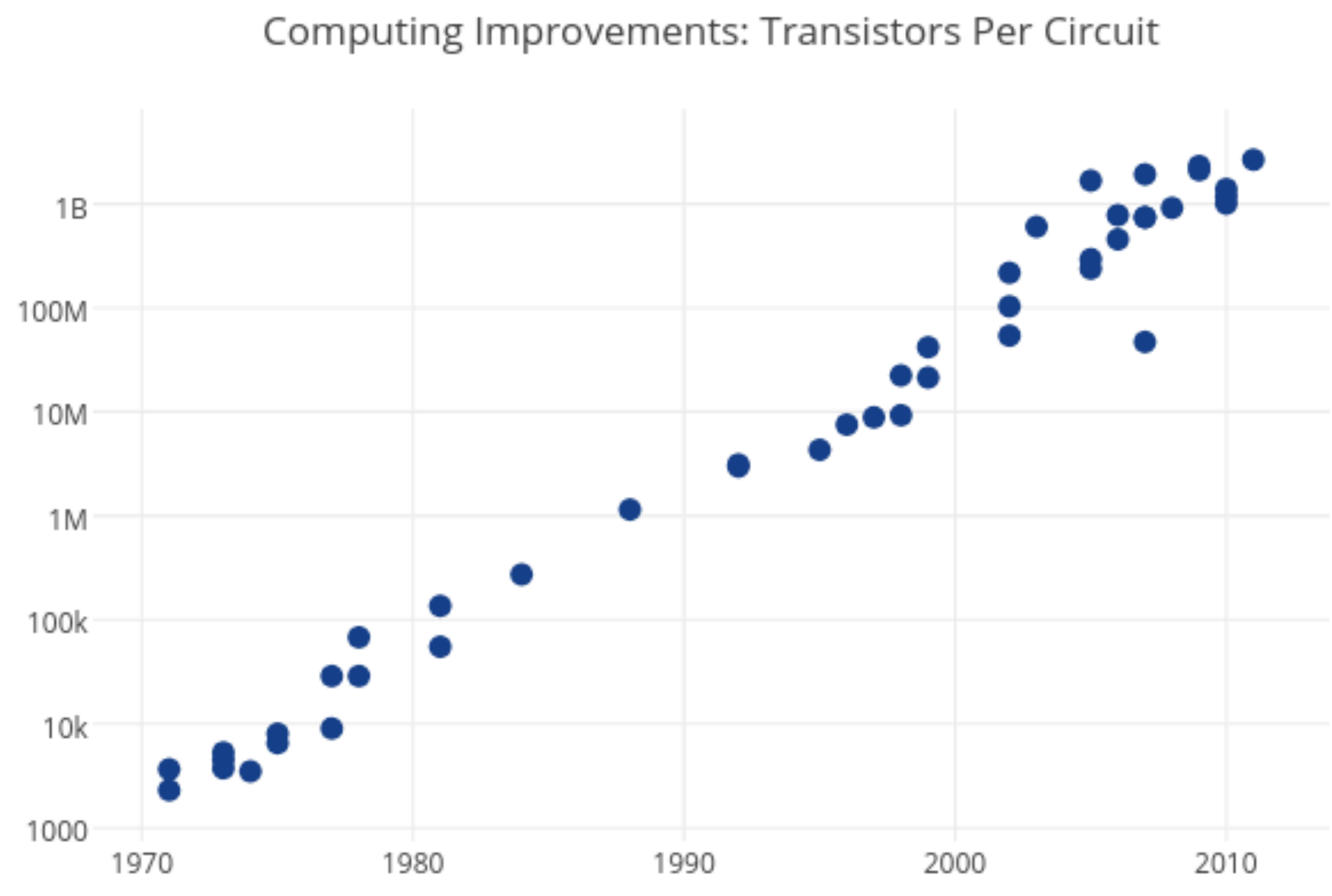
Continuous Measurements

- So far, looked at relationships between *discrete* outcomes
- For pair of *continuous* outcomes, use a **scatter plot**

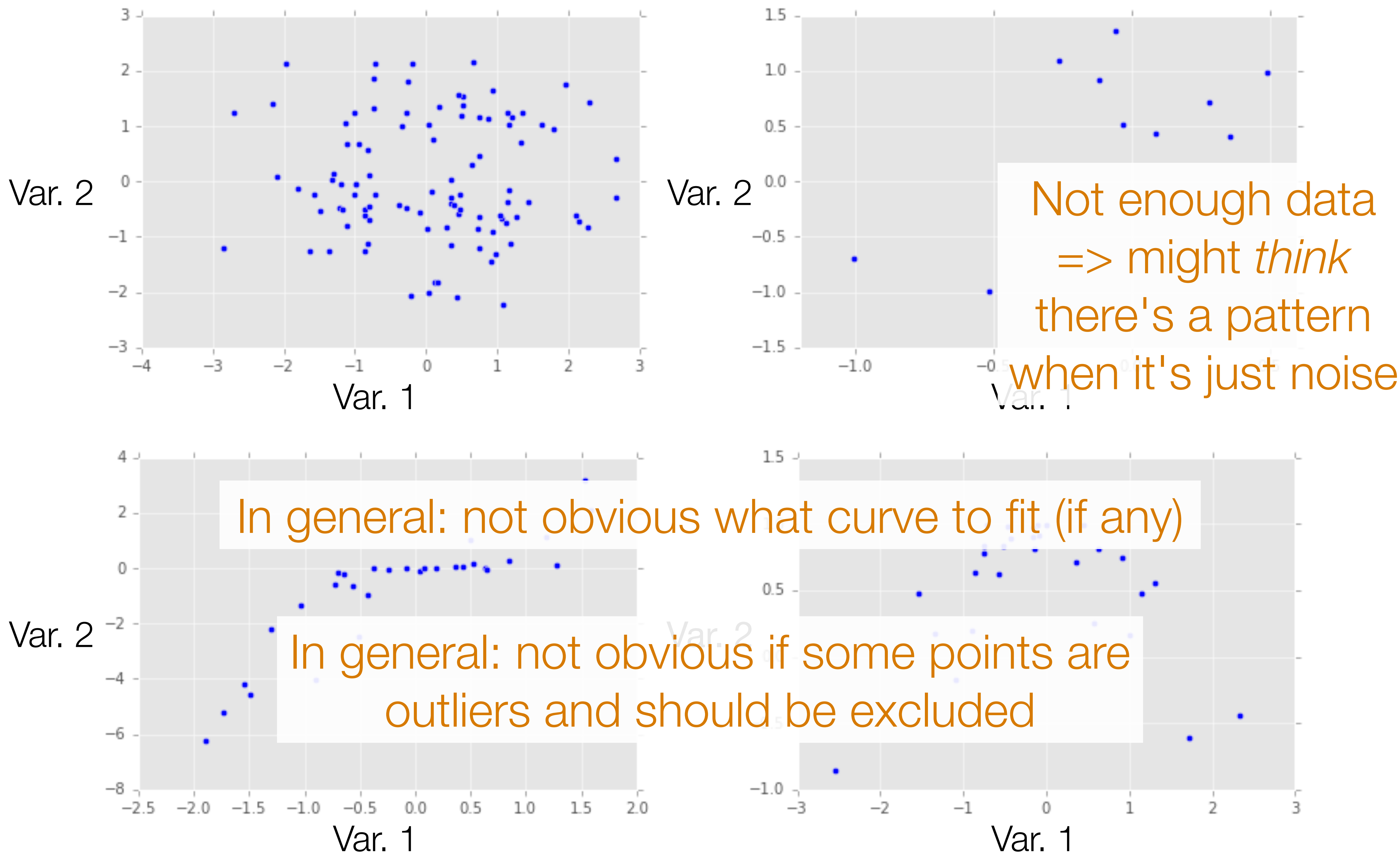


Of course, not all trends look like a line

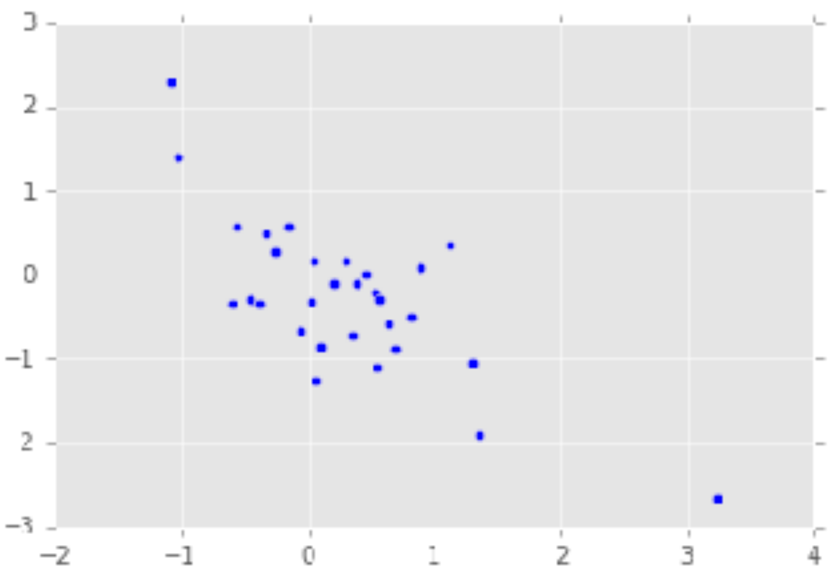
(so don't just do linear regression!)

Image source: https://plot.ly/~MattSundquist/5405.png

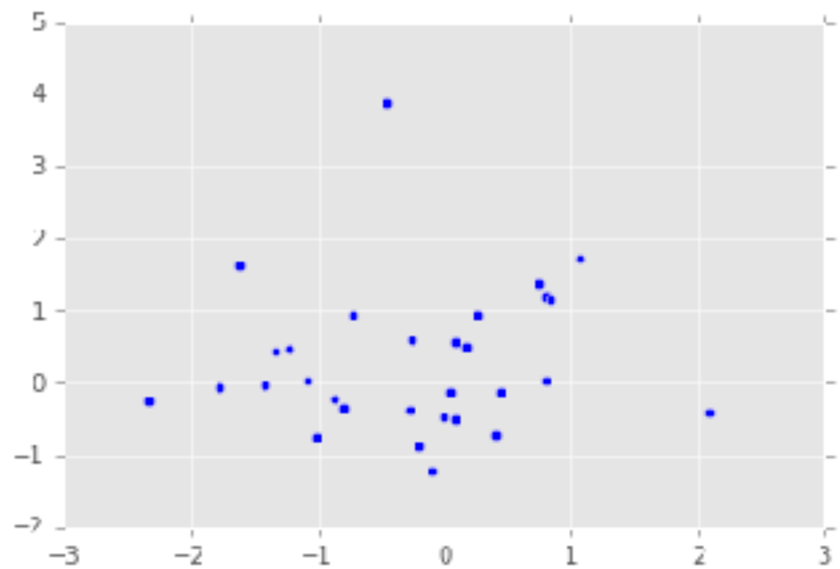
The Importance of Staring at Data



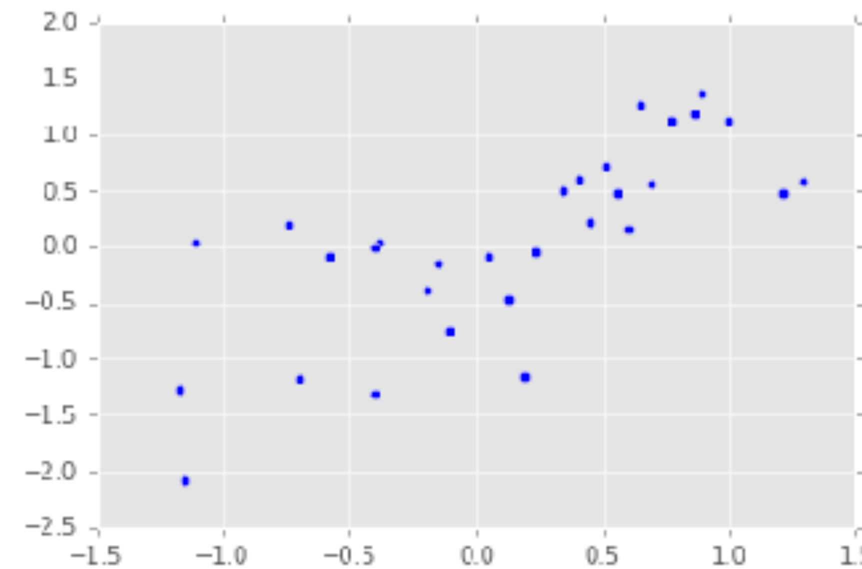
Correlation



Negatively correlated



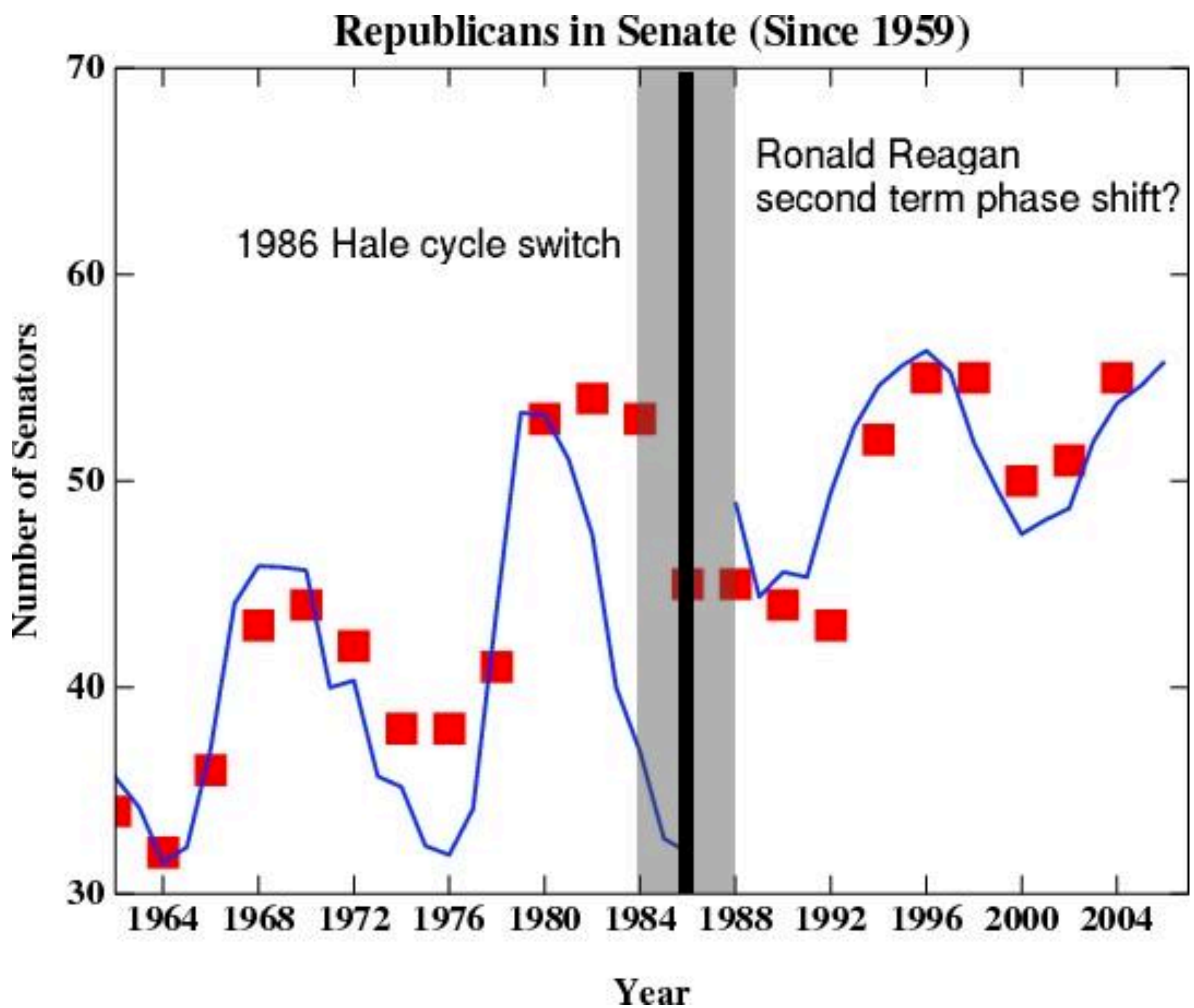
Not really correlated



Positively correlated

Beware: Just because two variables appear correlated doesn't mean that one can predict the other

Correlation ≠ Causation



Blue: Scaled sunspot number (inverted after Reagan's 2nd term)

Red: Number of Republican senators

Moreover, just because we find correlation in data doesn't mean it has predictive value!

Image source: http://www.realclimate.org/index.php/archives/2007/05/fun-with-correlations/

Important: At this point in the course, we are finding *possible* relationships between two entities

We are *not* yet making statements about prediction (we'll see prediction later in the course)

We are *not* making statements about causality (beyond the scope of this course)

Causality

Studies in 1960's: Coffee drinkers have higher rates of lung cancer

Can we claim that coffee is a cause of lung cancer?

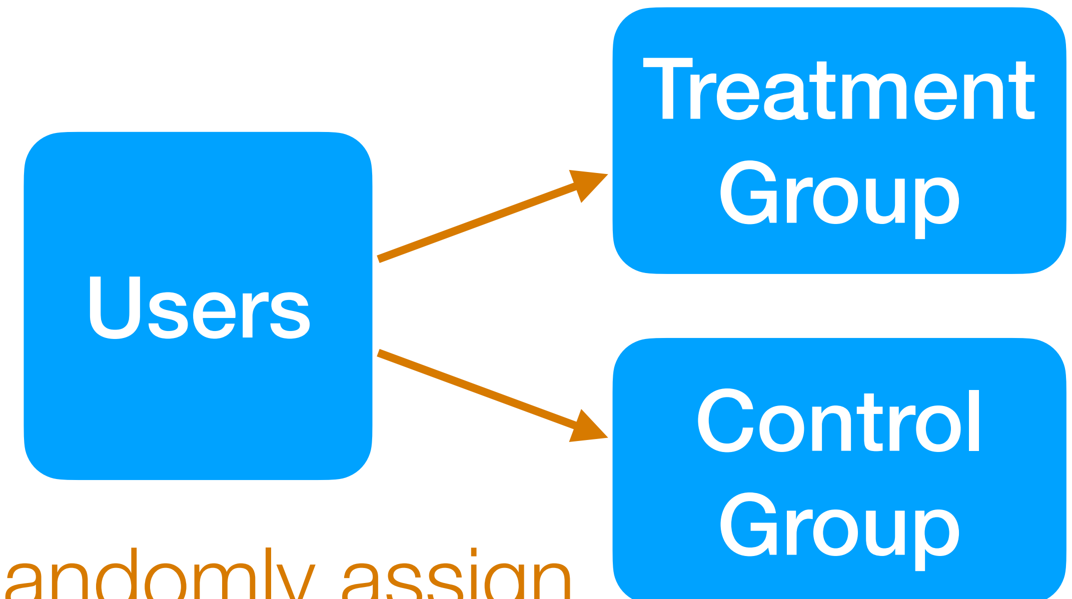
Back then: coffee drinkers also tended to smoke more than non-coffee drinkers (smoking is a **confounding variable**)

To establish causality, groups getting different treatments need to appear similar so that the only difference is the treatment

Image source: George Chen

Establishing Causality

If you control data collection



Randomly assign

Compare outcomes of two groups

Randomized controlled trial (RCT)
also called **A/B testing**

Example: figure out webpage layout to maximize revenue (Amazon)

Example: figure out how to present educational material to improve learning (Khan Academy)

If you do not control data collection

In general: *not* obvious establishing what caused what

Course Outline

Part I: Exploratory data analysis

Identify structure present in "unstructured" data

- Frequency and co-occurrence analysis *Basic probability & statistics*
- Visualizing high-dimensional data/dimensionality reduction
- Clustering
- Topic modeling

Part II: Predictive data analysis

Make predictions using known structure in data

- Classical classification methods
- Neural nets and deep learning for analyzing images and text

Carnegie Mellon University
Heinz College

Unstructured Data Analysis

Lecture 4: Visualizing high-dimensional data

George Chen

So Far...

Text doc #1 → Feature vector #1 (histogram)

We can visualize this histogram

Text doc #2 → Feature vector #2 (histogram)

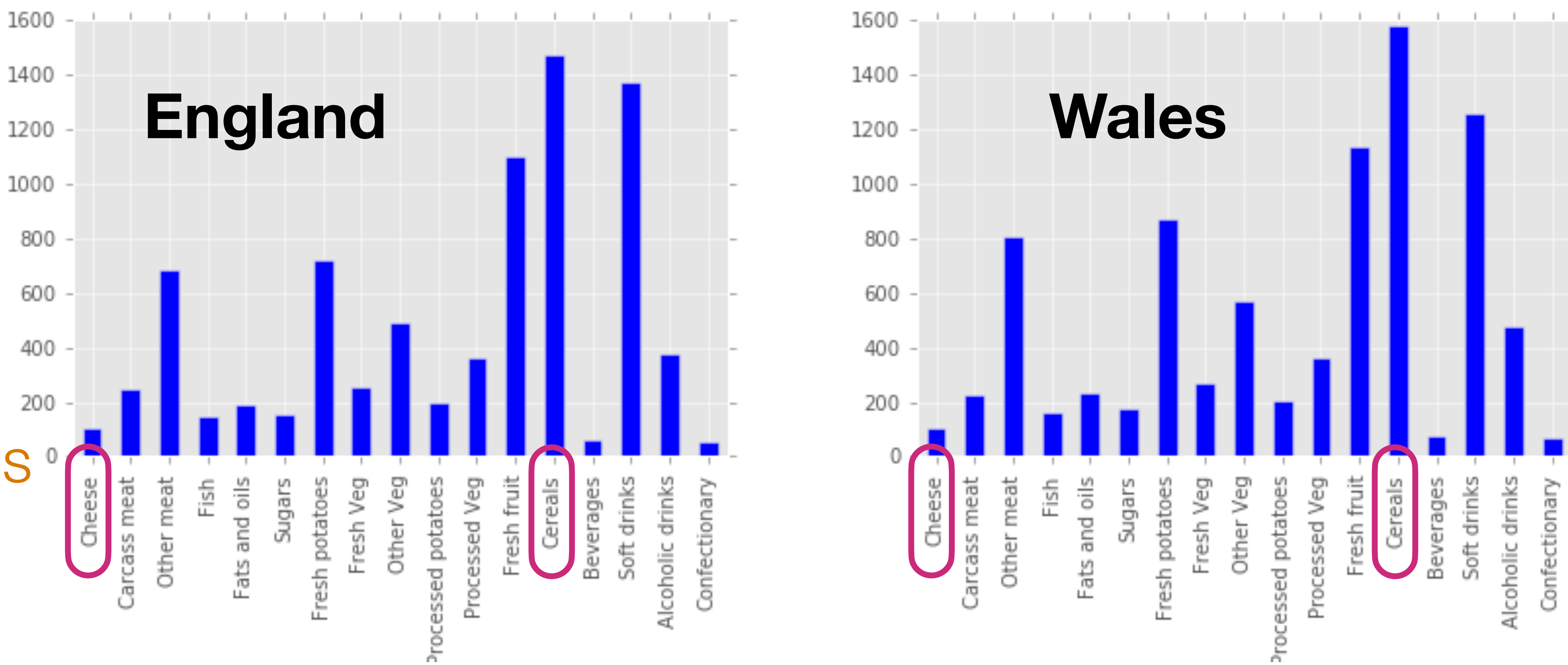
⋮

Text doc #*n* → Feature vector #*n* (histogram)

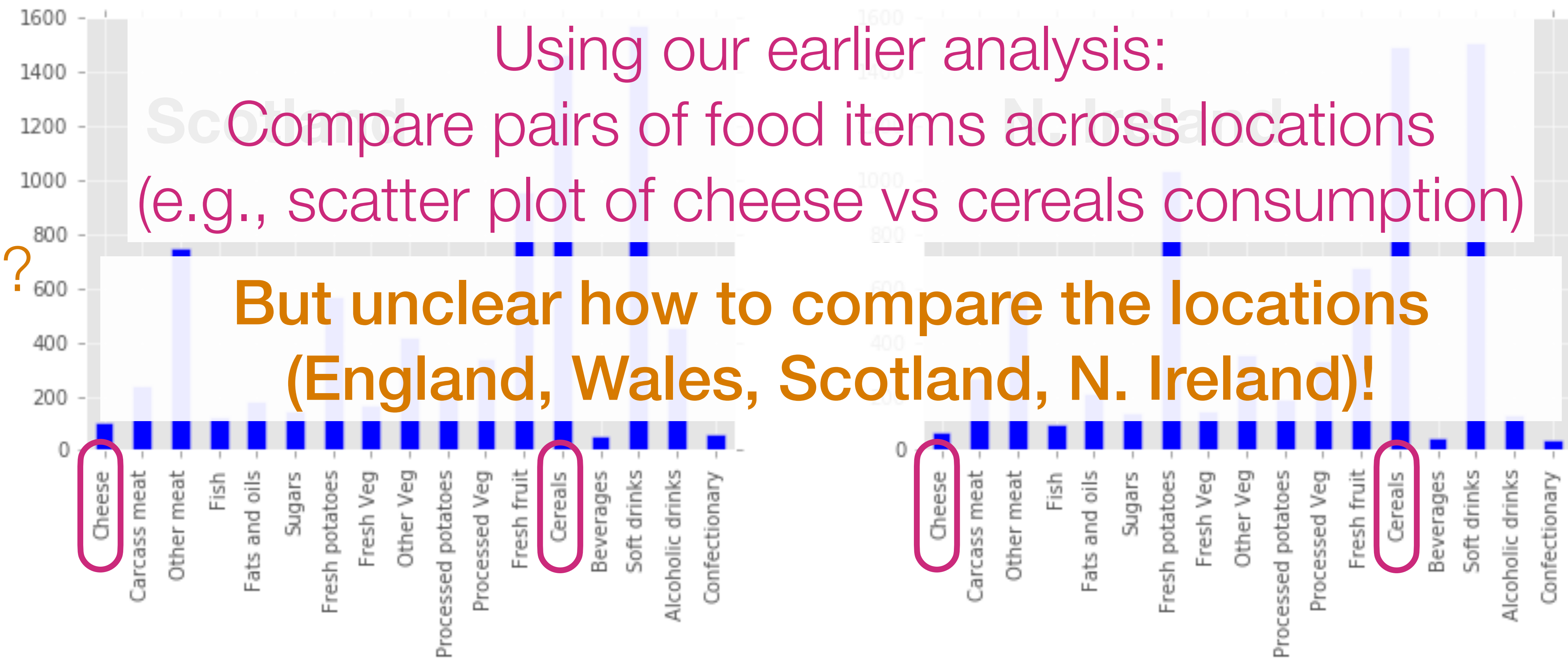
How do we visualize all *n* text doc's at once if *n* is large?

Here’s another concrete example

Imagine we had hundreds of these



How to visualize these for comparison?



Using our earlier analysis:
Compare pairs of food items across locations
(e.g., scatter plot of cheese vs cereals consumption)

But unclear how to compare the locations (England, Wales, Scotland, N. Ireland)!

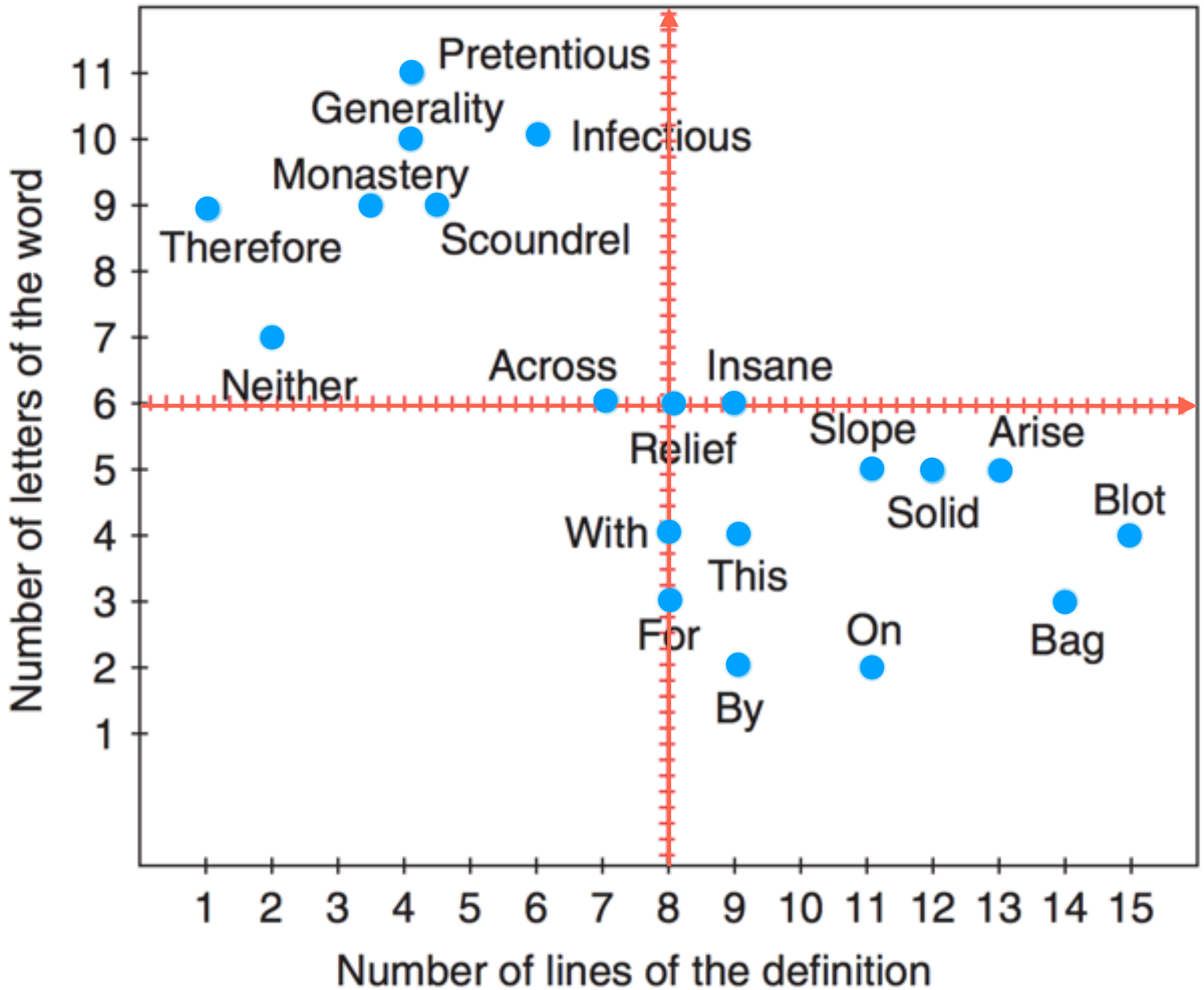
Source: http://setosa.io/ev/principal-component-analysis/

The issue is that as humans we can only really visualize up to 3 dimensions easily

Goal: Somehow reduce the dimensionality of the data preferably to 1, 2, or 3

Principal Component Analysis (PCA)

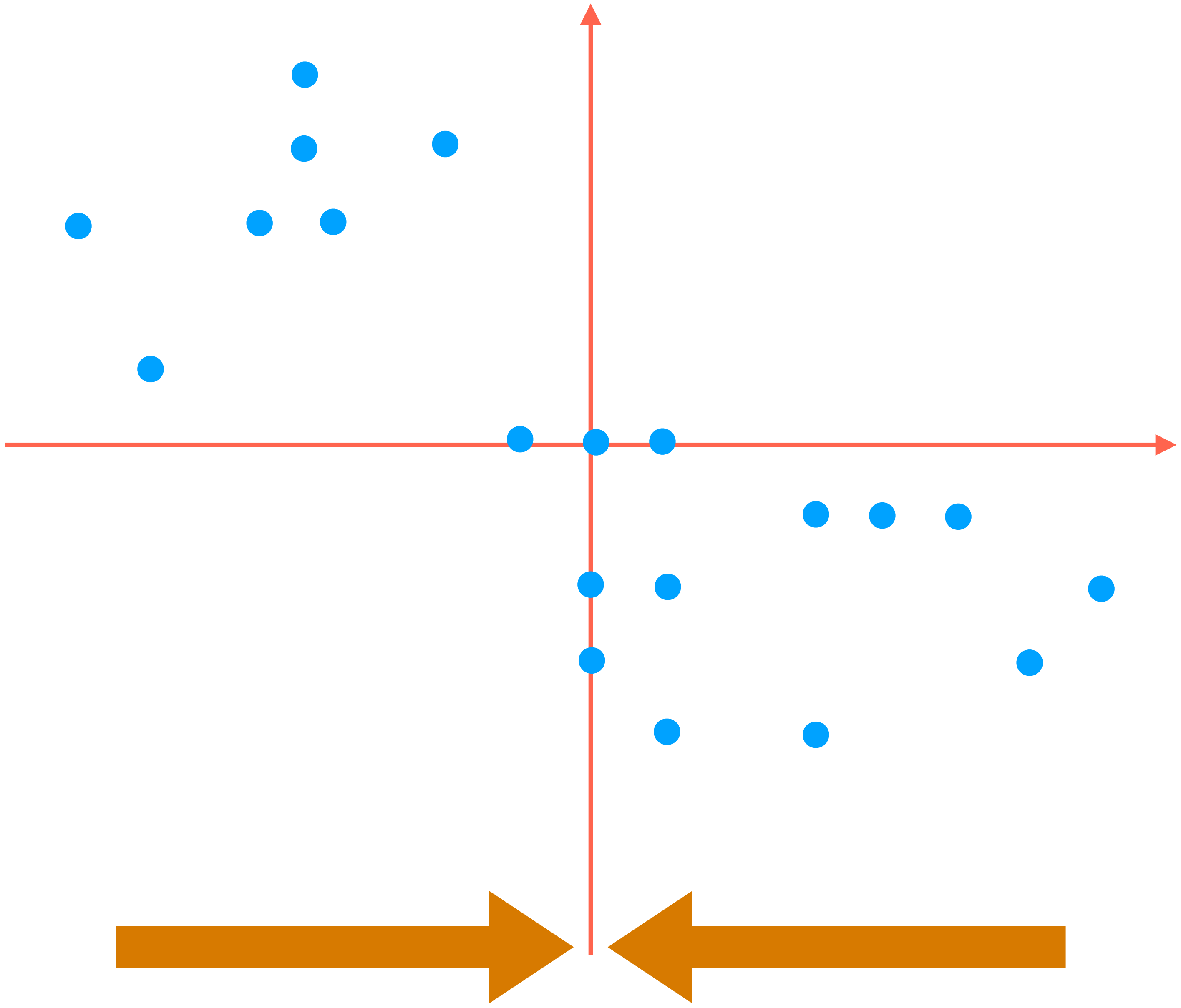
How to project 2D data down to 1D?



Hervé Abdi and Lynne J. Williams. Principal component analysis. Wiley Interdisciplinary Reviews: Computational Statistics. 2010.

Principal Component Analysis (PCA)

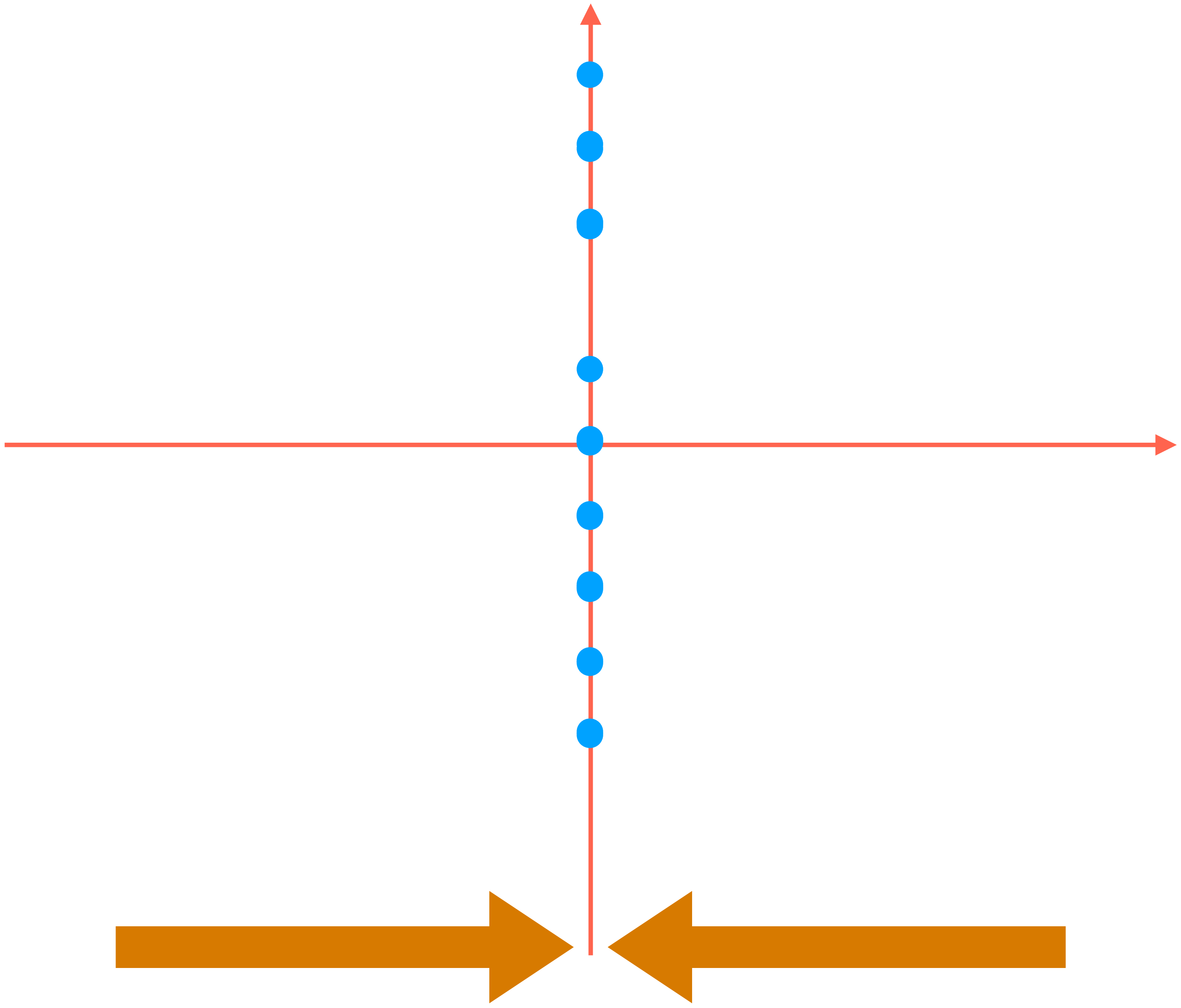
How to project 2D data down to 1D?



Simplest thing to try: flatten to one of the red axes

Principal Component Analysis (PCA)

How to project 2D data down to 1D?

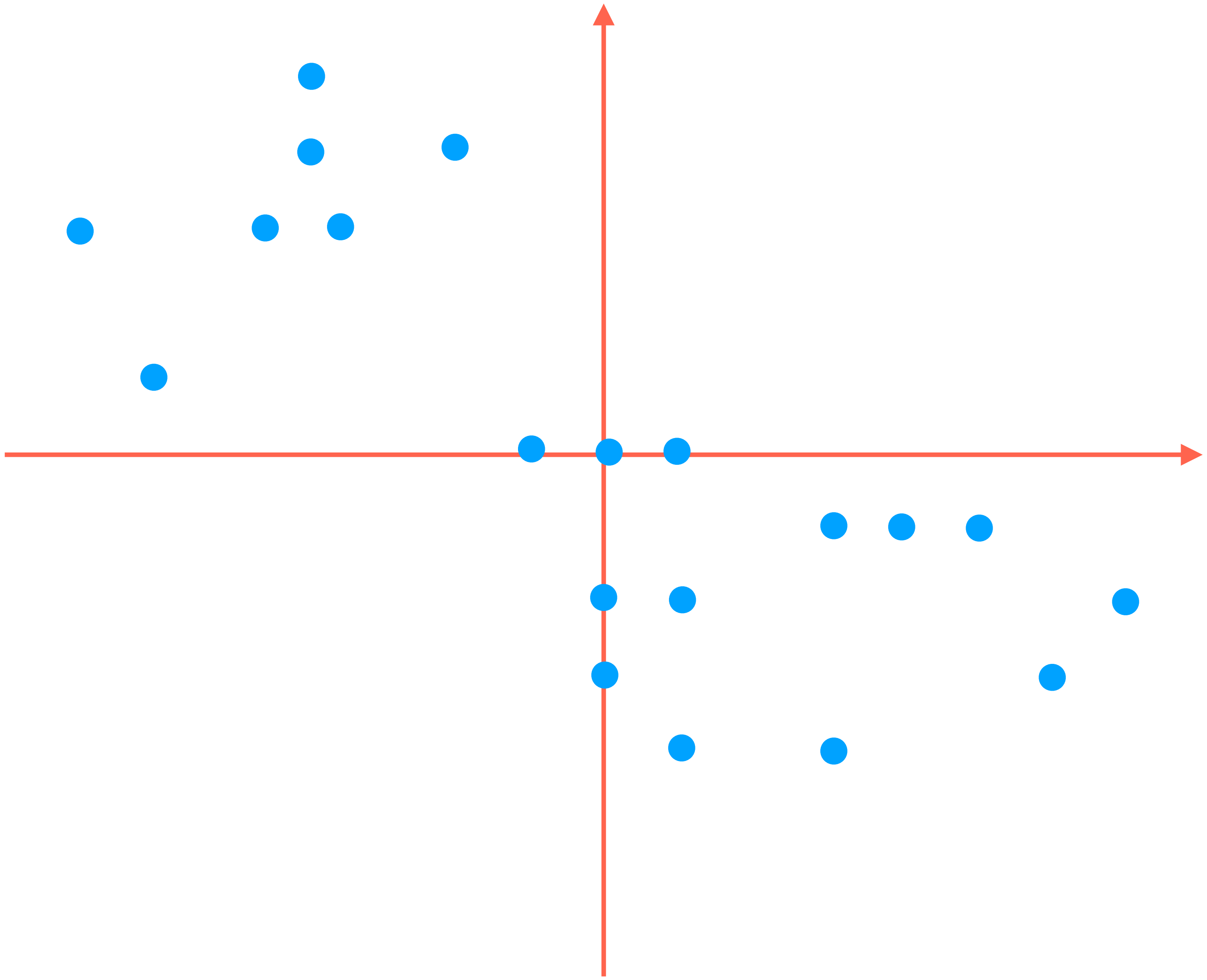


Simplest thing to try: flatten to one of the red axes

(We could of course flatten to the other red axis)

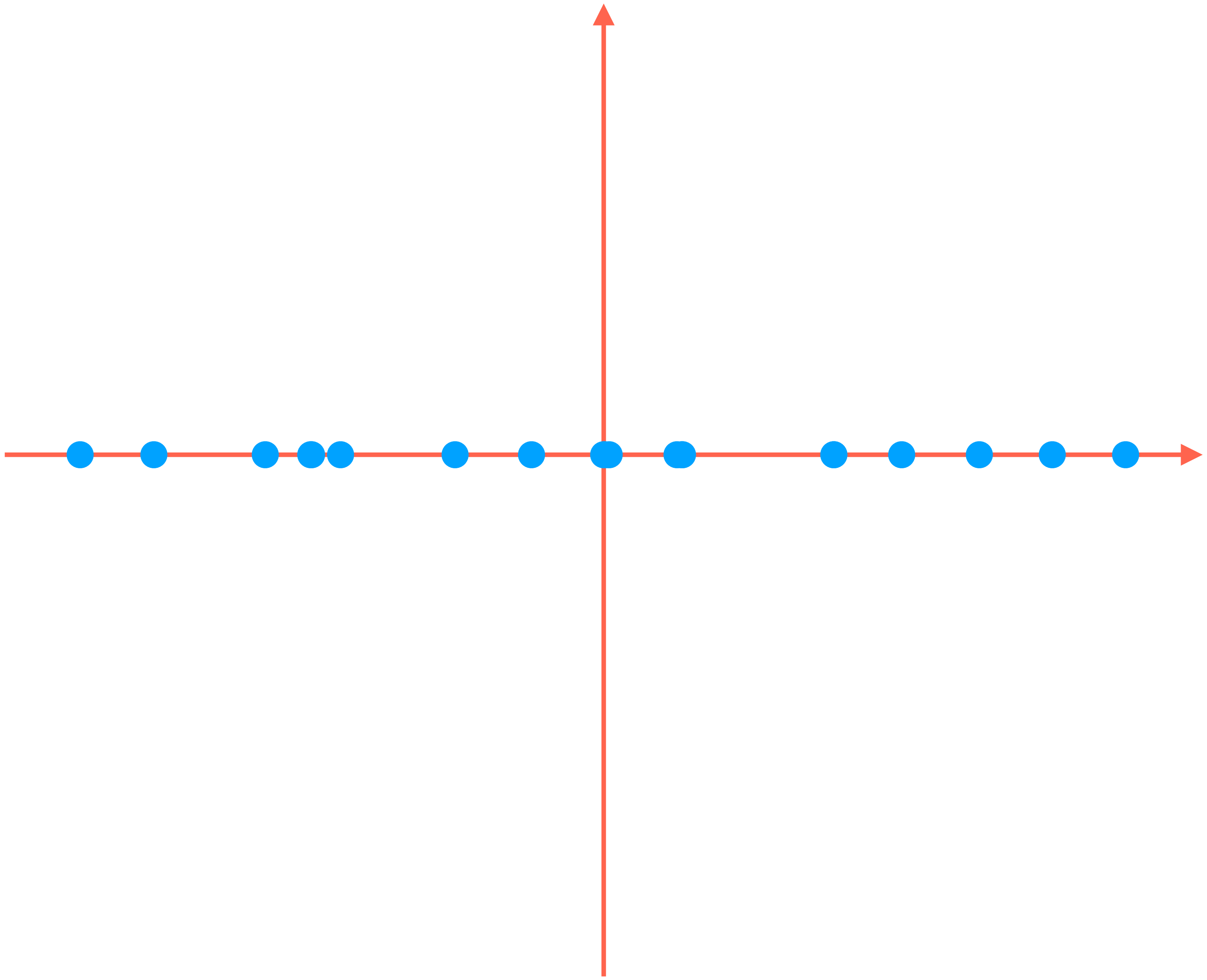
Principal Component Analysis (PCA)

How to project 2D data down to 1D?



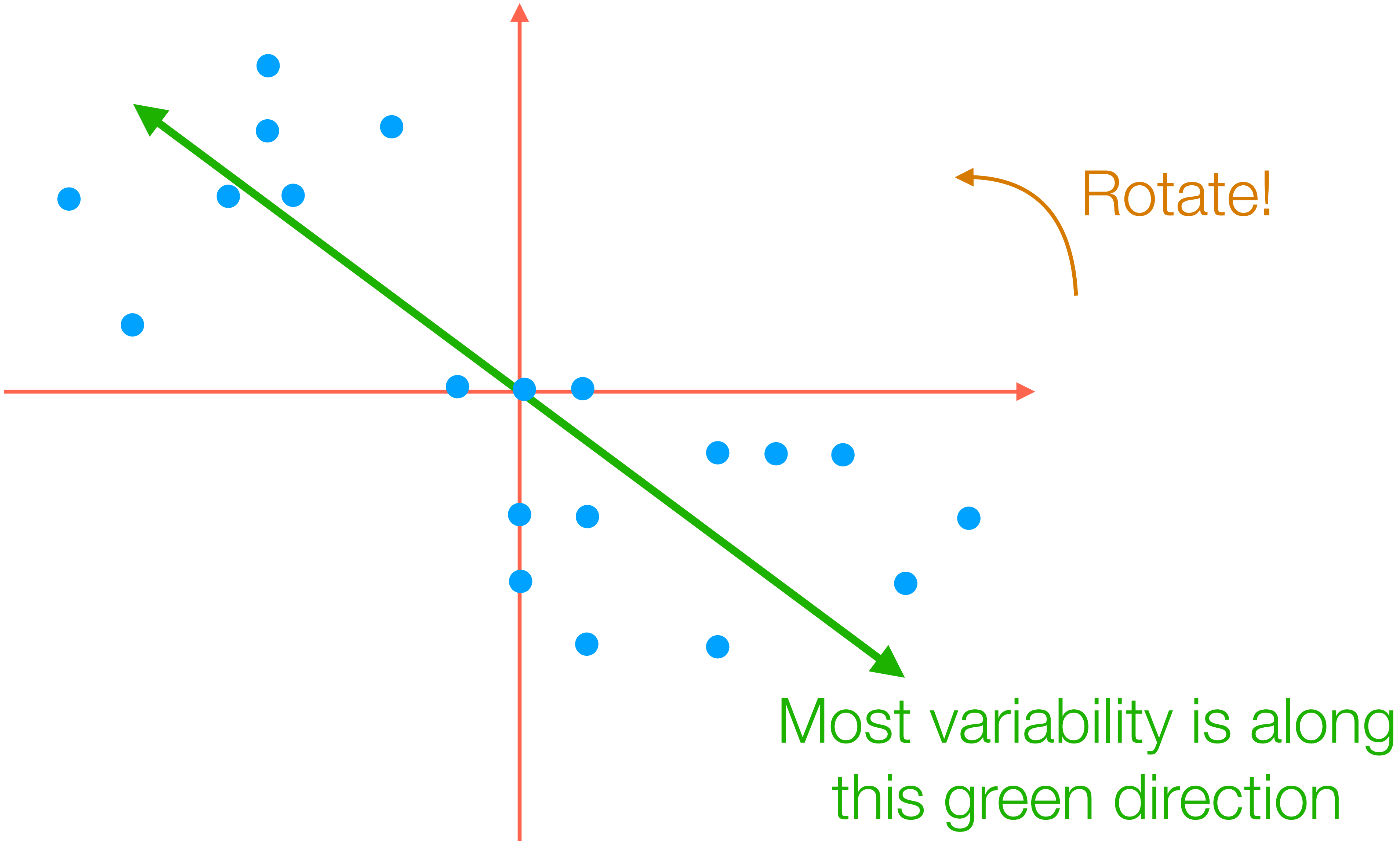
Principal Component Analysis (PCA)

How to project 2D data down to 1D?



Principal Component Analysis (PCA)

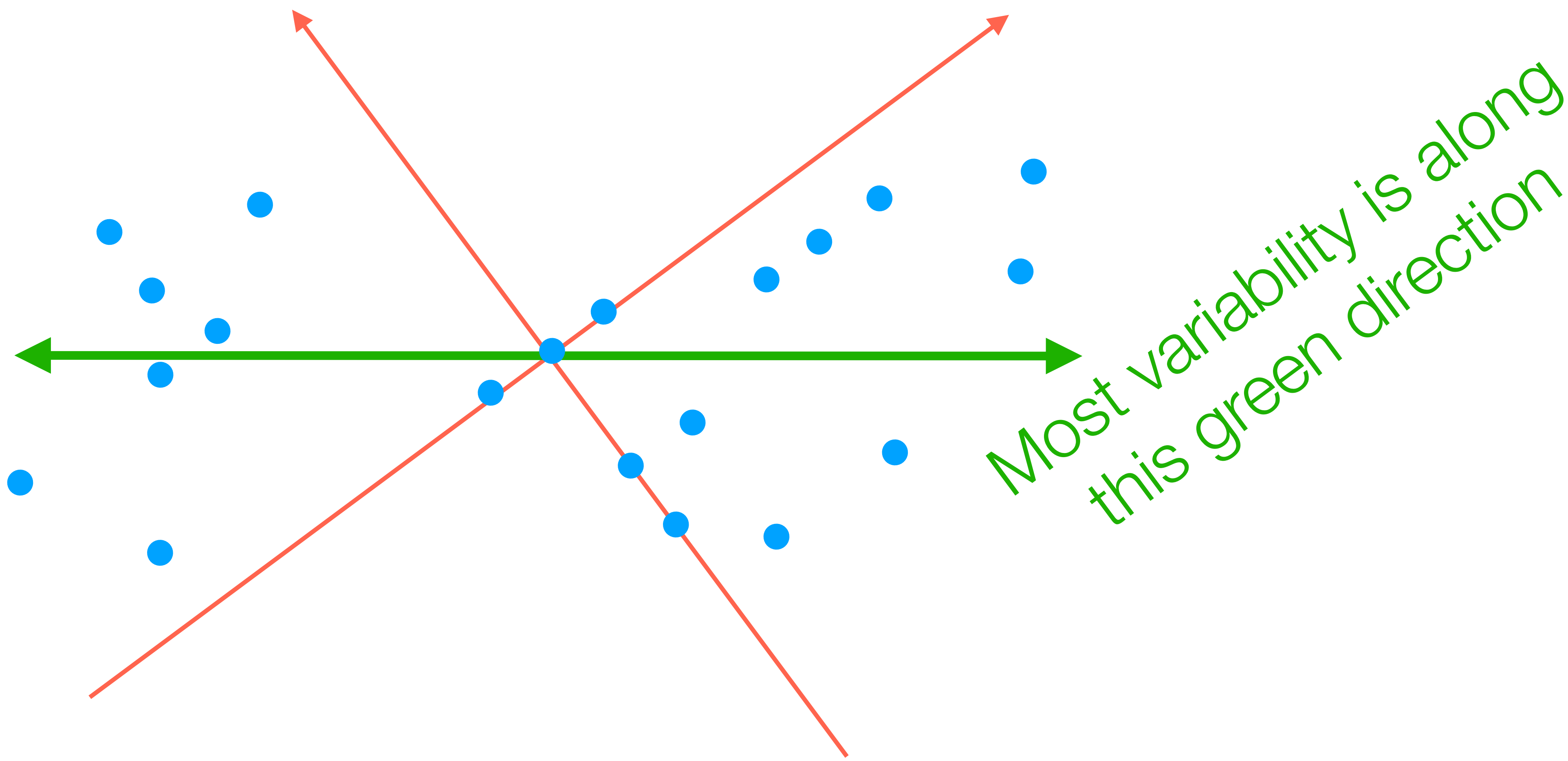
How to project 2D data down to 1D?



But notice that most of the variability in the data is *not* aligned with the red axes!

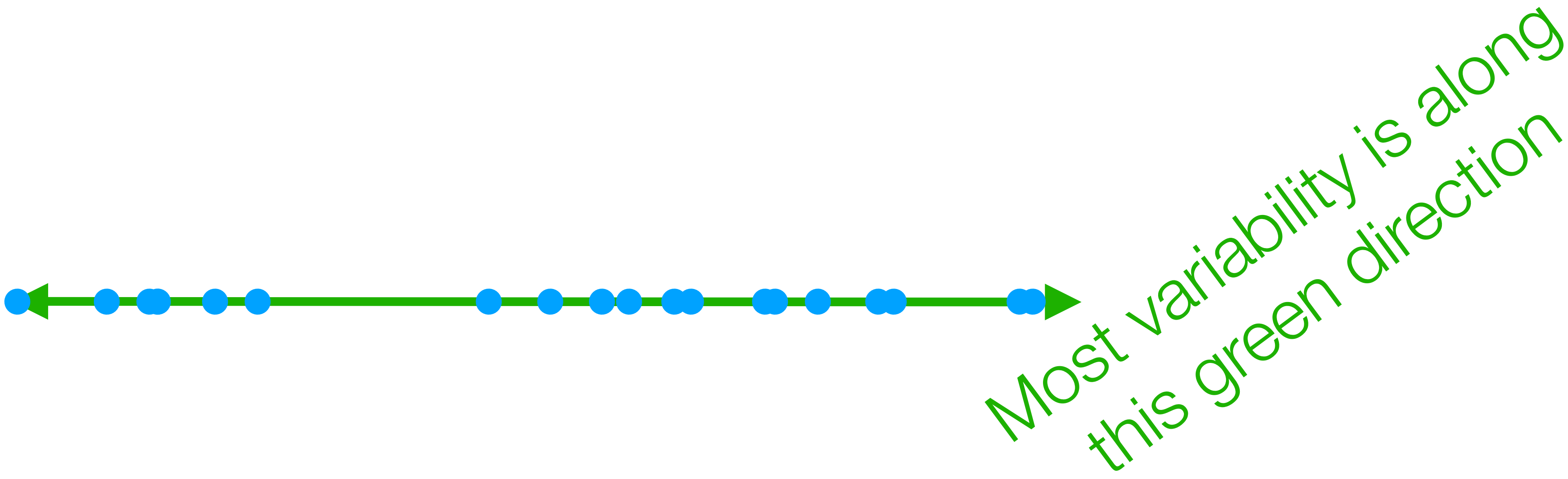
Principal Component Analysis (PCA)

How to project 2D data down to 1D?



Principal Component Analysis (PCA)

How to project 2D data down to 1D?

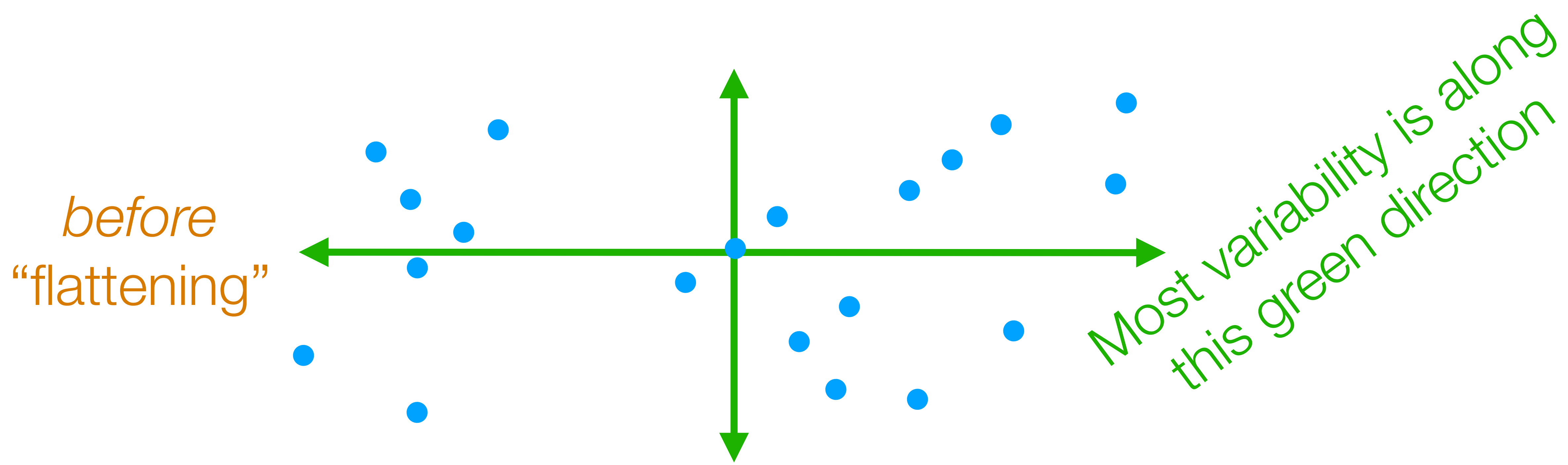


The idea of PCA actually works for 2D ➔ 2D as well
(and just involves rotating, and not "flattening" the data)

Principal Component Analysis (PCA)

~~How to project 2D data down to 1D?~~

How to rotate 2D data so 1st axis has most variance



The idea of PCA actually works for 2D ➔ 2D as well
(and just involves rotating, and not "flattening" the data)

2nd green axis chosen to be 90° ("orthogonal") from first green axis

Principal Component Analysis (PCA)

- Finds top *k* orthogonal directions that explain the most variance in the data
  - 1st component: explains most variance along 1 dimension
  - 2nd component: explains most of remaining variance along next dimension that is orthogonal to 1st dimension
  - …
- "Flatten" data to the top *k* dimensions to get lower dimensional representation (if $k <$ original dimension)

Principal Component Analysis (PCA)

3D example from:
http://setosa.io/ev/principal-component-analysis/

Principal Component Analysis (PCA)

Demo