

Statistics with two variables

MOL518, Lecture #12

Overview and notation

- For this lecture, we will consider two variables, X and Y
- You can think of X and Y as molecular concentrations:
 - The expression levels of two genes (RNA or protein)
 - The RNA and protein levels of the same gene
 - Metabolite, or lipid levels
- We will examine both linear and nonlinear relationships between X and Y
- Aside: notation in statistics is very confusing, certain letters get overused

Why does this matter?

- Can help us determine if X regulates Y (activation or repression)
- Alternatively, X and Y could be co-regulated by some other factor Z
- Each of these scenarios generates a testable hypothesis!
- Correlation and regression also help with testing a new method: how does it compare to the state of the art?

Outline

- Pearson correlation
- Linear regression and least-squares fitting
- Logistic regression
- Rank-based correlation

Outline

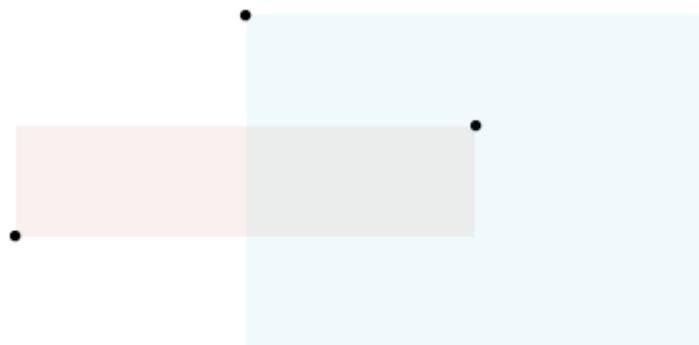
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Defining covariance mathematically using the expected value

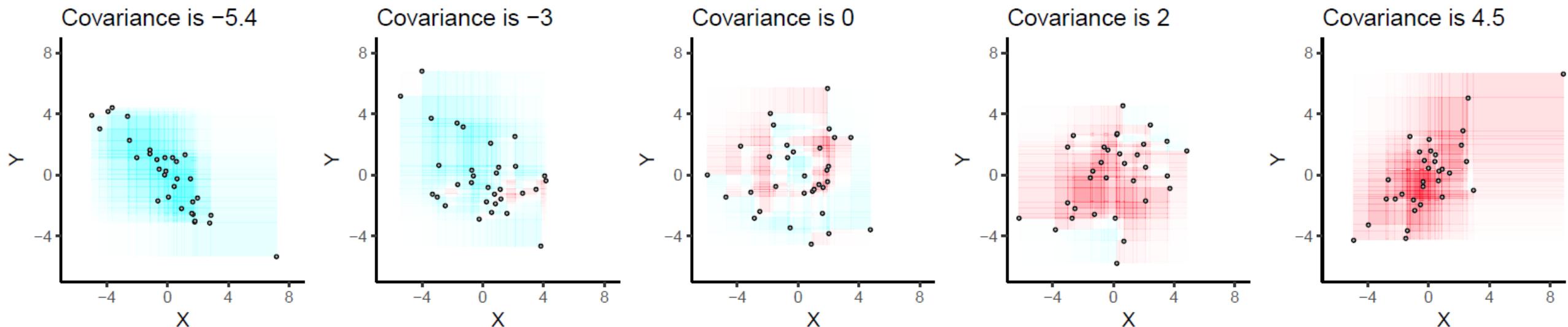
- Define the expected value E
- $E[X] = \sum_{i=1}^n x_i p_i$, where n is the sample size
- x_i are possible outcomes of X and p_i are there corresponding probabilities
- Then $\text{cov}(X, Y) = E[(X - \mu_X)(Y - \mu_Y)]$
- A special case: $\text{cov}(X, X) = \text{var}(X) = \sigma_X^2$

A visual explanation of covariance

- Make a scatterplot of your data
- Draw all possible rectangles through the data
- Color the rectangles:
 - Red = upward sloping
 - Blue = downward sloping
- Treat red as positive values and blue as negative
- The covariance is the net amount of red in the plot
- ***Technically this measures 2x the covariance



A visual explanation of covariance

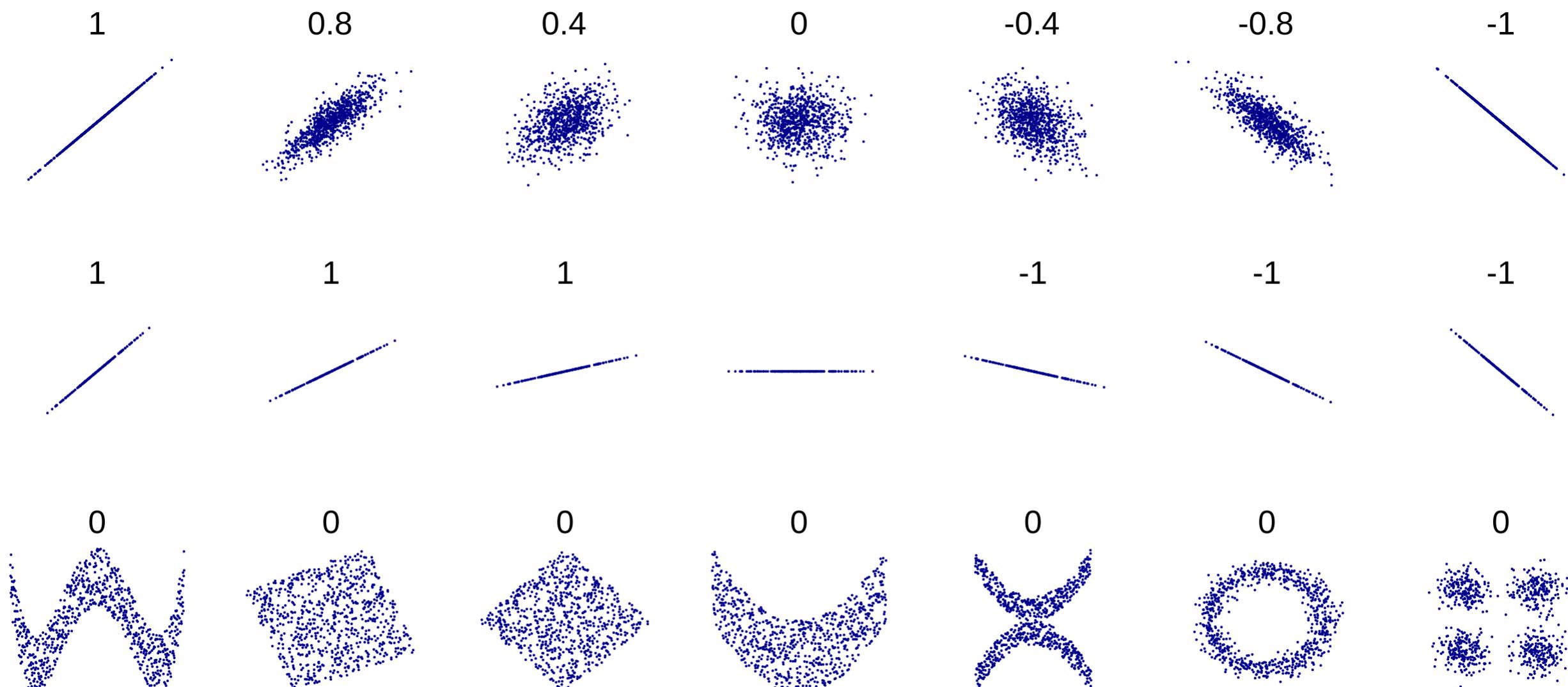


- Covariance is proportional to the scale of the plot (because it's proportional to area)
- Covariance is great for linear relationships
- Covariance is sensitive to outliers (because they create many large rectangles)

Pearson correlation is a normalized covariance

- Are two variables (X and Y) linearly related to one another?
- In the real world, we can estimate the correlation r using by estimating the covariances and variances of X and Y
- $r_{xy} = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2} \sqrt{\sum_{i=1}^n (y_i - \bar{y})^2}} = \frac{\text{estimated cov}(X,Y)}{\text{estimated } \sigma_X \sigma_Y}$; here, n is the sample size
- Due to normalization, r can vary from -1 to $+1$
- This is important so that r does not depend on the scale of the data!!

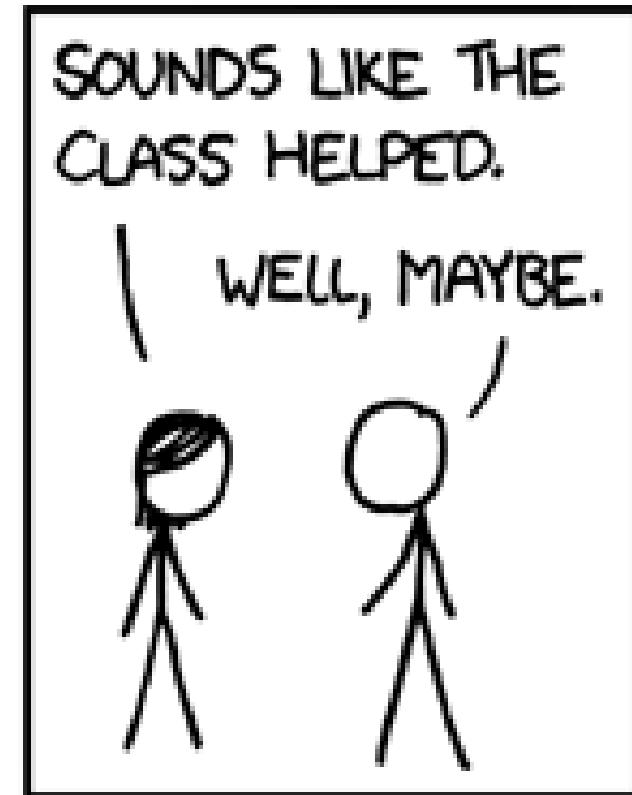
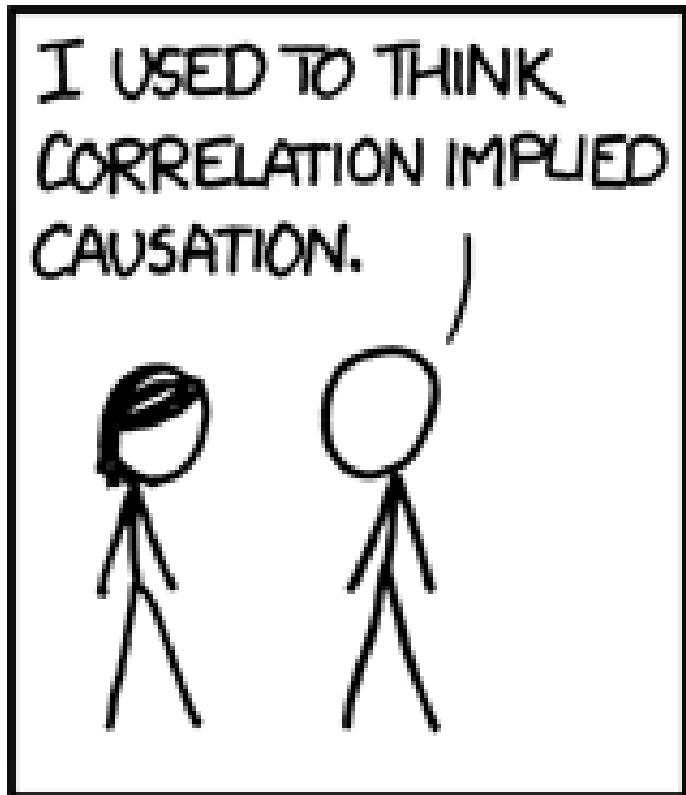
Pearson correlation coefficient examples



Some correlation pitfalls

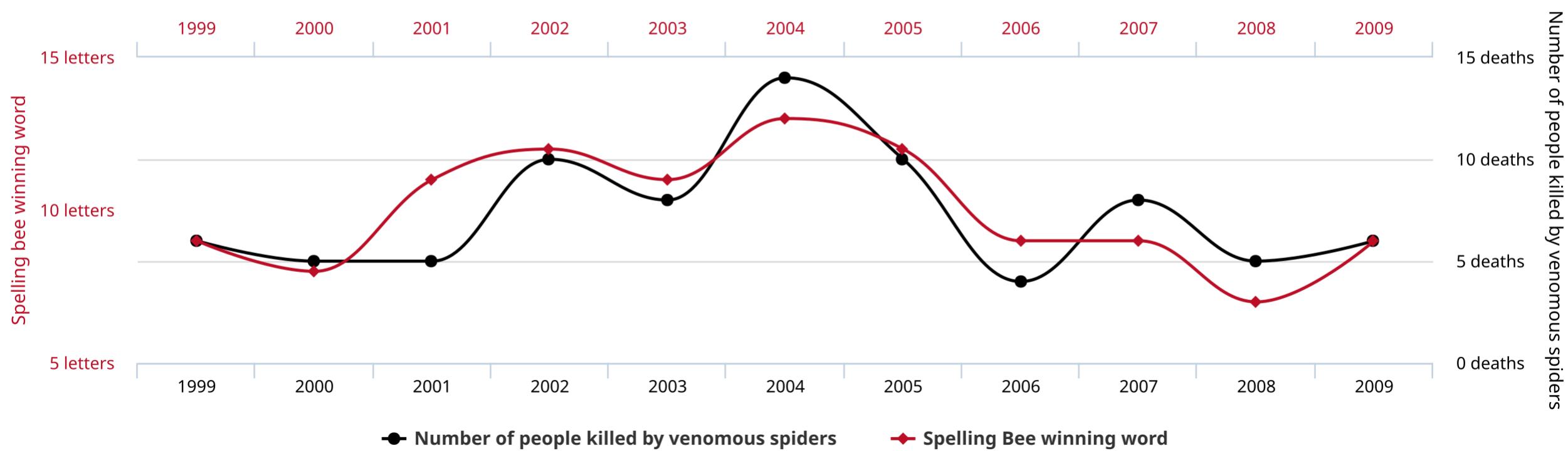
1. $r = 1$ is very unlikely to happen by chance in biology,
 - Example: temperature in Fahrenheit vs. Celsius
2. Many relationships between two biological variables are not linear!
3. Repeated measurements or time series are **not independent**
4. When in doubt, plot the data – scatterplots are your friend ☺

Correlation does not imply causation



Another example of spurious correlation

Letters in winning word of Scripps National Spelling Bee
correlates with
Number of people killed by venomous spiders



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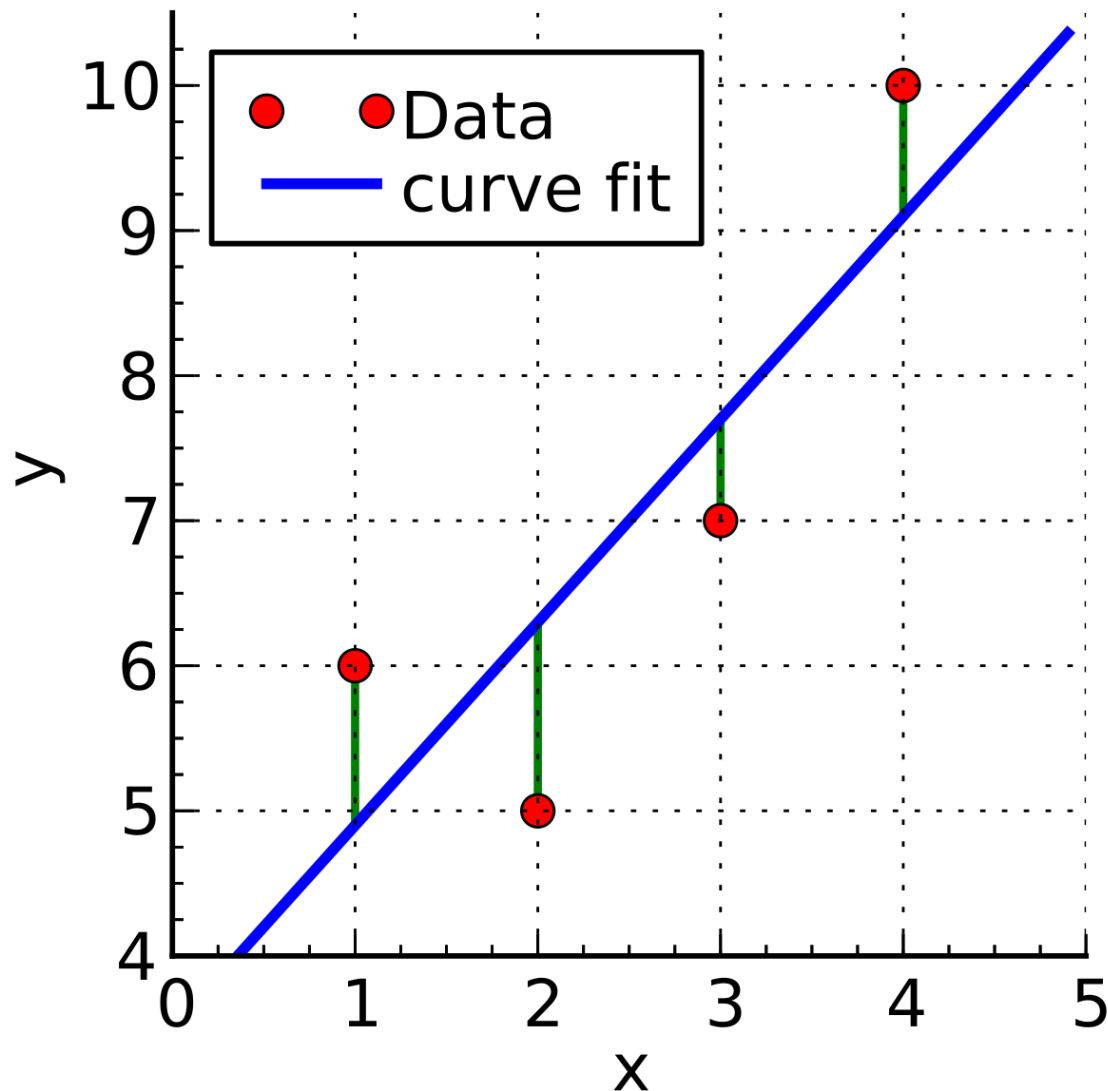
Why do we want to do linear regression?

- In general, so that we can predict some variable Y based on a known variable X
- This dates all the way back to Isaac Newton in 1700, who tried to predict the timing of equinoxes
- The least squares method was first performed by Legendre and Gauss in the early 1800s

How does linear regression work?

- Draw a regression line through the data (x_i, y_i)
 - We are trying to find the line that best fits the data: $\hat{Y} = a + bX$
 - This sounds easy but is tricky in practice
-
- Typically, this is done by minimizing the sum of the squared vertical distance between the line and the data:
 - $\sum_{i=1}^n (y_i - \hat{Y})^2$

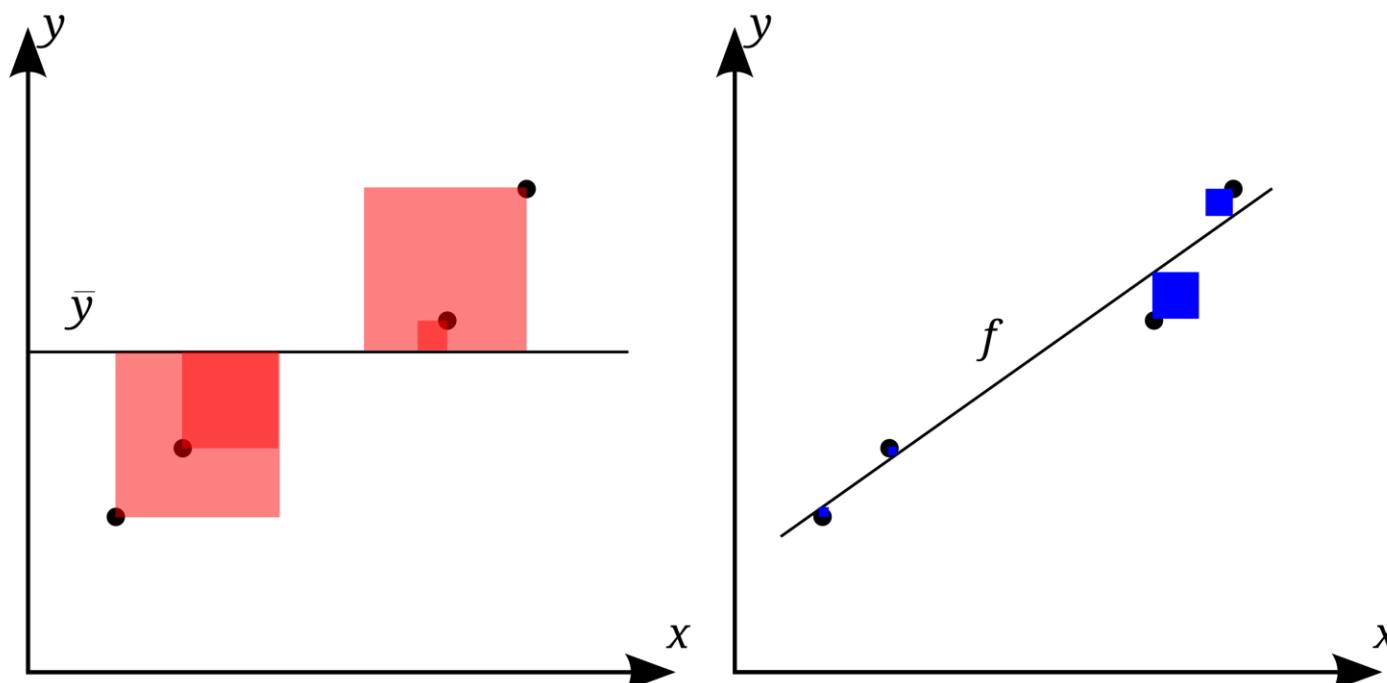
Assumptions associated with linear regression



- X values are fixed (no error)
- Linearity
- Constant variance
- Errors in Y are uncorrelated with one another
- No outliers

How do we know if the fit is good

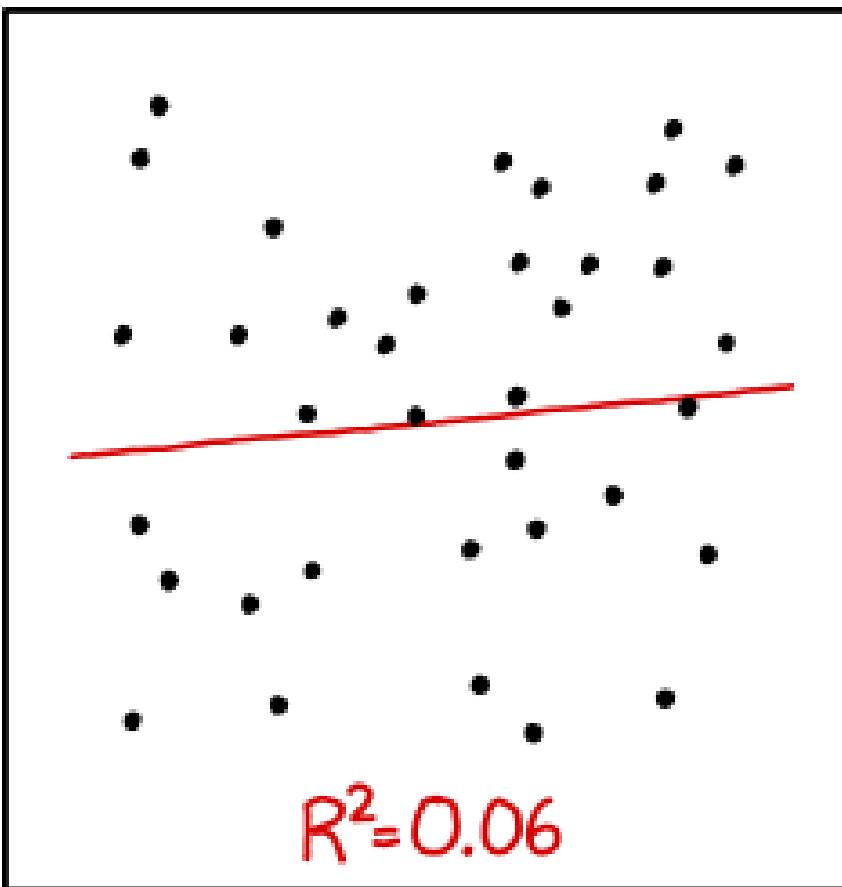
- Calculate a coefficient of determination R^2 , which is the proportion of variation we can predict
- It turns out that R^2 is the square of the Pearson correlation coefficient!
- As such, it scales between 0 and 1



Comparing Pearson correlation and linear regression

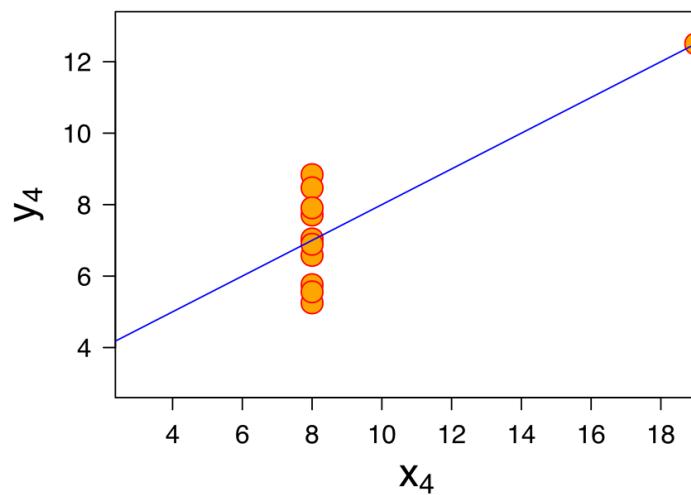
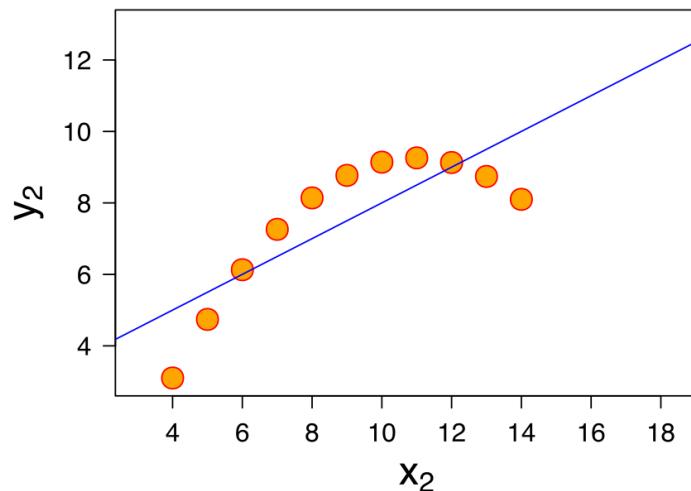
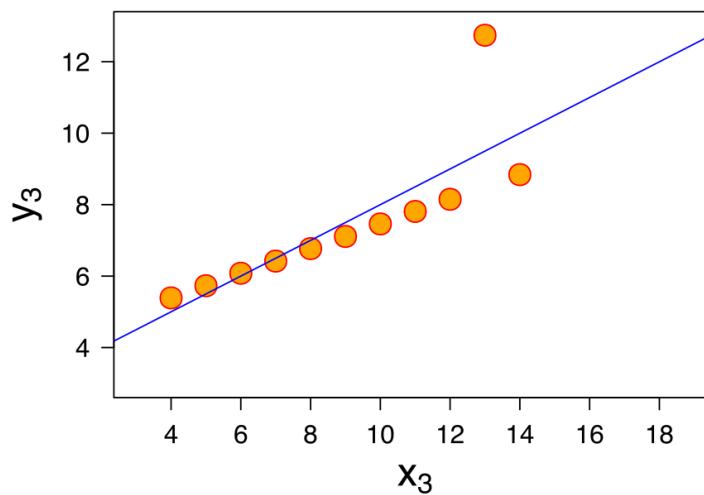
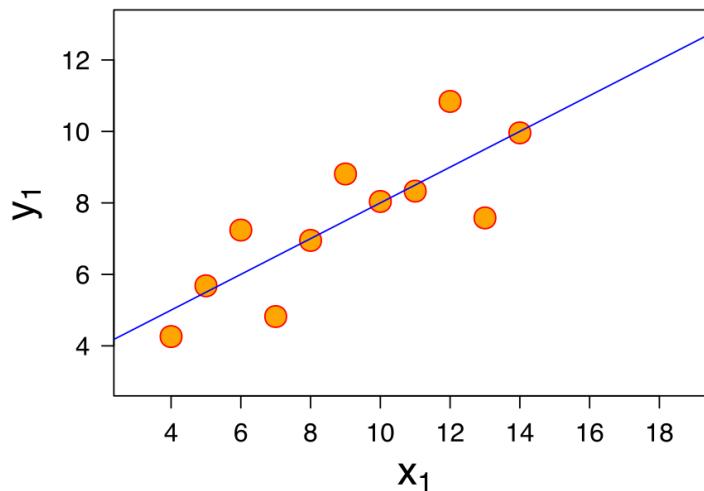
- R^2 from a simple linear regression is the square of Pearson's $r!!!$
- Linear regression allows you to predict Y from X
- Pearson correlation between X and Y is symmetric
- Linear regression between X and Y is **not symmetric** because we are trying to predict Y from X or vice-versa

Some limitations of linear regressions



I DON'T TRUST LINEAR REGRESSIONS WHEN IT'S HARDER
TO GUESS THE DIRECTION OF THE CORRELATION FROM THE
SCATTER PLOT THAN TO FIND NEW CONSTELLATIONS ON IT.

Limitations of linear analyses: Anscombe's quartet



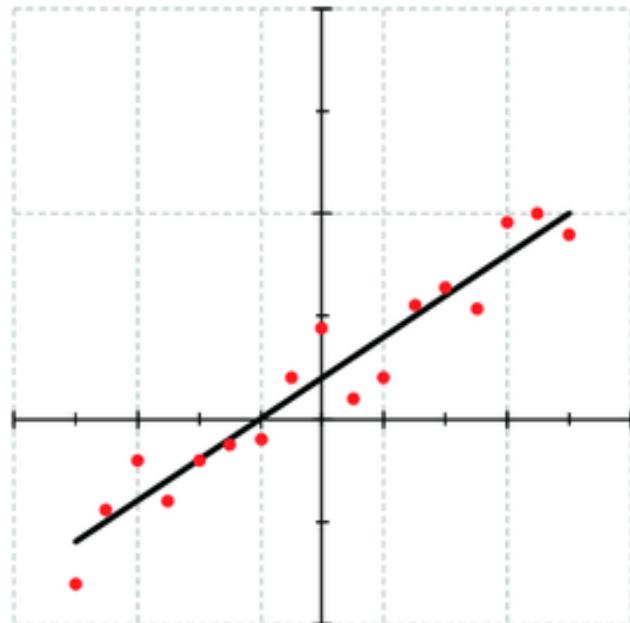
Property	Value	Accuracy
Mean of x	9	exact
Sample variance of x : s_x^2	11	exact
Mean of y	7.50	to 2 decimal places
Sample variance of y : s_y^2	4.125	± 0.003
Correlation between x and y	0.816	to 3 decimal places
Linear regression line	$y = 3.00 + 0.500x$	to 2 and 3 decimal places, respectively
Coefficient of determination of the linear regression: R^2	0.67	to 2 decimal places

Help! My data are nonlinear! What do I do?

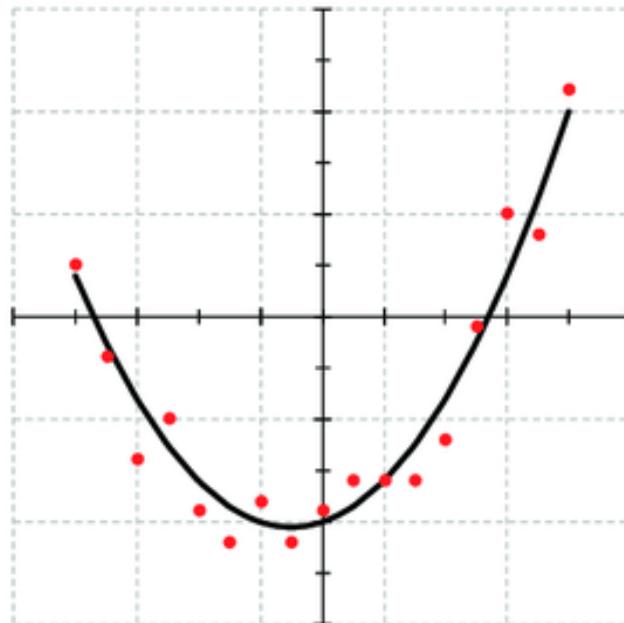
- Fit a more complicated function:
 - Polynomial
 - Exponential
 - Sine wave
- Rank-based correlation

Polynomial regression examples

a. Linear fitting



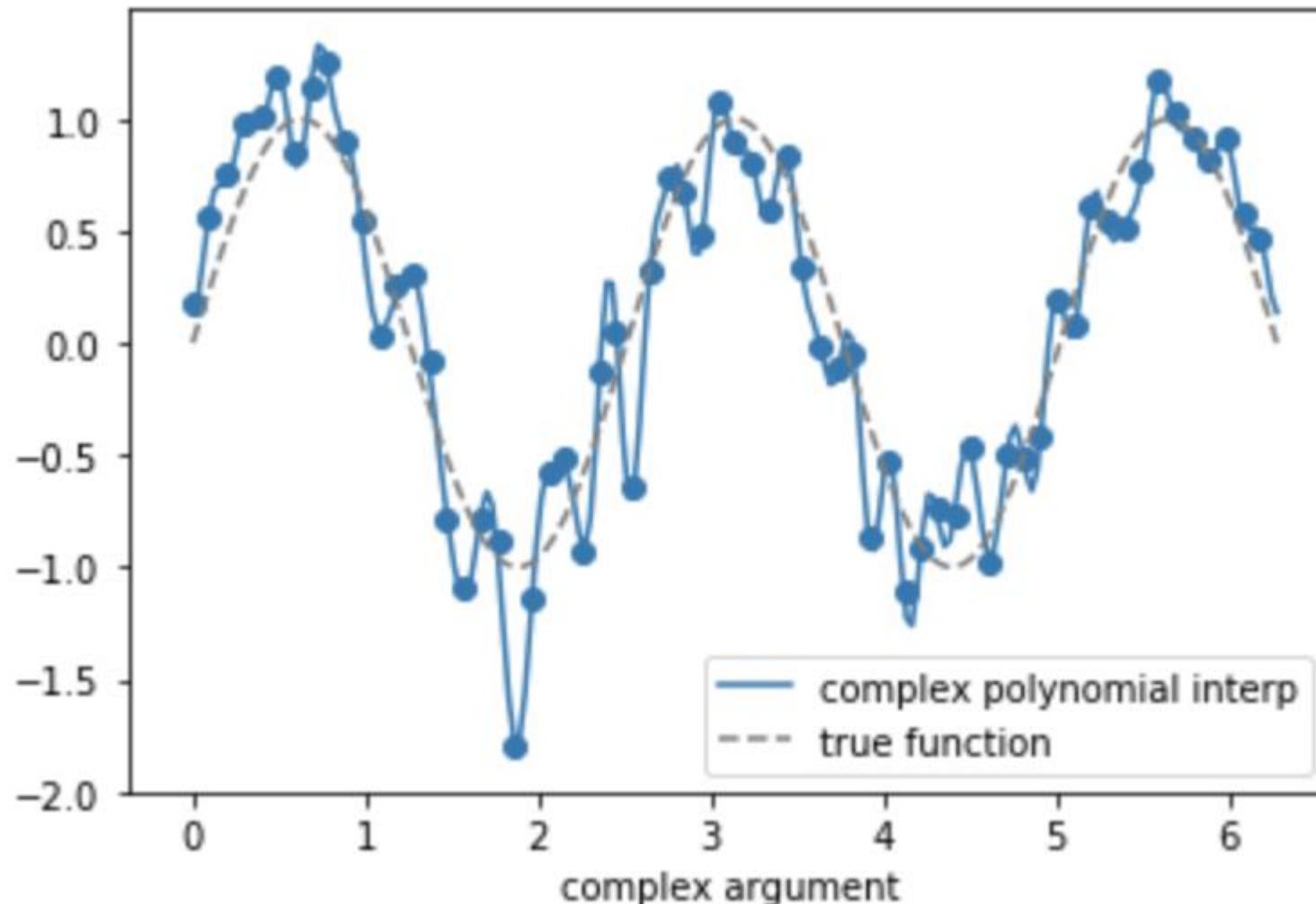
b. Quadratic fitting



c. Cubic fitting



Overfitting is a challenge when doing computational work!

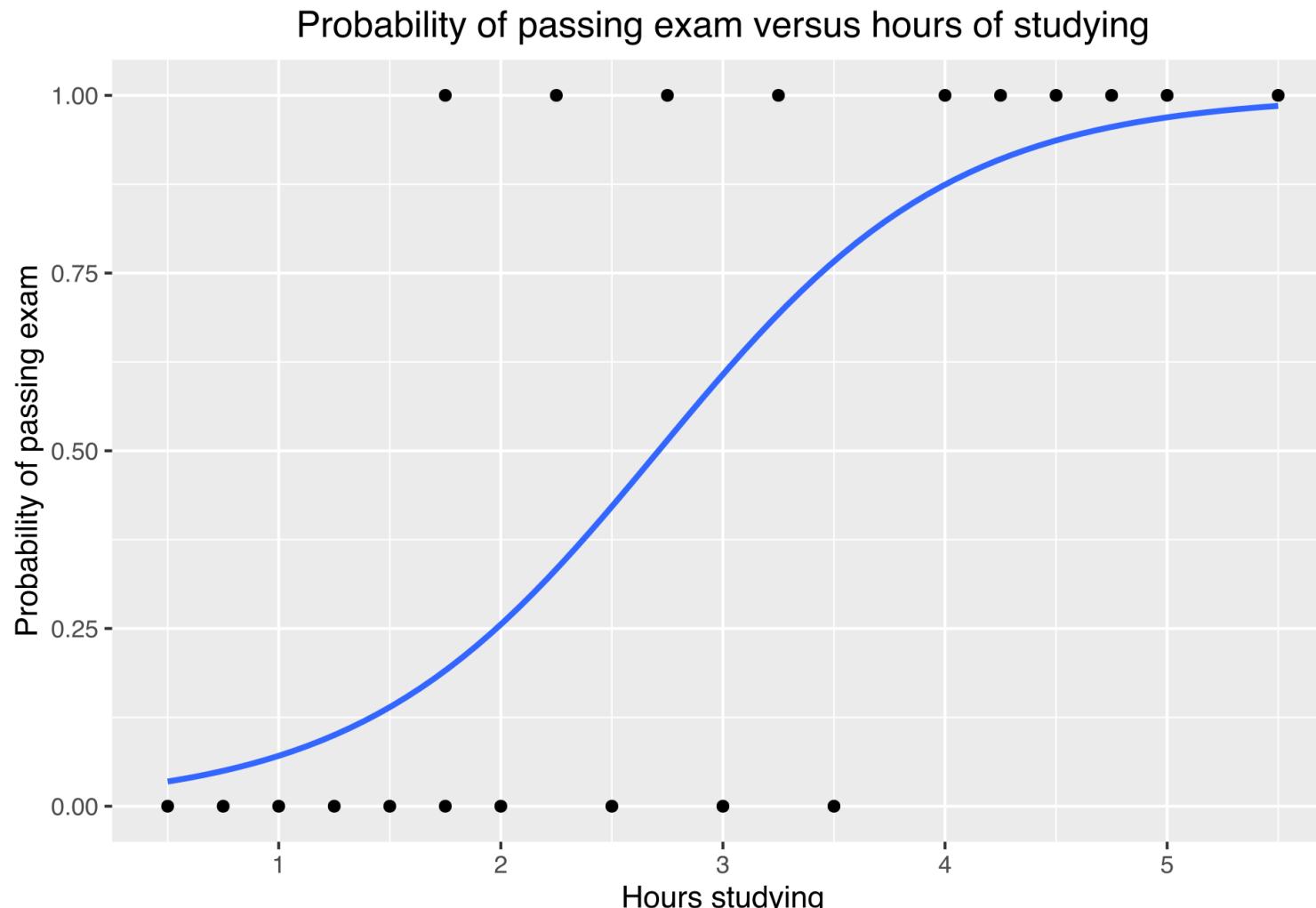


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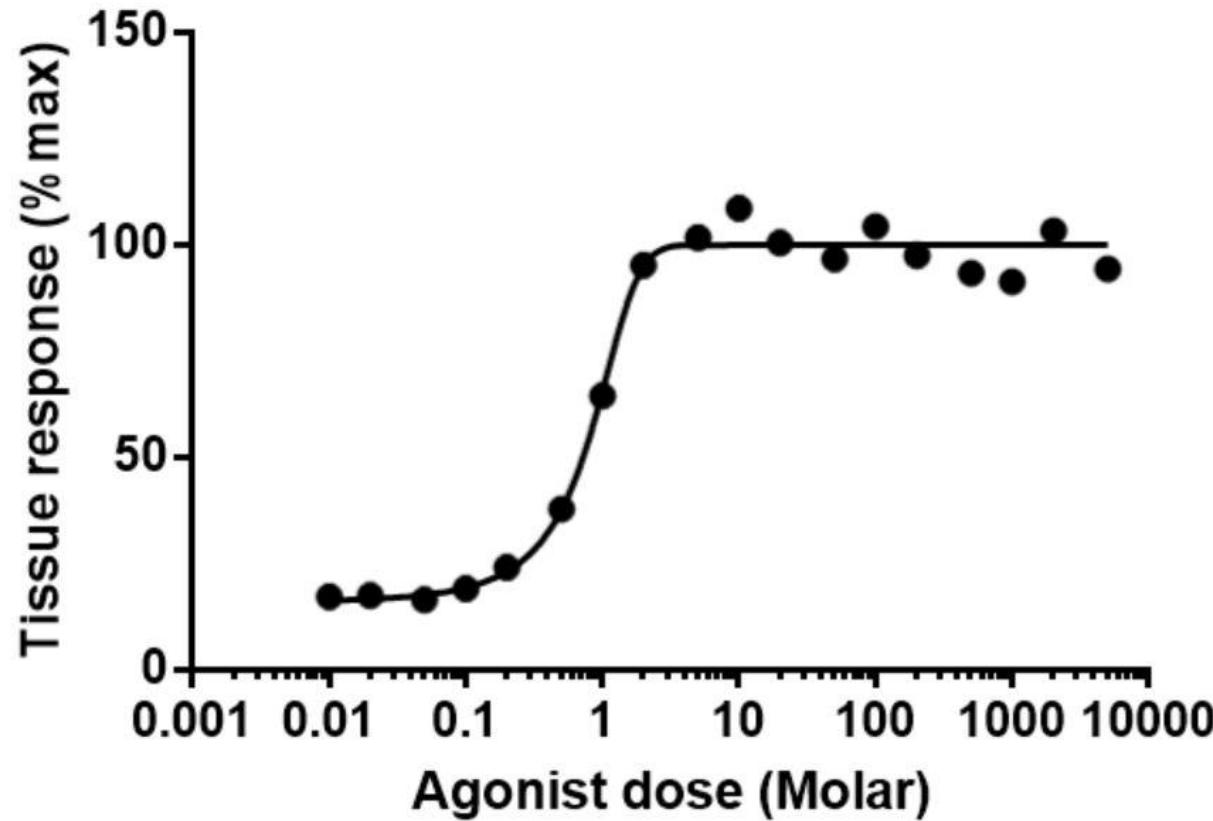
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What is logistic regression?

- Logistic regression is a special case when the Y axis is a probability (or binary)



Logistic regression is useful for dose-response curves



We will discuss this in more detail later in the course!

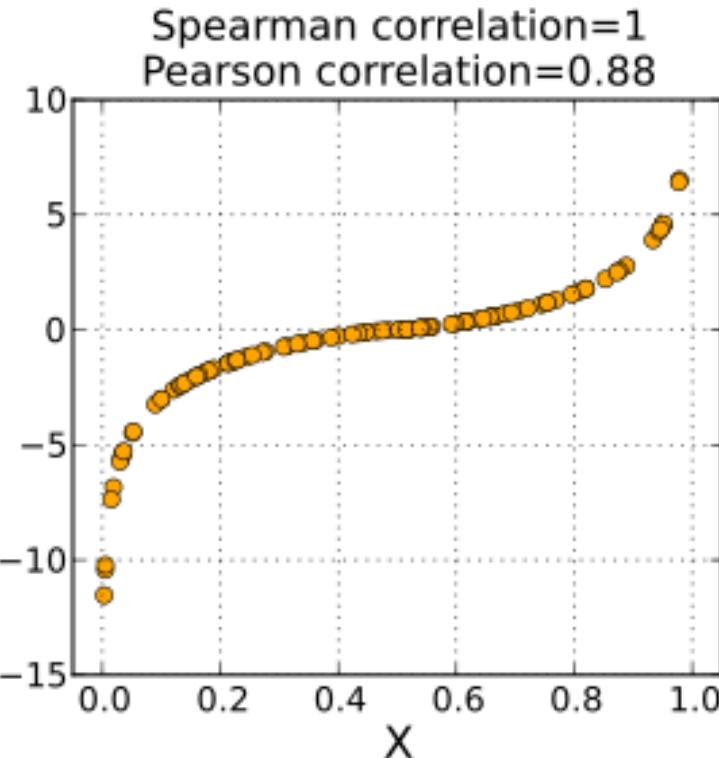
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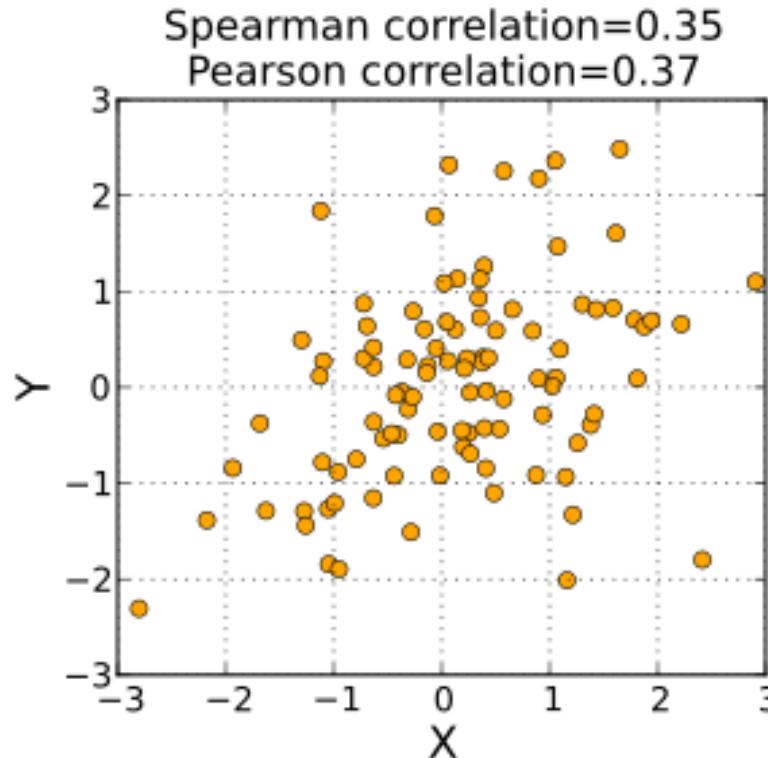
Spearman's ρ (rank-based correlation)

- Like Pearson correlation, but for ranks rather than actual values:
- Let $R[X]$ be the ranks of X , and $R[Y]$ be the ranks of Y
- $X = 1, 4, 7; Y = 4, 6, 10$
- $R[X] = 1, 2, 3; R[Y] = 1, 2, 3$
- $$\rho = \frac{\text{cov}(R[X], R[Y])}{\sigma_{R_X} \sigma_{R_Y}}$$
- This is the same calculation we did for Pearson correlation, but with ranks

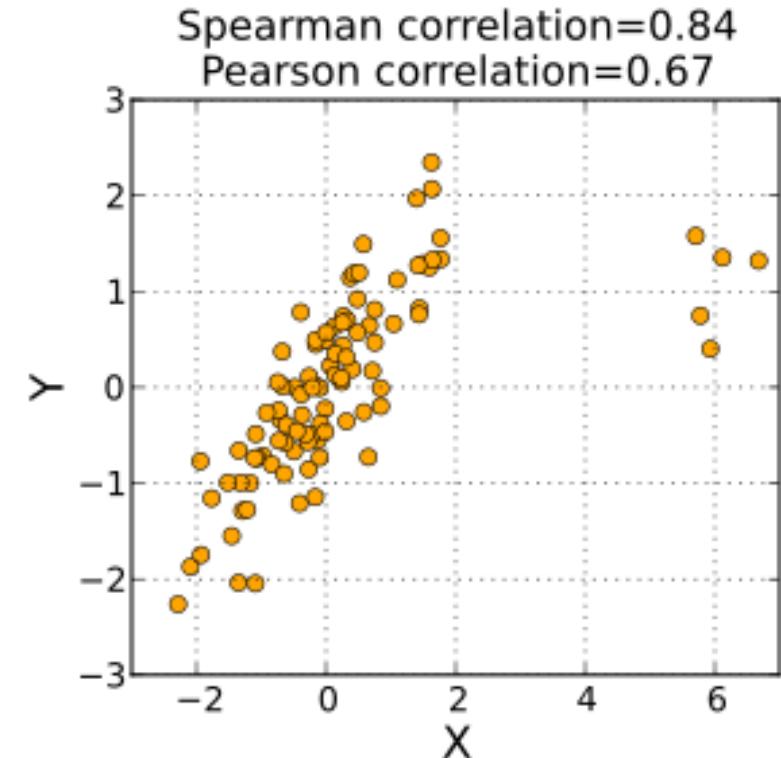
Spearman vs. Pearson correlation



Spearman correlation
is **nonlinear**



Sometimes both
methods are similar



Spearman correlation
is **less sensitive to
outliers**

When should you use Spearman correlation?

1. When there are outliers in your data
2. When your data are nonlinear

Extra Slides