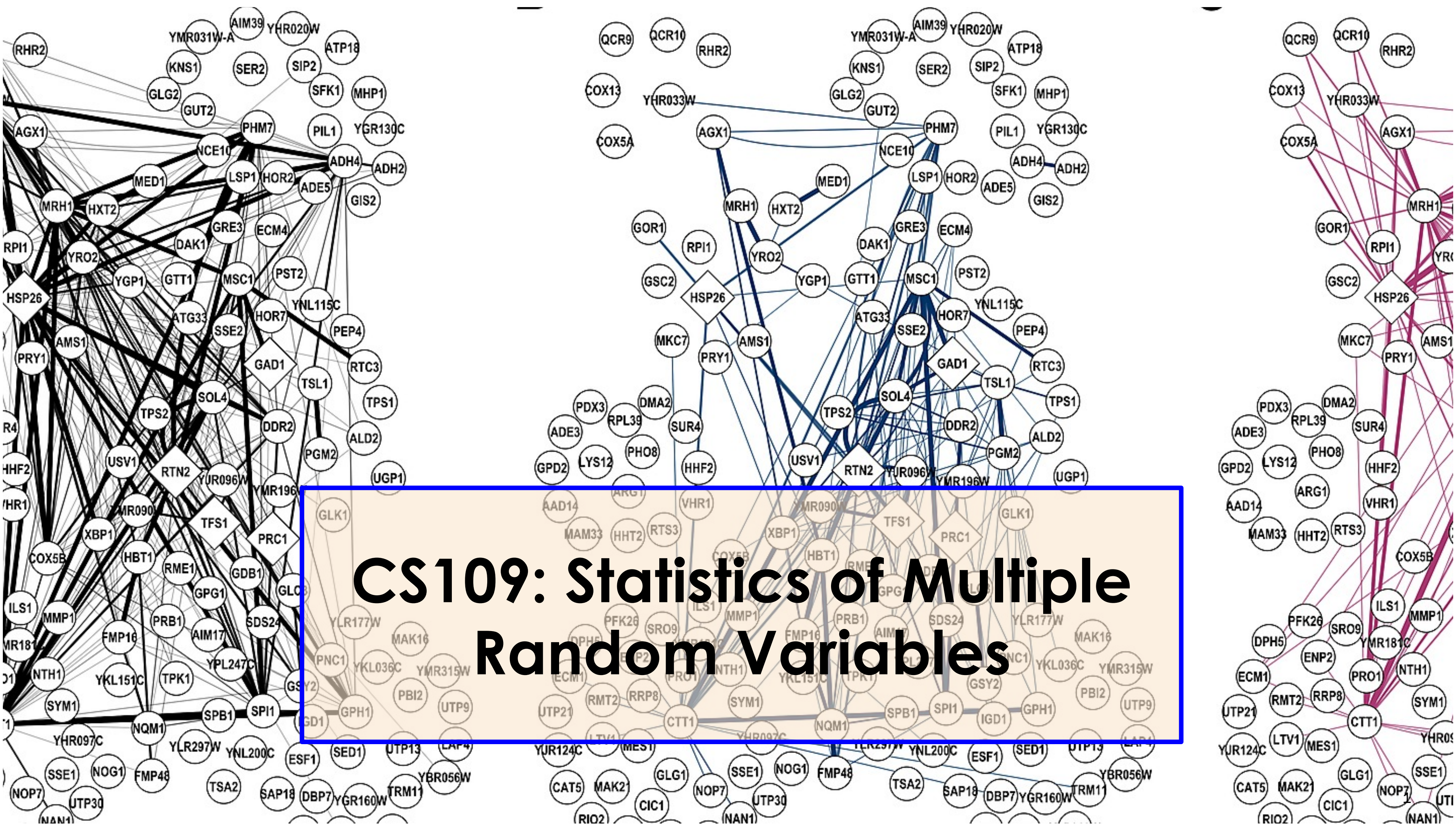
CS109: Statistics of Multiple Random Variables



Where are we now? A roadmap of CS109

Last week: Joint distributions

$p_{X,Y}(x, y)$

Today: Statistics of multiple RVs!

$\text{Var}(X + Y)$

$E[X + Y]$

$\text{Cov}(X, Y)$

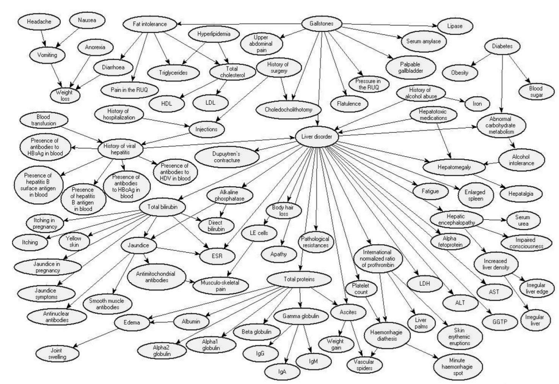
$\rho(X, Y)$

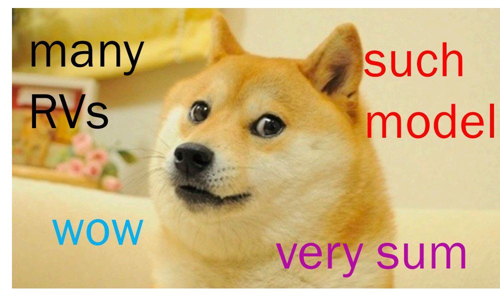
Friday:
Conditional distributions

$p_{X|Y}(x|y)$

$E[X|Y]$

Next Week: Modeling with Bayesian Networks





Expectation of Common RVs

Linearity of Expectation is useful

Expectation is a linear mathematical operation. If $X = \sum_{i=1}^{n} X_i$:

$$E[X] = E\left[\sum_{i=1}^{n} X_i\right] = \sum_{i=1}^{n} E[X_i]$$

- Even if you don't know the **distribution** of X (e.g., because the joint distribution of $(X_1, \dots, X_n)$ is unknown), you can still compute **expectation** of X!!

- Problem-solving key:
  Define X_i such that $X = \sum_{i=1}^{n} X_i$

Most common use cases:
- $E[X_i]$ easy to calculate
- Or sum of dependent RVs

Don't we already know linearity of expectation?

Expectation is a linear mathematical operation. If $X = \sum_{i=1}^{n} X_i$:

$$E[X] = E\left[\sum_{i=1}^{n} X_i\right] = \sum_{i=1}^{n} E[X_i]$$

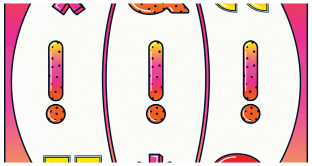
We covered this back in Lecture 6 (when we first learned expectation)!

- Proved binomial: sum of 1s or 0s
- Hat check (section): sum of 1s or 0s
- We ignored (in)dependence of **events**.

Why are we learning this again?

- Well, now we can prove it!
- We can now ignore any **random variables** dependencies!
- Our approach is still the same!

exclamation point jackpot



Proof of expectation of a sum of RVs

$E[X+Y] = E[X] + E[Y]$

$$E[X+Y] = \sum_x \sum_y (x+y) p_{X,Y}(x,y)$$

LOTUS,
$g(X,Y) = X + Y$

$$= \sum_x \sum_y x p_{X,Y}(x,y) + \sum_x \sum_y y p_{X,Y}(x,y)$$

$$= \sum_x x \sum_y p_{X,Y}(x,y) + \sum_y y \sum_x p_{X,Y}(x,y)$$

Linearity of summations (and integrals, btw)

$$= \sum_x x p_X(x) + \sum_y y p_Y(y)$$

Marginal PMFs for X and Y

$$= E[X] + E[Y]$$

Expectations of common RVs: Binomial

$X \sim \text{Bin}(n, p) \quad E[X] = np$

# of successes in n independent trials with probability of success p

Recall: $\text{Bin}(1, p) = \text{Ber}(p)$

$$X = \sum_{i=1}^{n} X_i$$

Let $X_i = i$th trial is heads
$X_i \sim \text{Ber}(p), E[X_i] = p$

$$E[X] = E\left[\sum_{i=1}^{n} X_i\right] = \sum_{i=1}^{n} E[X_i] = \sum_{i=1}^{n} p = np$$

Expectations of common RVs: Negative Binomial

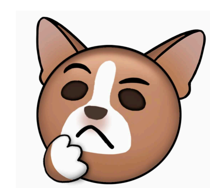
$Y \sim \text{NegBin}(r, p) \quad E[Y] = \frac{r}{p}$

# of independent trials with probability of success p until r successes

Recall: $\text{NegBin}(1, p) = \text{Geo}(p)$

$$Y \overset{?}{=} \sum_{i=1}^{?} Y_i$$

1. How should we define Y_i?
2. How many terms are in our summation?



Expectations of common RVs: Negative Binomial

$Y \sim \text{NegBin}(r, p)$ $\quad E[Y] = \frac{r}{p}$

# of independent trials with probability of success p until r successes

Recall: $\text{NegBin}(1, p) = \text{Geo}(p)$

$$Y \stackrel{?}{=} \sum_{i=1} Y_i$$

Let Y_i = # trials to get ith success (after $(i-1)$th success)

$Y_i \sim \text{Geo}(p)$, $E[Y_i] = \frac{1}{p}$

$$E[Y] = E\left[\sum_{i=1}^{r} Y_i\right] = \sum_{i=1}^{r} E[Y_i] = \sum_{i=1}^{r} \frac{1}{p} = \frac{r}{p}$$

Coupon Collecting Problems

Linearity of Expectation is useful

Expectation is a linear mathematical operation. If $X = \sum_{i=1}^{n} X_i$:

$$E[X] = E\left[\sum_{i=1}^{n} X_i\right] = \sum_{i=1}^{n} E[X_i]$$

- Even if you *don't know* the distribution of X (e.g., because the joint distribution of $(X_1, \dots, X_n)$ is unknown), you can still compute *expectation* of the sum!

- Problem-solving key: Define X_i such that $X = \sum_{i=1}^{n} X_i$

Most common use cases:
- $E[X_i]$ easy to calculate
- Or sum of dependent RVs

Coupon collecting problems: Server requests

The **coupon collector's problem** in probability theory:

- You buy boxes of cereal.
- There are k different types of coupons
- For each box you buy, you "collect" a coupon of type i.

1. How many coupons do you expect after buying n boxes of cereal?

<u>Servers</u>

requests

k servers

request to server i

What is the expected number of utilized servers after n requests?

* 52% of Amazon profits
** more profitable than Amazon's North America commerce operations
source

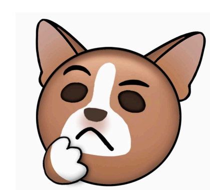
Computer cluster utilization

$$E\left[\sum_{i=1}^{n} X_i\right] = \sum_{i=1}^{n} E[X_i]$$

Consider a computer cluster with k servers. We send n requests.

- Requests independently go to server i with probability p_i
- Let $X =$ # servers that receive ≥ 1 request.

What is $E[X]$?



Computer cluster utilization

$$E\left[\sum_{i=1}^{n} X_i\right] = \sum_{i=1}^{n} E[X_i]$$

Consider a computer cluster with k servers. We send n requests.

- Requests independently go to server i with probability p_i
- Let X = # servers that receive ≥ 1 request.

What is $E[X]$?

1. Define additional random variables.

Let: A_i = event that server i receives ≥ 1 request

X_i = indicator for A_i

$$P(A_i) = 1 - P(\text{no requests to } i) = 1 - (1 - p_i)^n$$

Note: A_i are dependent!

2. Solve.

$$E[X_i] = P(A_i) = 1 - (1 - p_i)^n$$

$$E[X] = E\left[\sum_{i=1}^{k} X_i\right] = \sum_{i=1}^{k} E[X_i] = \sum_{i=1}^{k} \left(1 - (1 - p_i)^n\right)$$

$$= \sum_{i=1}^{k} 1 - \sum_{i=1}^{k} (1 - p_i)^n = k - \sum_{i=1}^{k} (1 - p_i)^n$$

Coupon collecting problems: Hash tables

The **coupon collector's problem** in probability theory:

- You buy boxes of cereal.
- There are k different types of coupons
- For each box you buy, you "collect" a coupon of type i.

Servers	Hash Tables
requests	strings
k servers	k buckets
request to server i	hashed to bucket i

1. How many coupons do you expect after buying n boxes of cereal? → What is the expected number of utilized servers after n requests?

2. How many boxes do you expect to buy until you have one of each coupon? → What is the expected number of strings to hash until each bucket has ≥ 1 string?

Hash Over Hashing

Let's take a 90-second break to take in a lemon poppy seed muffin and some English breakfast tea.

Once we've nourished and hydrated, we'll come back and take on this next problem about hash tables.

Hash Tables

$$E\left[\sum_{i=1}^{n} X_i\right] = \sum_{i=1}^{n} E[X_i]$$

Consider a hash table with k buckets.

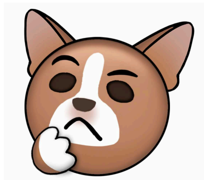
- Strings are equally likely to get hashed into any bucket (independently).
- Let Y = # strings to hash until each bucket ≥ 1 string.

What is $E[Y]$?

1. Define additional random variables.

   How should we define Y_i such that $Y = \sum_i Y_i$?

2. Solve.



Hash Tables

$$E\left[\sum_{i=1}^{n} X_i\right] = \sum_{i=1}^{n} E[X_i]$$

Consider a hash table with k buckets.

- Strings are equally likely to get hashed into any bucket (independently).
- Let Y = # strings to hash until each bucket $\geq$ 1 string.

What is $E[Y]$?

1. Define additional random variables.

Let: Y_i = # of trials to get success after i-th success

- Success: hash string to previously empty bucket
- If i non-empty buckets: $P(\text{success}) = \frac{k-i}{k}$

2. Solve.

$$P(Y_i = n) = \left(\frac{i}{k}\right)^{n-1} \left(\frac{k-i}{k}\right)$$

Equivalently, $Y_i \sim \text{Geo}\left(p = \frac{k-i}{k}\right)$ $\quad E[Y_i] = \frac{1}{p} = \frac{k}{k-i}$

Hash Tables

$$E\left[\sum_{i=1}^{n} X_i\right] = \sum_{i=1}^{n} E[X_i]$$

Consider a hash table with k buckets.

- Strings are equally likely to get hashed into any bucket (independently).
- Let Y = # strings to hash until each bucket $\geq$ 1 string.

What is $E[Y]$?

1. Define additional random variables.

Let: Y_i = # of trials to get success after i-th success

$$Y_i \sim \text{Geo}\left(p = \frac{k-i}{k}\right), \qquad E[Y_i] = \frac{1}{p} = \frac{k}{k-i}$$

2. Solve. $Y = Y_0 + Y_1 + \cdots + Y_{k-1}$

$$E[Y] = E[Y_0] + E[Y_1] + \cdots + E[Y_{k-1}]$$

$$= \frac{k}{k} + \frac{k}{k-1} + \frac{k}{k-2} + \cdots + \frac{k}{1} = k\left[\frac{1}{k} + \frac{1}{k-1} + \cdots + 1\right] \quad = O(k \log k)$$

Covariance

Statistics of sums of RVs

For any random variables X and Y,

$$E[X+Y] = E[X] + E[Y]$$

$$\text{Var}(X+Y) = \quad ?$$

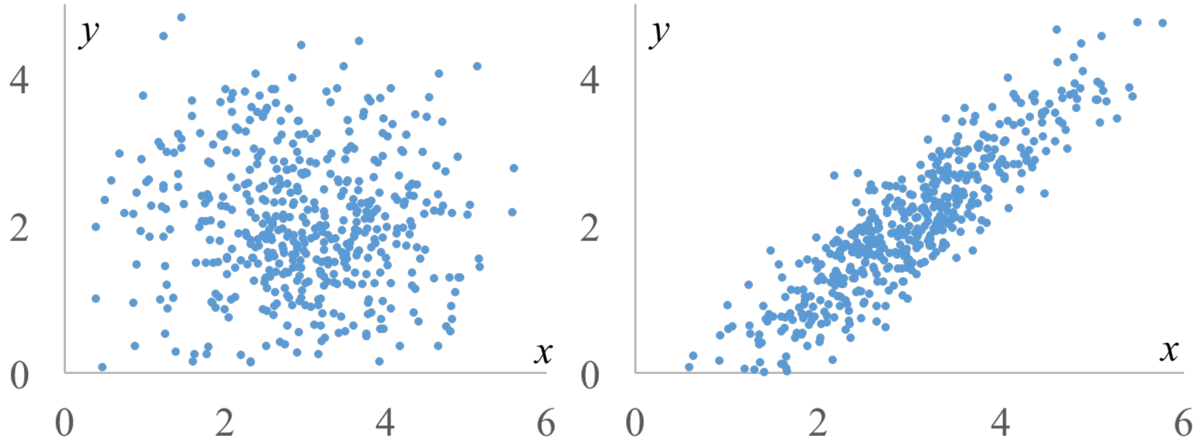
But first...
a new statistic!

Spot the difference

Compare/contrast the following two distributions:

Assume all points are equally likely.

$$P(X = x, Y = y) = \frac{1}{N}$$



Both distributions have the same $E[X]$, $E[Y]$, Var(X), and Var(Y)

Difference: how the two variables vary with ***each other***.

Covariance

The covariance of two variables X and Y is:

$$\text{Cov}(X,Y) = E[(X - E[X])(Y - E[Y])]$$
$$= E[XY] - E[X]E[Y]$$

Proof of second part:

$$\begin{aligned}
\text{Cov}(X,Y) &= E[(X - E[X])(Y - E[Y])] \\
&= E\big[XY - XE[Y] - E[X]Y + E[X]E[Y]\big] \\
&= E[XY] - E\big[XE[Y]\big] - E[E[X]Y] + E\big[E[X]E[Y]\big] \\
&= E[XY] - E[X]E[Y] - E[X]E[Y] + E[X]E[Y] \\
&= E[XY] - E[X]E[Y]
\end{aligned}$$

(linearity of expectation)

($E[X]$, $E[Y]$ are scalars)

Covariance

The covariance of two variables X and Y is:

$$\text{Cov}(X, Y) = E[(X - E[X])(Y - E[Y])]$$
$$= E[XY] - E[X]E[Y]$$

Covariance measures how one random variable varies with a second.

- Outside temperature and utility bills have a negative covariance.
- Handedness and musical ability have near zero covariance.
- Product demand and price have a positive covariance.

Covarying humans

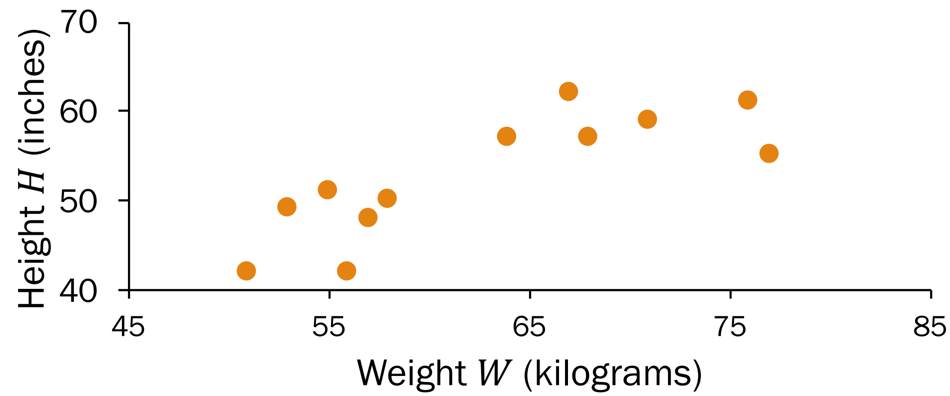
$$\text{Cov}(X,Y) = E[(X - E[X])(Y - E[Y])]$$
$$= E[XY] - E[X]E[Y]$$

Weight (kg)	Height (in)	W · H
64	57	3648
71	59	4189
53	49	2597
67	62	4154
55	51	2805
58	50	2900
77	55	4235
57	48	2736
56	42	2352
51	42	2142
76	61	4636
68	57	3876

$E[W] = 62.75$ $E[H] = 52.75$ $E[WH] = 3355.83$

What is the covariance of weight W and height H?

$$\begin{aligned} \text{Cov}(W,H) &= E[WH] - E[W]E[H] \\ &= 3355.83 - (62.75)(52.75) \\ \text{(positive)} \quad &= 45.77 \end{aligned}$$

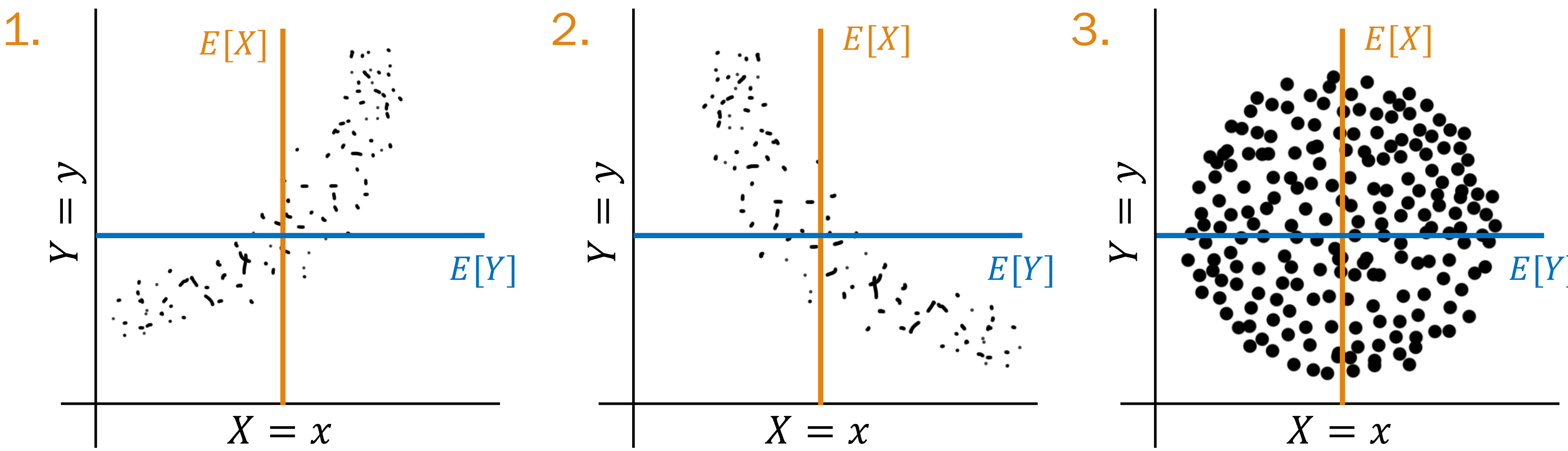


Covariance > 0: one variable ↑, other variable ↑

Feel the covariance

$$\text{Cov}(X, Y) = E[(X - E[X])(Y - E[Y])]$$
$$= E[XY] - E[X]E[Y]$$

Is the covariance positive, negative, or zero?



Feel the covariance

$$\text{Cov}(X, Y) = E[(X - E[X])(Y - E[Y])]$$
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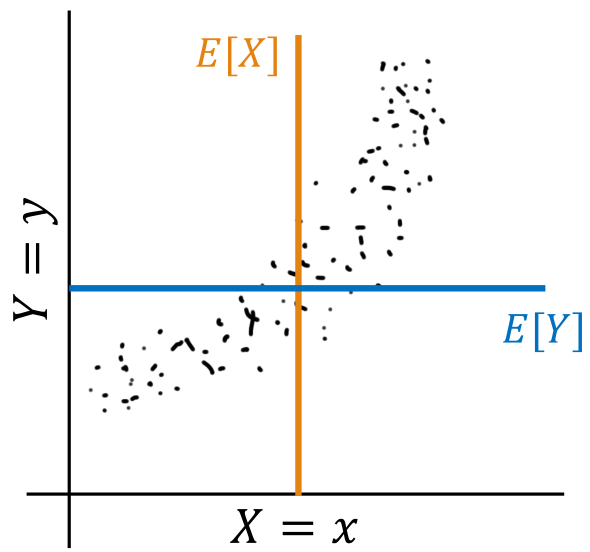
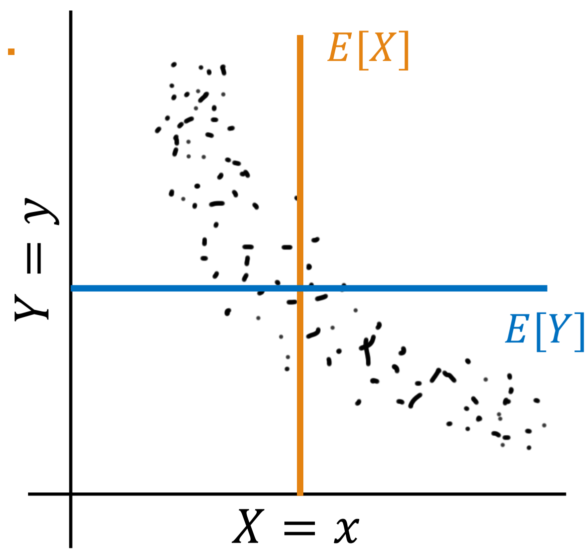
1.



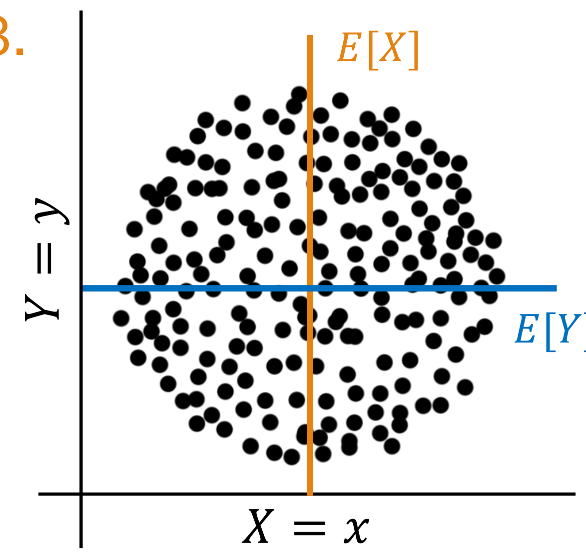
positive

2.



negative

3.



zero

Properties of Covariance

The **covariance** of two variables X and Y is:

$$\text{Cov}(X,Y) = E[(X - E[X])(Y - E[Y])]$$
$$= E[XY] - E[X]E[Y]$$

Properties:

1. $\text{Cov}(X,Y) = \text{Cov}(Y,X)$
2. $\text{Var}(X) = E[X^2] - (E[X])^2 = \text{Cov}(X,X)$
3. Covariance of sums = sum of all pairwise covariances (proof left to you)
   $\text{Cov}(X_1 + X_2, Y_1 + Y_2) = \text{Cov}(X_1, Y_1) + \text{Cov}(X_2, Y_1) + \text{Cov}(X_1, Y_2) + \text{Cov}(X_2, Y_2)$
4. Covariance is non-linear: $\text{Cov}(aX + b, Y) = a\text{Cov}(X,Y)$

13d_variance_sum

Variance of sums of RVs

Statistics of sums of RVs

For any random variables X and Y,

$$E[X + Y] = E[X] + E[Y]$$

$$\text{Var}(X + Y) = \text{Var}(X) + 2 \cdot \text{Cov}(X, Y) + \text{Var}(Y)$$

Variance of general sum of RVs

For any random variables X and Y,

$$\text{Var}(X+Y) = \text{Var}(X) + 2 \cdot \text{Cov}(X,Y) + \text{Var}(Y)$$

Proof:

$$\begin{aligned}\text{Var}(X+Y) &= \text{Cov}(X+Y, X+Y) && \text{Var}(X) = \text{Cov}(X,X)\\ &= \text{Cov}(X,X) + \text{Cov}(X,Y) + \text{Cov}(Y,X) + \text{Cov}(Y,Y) && \text{covariance of all pairs}\\ &= \text{Var}(X) + 2 \cdot \text{Cov}(X,Y) + \text{Var}(Y) && \text{Symmetry of covariance + } \text{Cov}(X,X) = \text{Var}(X)\end{aligned}$$

More generally:

$$\text{Var}\left(\sum_{i=1}^{n} X_i\right) = \sum_{i=1}^{n} \text{Var}(X_i) + 2 \sum_{i=1}^{n} \sum_{j=\text{i}+1}^{n} \text{Cov}\left(X_i, X_j\right)$$

(proof in extra slides)

Statistics of sums of RVs

For any random variables X and Y,

$$E[X+Y] = E[X] + E[Y]$$

$$\text{Var}(X+Y) = \text{Var}(X) + 2 \cdot \text{Cov}(X,Y) + \text{Var}(Y)$$

For independent X and Y,

$$E[XY] = E[X]E[Y]$$

(Lemma: proof in extra slides)

$$\text{Var}(X+Y) = \text{Var}(X) + \text{Var}(Y)$$

Variance of sum of independent RVs

For independent X and Y,

$$\text{Var}(X+Y) = \text{Var}(X) + \text{Var}(Y)$$

Proof:

1. $\text{Cov}(X,Y) = E[XY] - E[X]E[Y]$ — def. of covariance
   $= E[X]E[Y] - E[X]E[Y]$ — X and Y are independent
   $= 0$

2. $\text{Var}(X+Y) = \text{Var}(X) + 2 \cdot \text{Cov}(X,Y) + \text{Var}(Y)$
   $= \text{Var}(X) + \text{Var}(Y)$

NOT bidirectional:
$\text{Cov}(X,Y) = 0$ does NOT imply independence of X and Y!

Proving Variance of the Binomial

$X \sim \text{Bin}(n, p) \quad \text{Var}(X) = np(1-p)$

To simplify the algebra a bit, let $q = 1 - p$, so $p + q = 1$.

So:

$$
\begin{aligned}
\text{E}\left(X^2\right) &= \sum_{k \geq 0}^{n} k^2 \binom{n}{k} p^k q^{n-k} && \text{Definition of Binomial Distribution: } p + q = 1 \\
&= \sum_{k=0}^{n} kn \binom{n-1}{k-1} p^k q^{n-k} && \text{Factors of Binomial Coefficient: } k\binom{n}{k} = n\binom{n-1}{k-1} \\
&= np \sum_{k=1}^{n} k \binom{n-1}{k-1} p^{k-1} q^{(n-1)-(k-1)} && \text{Change of limit: term is zero when } k - 1 = 0 \\
&= np \sum_{j=0}^{m} (j+1) \binom{m}{j} p^j q^{m-j} && \text{putting } j = k - 1, m = n - 1 \\
&= np\left(\sum_{j=0}^{m} j \binom{m}{j} p^j q^{m-j} + \sum_{j=0}^{m} \binom{m}{j} p^j q^{m-j}\right) && \text{splitting sum up into two} \\
&= np\left(\sum_{j=0}^{m} m \binom{m-1}{j-1} p^j q^{m-j} + \sum_{j=0}^{m} \binom{m}{j} p^j q^{m-j}\right) && \text{Factors of Binomial Coefficient: } j\binom{m}{j} = m\binom{m-1}{j-1} \\
&= np\left((n-1)p \sum_{j=1}^{m} \binom{m-1}{j-1} p^{j-1} q^{(m-1)-(j-1)} + \sum_{j=0}^{m} \binom{m}{j} p^j q^{m-j}\right) && \text{Change of limit: term is zero when } j - 1 = 0 \\
&= np\left((n-1)p(p+q)^{m-1} + (p+q)^m\right) && \text{Binomial Theorem} \\
&= np((n-1)p + 1) && \text{as } p + q = 1 \\
&= n^2 p^2 + np(1-p) && \text{by algebra}
\end{aligned}
$$

Then:

$$
\begin{aligned}
\text{var}(X) &= \text{E}\left(X^2\right) - (\text{E}(X))^2 \\
&= np(1-p) + n^2 p^2 - (np)^2 && \text{Expectation of Binomial Distribution: } \text{E}(X) = np \\
&= np(1-p)
\end{aligned}
$$

as required.

proofwiki.org

Let's instead prove this using independence and variance!

Proving Variance of the Binomial

$X \sim \text{Bin}(n, p)$ $\quad \text{Var}(X) = np(1-p)$

Let $\quad X = \sum_{i=1}^{n} X_i$

Let $X_i = i$th trial is heads

$X_i \sim \text{Ber}(p)$

$\text{Var}(X_i) = p(1-p)$

X_i are independent

(by definition)

$$\text{Var}(X) = \text{Var}\left(\sum_{i=1}^{n} X_i\right)$$

$$= \sum_{i=1}^{n} \text{Var}(X_i)$$

X_i are independent, therefore variance of sum = sum of variance

$$= \sum_{i=1}^{n} p(1-p)$$

Variance of Bernoulli

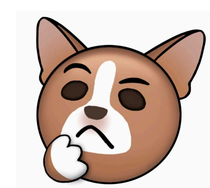
$$= np(1-p)$$

Zero covariance does **not** imply independence

Let X take on values $\{-1,0,1\}$ with equal probability $1/3$.

Define $Y = \begin{cases} 1 & \text{if } X = 0 \\ 0 & \text{otherwise} \end{cases}$

What is the joint PMF of X and Y?



Zero covariance does not imply independence

Let X take on values $\{-1,0,1\}$ with equal probability $1/3$.

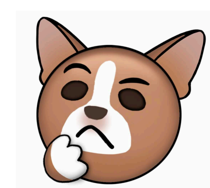
Define $Y = \begin{cases} 1 & \text{if } X = 0 \\ 0 & \text{otherwise} \end{cases}$

Y \ X	-1	0	1	
0	1/3	0	1/3	2/3
1	0	1/3	0	1/3
	1/3	1/3	1/3	

Marginal PMF of Y, $p_Y(y)$

Marginal PMF of X, $p_X(x)$

1. $E[X] =$ $\qquad E[Y] =$
2. $E[XY] =$
3. $\text{Cov}(X,Y) =$
4. Are X and Y independent?



Zero covariance does not imply independence

Let X take on values $\{-1,0,1\}$ with equal probability $1/3$.

Define $Y = \begin{cases} 1 & \text{if } X = 0 \\ 0 & \text{otherwise} \end{cases}$

	X			
Y	-1	0	1	
0	1/3	0	1/3	2/3
1	0	1/3	0	1/3
	1/3	1/3	1/3	

Marginal PMF of Y, $p_Y(y)$

Marginal PMF of X, $p_X(x)$

1. $E[X] = -1\left(\frac{1}{3}\right) + 0\left(\frac{1}{3}\right) + 1\left(\frac{1}{3}\right) = 0$ $\quad E[Y] = 0\left(\frac{2}{3}\right) + 1\left(\frac{1}{3}\right) = 1/3$

2. $E[XY] = (-1 \cdot 0)\left(\frac{1}{3}\right) + (0 \cdot 1)\left(\frac{1}{3}\right) + (1 \cdot 0)\left(\frac{1}{3}\right)$
$= 0$

3. $\text{Cov}(X,Y) = E[XY] - E[X]E[Y]$
$= 0 - 0(1/3) = 0$

⚠ does not imply independence!

4. Are X and Y independent? ❌
$P(Y = 0|X = 1) = 1$
$\neq \quad P(Y = 0) = 2/3$

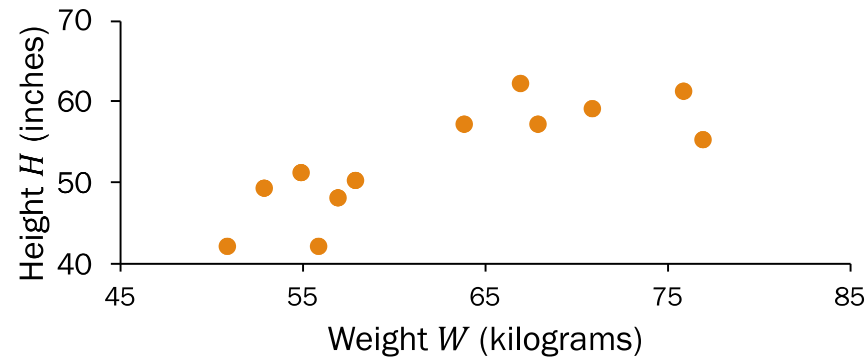
Correlation

Covarying humans

$$\text{Cov}(X,Y) = E[(X - E[X])(Y - E[Y])]$$
$$= E[XY] - E[X]E[Y]$$

What is the covariance of weight W and height H?

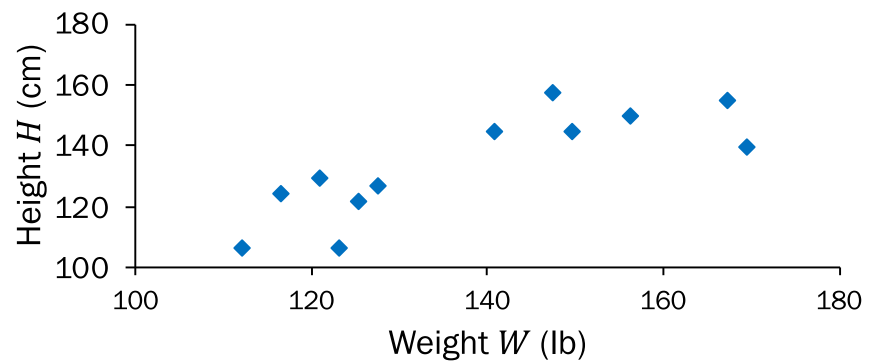
$$\text{Cov}(W,H) = E[WH] - E[W]E[H]$$
$$= 3355.83 - (62.75)(52.75)$$
$$= 45.77 \quad \text{(positive)}$$



What about weight (lb) and height (cm)?

$$\text{Cov}(2.20W, 2.54H)$$
$$= E[2.20W \cdot 2.54H] - E[2.20W]E[2.54H]$$
$$= 18752.38 - (138.05)(133.99)$$
$$= 255.06 \quad \text{(positive)}$$

⚠ Covariance depends on units!



Sign of covariance (+/−) more meaningful than magnitude

Correlation

The **correlation** of two variables X and Y is:

$$\rho(X, Y) = \frac{\text{Cov}(X, Y)}{\sigma_X \, \sigma_Y}$$

$\sigma_X^2 = \text{Var}(X)$,
$\sigma_Y^2 = \text{Var}(Y)$

- Note: $-1 \leq \rho(X, Y) \leq 1$
- Correlation measures the **linear relationship** between X and Y:

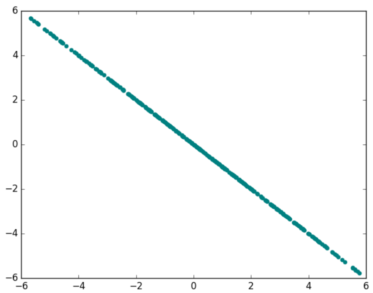
$$\begin{aligned}
\rho(X,Y) &= 1 && \Longrightarrow Y = aX + b, \text{where } a = \sigma_Y/\sigma_X \\
\rho(X,Y) &= -1 && \Longrightarrow Y = aX + b, \text{where } a = -\sigma_Y/\sigma_X \\
\rho(X,Y) &= 0 && \Longrightarrow \text{“uncorrelated” (absence of linear relationship)}
\end{aligned}$$

Correlation reps

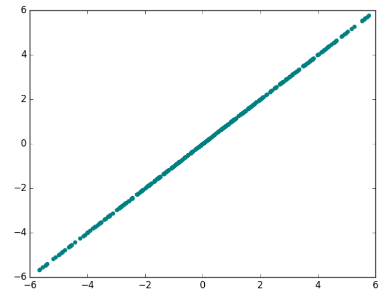
A. $\rho(X, Y) = 1$
B. $\rho(X, Y) = -1$
C. $\rho(X, Y) = 0$
D. Other

What is the correlation coefficient $\rho(X, Y)$?

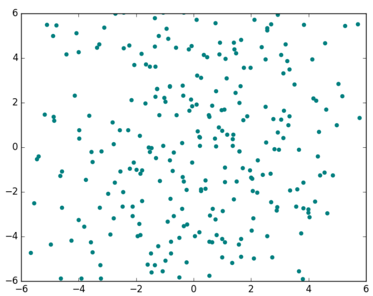
1.



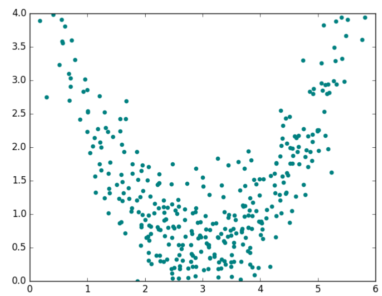
2.



3.



4.



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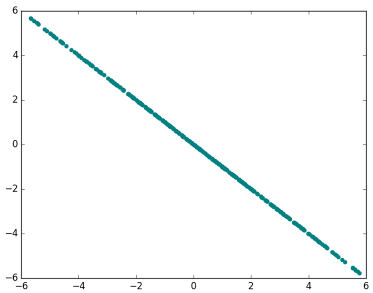
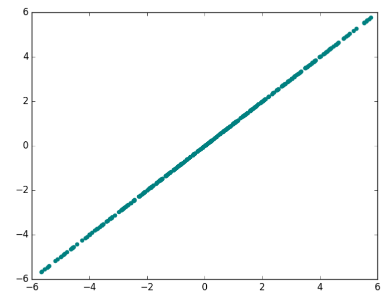


B. $\rho(X, Y) = -1$

$$Y = -aX + b$$
$$a > 0$$

2.



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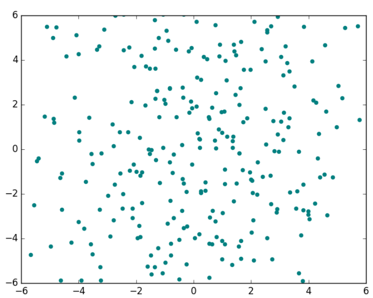
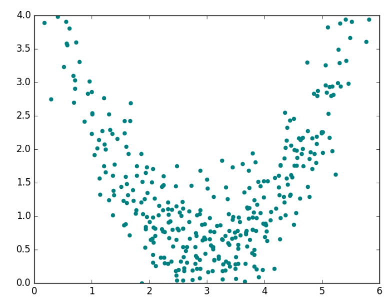


C. $\rho(X, Y) = 0$

"uncorrelated"

4.

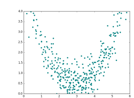


C. $\rho(X, Y) = 0$

$$Y = X^2$$

X and Y can be nonlinearly related even if $\rho(X, Y) = 0$.

Throwback to CS103: Conditional statements

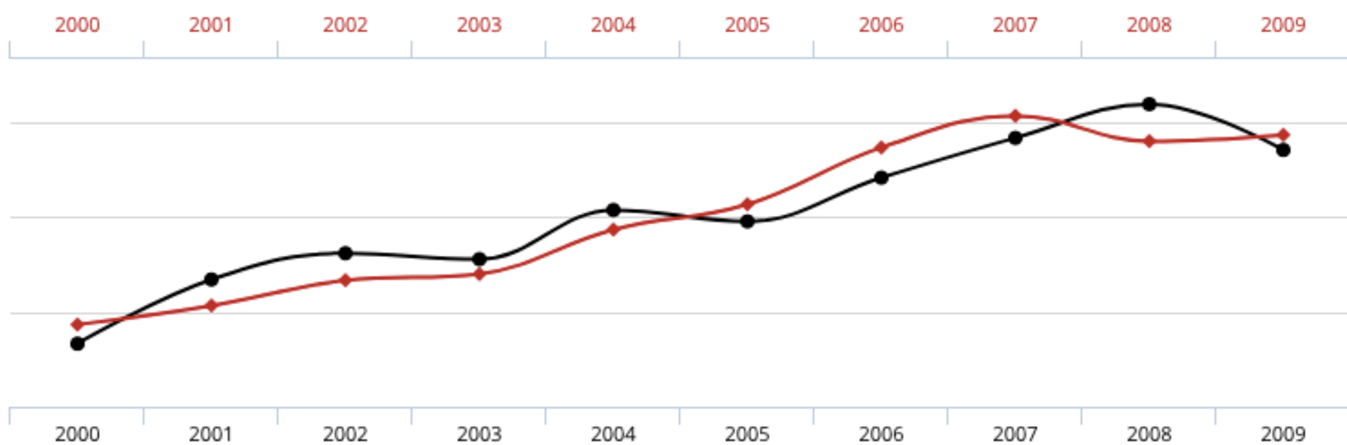
Statement $P \to Q$:	Independence → No correlation	✅
Contrapositive $\neg Q \to \neg P$:	Correlation → Dependence	✅ (logically equivalent)
Inverse $\neg P \to \neg Q$:	Dependence → Correlation	❌ (not always) $Y = X^2$ $\rho(X, Y) = 0$ 
Converse $Q \to P$:	No correlation → Independence	❌ (not always) Slide 45

"Correlation does not imply causation"

Spurious Correlations

$\rho(X, Y)$ is used a lot to statistically quantify the relationship b/t X and Y.

Correlation: 0.947091



[Spurious correlations]

Spurious Correlations

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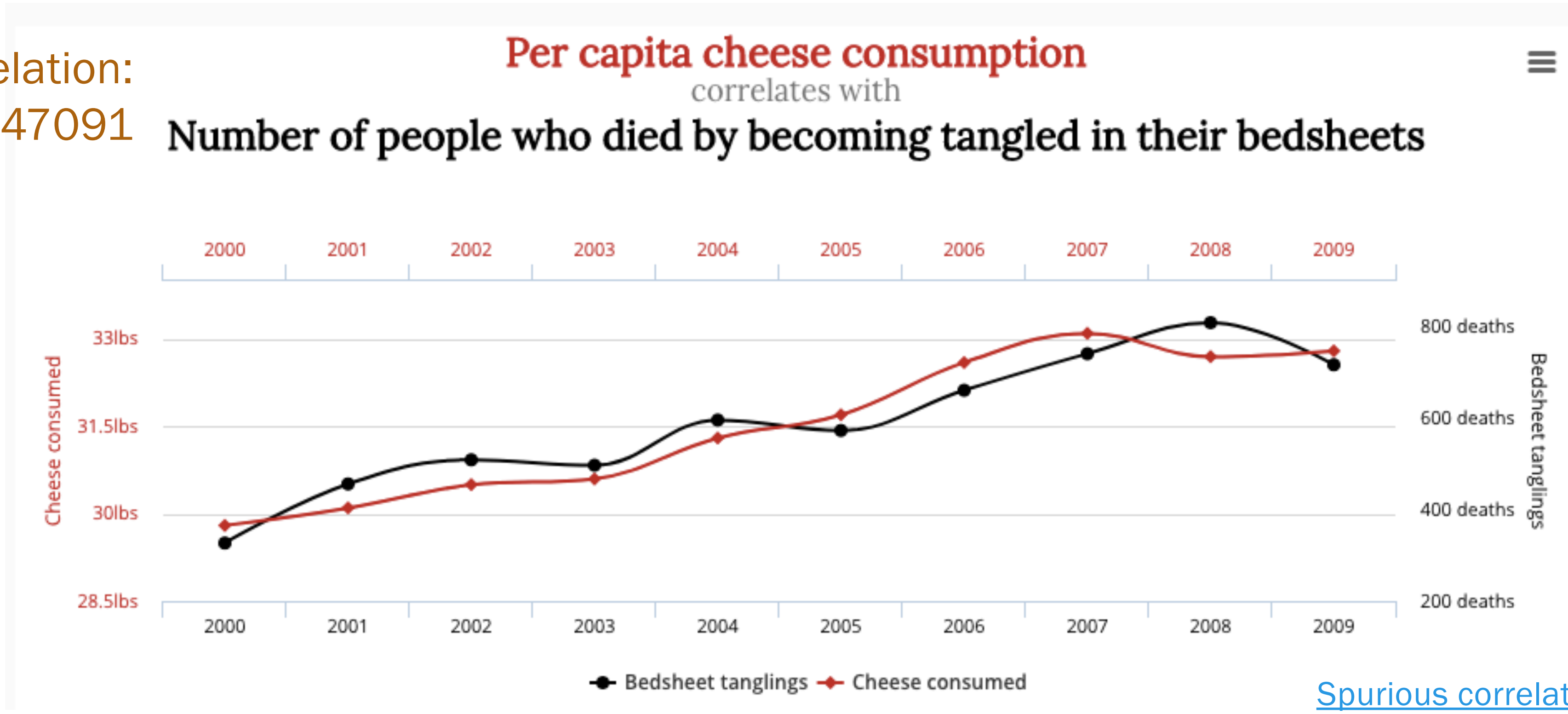
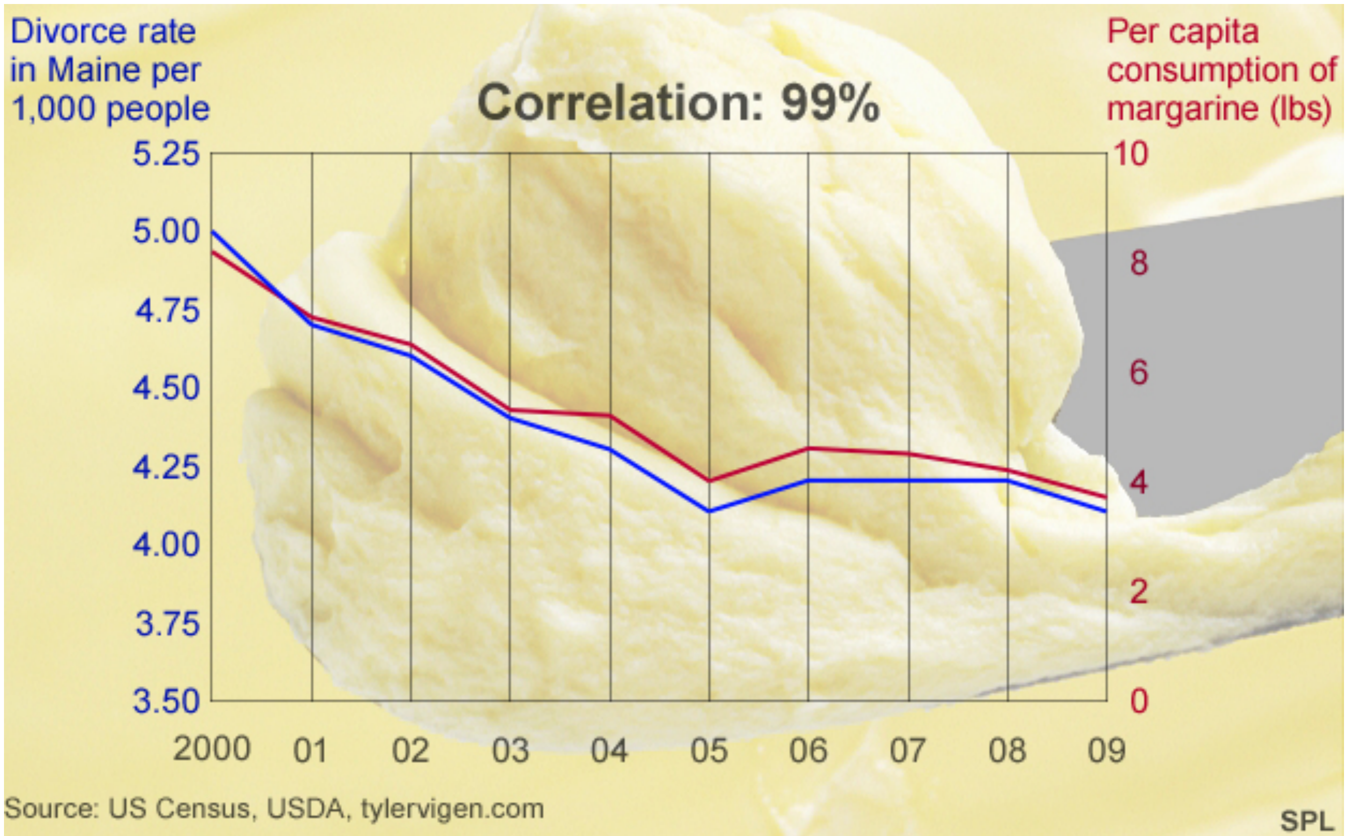


[Spurious correlations]

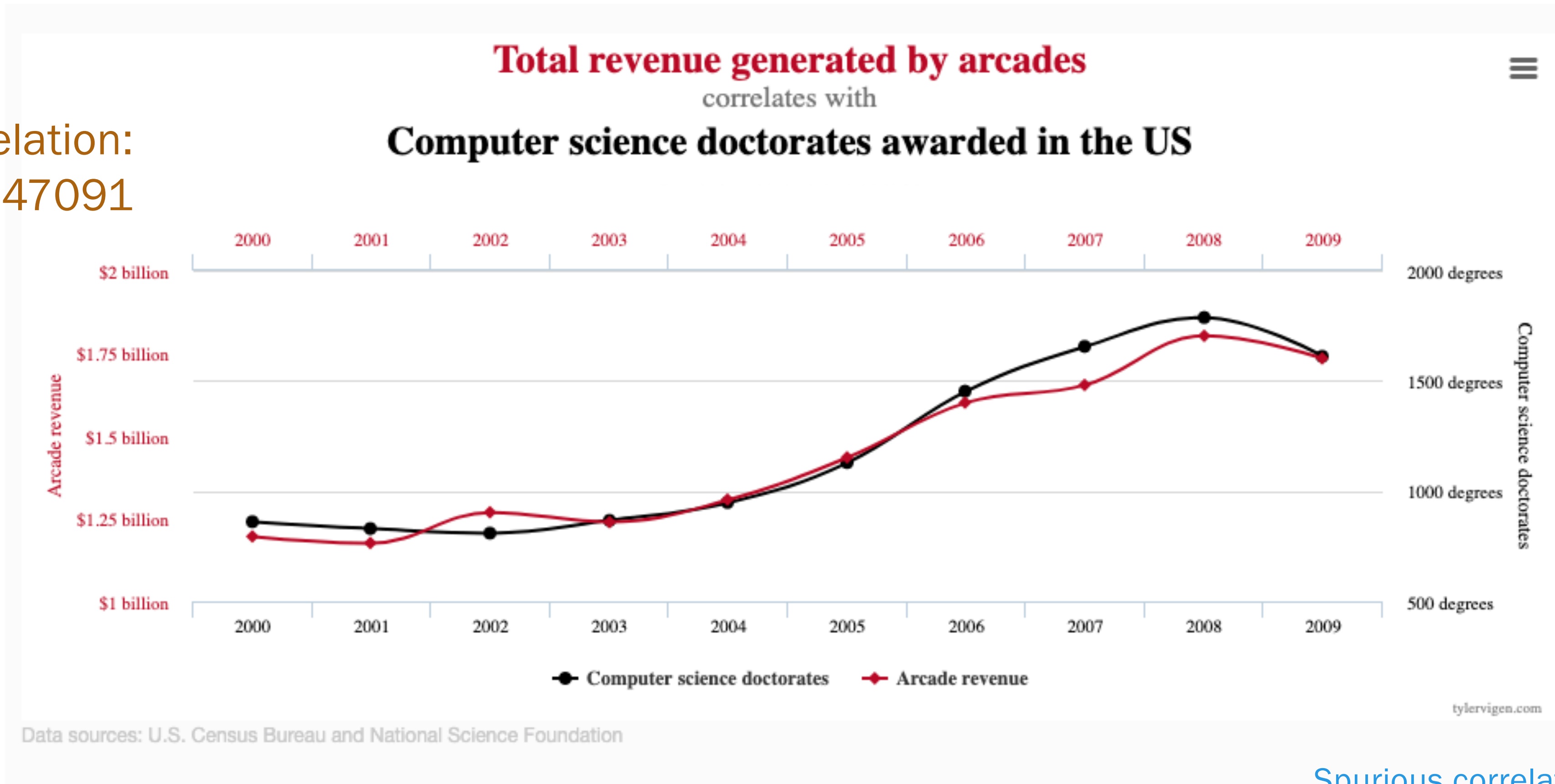
Divorce vs. Margarine



http://www.bbc.com/news/magazine-27537142

Arcade revenue vs. CS PhDs

Correlation:
0.947091



[Spurious correlations]

Extras

Expectation of product of independent RVs

If X and Y are independent, then

$$E[XY] = E[X]E[Y]$$
$$E[g(X)h(Y)] = E[g(X)]E[h(Y)]$$

Proof: $E[g(X)h(Y)]$

$$= \sum_y \sum_x g(x)h(y)p_{X,Y}(x,y)$$

(for continuous proof, replace summations with integrals)

$$= \sum_y \sum_x g(x)h(y)p_X(x)p_Y(y)$$

X and Y are independent

$$= \sum_y \left(h(y)p_Y(y) \sum_x g(x)p_X(x) \right)$$

Terms dependent on y are constant in integral of x

$$= \left(\sum_x g(x)p_X(x) \right) \left(\sum_y h(y)p_Y(y) \right)$$

Summations separate

$$= E[g(X)]E[h(Y)]$$

Variance of Sums of Variables

$$\text{Var}\left(\sum_{i=1}^{n} X_i\right) = \sum_{i=1}^{n} \text{Var}(X_i) + 2\sum_{i=1}^{n} \sum_{j=i+1}^{n} \text{Cov}\left(X_i, X_j\right)$$

Proof:

$$\text{Var}\left(\sum_{i=1}^{n} X_i\right) \underset{\substack{\text{Var}(X) \\ = \text{Cov}(X,X)}}{=} \text{Cov}\left(\sum_{i=1}^{n} X_i, \sum_{i=1}^{n} X_i\right) \underset{\substack{\text{covariance of} \\ \text{all pairs}}}{=} \sum_{i=1}^{n}\sum_{j=1}^{n} \text{Cov}(X_i, X_j)$$

$$= \sum_{i=1}^{n} \text{Var}(X_i) + \sum_{i=1}^{n} \sum_{j=1, j\neq i}^{n} \text{Cov}\left(X_i, X_j\right)$$

Symmetry of covariance
$\text{Cov}(X, X) = \text{Var}(X)$

$$= \sum_{i=1}^{n} \text{Var}(X_i) + 2\sum_{i=1}^{n} \sum_{j=i+1}^{n} \text{Cov}\left(X_i, X_j\right)$$

Adjust summation bounds