Probability, continued

CMPUT 296: Basics of Machine Learning

§2.2-2.4

Recap

- Probabilities are a means of **quantifying uncertainty**
- A probability distribution is defined on a measurable space consisting of a **sample space** and an **event space**.
- **Discrete** sample spaces (and random variables) are defined in terms of **probability mass functions** (PMFs)
- **Continuous** sample spaces (and random variables) are defined in terms of **probability density functions** (PDFs)

Outline

1. Multiple Random Variables
2. Independence
3. Expectations and Moments

Recap: Random Variables

Random variables are a way of reasoning about a complicated underlying probability space in a more straightforward way.

Example: Suppose we observe both a die's number, and where it lands.

$$\Omega = \{(left,1), (right,1), (left,2), (right,2), \ldots, (right,6)\}$$

We might want to think about the probability that we get a large number, without thinking about where it landed.

We could ask about $P(X \geq 4)$, where X = number that comes up.

What About Multiple Variables?

- So far, we've really been thinking about a single random variable at a time
- Straightforward to define multiple random variables on a single probability space

Example: Suppose we observe both a die's number, and where it lands.

$$\Omega = \{(left,1), (right,1), (left,2), (right,2), \ldots, (right,6)\}$$

$$X(\omega) = \omega_2 = \text{number}$$

$$Y(\omega) = \begin{cases} 1 & \text{if } \omega_1 = left \\ 0 & \text{otherwise.} \end{cases} = 1 \text{ if landed on left}$$

$$P(Y = 1) = P(\{\omega \mid Y(\omega) = 1\})$$

$$P(X \geq 4 \wedge Y = 1) = P(\{\omega \mid X(\omega) \geq 4 \wedge Y(\omega) = 1\})$$

Joint Distribution

We typically be model the **interactions** of different random variables.

Joint probability mass function: $p(x, y) = P(X = x, Y = y)$

$$\sum_{x \in \mathcal{X}} \sum_{y \in \mathcal{Y}} p(x, y) = 1$$

Example: $\mathcal{X} = \{0,1\}$ (young, old) and $\mathcal{Y} = \{0,1\}$ (no arthritis, arthritis)

	Y=0	**Y=1**
X=0	P(X=0,Y=0) = 1/2	P(X=0, Y=1) = 1/100
X=1	P(X=1, Y=0) = 1/10	P(X=1, Y=1) = 39/100

Questions About Multiple Variables

Example: $\mathscr{X} = \{0,1\}$ (young, old) and $\mathscr{Y} = \{0,1\}$ (no arthritis, arthritis)

	Y=0	**Y=1**
X=0	P(X=0,Y=0) = 1/2	P(X=0, Y=1) = 1/100
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- Are these two variables related at all? Or do they change **independently**?
- Given this distribution, can we determine the distribution over just Y? I.e., what is $P(Y = 1)$? (**marginal distribution**)
- If we knew something about one variable, does that tell us something about the distribution over the other? E.g., if I know $X = 0$ (person is young), does that tell me the **conditional probability** $P(Y = 1 \mid X = 1)$? (Prob. that person we know is young has arthritis)

Conditional Distribution

Definition: Conditional probability distribution

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

This same equation will hold for the corresponding PDF or PMF:

$$p(y \mid x) = \frac{p(x, y)}{p(x)}$$

Question: if $p(x, y)$ is small, does that imply that $p(y \mid x)$ is small?

e.g., imagine x = arthritis and y = old

PMFs and PDFs of Many Variables

In general, we can consider a d-dimensional random variable $\vec{X} = (X_1, \ldots, X_d)$ with vector-valued outcomes $\vec{x} = (x_1, \ldots, x_d)$, with each x_i chosen from some $\mathscr{X}_i$. Then,

Discrete case:

$p : \mathscr{X}_1 \times \mathscr{X}_2 \times \ldots \times \mathscr{X}_d \to [0,1]$ is a **(joint) probability mass function** if

$$\sum_{x_1 \in \mathscr{X}_1} \sum_{x_2 \in \mathscr{X}_2} \cdots \sum_{x_d \in \mathscr{X}_d} p(x_1, x_2, \ldots, x_d) = 1$$

Continuous case:

$p : \mathscr{X}_1 \times \mathscr{X}_2 \times \ldots \times \mathscr{X}_d \to [0,\infty)$ is a **(joint) probability density function** if

$$\int_{\mathscr{X}_1} \int_{\mathscr{X}_2} \cdots \int_{\mathscr{X}_d} p(x_1, x_2, \ldots, x_d)\, dx_1 dx_2 \ldots dx_d = 1$$

Marginal Distributions

A **marginal distribution** is defined for a subset of $\overrightarrow{X}$ by summing or integrating out the remaining variables. (We will often say that we are "marginalizing over" or "marginalizing out" the remaining variables).

Discrete case: $p(x_i) = \sum_{x_1 \in \mathcal{X}_1} \cdots \sum_{x_{i-1} \in \mathcal{X}_{i-1}} \sum_{x_{i+1} \in \mathcal{X}_{i+1}} \cdots \sum_{x_d \in \mathcal{X}_d} p(x_1, \ldots, x_{i-1}, x_{i+1}, \ldots, x_d)$

Continuous: $p(x_i) = \int_{\mathcal{X}_1} \cdots \int_{\mathcal{X}_{i-1}} \int_{\mathcal{X}_{i+1}} \cdots \int_{\mathcal{X}_d} p(x_1, \ldots, x_{i-1}, x_{i+1}, \ldots, x_d)\, dx_1 \ldots dx_{i-1} dx_{i+1} \ldots dx_d$

Back to our example

Example: $\mathscr{X} = \{0,1\}$ (young, old) and $\mathscr{Y} = \{0,1\}$ (no arthritis, arthritis)

	Y=0	**Y=1**
X=0	P(X=0,Y=0) = 1/2	P(X=0, Y=1) = 1/100
X=1	P(X=1, Y=0) = 1/10	P(X=1, Y=1) = 39/100

- **Exercise**: Check if $\sum_{x \in \{0,1\}} \sum_{y \in \{0,1\}} p(x, y) = 1$
- **Exercise**: Compute marginal $p(y) = \sum_{x \in \{0,1\}} p(x, y)$

Back to our example (cont)

Example: $\mathscr{X} = \{0,1\}$ (young, old) and $\mathscr{Y} = \{0,1\}$ (no arthritis, arthritis)

	Y=0	**Y=1**
X=0	P(X=0,Y=0) = 1/2	P(X=0, Y=1) = 1/100
X=1	P(X=1, Y=0) = 1/10	P(X=1, Y=1) = 39/100

- **Exercise**: Check if $\sum_{x\in\{0,1\}} \sum_{y\in\{0,1\}} p(x,y) = 1/2 + 1/100 + 1/10 + 39/100 = 1$
- **Exercise**: Compute marginal $p(y=1) = \sum_{x\in\{0,1\}} p(x, y=1) = 40/100,$

$p(y=0) = 1 - p(y=1) = 60/100$

Marginal Distributions

A **marginal distribution** is defined for a subset of $\overrightarrow{X}$ by summing or integrating out the remaining variables. (We will often say that we are "marginalizing over" or "marginalizing out" the remaining variables).

Discrete case: $p(x_i) = \sum_{x_1 \in \mathcal{X}_1} \cdots \sum_{x_{i-1} \in \mathcal{X}_{i-1}} \sum_{x_{i+1} \in \mathcal{X}_{i+1}} \cdots \sum_{x_d \in \mathcal{X}_d} p(x_1, \ldots, x_{i-1}, x_{i+1}, \ldots, x_d)$

Continuous: $p(x_i) = \int_{\mathcal{X}_1} \cdots \int_{\mathcal{X}_{i-1}} \int_{\mathcal{X}_{i+1}} \cdots \int_{\mathcal{X}_d} p(x_1, \ldots, x_{i-1}, x_{i+1}, \ldots, x_d) \, dx_1 \ldots dx_{i-1} dx_{i+1} \ldots dx_d$

Question: How do we get $p(x_i, x_j)$ for some i, j?

Question: Why p for $p(x_i)$ and $p(x_1, \ldots, x_d)$?

- They can't be the same function, they have different domains!

Are these really the same function?

- **No.** They're not the same function.
- But they are **derived** from the **same joint distribution**.
- So for brevity we will write

$$p(y \mid x) = \frac{p(x, y)}{p(x)}$$

- Even though it would be more precise to write something like

$$p_{Y|X}(y \mid x) = \frac{p(x, y)}{p_X(x)}$$

    - We can tell which function we're talking about from context (i.e., arguments)

Chain Rule

From the definition of conditional probability:

$$p(y \mid x) = \frac{p(x, y)}{p(x)}$$

$$\iff p(y \mid x)p(x) = \frac{p(x, y)}{p(x)}p(x)$$

$$\iff p(y \mid x)p(x) = p(x, y)$$

This is called the **Chain Rule**.

Multiple Variable Chain Rule

The chain rule generalizes to multiple variables:

$$p(x, y, z) = p(x, y \mid z)p(z) = p(x \mid y, z)\underbrace{p(y \mid z)p(z)}_{p(y,z)}$$

Definition: Chain rule

$$p(x_1, \ldots, x_d) = p(x_d)\prod_{i=1}^{d-1} p(x_i \mid x_{i+1}, \ldots x_d)$$

$$= p(x_1)\prod_{i=2}^{d} p(x_i \mid x_i, \ldots x_{i-1})$$

Bayes' Rule

From the chain rule, we have:

$$p(x, y) = p(y \mid x)p(x)$$
$$= p(x \mid y)p(y)$$

- Often, $p(x \mid y)$ is easier to compute than $p(y \mid x)$
  - e.g., where x is **features** and y is **label**

Definition: Bayes' rule

$$p(y \mid x) = \frac{p(x \mid y)\,p(y)}{p(x)}$$

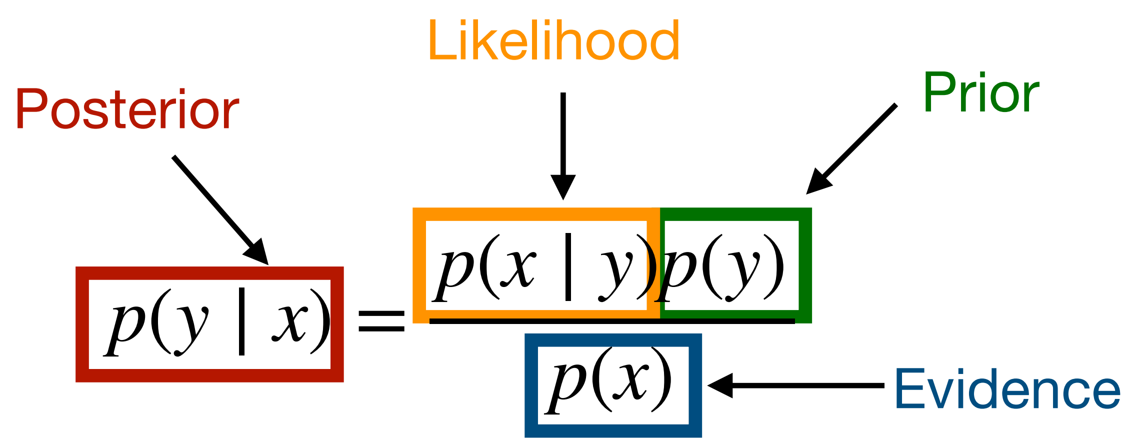
Posterior: $p(y \mid x)$

Likelihood: $p(x \mid y)$

Prior: $p(y)$

Evidence: $p(x)$

Example:
Disease Test



Example:

$$p(Test = pos \mid Dis = T) = 0.99$$
$$p(Test = pos \mid Dis = F) = 0.03$$
$$p(Dis = T) = 0.005$$

Questions:

1. What is the likelihood?
2. What is the prior?
3. What is $p(Dis = T \mid Test = pos)$?

Independence of Random Variables

Definition: X and Y are **independent** if:

$$p(x, y) = p(x)p(y)$$

X and Y are **conditionally independent given** Z if:

$$p(x, y \mid z) = p(x \mid z)p(y \mid z)$$

Another Marginalization Example

- Imagine you get to draw two random candies from a bag of treats
- Say there are 5 types of candies (1, 2, 3, 4, 5), equally distributed in the bag
- Let $X =$ First Candy You Got and $Y =$ Second Candy You Got
- What is $p(X = 1)$?
- What is $p(X = 1, Y = 3)$?

Independence of Random Variables

Definition: X and Y are **independent** if:

$$p(x, y) = p(x)p(y)$$

X and Y are **conditionally independent given Z** if:

$$p(x, y \mid z) = p(x \mid z)p(y \mid z)$$

Example: Coins
(Ex.7 in the course text)

- Suppose you have a biased coin: It does not come up heads with probability 0.5. Instead, it is more likely to come up heads.
- Let Z be the bias of the coin, with $\mathcal{Z} = \{0.3, 0.5, 0.8\}$ and probabilities $P(Z = 0.3) = 0.7$, $P(Z = 0.5) = 0.2$ and $P(Z = 0.8) = 0.1$.
  - **Question:** What other outcome space could we consider?
  - **Question:** What kind of distribution is this?
  - **Question:** What other kinds of distribution could we consider?

Example: Coins (2)

- Now imagine I told you $Z = 0.3$ (i.e., probability of heads is 0.3)
- Let X and Y be two consecutive flips of the coin
- What is $P(X = Heads \mid Z = 0.3)$? What about $P(X = Tails \mid Z = 0.3)$?
- What is $P(Y = Heads \mid Z = 0.3)$? What about $P(Y = Tails \mid Z = 0.3)$?
- Is $P(X = x, Y = y \mid Z = 0.3) = P(X = x \mid Z = 0.3)P(Y = y \mid Z = 0.3)$?

Example: Coins (3)

- Now imagine we do not know Z
  - e.g., you randomly grabbed it from a bin of coins with probabilities $P(Z = 0.3) = 0.7$, $P(Z = 0.5) = 0.2$ and $P(Z = 0.8) = 0.1$
- What is $P(X = Heads)$?

$$P(X = Heads) = \sum_{z \in \{0.3, 0.5, 0.8\}} P(X = Heads \mid Z = z) p(Z = z)$$

$$= P(X = Heads \mid Z = 0.3) p(Z = 0.3)$$

$$+ P(X = Heads \mid Z = 0.5) p(Z = 0.5)$$

$$+ P(X = Heads \mid Z = 0.8) p(Z = 0.8)$$

$$= 0.3 \times 0.7 + 0.5 \times 0.2 + 0.8 \times 0.1 = 0.39$$

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Example: Coins (4)

- Now imagine we do not know Z
  - e.g., you randomly grabbed it from a bin of coins with probabilities $P(Z = 0.3) = 0.7$, $P(Z = 0.5) = 0.2$ and $P(Z = 0.8) = 0.1$
- Is $P(X = Heads, Y = Heads) = P(X = Heads)p(Y = Heads)$?
  - For brevity, lets use h for Heads

$$P(X = h, Y = h) = \sum_{z \in \{0.3, 0.5, 0.8\}} P(X = h, Y = h \mid Z = z)p(Z = z)$$

- $$= \sum_{z \in \{0.3, 0.5, 0.8\}} P(X = h \mid Z = z)P(Y = h \mid Z = z)p(Z = z)$$

Example: Coins (4)

- $P(Z=0.3)=0.7$, $P(Z=0.5)=0.2$ and $P(Z=0.8)=0.1$
- Is $P(X=Heads, Y=Heads) = P(X=Heads)p(Y=Heads)$?

$$P(X=h, Y=h) = \sum_{z \in \{0.3,0.5,0.8\}} P(X=h, Y=h \mid Z=z)p(Z=z)$$

$$= \sum_{z \in \{0.3,0.5,0.8\}} P(X=h \mid Z=z)P(Y=h \mid Z=z)p(Z=z)$$

$$= P(X=h \mid Z=0.3)P(Y=h \mid Z=0.3)p(Z=0.3)$$

$$+P(X=h \mid Z=0.5)P(Y=h \mid Z=0.5)p(Z=0.5)$$

- $$+P(X=h \mid Z=0.8)p(Y=h \mid Z=0.8)p(Z=0.8)$$

$$= 0.3 \times 0.3 \times 0.7 + 0.5 \times \times 0.5 \times 0.2 + 0.8 \times 0.8 \times 0.1$$

$$= 0.177 \neq 0.39 * 0.39 = 0.1521$$

Example: Coins (4)

- Let Z be the bias of the coin, with $\mathscr{Z} = \{0.3, 0.5, 0.8\}$ and probabilities $P(Z = 0.3) = 0.7$, $P(Z = 0.5) = 0.2$ and $P(Z = 0.8) = 0.1$.
- Let X and Y be two consecutive flips of the coin
- **Question:** Are X and Y conditionally independent given Z?
  - i.e., $P(X = x, Y = y \mid Z = z) = P(X = x \mid Z = z)P(Y = y \mid Z = z)$
- **Question:** Are X and Y independent?
  - i.e. $P(X = x, Y = y) = P(X = x)P(Y = y)$

The Distribution Changes Based on What We Know

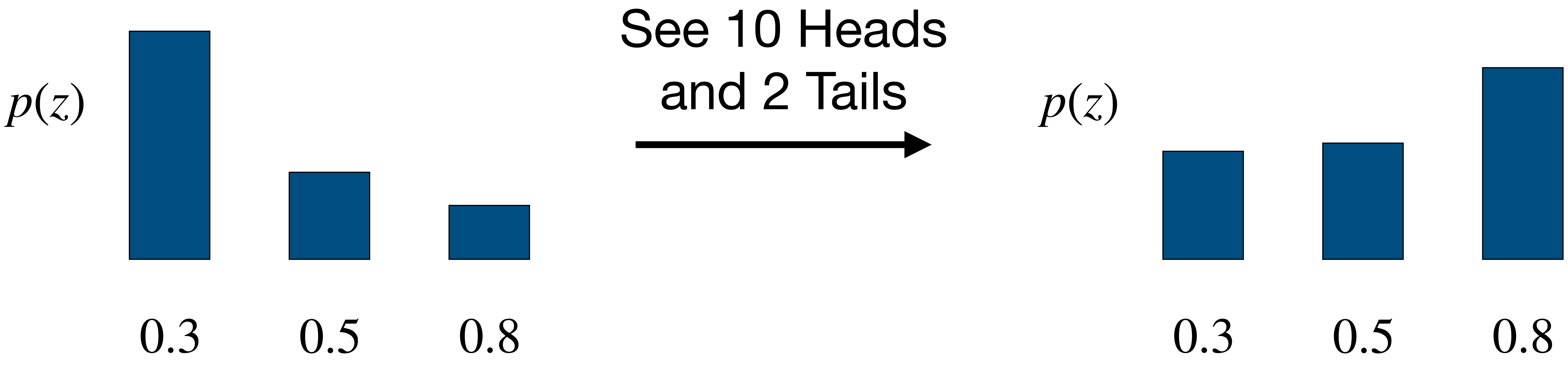
- The coin has some true bias z
- If we know that bias, we reason about $P(X = x \mid Z = z)$
  - Namely, the probability of x **given** we know the bias is z
- If we know do not know that bias, then from our perspective the coin outcomes follows probabilities $P(X = x)$
  - The world still flips the coin with bias z
- Conditional independence is a property of the distribution we are reasoning about, not an objective truth about outcomes

A bit more intuition

- If we know do not know that bias, then from our perspective the coin outcomes follows probabilities $P(X = x, Y = y)$
  - and X and Y are correlated
- If we know $X = h$, do we think it's more likely $Y = h$? i.e., is $P(X = h, Y = h) > P(X = h, Y = t)$?

My brain hurts, why do I need to know about coins?

- i.e., how is this relevant
- Let's imagine you want to infer (or learn) the bias of the coin, from data
  - data in this case corresponds to a sequence of flips $X_1, X_2, \ldots, X_n$
- You can ask: $P(Z = z \mid X_1 = H, X_2 = H, X_3 = T, \ldots, X_n = H)$



More uses for independence and conditional independence

- If I told you X = roof type was **independent** of Y = house price, would you use X as a feature to predict Y?
- Imagine you want to predict Y = Has Lung Cancer and you have an indirect correlation with X = Location since in Location 1 more people smoke on average. If you could measure Z = Smokes, then X and Y would be **conditionally independent** given Z.
  - Suggests you could look for such causal variables, that explain these correlations
- We will see the utility of conditional independence for learning models

Expected Value

The expected value of a random variable is the **weighted average** of that variable over its domain.

Definition: Expected value of a random variable

$$\mathbb{E}[X] = \begin{cases} \sum_{x \in \mathcal{X}} x p(x) & \text{if } X \text{ is discrete} \\ \int_{\mathcal{X}} x p(x)\, dx & \text{if } X \text{ is continuous.} \end{cases}$$

Relationship to Population Average and Sample Average

- Or Population Mean and Sample Mean
- Population Mean = Expected Value, Sample Mean estimates this number
- e.g., Population Mean = average height of the entire population
- For RV X = height, p(x) gives the probability that a randomly selected person has height x
- Sample average: you randomly sample n heights from the population
  - implicitly you are sampling heights proportionally to p
- As n gets bigger, the sample average approaches the true expected value

Expected Value with Functions

The expected value of a function $f : \mathcal{X} \to \mathbb{R}$ of a random variable is the **weighted average** of that function's value over the domain of the variable.

Definition: Expected value of a function of a random variable

$$\mathbb{E}[f(X)] = \begin{cases} \sum_{x \in \mathcal{X}} f(x)p(x) & \text{if } X \text{ is discrete} \\ \int_{\mathcal{X}} f(x)p(x)\, dx & \text{if } X \text{ is continuous.} \end{cases}$$

Example:
Suppose you get $10 if heads is flipped, or lose $3 if tails is flipped.
What are your winnings **on expectation**?

Expected Value Example

Example:
Suppose you get $10 if heads is flipped, or lose $3 if tails is flipped.
What are your winnings **on expectation**?

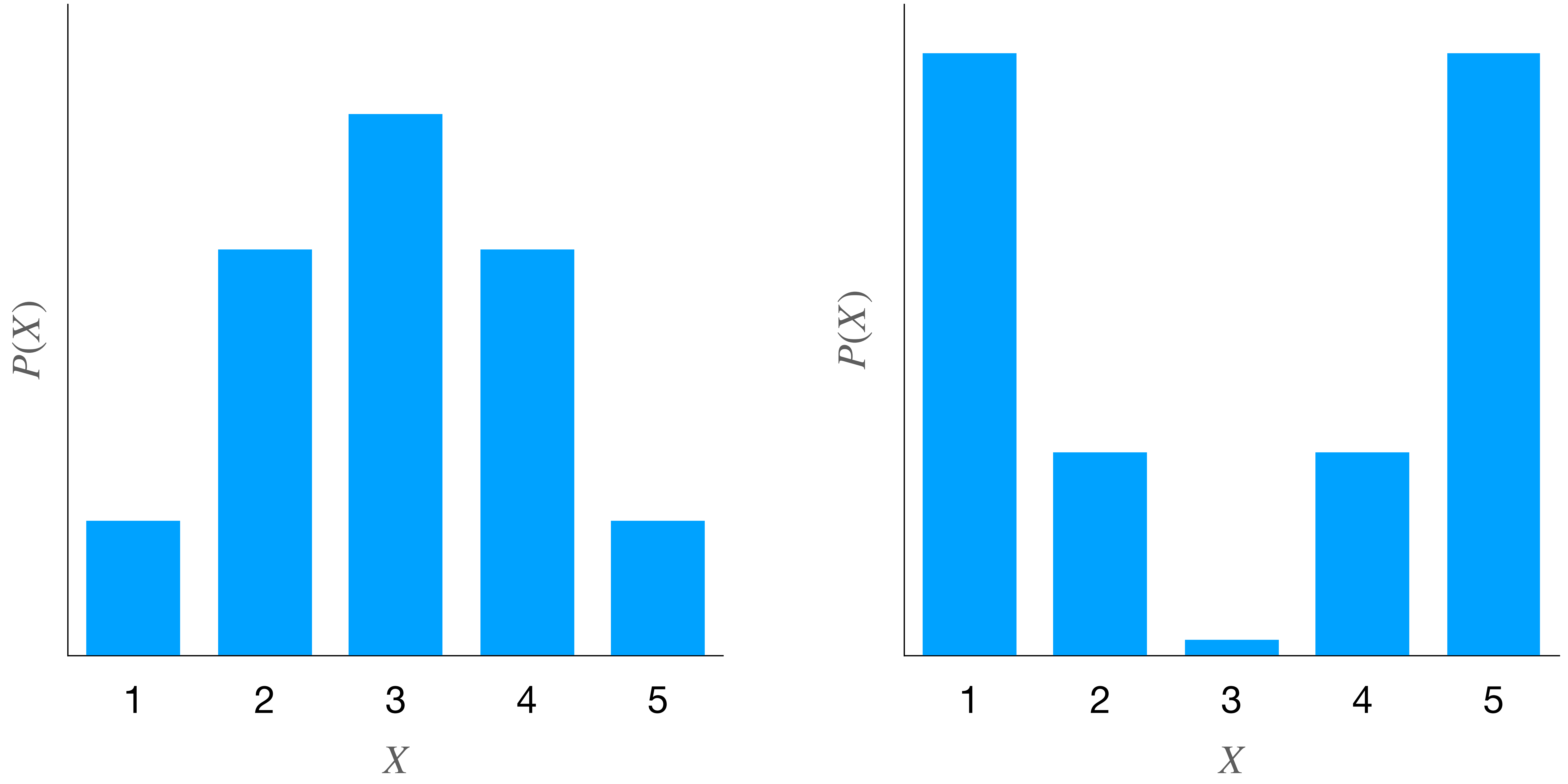
X is the outcome of the coin flip, 1 for heads and 0 for tails

$$f(x) = \begin{cases} 3 & \text{if } X = 0 \\ 10 & \text{if } X = 1 \end{cases}$$

$Y = f(X)$ is a new random variable

$$\mathbb{E}[Y] = \mathbb{E}[f(X)] = \sum_{x \in \mathcal{X}} f(x)p(x) = f(0)p(0) + f(1)p(1) = .5 \times 3 + .5 \times 10 = 6.5$$

Expected Value is a Lossy Summary



$$\mathbb{E}[X] = 3$$
$$\mathbb{E}[X^2] \simeq 10$$

$$\mathbb{E}[X] = 3$$
$$\mathbb{E}[X^2] \simeq 12$$

Conditional Expectations

Definition:

The **expected value of Y conditional on $X = x$** is

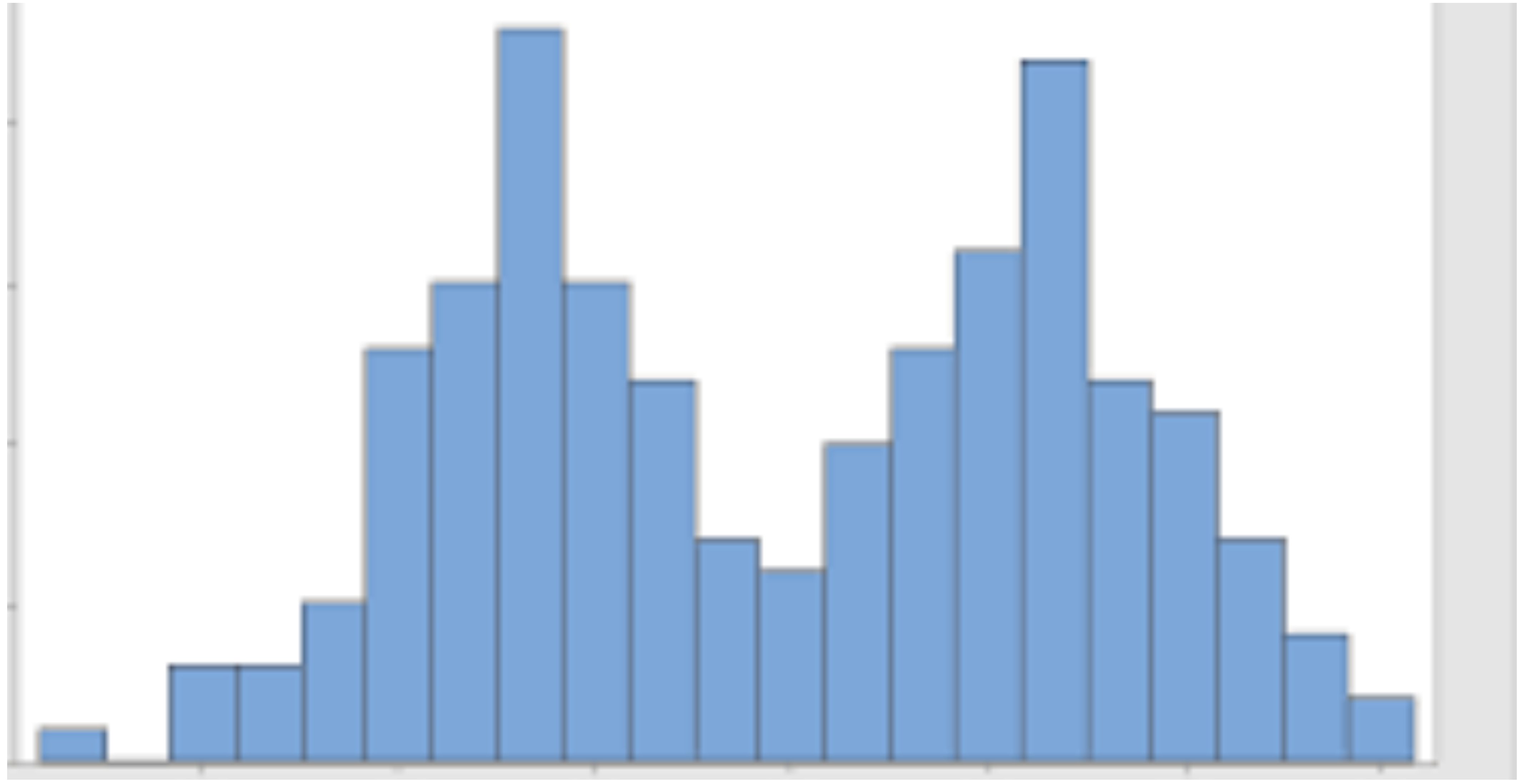
$$\mathbb{E}[Y \mid X = x] = \begin{cases} \sum_{y \in \mathcal{Y}} y p(y \mid x) & \text{if } Y \text{ is discrete,} \\ \int_{\mathcal{Y}} y p(y \mid x) \, dy & \text{if } Y \text{ is continuous.} \end{cases}$$

Conditional Expectation Example

- X is the type of a book, 0 for fiction and 1 for non-fiction
  - $p(X = 1)$ is the proportion of all books that are non-fiction
- Y is the number of pages
  - $p(Y = 100)$ is the proportion of all books with 100 pages
- $\mathbb{E}[Y | X = 0]$ is different from $\mathbb{E}[Y | X = 1]$
  - e.g. $\mathbb{E}[Y | X = 0] = 70$ is different from $\mathbb{E}[Y | X = 1] = 150$
- Another example: $\mathbb{E}[X | Z = 0.3]$ the expected outcome of the coin flip given that the bias is 0.3 ($\mathbb{E}[X | Z = 0.3] = 0 \times 0.7 + 1 \times 0.3 = 0.3$)

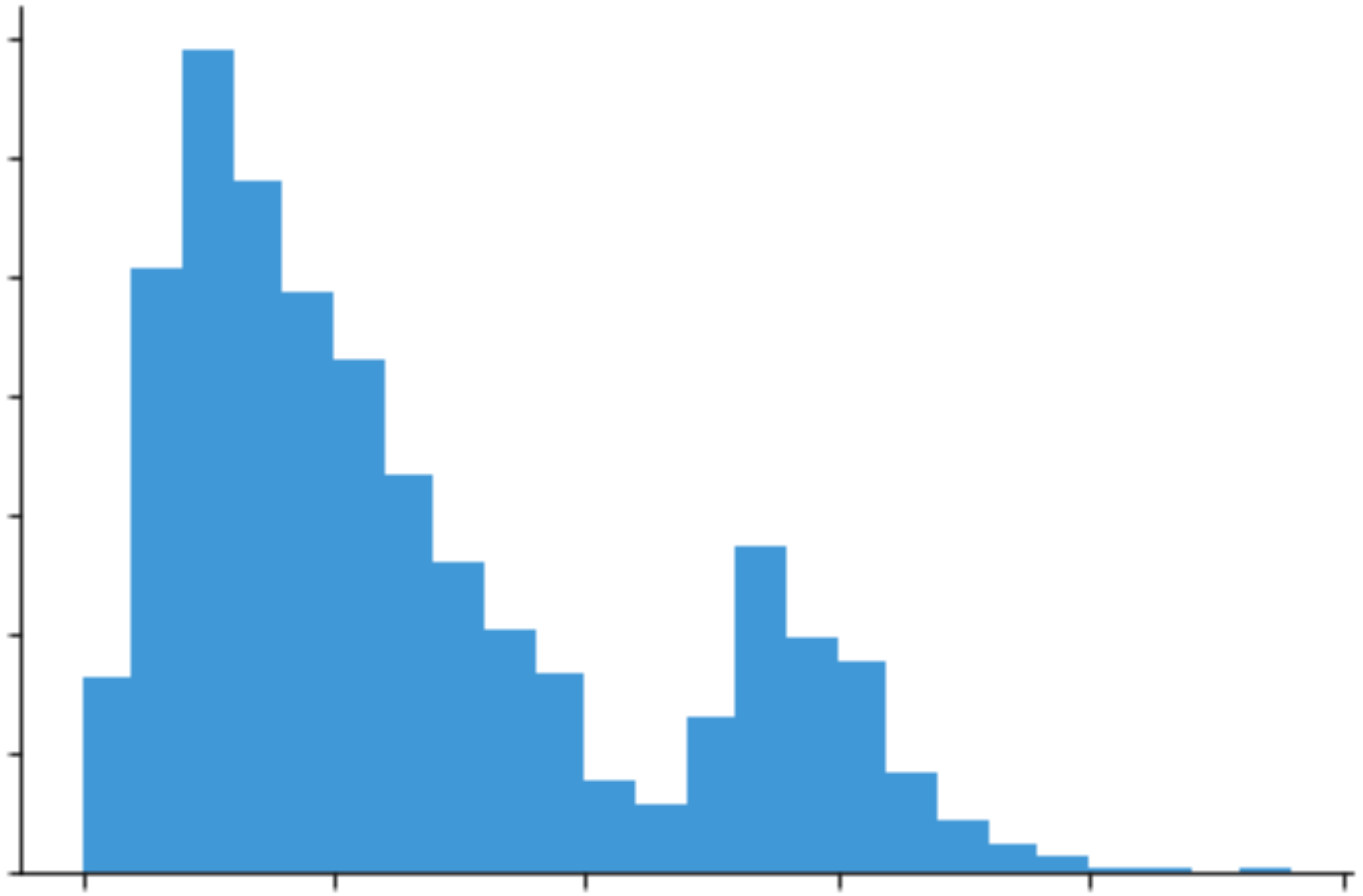
Conditional Expectation Example (cont)

- What do we mean by $p(y \mid X = 0)$? How might it differ from $p(y \mid X = 1)$



Lots of shorter books

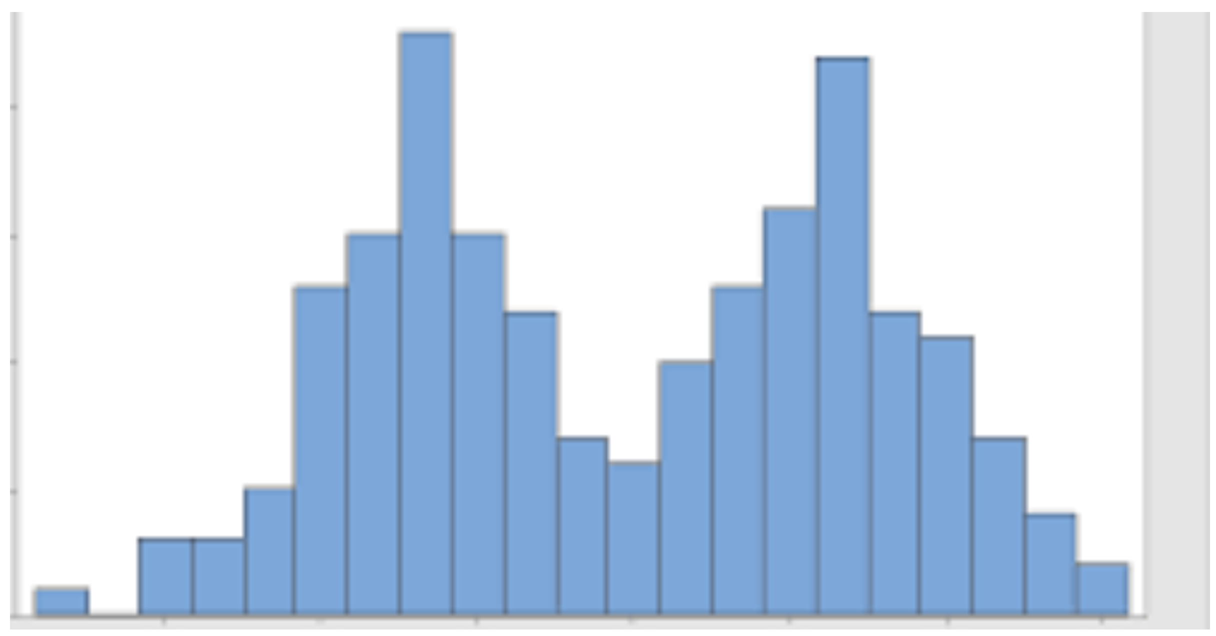
Lots of medium length books

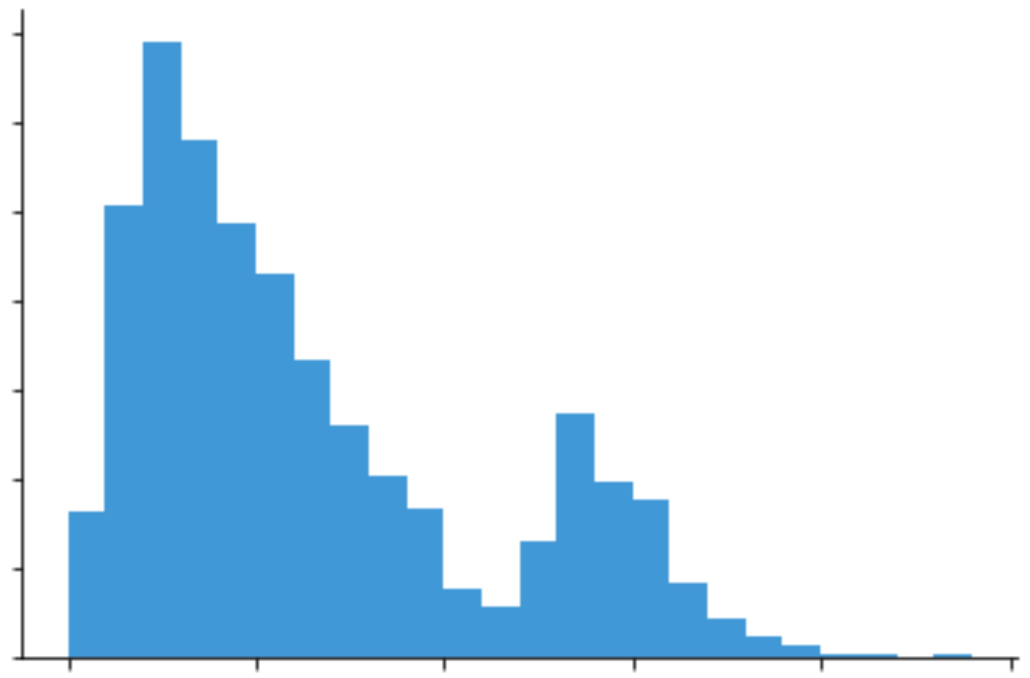


A long tail, a few very long books

Conditional Expectation Example (cont)

- What do we mean by $p(y \mid X = 0)$? How might it differ from $p(y \mid X = 1)$





- $\mathbb{E}[Y \mid X = 0]$ is the expectation over Y under distribution $p(y \mid X = 0)$
- $\mathbb{E}[Y \mid X = 1]$ is the expectation over Y under distribution $p(y \mid X = 1)$

Conditional Expectations

Definition:

The **expected value of Y conditional on $X = x$** is

$$\mathbb{E}[Y \mid X = x] = \begin{cases} \sum_{y \in \mathcal{Y}} y p(y \mid x) & \text{if } Y \text{ is discrete,} \\ \int_{\mathcal{Y}} y p(y \mid x)\, dy & \text{if } Y \text{ is continuous.} \end{cases}$$

Question: What is $\mathbb{E}[Y \mid X]$?

Properties of Expectations

- Linearity of expectation:
  - $\mathbb{E}[cX] = c\mathbb{E}[X]$ for all constant c
  - $\mathbb{E}[X + Y] = \mathbb{E}[X] + \mathbb{E}[Y]$
- Products of expectations of **independent** random variables X, Y:
  - $\mathbb{E}[XY] = \mathbb{E}[X]\mathbb{E}[Y]$
- Law of Total Expectation:
  - $\mathbb{E}\left[\mathbb{E}\left[Y \mid X\right]\right] = \mathbb{E}[Y]$
- **Question:** How would you prove these?

$$
\begin{aligned}
\mathbb{E}[Y] &= \sum_{y \in \mathcal{Y}} y p(y) && \text{def. E[Y]} \\
&= \sum_{y \in \mathcal{Y}} y \sum_{x \in \mathcal{X}} p(x, y) && \text{def. marginal distribution} \\
&= \sum_{x \in \mathcal{X}} \sum_{y \in \mathcal{Y}} y p(x, y) && \text{rearrange sums} \\
&= \sum_{x \in \mathcal{X}} \sum_{y \in \mathcal{Y}} y p(y \mid x) p(x) && \text{Chain rule} \\
&= \sum_{x \in \mathcal{X}} \left(\sum_{y \in \mathcal{Y}} y p(y \mid x) \right) p(x) \\
&= \sum_{x \in \mathcal{X}} \left(\mathbb{E}[Y \mid X = x] \right) p(x) && \text{def. E[Y | X = x]} \\
&= \sum_{x \in \mathcal{X}} \left(\mathbb{E}[Y \mid X = x] \right) p(x) \\
&= \mathbb{E}\left(\mathbb{E}[Y \mid X] \right) \blacksquare && \text{def. expected value of function}
\end{aligned}
$$

Variance

Definition: The **variance** of a random variable is

$$\text{Var}(X) = \mathbb{E}\left[(X - \mathbb{E}[X])^2\right].$$

i.e., $\mathbb{E}[f(X)]$ where $f(x) = (x - \mathbb{E}[X])^2$.

Equivalently,

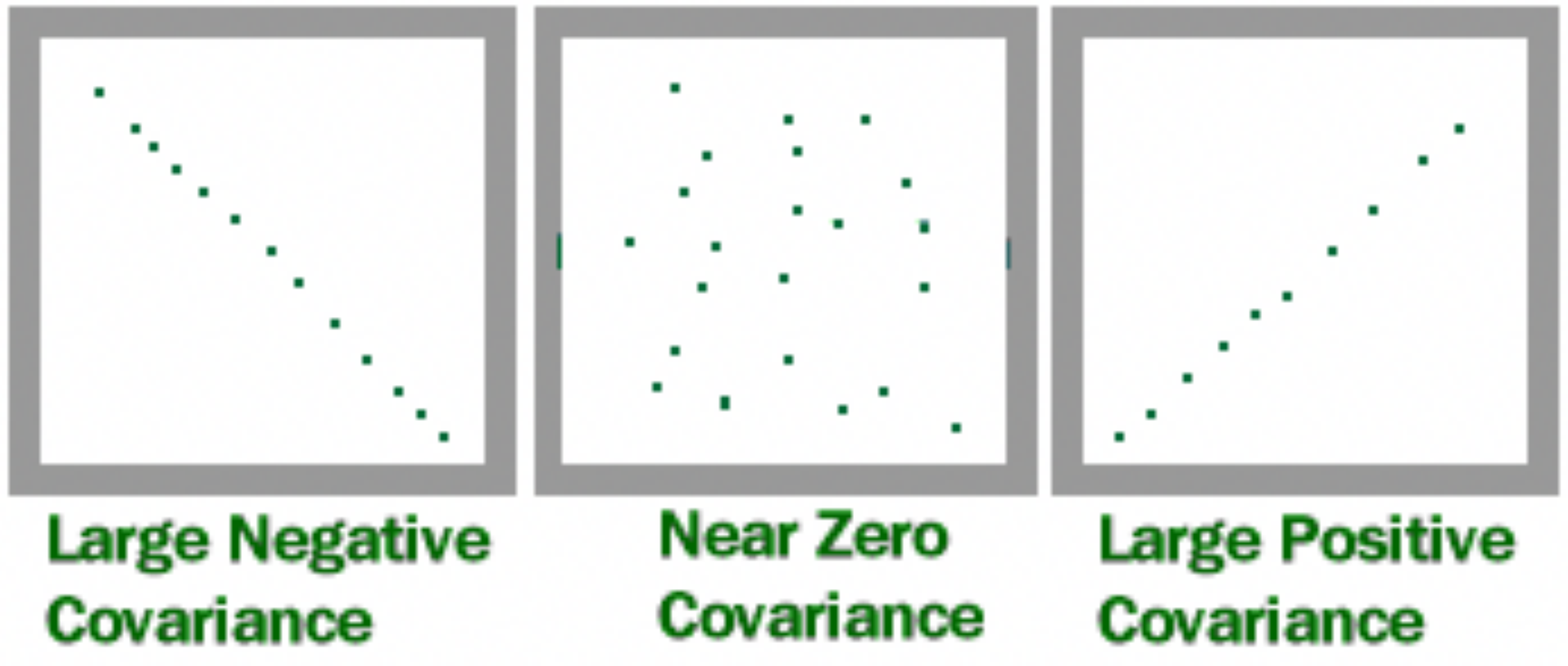
$$\text{Var}(X) = \mathbb{E}\left[X^2\right] - (\mathbb{E}[X])^2$$

(**Exercise:** Show that this is true)

Covariance

Definition: The covariance of two random variables is

$$\text{Cov}(X, Y) = \mathbb{E}\left[(X - \mathbb{E}[X])^2\right]$$
$$= \mathbb{E}[XY] - \mathbb{E}[X]\mathbb{E}[Y]\,.$$

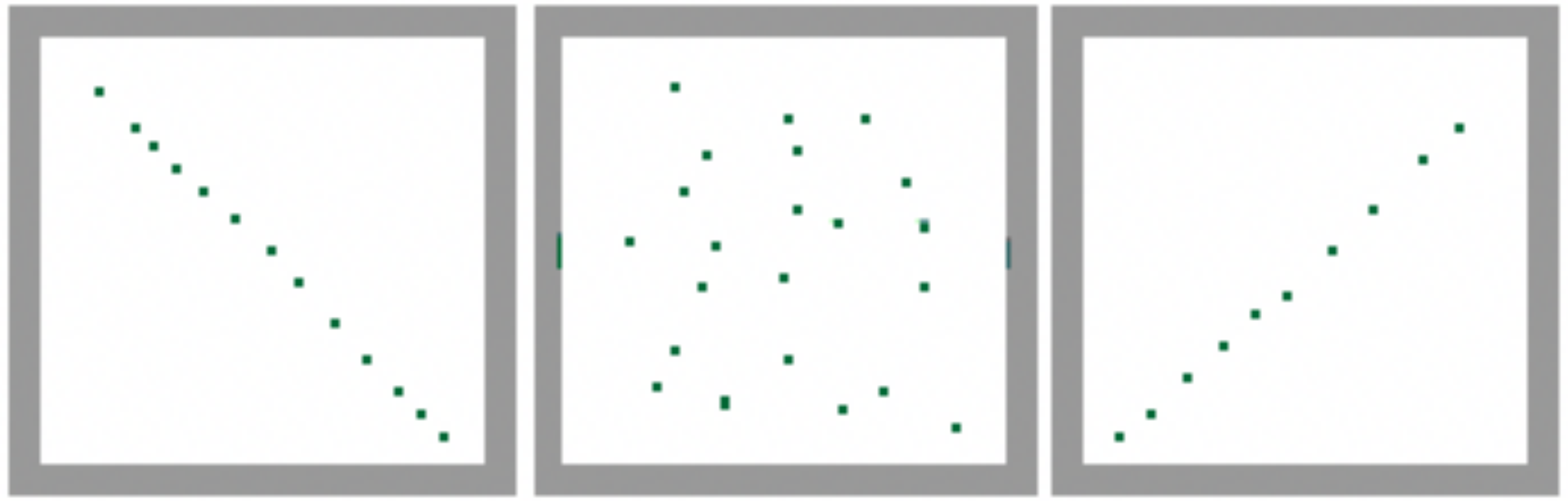


Question: What is the range of Cov(X, Y)?

Correlation

Definition: The correlation of two random variables is

$$\text{Corr}(X, Y) = \frac{\text{Cov}(X, Y)}{\sqrt{\text{Var}(X)\text{Var}(Y)}}$$



Question: What is the range of $\text{Corr}(X, Y)$?

hint: $\text{Var}(X) = \text{Cov}(X, X)$

Properties of Variances

- $\text{Var}[c] = 0$ for constant c
- $\text{Var}[cX] = c^2\text{Var}[X]$ for constant c
- $\text{Var}[X + Y] = \text{Var}[X] + \text{Var}[Y] + 2\text{Cov}[X, Y]$
- For **independent** X, Y,
  $\text{Var}[X + Y] = \text{Var}[X] + \text{Var}[Y]$ (**why?**)

Independence and Decorrelation

- Recall if X and Y are independent, then $\mathbb{E}[XY] = \mathbb{E}[X]\mathbb{E}[Y]$
- Independent RVs have zero correlation (**why?**)

  hint: Cov$[X, Y] = \mathbb{E}[XY] - \mathbb{E}[X]\mathbb{E}[Y]$

- Uncorrelated RVs (i.e., Cov$(X, Y) = 0$) **might be dependent** (i.e., $p(x, y) \neq p(x)p(y)$).
  - Correlation (**Pearson's correlation coefficient**) shows linear relationships; but can miss nonlinear relationships
  - **Example:** $X \sim$ Uniform$\{-2, -1,0,1,2\}$, $Y = X^2$
    - $\mathbb{E}[XY] = .2(-2 \times 4) + .2(2 \times 4) + .2(-1 \times 1) + .2(1 \times 1) + .2(0 \times 0)$
    - $\mathbb{E}[X] = 0$
    - So $\mathbb{E}[XY] - \mathbb{E}[X]\mathbb{E}[Y] = 0 - 0\mathbb{E}[Y] = 0$

Summary

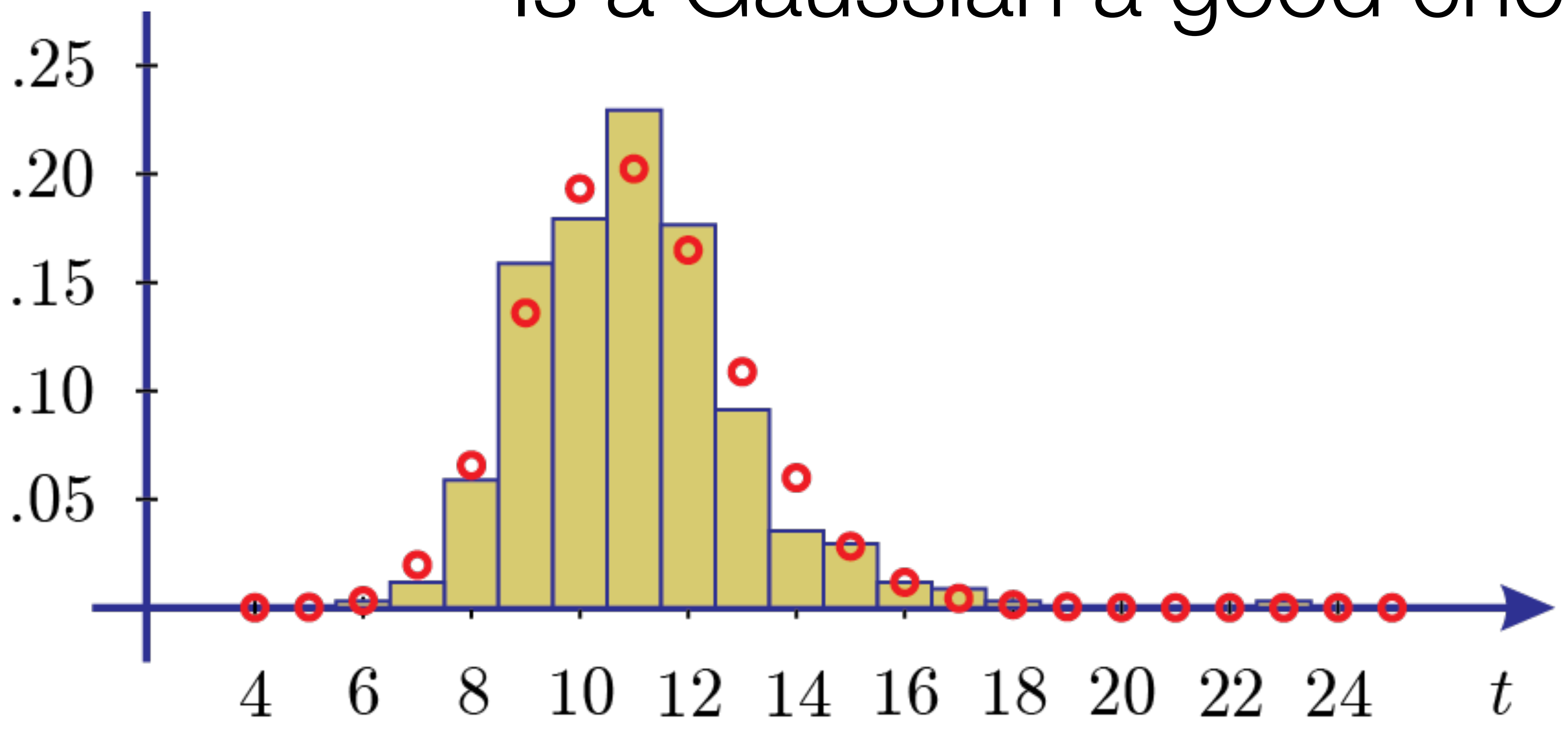
- **Random variables** takes different values with some probability
- The value of one variable can be informative about the value of another
  - Distributions of multiple random variables are described by the **joint** probability distribution (joint PMF or joint PDF)
  - You can have a new distribution over one variable when you **condition** on the other
- The **expected value** of a random variable is an **average** over its values, **weighted** by the probability of each value
- The **variance** of a random variable is the expected squared distance from the mean
- The **covariance** and **correlation** of two random variables can summarize how changes in one are informative about changes in the other.

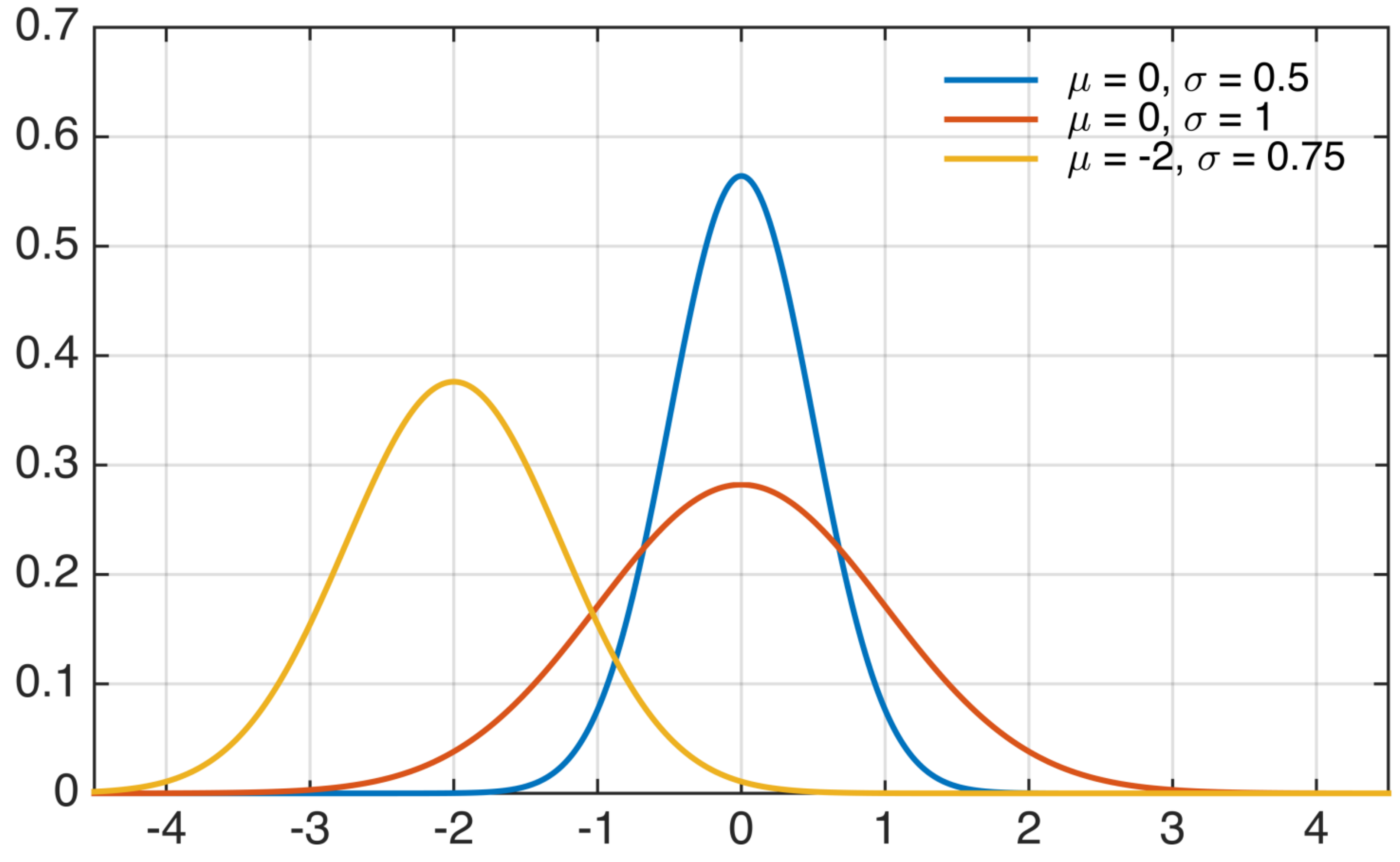
Exercise applying your knowledge

- Let's revisit the commuting example, and assume we collect continuous commute times

$$p(\omega) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2\sigma^2}(\omega-\mu)^2}$$

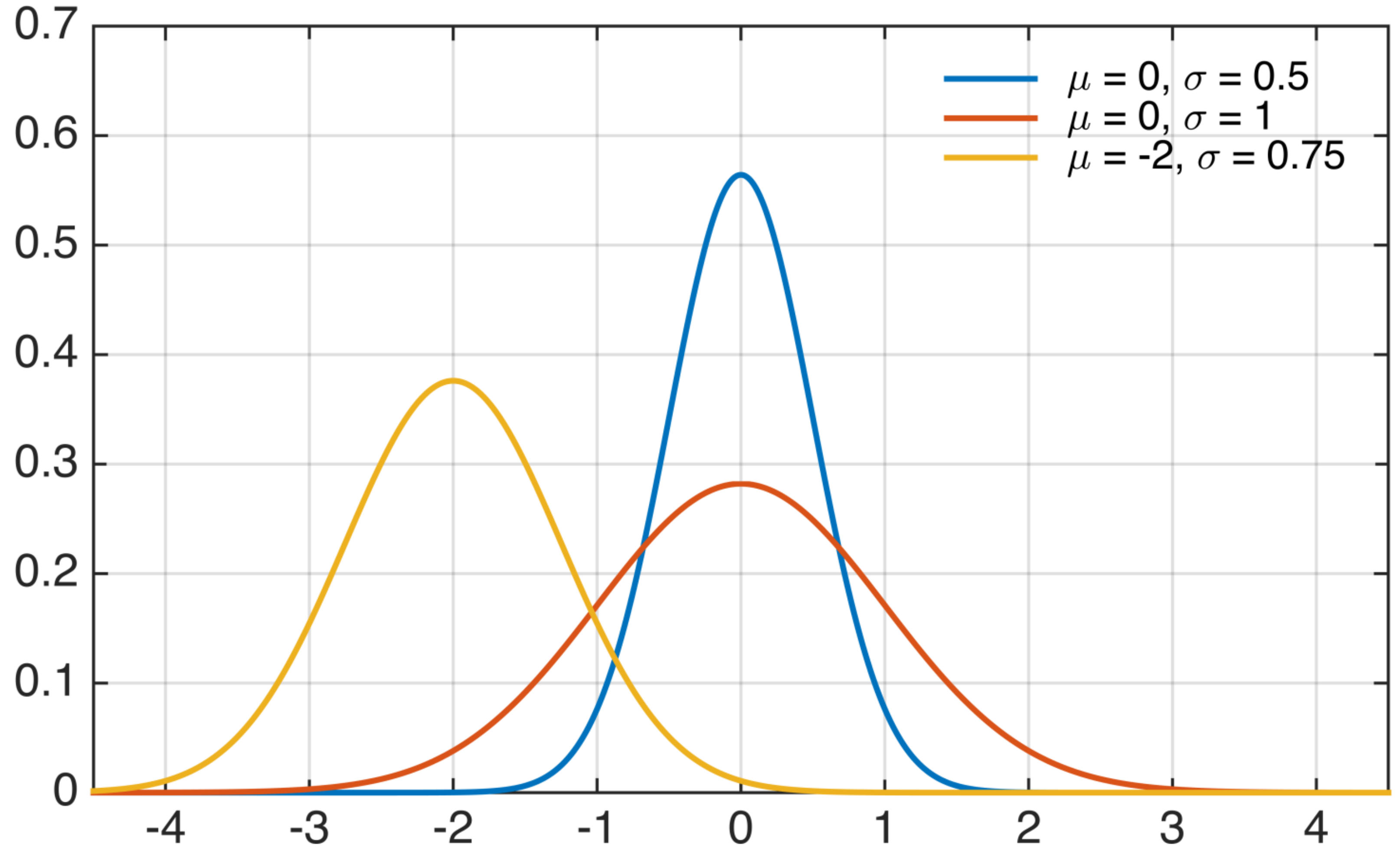
- We want to model commute time as a Gaussian
- What parameters do I have to specify (or learn) to model commute times with a Gaussian?
- Is a Gaussian a good choice?

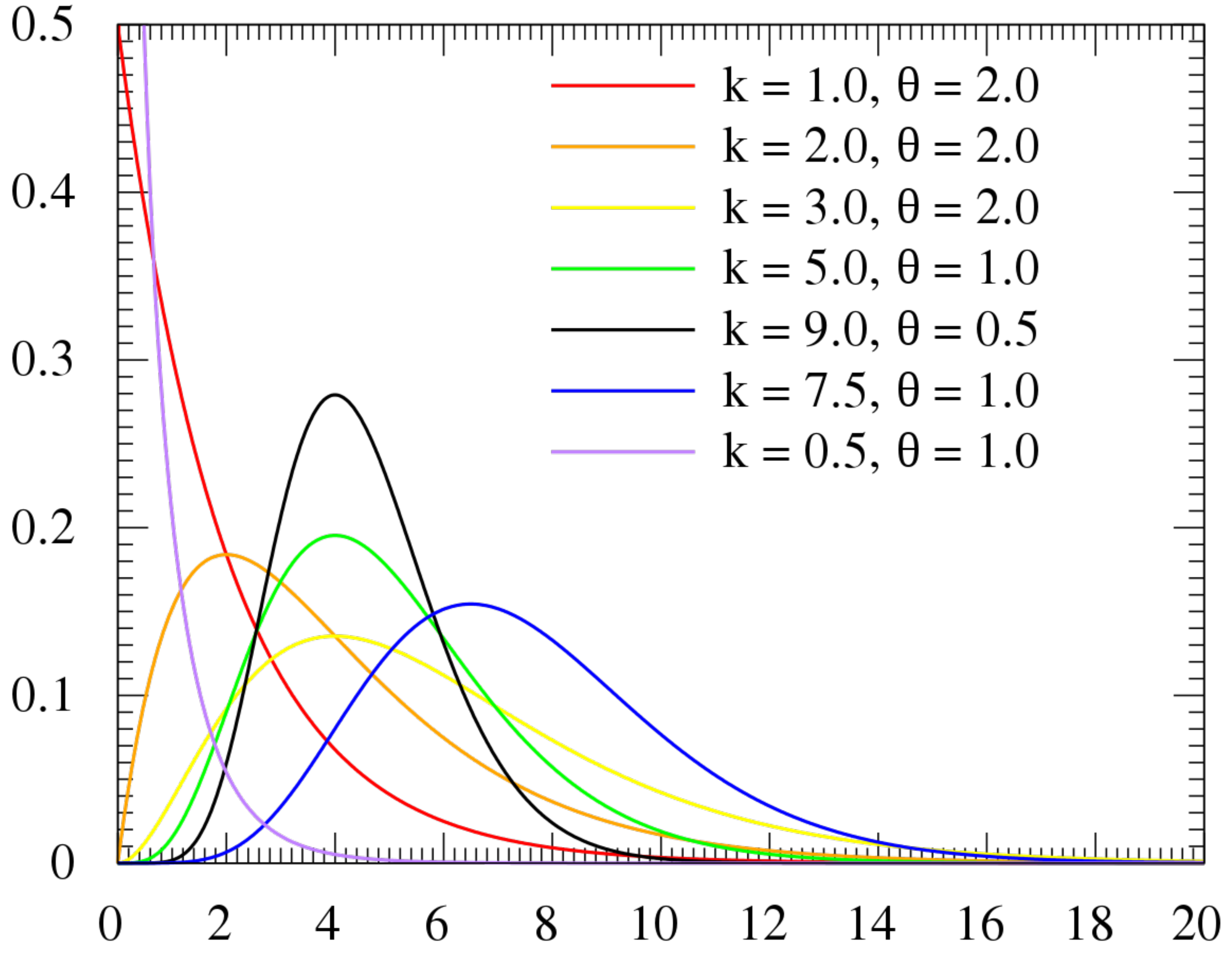


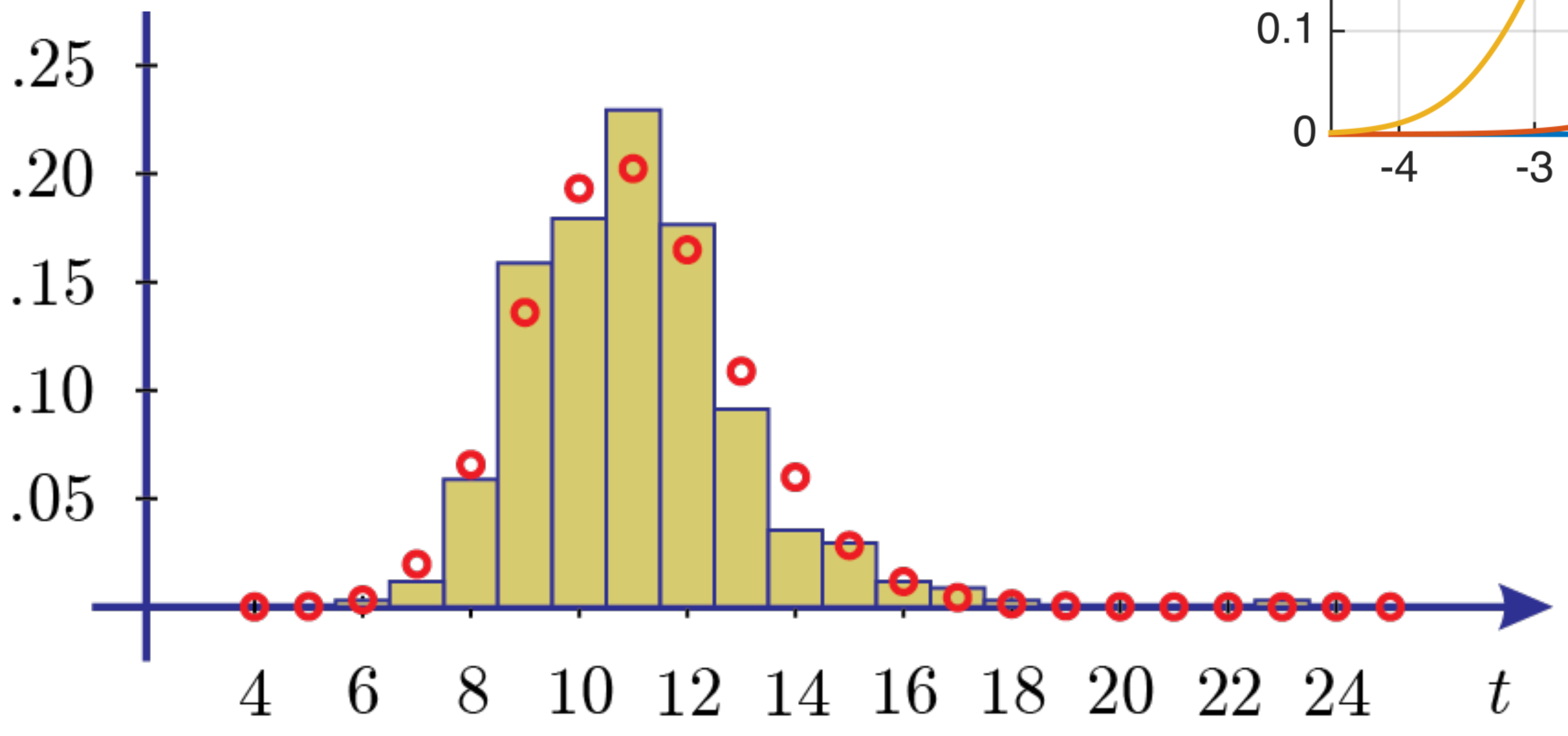


Exercise applying your knowledge

- A better choice is actually what is called a Gamma distribution

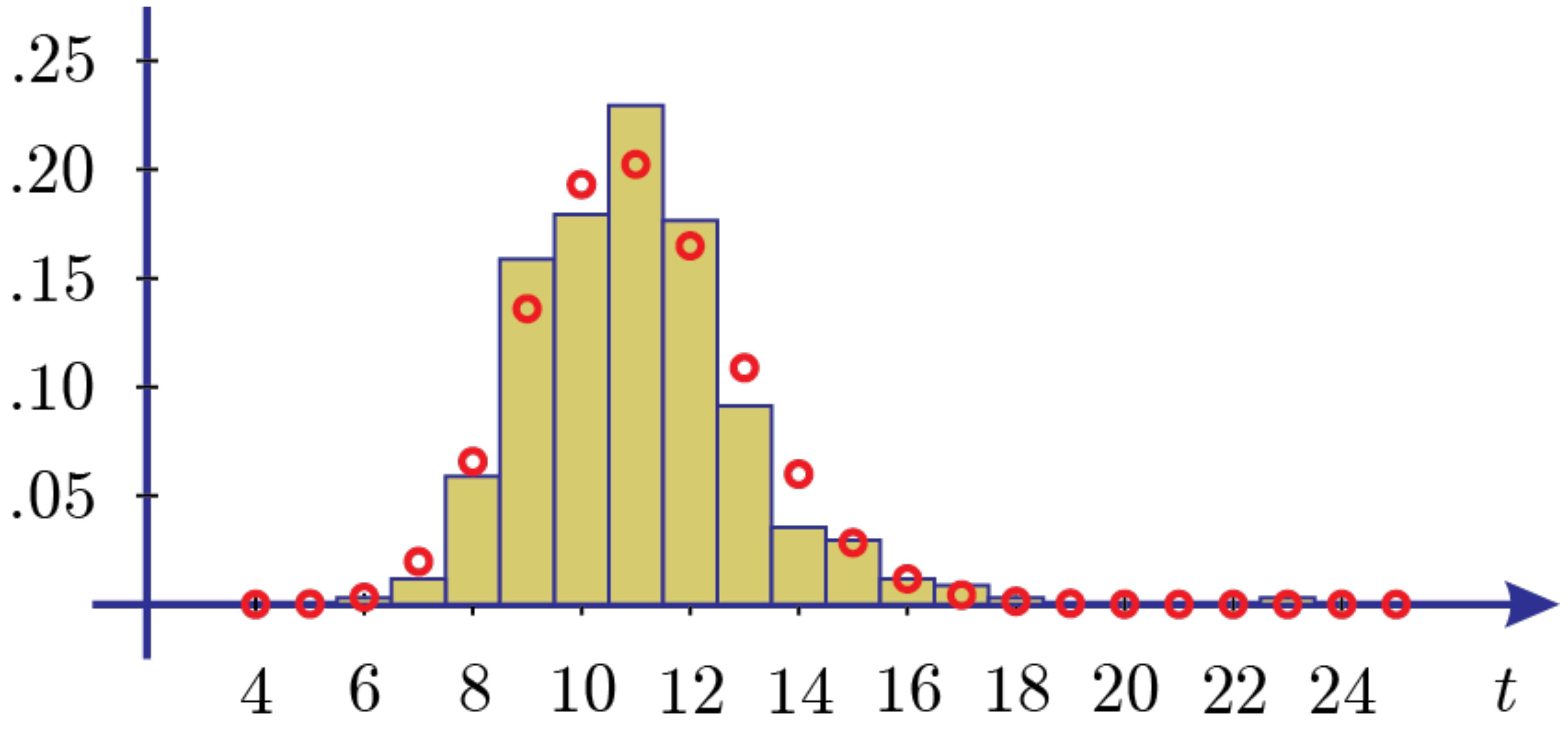






Exercise applying your knowledge

- We can also consider conditional distributions $p(y \mid x)$
- Y is the commute time, let X be the month
- Why is it useful to know $p(y \mid X = \text{Feb})$ and $p(y \mid X = \text{Sept})$?
- What else could we use for X and why pick it?

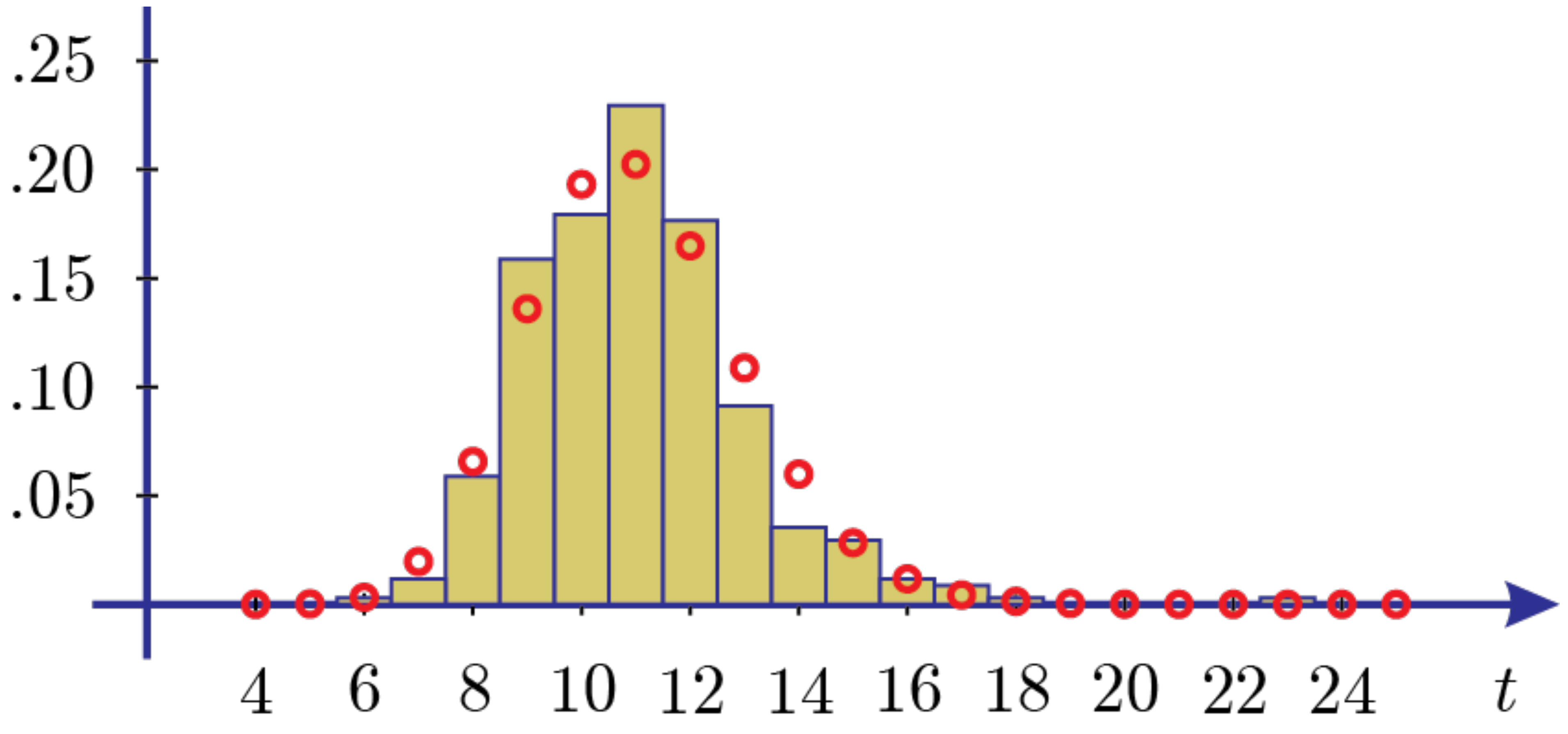


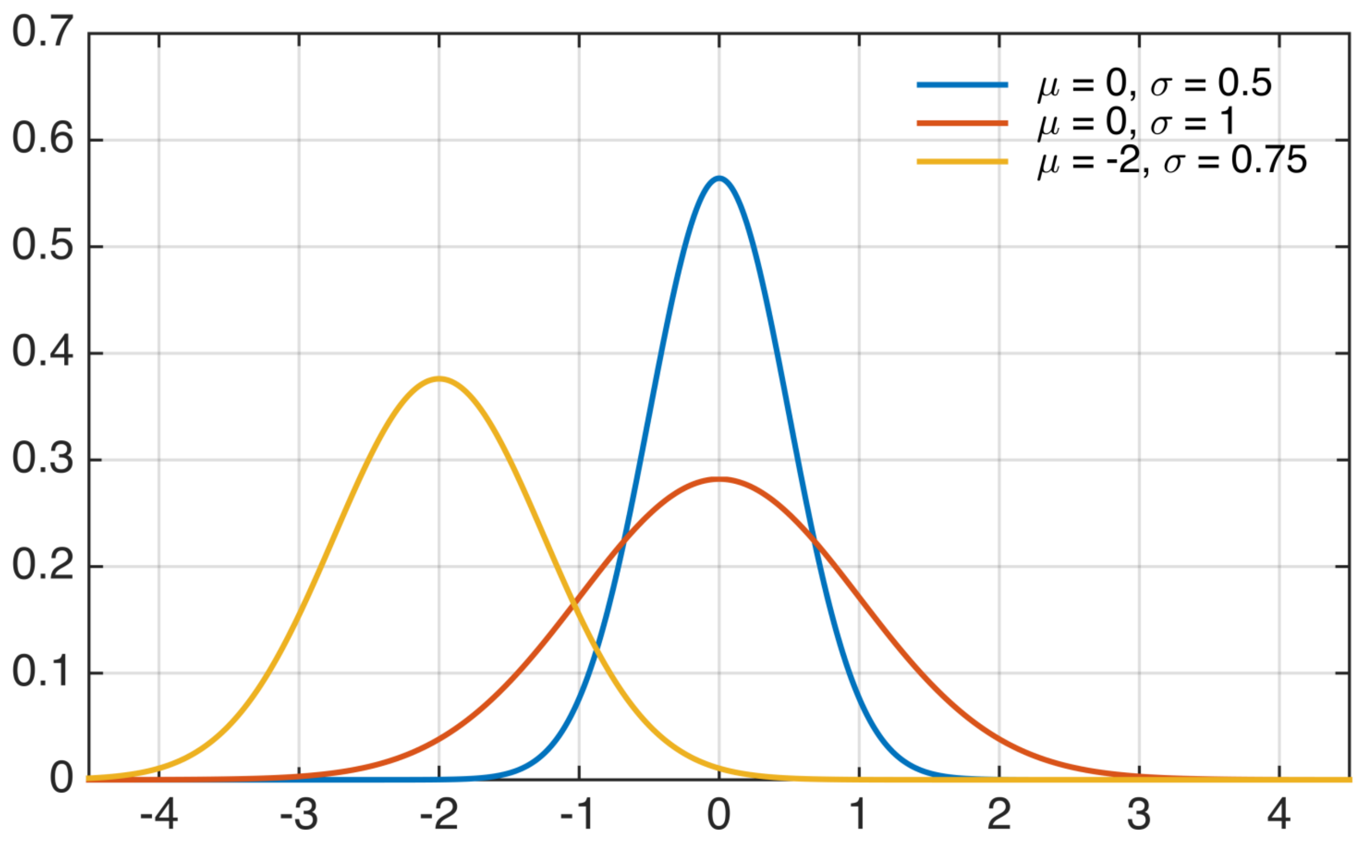
Exercise applying your knowledge

- Let use a simple X, where it is 1 if it is slippery out and 0 otherwise
- Then we could model two Gaussians, one for the two types of conditions

$$p(y|X=0) = \mathcal{N}\left(\mu_0, \sigma_0^2\right)$$
$$p(y|X=1) = \mathcal{N}\left(\mu_1, \sigma_1^2\right)$$

Gaussian denoted by N





Exercise applying your knowledge

- Eventually we will see how to model the distribution over Y using functions of other variables (features) X

$$p(y|\mathbf{x}) = \mathcal{N}\left(\mu = \sum_{j=1}^{d} w_i x_i, \sigma^2\right)$$