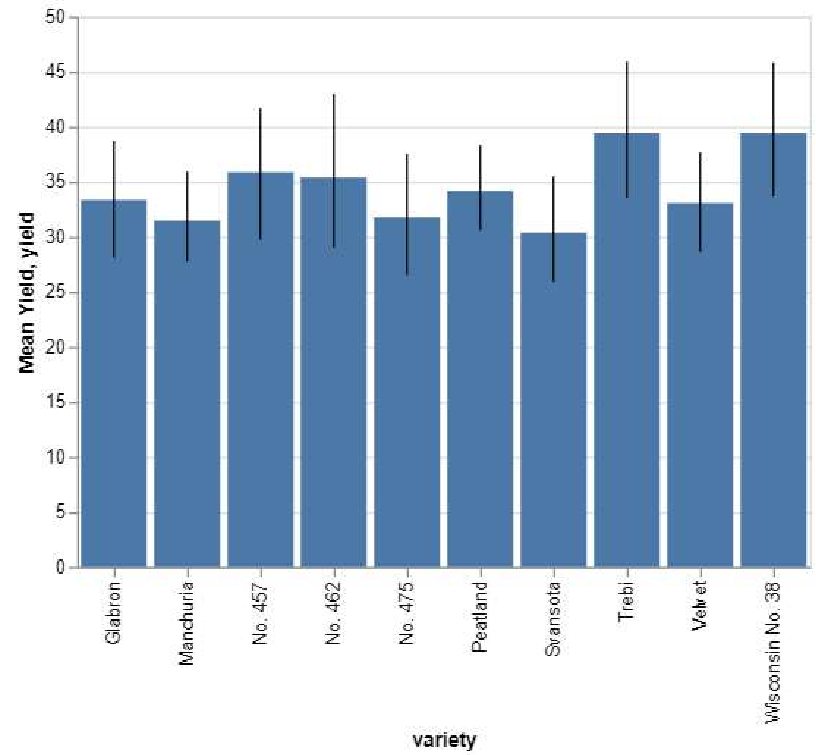
https://github.com/ubco-mds-2022/Data-550

Bars Charts with Error bars

```
bars = alt.Chart(
).mark_bar().encode(
    alt.X('variety'),
    alt.Y('mean(yield):Q', title='
)

error_bars = alt.Chart(
).mark_errorbar(extent='ci'
).encode(
    x='variety',
    y='yield:Q'
)

alt.layer(bars, error_bars, data=s
```



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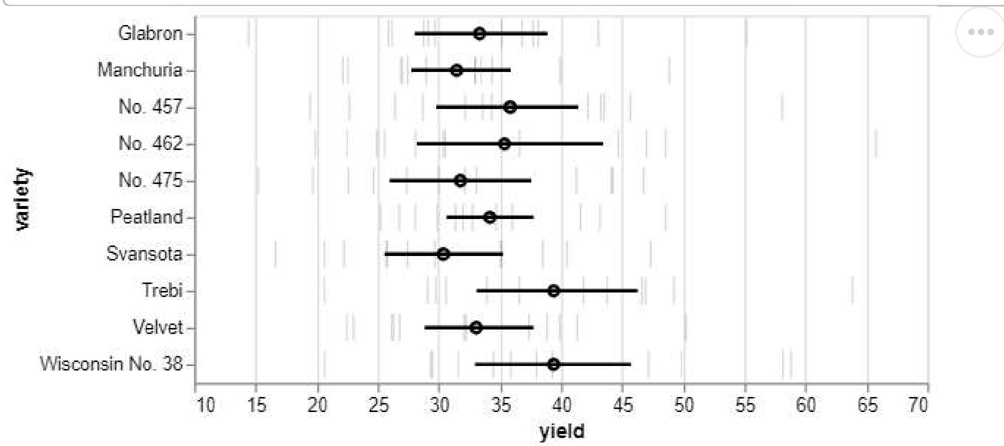
A common alternative called a *dynamite plot* plot only the error bar on top.

Better Alternative

```
err_bars = alt.Chart(source).mark_errorbar(extent='ci', rule=alt.LineConfig
    x=alt.X('yield', scale=alt.Scale(zero=False)),
    y='variety')

(err_bars.mark_tick(color='grey', opacity=0.3)
 + err_bars
 + err_bars.mark_point(color='black').encode(x='mean(yield)'))
```



Another good alternative would be violin plots

Uncertainty of Trendlines

- Trend estimates also have uncertainty associated with them.
- A commonly used approach to show the uncertainty in a trend line with a confidence band
- The confidence band provides us with a range of different fit lines that would be compatible with the data
- To draw a confidence band, we need to specify a confidence level (95% is typical)

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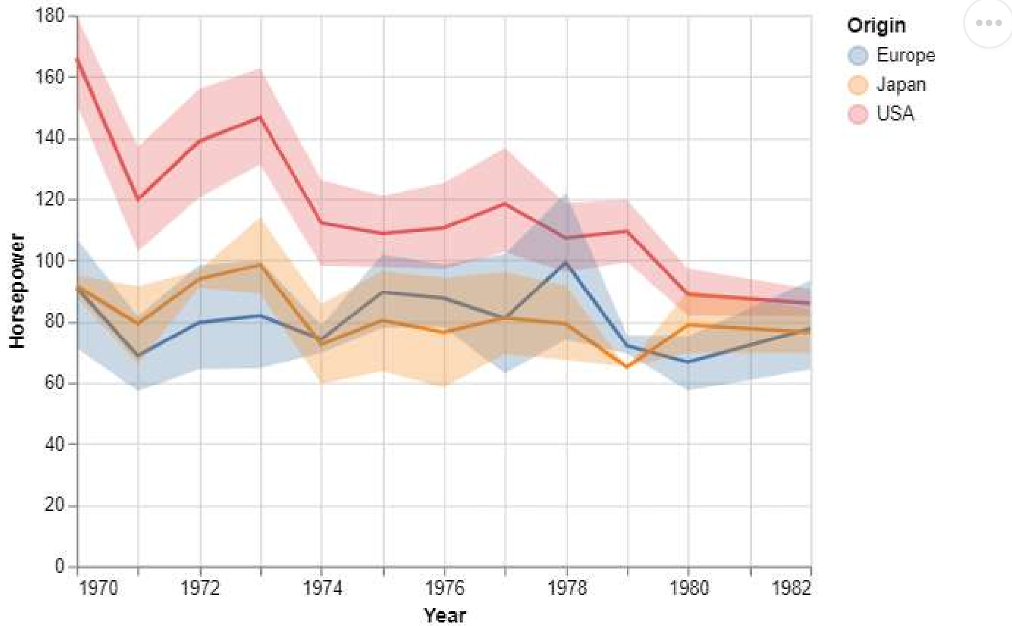
Confidence Bands

- To show the confidence interval of the points as a band, we can use `mark_errorband`.
- As documented here we can set `extent` to:
  - `ci` for confidence interval
  - `stderr` standard error
  - `stdev` for standard deviation
  - `iqr` Extend the band to the q1 and q3.

Average with Confidence bands

```
yearly_avg = points.encode(y='mean(Horsepower)').mark_line()
yearly_avg_ci = points.mark_errorband(extent='ci')
yearly_avg + yearly_avg_ci
```



We can add in the mean line.

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