



Probability

Basics of probability

Example: Independent Events

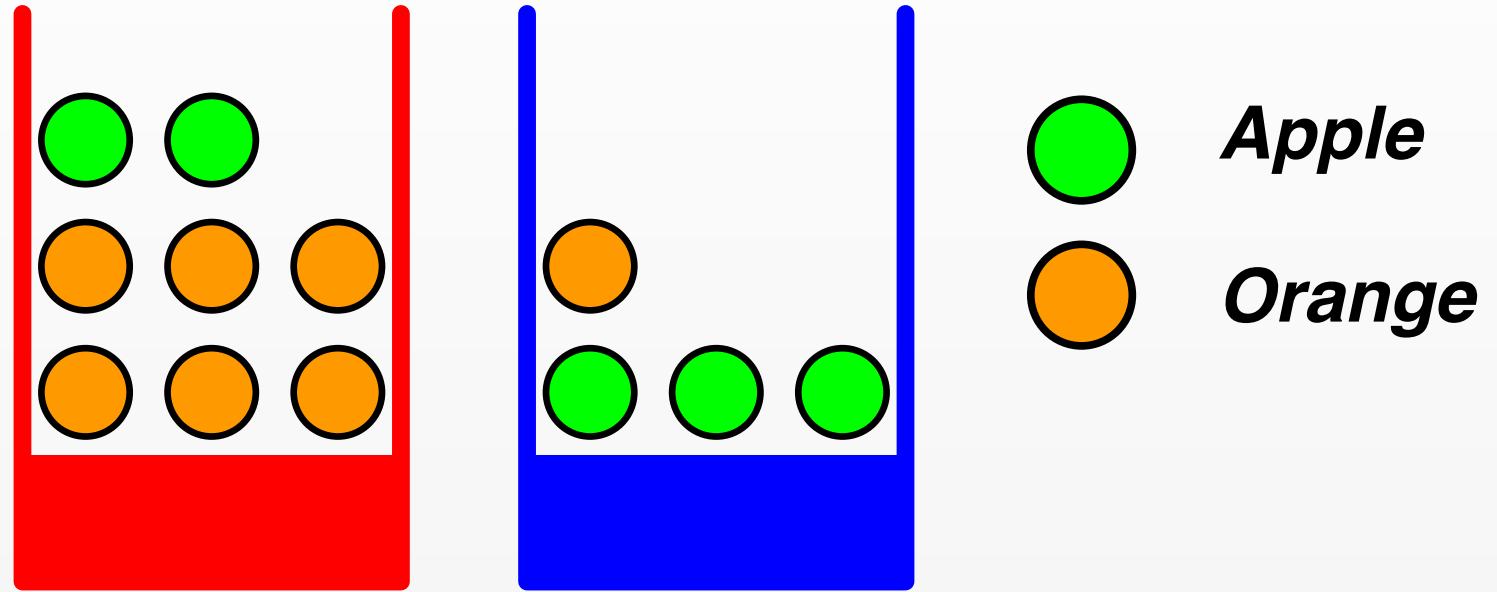
1. What's the probability of getting a sequence of 1,2,3,4,5,6 if we roll a dice six times

Answer: $(1 / 6)^6$

2. A school survey found that 9 out of 10 students like pizza. If three students are chosen at random, what is the probability that all three students like pizza

Answer: $(9 / 10)^3$

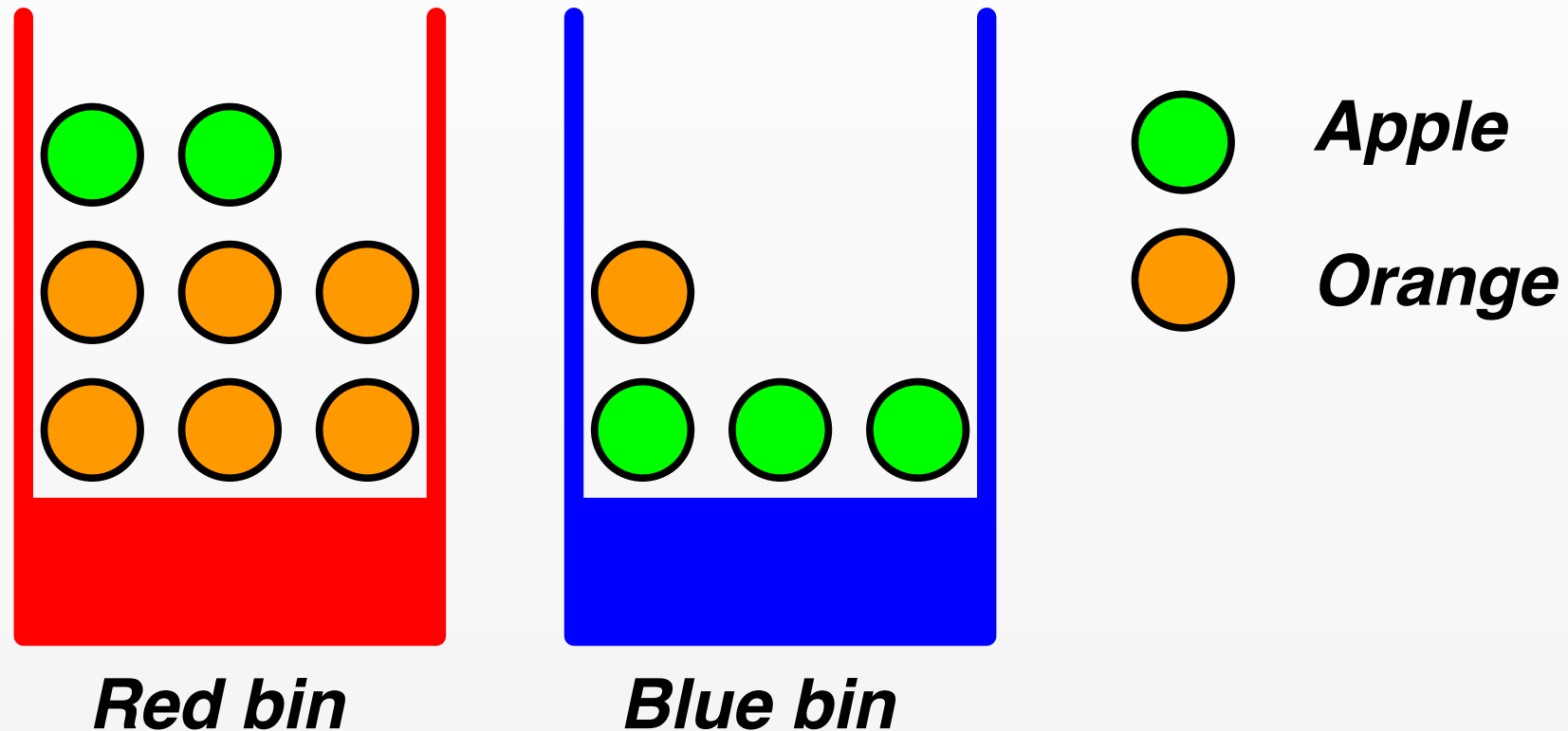
Dependent Events



What is the probability of picking an apple?

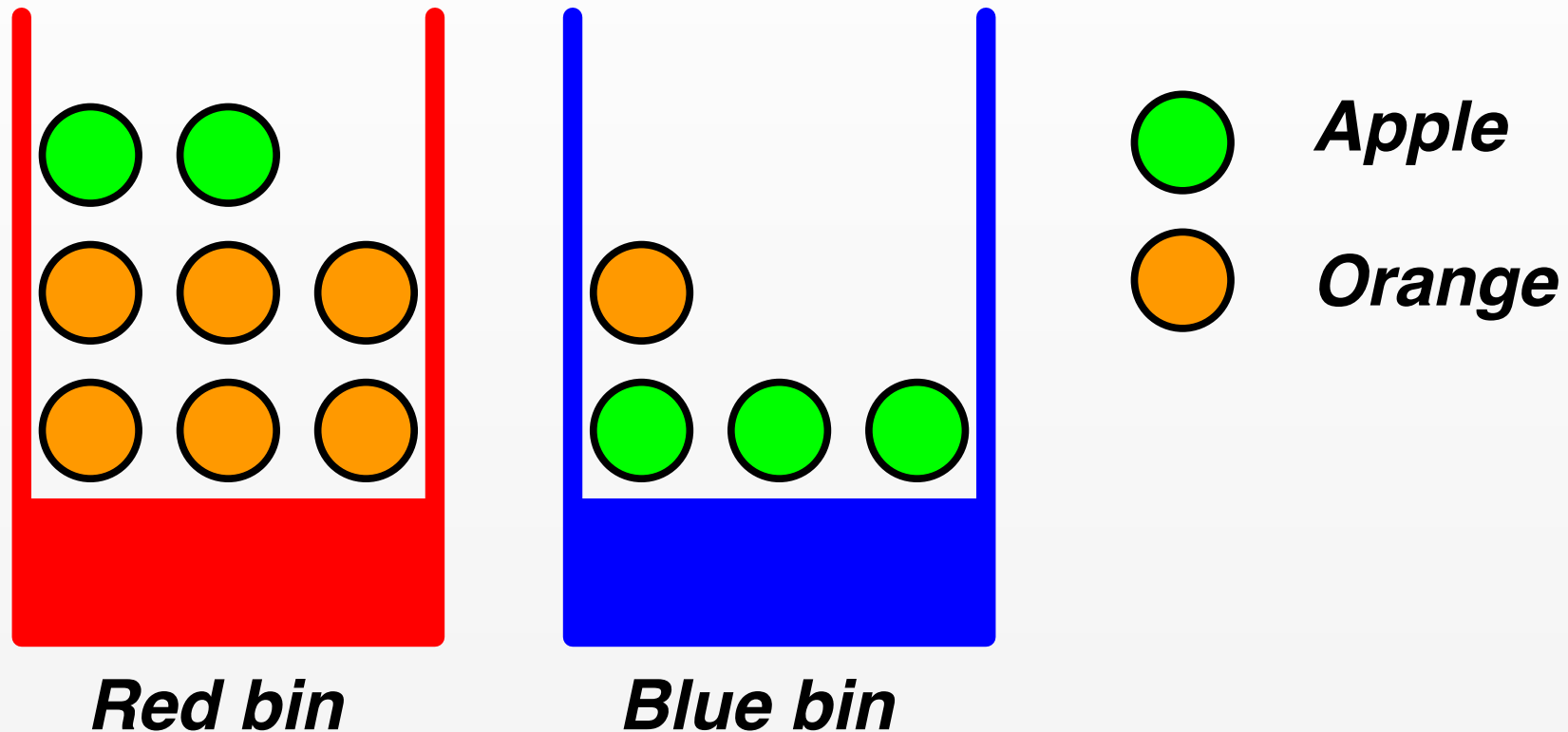
$$P(\text{fruit} = \text{apple}) = 5/12$$

Dependent Events



*If I randomly pick a fruit from the **red** bin,
what is the probability that I get an **apple**?*

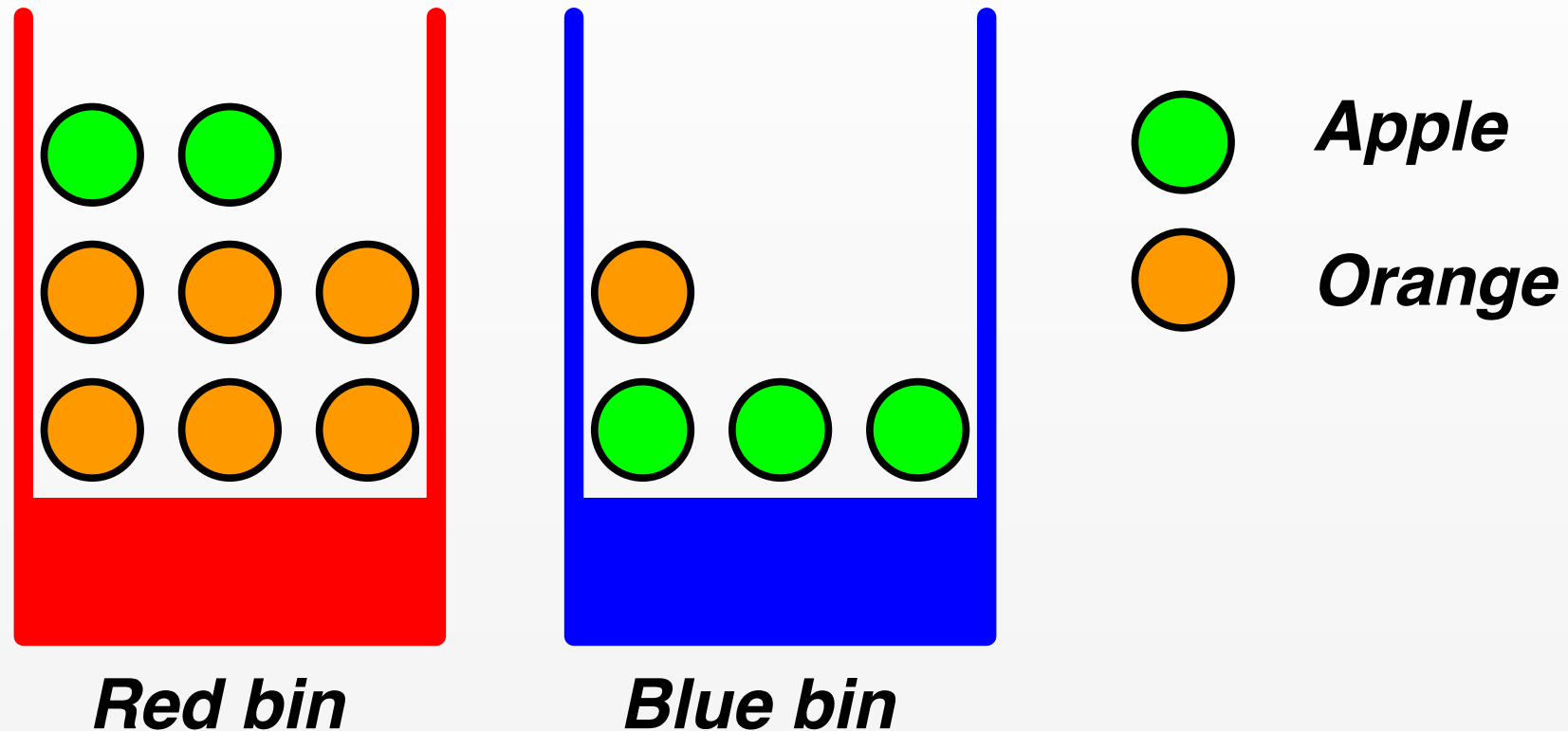
Dependent Events



Conditional Probability

$$P(\text{fruit} = \text{apple} \mid \text{bin} = \text{red}) = 2 / 8$$

Dependent Events



Conditional Probability

$$P(\text{fruit} = \text{apple} \mid \text{bin} = \text{blue}) = 3 / 4$$

Dependent Events

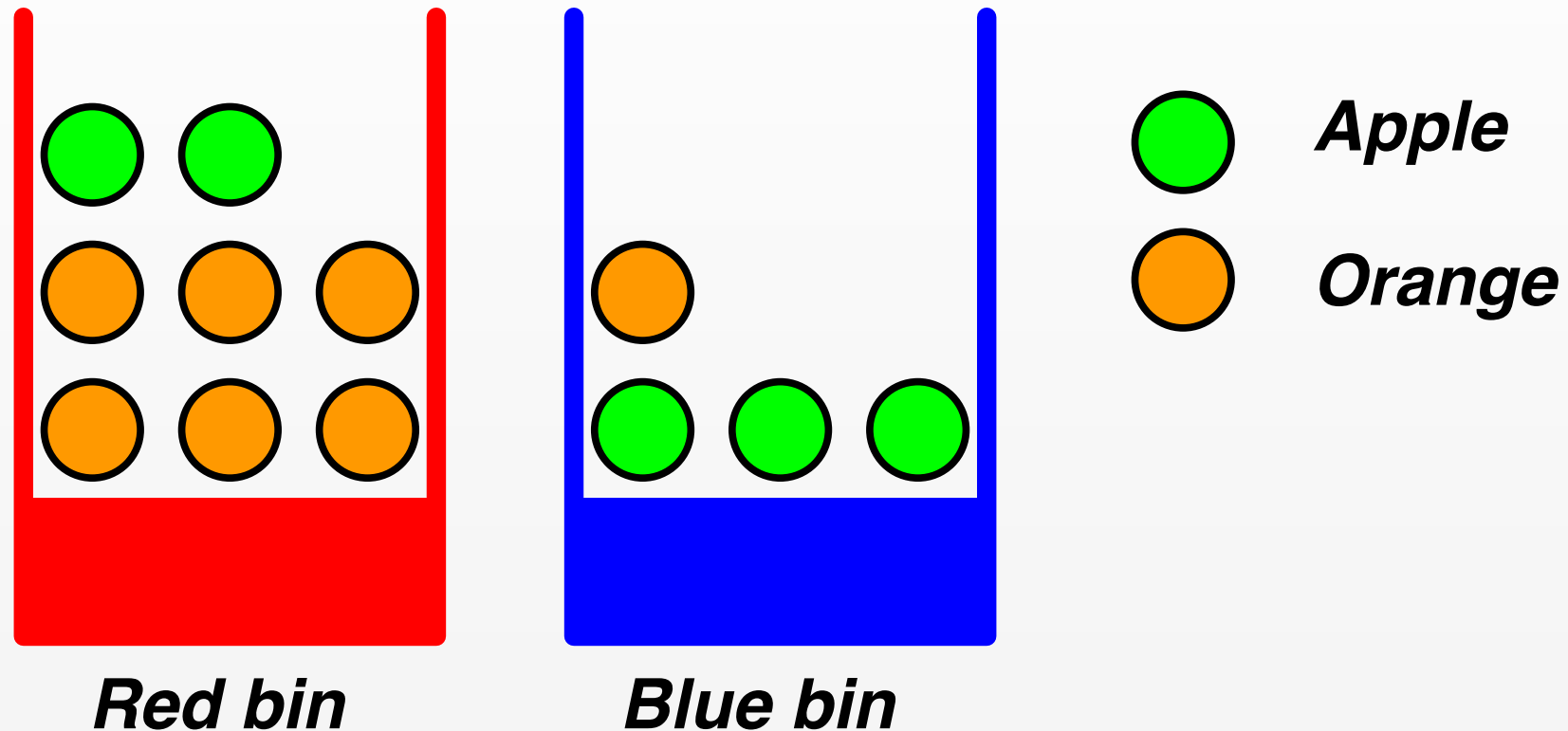
The probability of the event fruit = apple changes if we know which bin was selected.

$$P(\text{fruit} = \text{apple}) = 5/12$$

$$P(\text{fruit} = \text{apple} \mid \text{bin} = \text{red}) = 2 / 8$$

$$P(\text{fruit} = \text{apple} \mid \text{bin} = \text{blue}) = 3 / 4$$

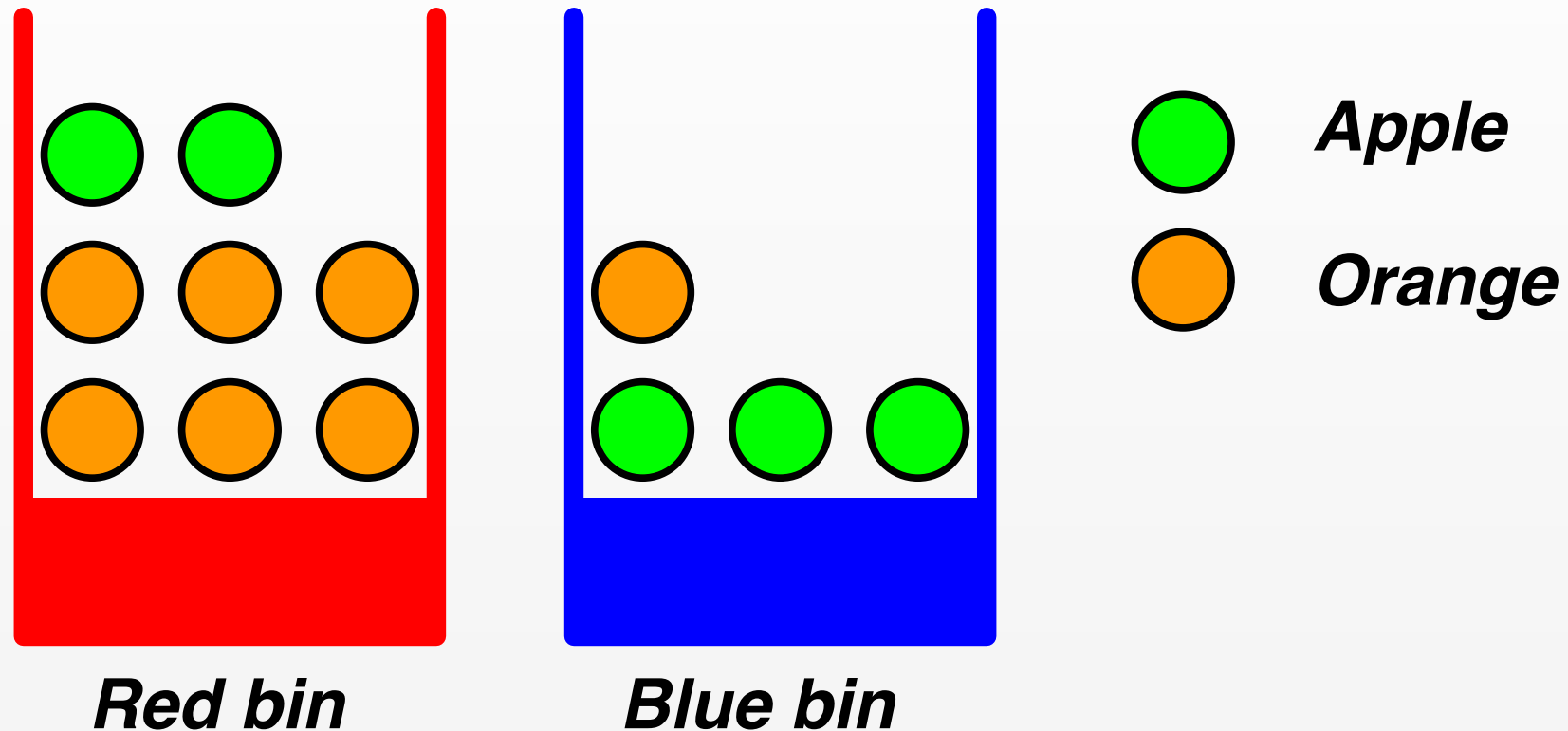
Dependent Events



Joint Probability

$$P(\text{fruit} = \text{apple}, \text{bin} = \text{red}) = 2 / 12$$

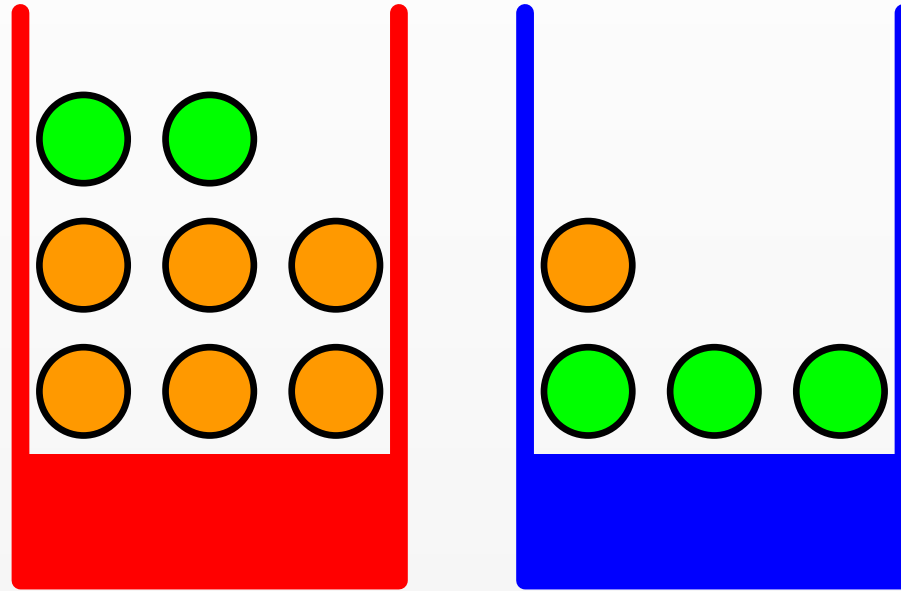
Dependent Events



Joint Probability

$$P(\text{fruit} = \text{apple}, \text{bin} = \text{blue}) = 3 / 12$$

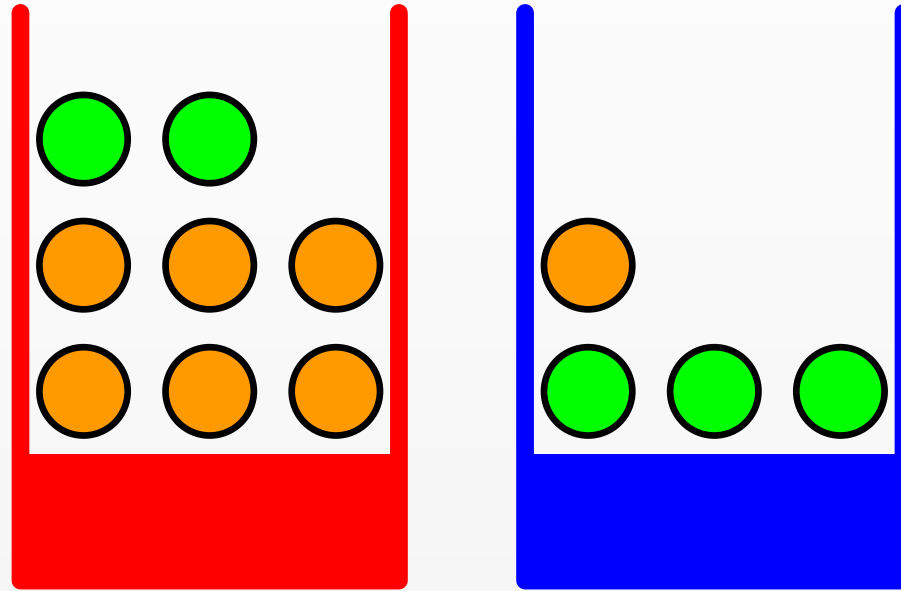
Two rules of Probability



1. Sum Rule (Marginal Probabilities)

$$\begin{aligned} P(\text{fruit} = \text{apple}) &= P(\text{fruit} = \text{apple}, \text{bin} = \text{blue}) \\ &\quad + P(\text{fruit} = \text{apple}, \text{bin} = \text{red}) \\ &= \end{aligned}$$

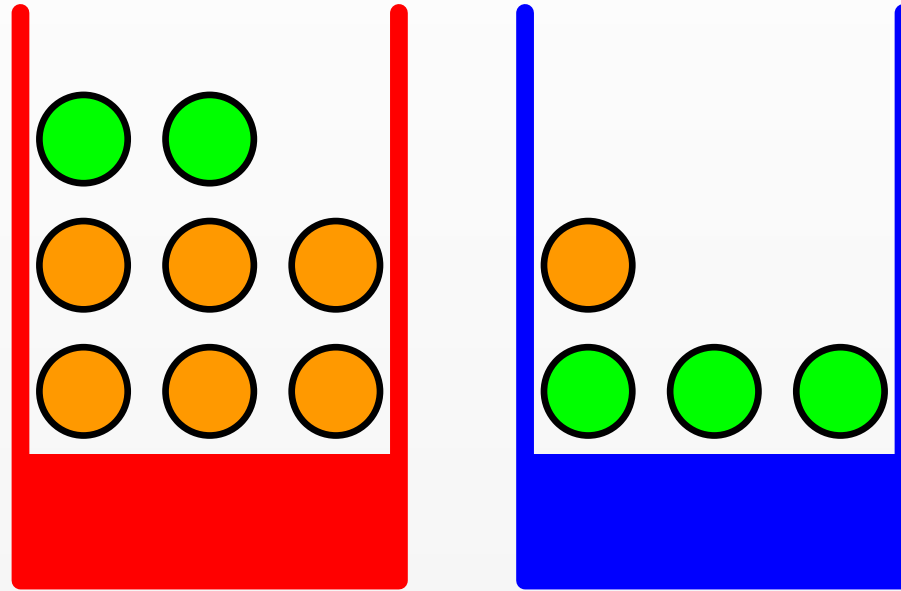
Two rules of Probability



1. Sum Rule (Marginal Probabilities)

$$\begin{aligned} P(\text{fruit} = \text{apple}) &= P(\text{fruit} = \text{apple}, \text{bin} = \text{blue}) \\ &\quad + P(\text{fruit} = \text{apple}, \text{bin} = \text{red}) \\ &= 3 / 12 + 2 / 12 = 5 / 12 \end{aligned}$$

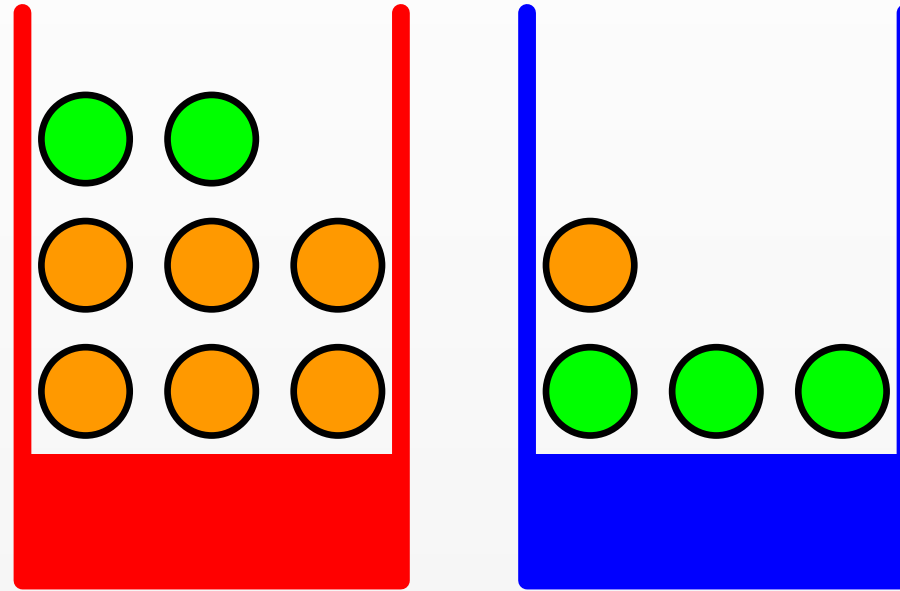
Two rules of Probability



1. Sum Rule (Marginal Probabilities)

$$\begin{aligned} P(\text{bin} = \text{red}) &= P(\text{fruit} = \text{apple}, \text{bin} = \text{red}) \\ &\quad + P(\text{fruit} = \text{orange}, \text{bin} = \text{red}) \\ &= 2 / 12 + 6 / 12 = 8 / 12 \end{aligned}$$

Two rules of Probability



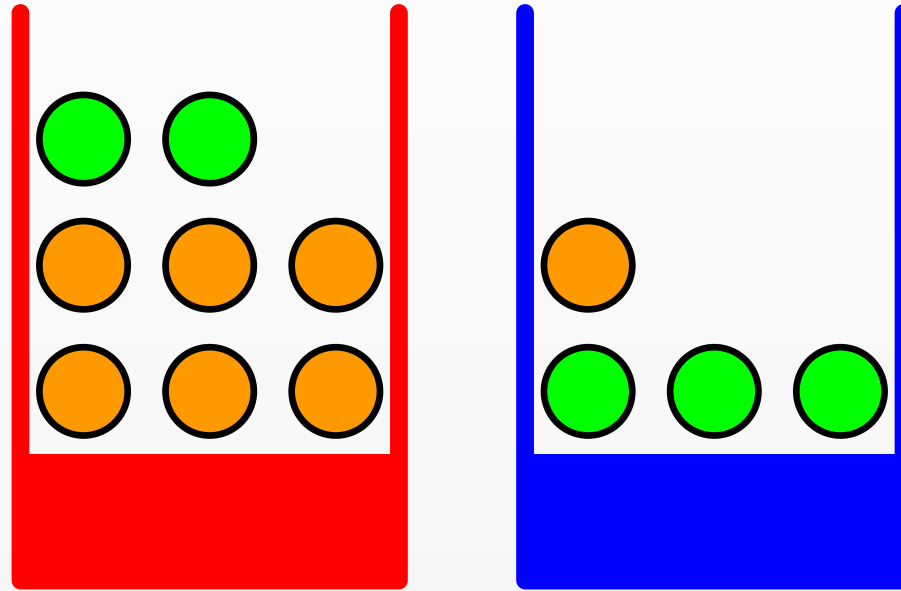
2. Product Rule

$P(\text{fruit} = \text{apple}, \text{bin} = \text{red}) =$

$P(\text{fruit} = \text{apple} \mid \text{bin} = \text{red}) p(\text{bin} = \text{red})$

$=$

Two rules of Probability



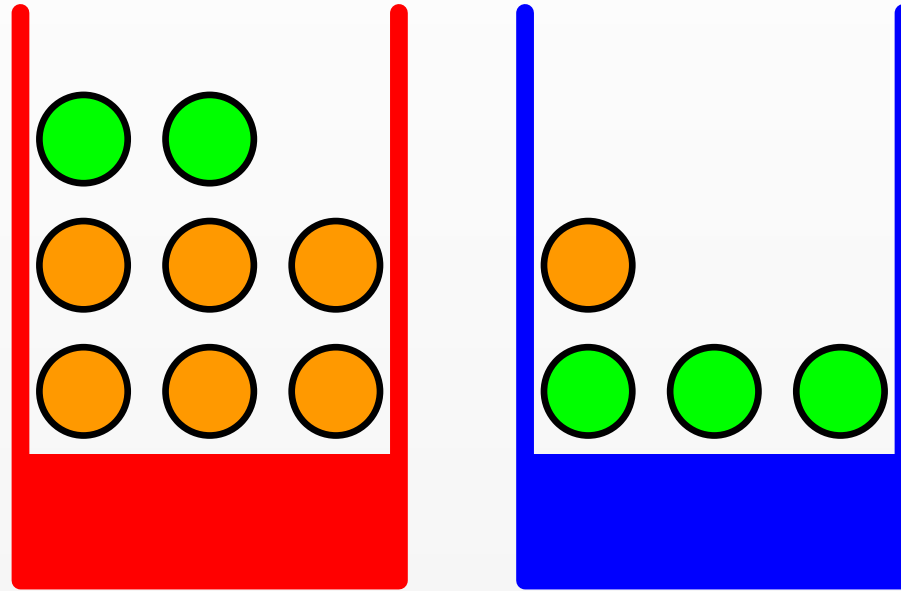
2. Product Rule

$P(\text{fruit} = \text{apple}, \text{bin} = \text{red}) =$

$P(\text{fruit} = \text{apple} \mid \text{bin} = \text{red}) \cdot p(\text{bin} = \text{red})$

$= 2 / 8 * 8 / 12 = 2 / 12$

Two rules of Probability



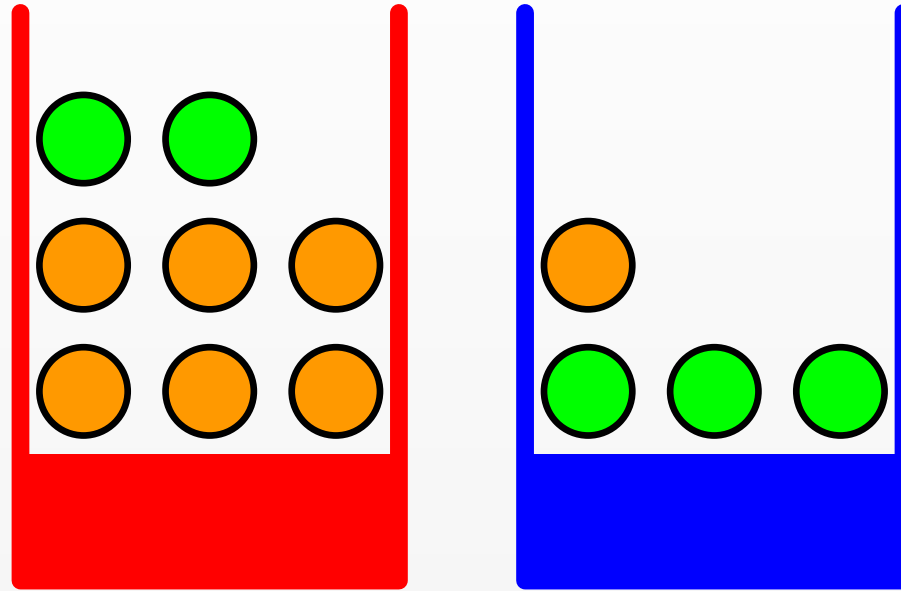
2. Product Rule (reversed)

$$P(\text{fruit} = \text{apple}, \text{bin} = \text{red}) =$$

$$P(\text{bin} = \text{red} \mid \text{fruit} = \text{apple}) p(\text{fruit} = \text{apple})$$

=

Two rules of Probability



2. Product Rule (reversed)

$$P(\text{fruit} = \text{apple}, \text{bin} = \text{red}) =$$

$$P(\text{bin} = \text{red} \mid \text{fruit} = \text{apple}) p(\text{fruit} = \text{apple})$$

$$= 2 / 5 * 5 / 12 = 2 / 12$$



Probability

Random variables Measures and Densities

Probability Measures

Definition: A probability space (Ω, \mathcal{F}, P) consists of

- A sample space Ω (i.e. the set of *outcomes*)
- A set of events \mathcal{F} (i.e. the set possible sets)
- A probability measure P (maps events to probabilities)

Axioms of Probability

$$P : \mathcal{F} \rightarrow [0,1] \quad P(E) \geq 0 \quad \forall E \in \mathcal{F} \quad P(\Omega) = 1$$

$$P(E_1 \cup E_2) = P(E_1) + P(E_2) \text{ when } E_1 \cap E_2 = \emptyset$$

Axiom that can be derived
from the basic axioms

$$P(E) = 1 - P(\neg E)$$

Complement of E

$$P(E_1 \cup E_2) = P(E_1) + P(E_2) - P(E_1 \cap E_2)$$

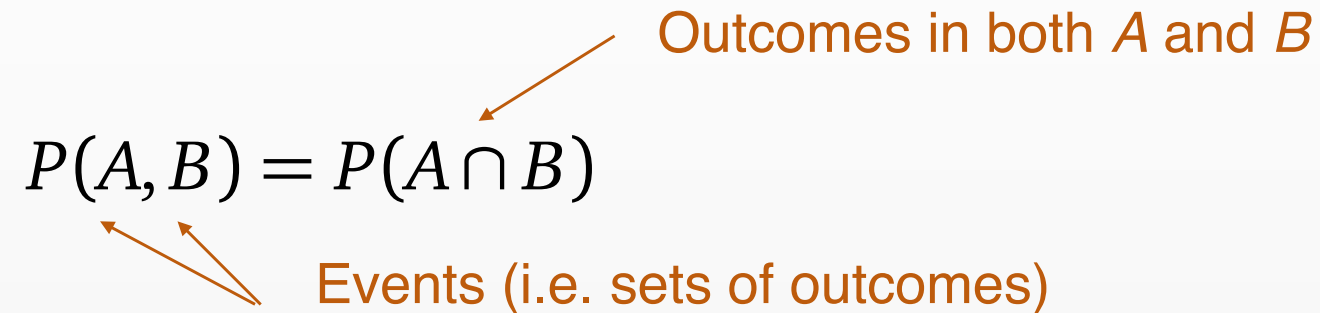
Joint and Conditional Probability

- **Definition:** Joint Probability

$$P(A, B) = P(A \cap B)$$

Outcomes in both A and B

Events (i.e. sets of outcomes)



- **Definition:** Conditional Probability

$$P(A | B) = \frac{P(A, B)}{P(B)}$$

The product rule can be derived from this formulae

Random Variables

- Gives a language to talk about probability of events.
- *Formalizes the relationship between two probability spaces.*
- *Allows expressing joint and conditional probabilities of events in different probability spaces.*

Random Variables

- **Random Variable:** A variable that takes value in the sample space $\Omega = \{1,2,3,4,5,6\}$

$$X \in \Omega$$

- **Event:** A set of *outcomes*

$$X \geq 3 \quad \{3, 4, 5, 6\}$$

$$X = 5 \quad \{5\}$$

- **Probability:** The chance that a randomly selected *outcome* is part of an *event*

$$P(X \geq 3) = 4 / 6$$

Random Variables

- **Define random variable**

$$Z : \Omega \rightarrow \{0,1\}$$

$$Z = \begin{cases} 1 & X \text{ is even} \\ 0 & X \text{ is odd} \end{cases}$$

- **Sample Space:**

$$\Omega_Z = \{0,1\}$$

- **Probability:** The chance that a randomly selected *outcome* is part of an *event*

$$P(Z = 1) = P(X \in \{2,4,6\}) = 3/6$$

Dependence of random variables

- *Joint probabilities of events in different probability spaces*

$$\begin{aligned}P(X = 2, Z = 1) &= P(X \in \{2\}, X \in \{2, 4, 6\}) \\&= P(X \in \{2\} \cap \{2, 4, 6\}) \\&= 1/6\end{aligned}$$

- *Conditional probabilities of events in different probability spaces*

$$\begin{aligned}P(X = 2 | Z = 1) &= P(X \in \{2\} | X \in \{2, 4, 6\}) \\&= P(X \in \{2\} \cap \{2, 4, 6\}) / P(X \in \{2, 4, 6\}) \\&= (1/6) / (3/6) \\&= 1/3\end{aligned}$$

Distribution

- Commonly used (or abused) shorthands:

Full Expression	Shorthand 1	Shorthand 2	Shorthand 3
$P(X \in E)$		$P_X(E)$	$P(E)$
$P(X \in \{x\})$	$P(X = x)$	$P_X(x)$	$P(x)$
$P(X \in [x, \infty])$	$P(X \geq x)$		
$P(X \in [x_1, x_2])$	$P(x_1 \leq X \leq x_2)$		

Bayes' Rule

Rules for singleton events

- Let X and Z be two random variables.
- Let Ω_X be the sample space of X .
- Let Ω_Z be the sample space of Z .

Sum rule

$$P(x) = \sum_{z \in \Omega_Z} P(x, z)$$

$$P(z) = \sum_{x \in \Omega_X} P(x, z)$$

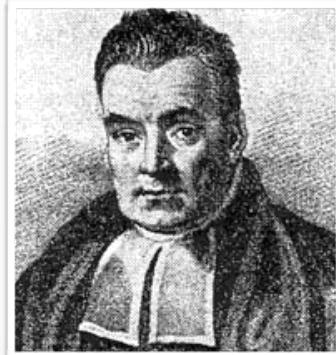
Product rule

$$P(x, z) = P(x | z)P(z) = P(z | x)P(x)$$

Bayes' rule

$$P(z | x) = \frac{P(x | z)P(z)}{P(x)}$$

Bayes' Rule



$$P(\underset{\text{Posterior}}{z} \mid \underset{\text{Likelihood}}{x}) = \frac{P(\underset{\text{Prior}}{x \mid z})P(z)}{P(x)}$$

$$\Omega_X = \{d, \neg d\}$$

$$\Omega_Z = \{t, \neg t\}$$

$P(d)$ *Probability of rare disease: 0.005*

$P(t \mid d)$ *Probability of detection: 0.98*

$P(t \mid \neg d)$ *Probability of false positive: 0.05*

$P(d \mid t)$ *Probability of disease when test positive?*

Bayes' Rule

$$\begin{aligned}P(d, t) &= P(t | d)P(d) \\&= 0.98 \times 0.005 \\&\approx 0.005\end{aligned}$$

$$\begin{aligned}P(\neg d, t) &= P(t | \neg d)P(\neg d) \\&= 0.05 \times 0.995 \\&\approx 0.05\end{aligned}$$

Product rule

$$\begin{aligned}P(t) &= P(t, d) + P(t, \neg d) \\&= 0.98 \times 0.005 \\&\approx 0.055\end{aligned}$$

Sum rule

$$P(d) = 0.005$$

$$P(t | d) = 0.98$$

$$P(t | \neg d) = 0.05$$

$$\begin{aligned}P(d | t) &= P(t | d)P(d)/P(t) \\&\approx 0.005/0.055 \\&= 0.09\end{aligned}$$

Bayes' rule

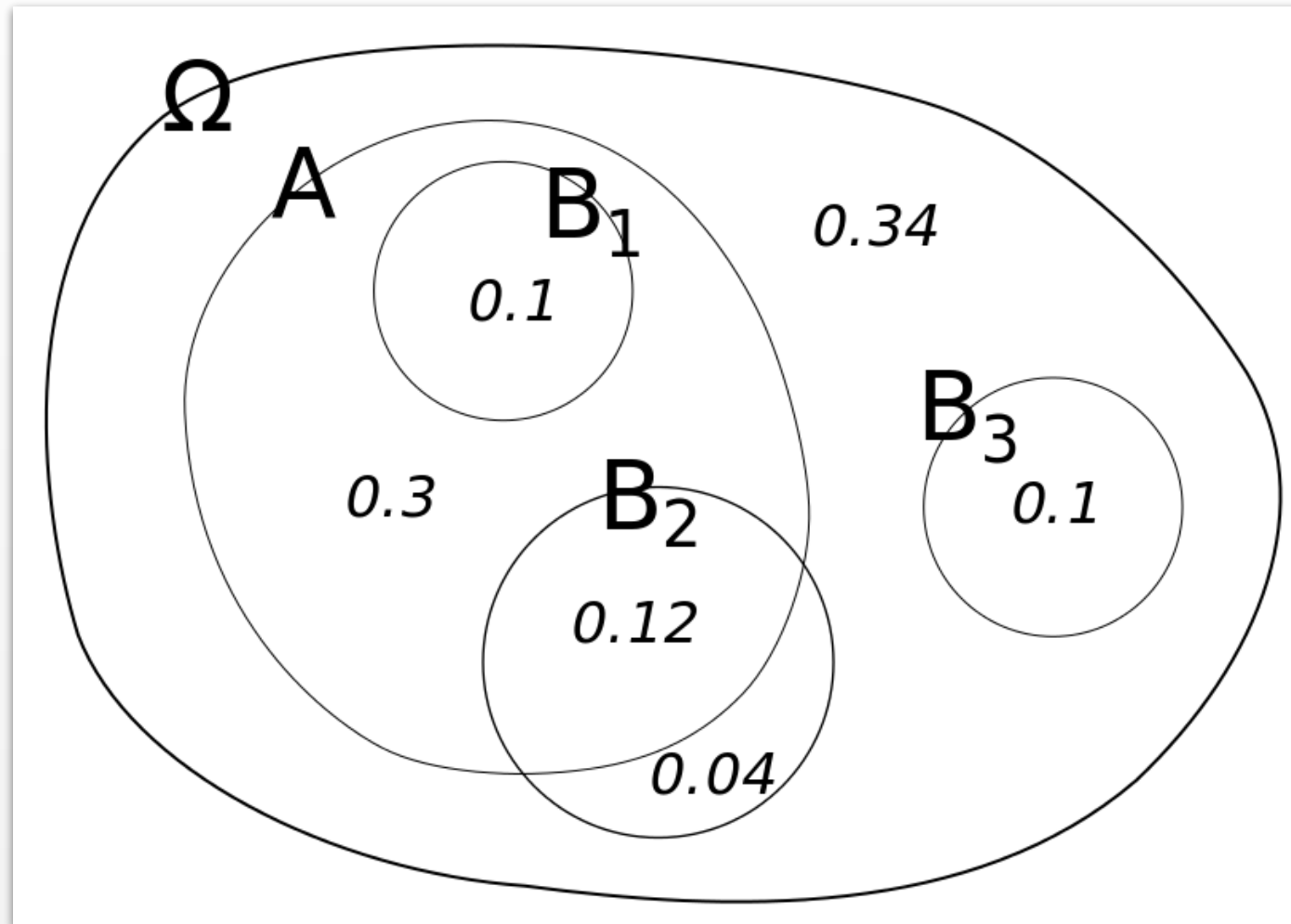
$$P(\textcolor{red}{z} | \textcolor{green}{x}) = \frac{P(\textcolor{green}{x} | \textcolor{red}{z})P(\textcolor{red}{z})}{P(\textcolor{green}{x})}$$

Probability Mass Function (pmf)

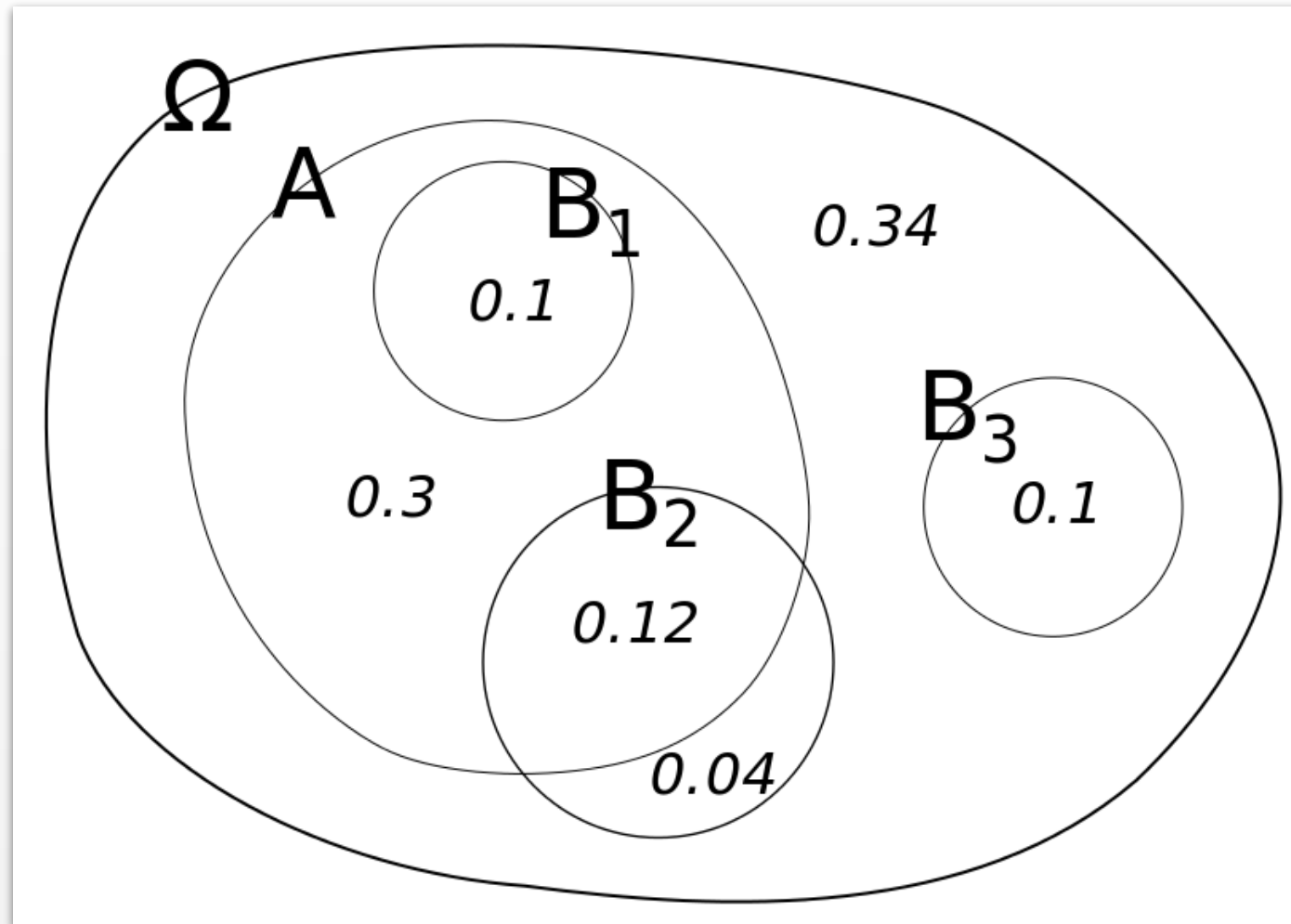
Assigns probability to each outcome of a discrete sample space.

- $P : \Omega \rightarrow [0,1]$
- Technically, it is different from the probability measure which assigns probability to a subset of Ω , instead of an element.
- However, it is same as the probability measure on a singleton set.
- We use the same notation for pmf and the corresponding probability measure.
- Dice roll: $P(1) = P(2) = P(3) = P(4) = P(5) = P(6) = 1/6$

Conditional Probability: Continuous distributions

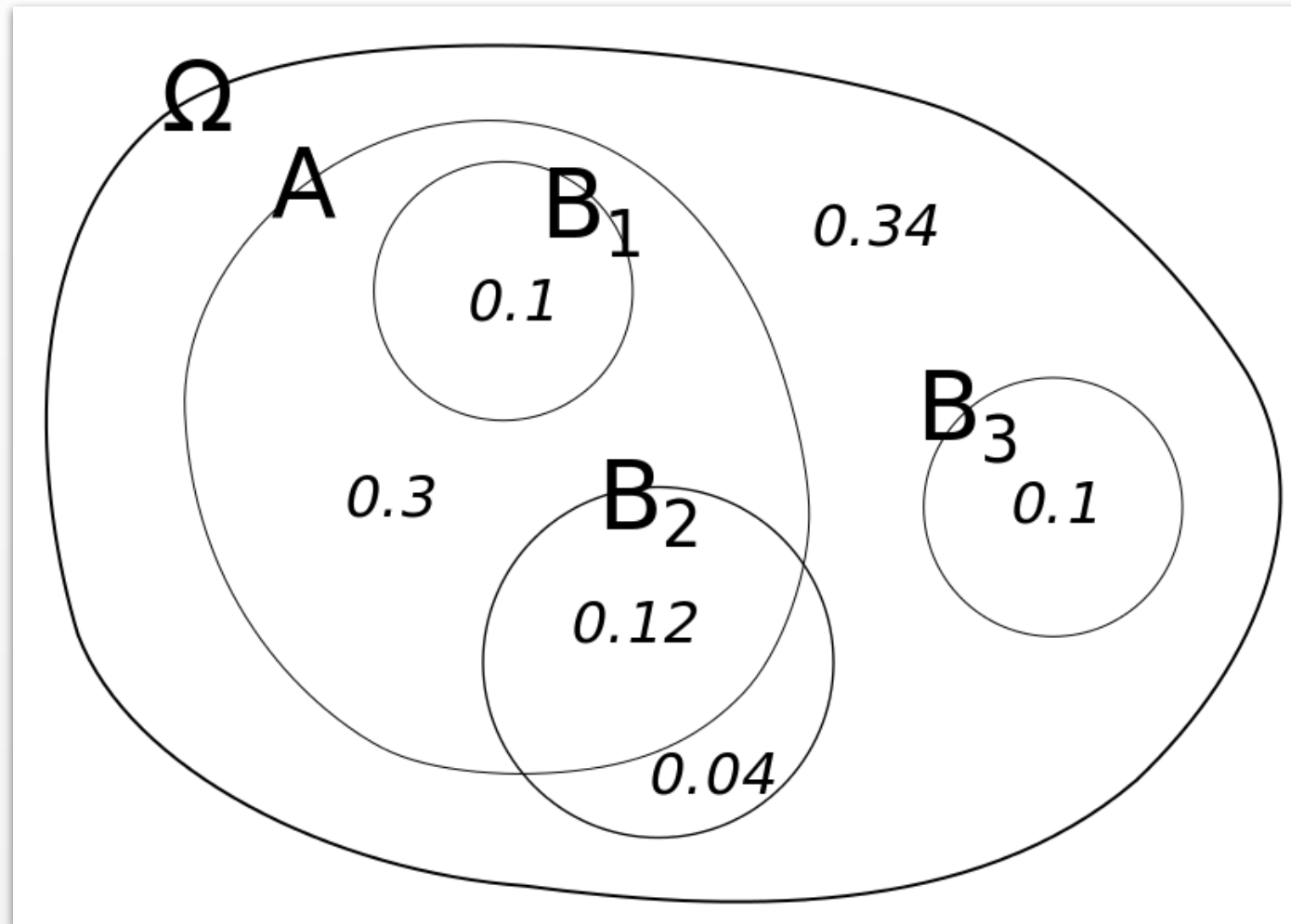


Conditional Probability: Continuous distributions



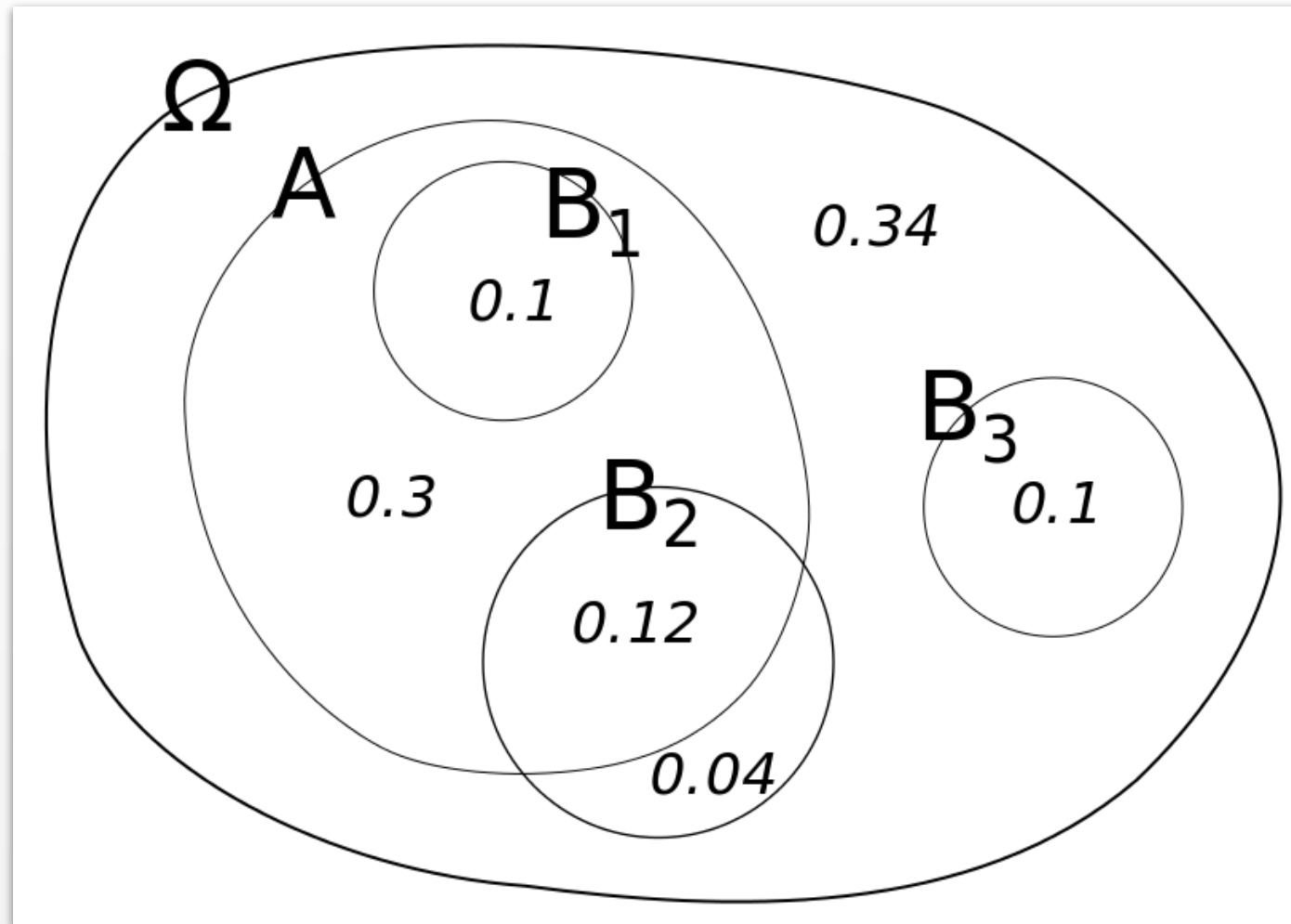
What is the probability $P(B_3)$? **0.1 / 0.34**

Conditional Probability: Continuous distributions



What is the probability $P(B_2 \mid A)$? **0.12 / 0.3**

Conditional Probability: Continuous distributions



What is the probability $P(B_1 \mid B_3)$? 0.0 / 0.1

Probability Density Functions

- **Problem:** If X is a *continuous* variable, then $P(X=x)$ is 0 for any outcome x

$$X \sim \text{Normal}(0, 1)$$

$$P(X = \pi) = 0$$

Single Outcome

$$P(3.1 \leq X \leq 3.2) \neq 0$$

Event

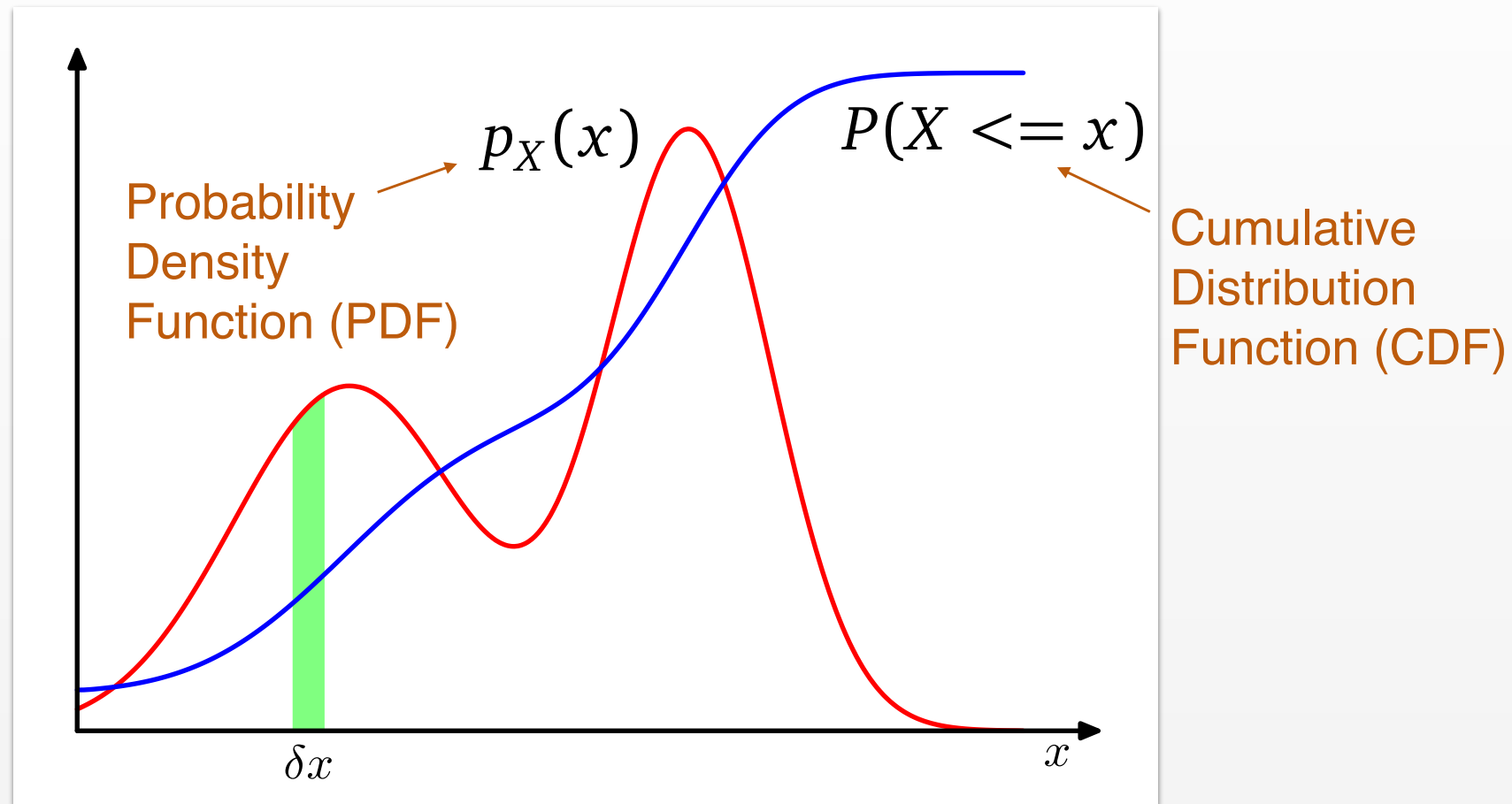
- **Solution:** Define a density function as a derivative

$$p_X(x) = \lim_{\delta \rightarrow 0} \frac{P(x - \delta < X < x + \delta)}{2\delta}$$

Capital P for probability

Small p for density

Probability Density Functions



$$p_X(x) = \lim_{\delta \rightarrow 0} \frac{P(x - \delta < X < x + \delta)}{2\delta}$$

Discrete vs. Continuous R.V.

		Discrete	Continuous
Sample Space		Any Finite or countably infinite set . e.g., $\{0,1\}$, set of all integers or rational numbers	Any uncountable set. e.g., real line, interval $[0,1]$.
pmf	$P : \Omega \rightarrow [0,1]$	$P(x)$	Does not exist
pdf	$p : \Omega \rightarrow \mathbf{R}^+$	Does not exist.	$p(x)$ or $f(x) = \frac{d}{dx}F(x)$
cdf	$F : \Omega \rightarrow [0,1]$	$F(x) = \sum_{t \leq x} P(t)$	$F(x) = \int_{-\infty}^x p(x)dx$
Probability measure	$P : \mathcal{F} \rightarrow [0,1]$	$P(A) = \sum_{x \in A} P(x)$	$P(A) = \int_{x \in A} p(x)dx$

Mixed R.V.

- There are distributions that are partly continuous and partly discrete.
 - Some points in the sample space have non-zero probabilities; e.g. zero inflated models: distribution of alcohol consumption (large fraction of individuals have 0 alcohol consumption).
 - Won't talk about this case further in this course.

Notation

The distribution of a random variable X can be specified in terms of a

- Probability measure: $X \sim P$
- Probability mass function: $X \sim P$
- Probability density function: $X \sim p$
- Cumulative distribution function: $X \sim F$
- Or by name of a well-known probability distribution: $X \sim \text{Normal}(\mu, \sigma)$

Multivariate Distributions/Random Vectors

- **Joint probability measure:** A distribution of a 2 dimensional random vector $\mathbf{X} = [X_1, X_2]$ is specified by a joint probability measure $(\Omega = \Omega_1 \times \Omega_2, \mathcal{F} = \mathcal{F}_1 \otimes \mathcal{F}_2, P)$, where Ω_1 and Ω_2 are the outcome spaces for X_1 and X_2 , respectively and \mathcal{F}_1 and \mathcal{F}_2 is the event space containing subsets of Ω_1 and Ω_2 , respectively.
 - If $\Omega_i = \mathbf{R}$ then $\Omega = \mathbf{R}^2$ and \mathcal{F} contains subsets of \mathbf{R}^2
 - $P : \mathcal{F} \rightarrow [0,1]$ assigns probabilities to subsets of \mathbf{R}^2 .



Multivariate Distributions/Random Vectors

- If Ω_1 and Ω_2 are discrete a joint pmf can be defined $P : \Omega_1 \times \Omega_2 \rightarrow [0,1]$
- If Ω_1 and Ω_2 are continuous a joint pdf can be defined $p : \Omega_1 \times \Omega_2 \rightarrow \mathbf{R}^+$
- What if Ω_1 is continuous, but Ω_2 is discrete?
 - We can define a function that acts like pdf in the first dimension and a pmf in the second dimension. We use p to denote this function: $p : \Omega_1 \times \Omega_2 \rightarrow \mathbf{R}^+$

Marginals

Marginal pdf $\rightarrow p_{X_1}(x_1) = \sum_{x_2 \in \Omega_2} p(x_1, x_2)$

Marginal pmf $\rightarrow P_{X_2}(x_2) = \int_{x_1 \in \Omega_1} p(x_1, x_2) dx_1$


Joint decomposition

$$\begin{aligned}
 p(x_1, x_2) &= \overset{\text{Conditional pdf}}{p_{X_1|X_2}(x_1 | x_2)} P_{X_2}(x_2) \longrightarrow \text{Marginal pmf} \\
 &= P_{X_2|X_1}(x_2 | x_1) \underset{\text{Conditional pmf}}{p_{X_1}(x_1)} \longrightarrow \text{Marginal pdf}
 \end{aligned}$$

Multivariate Distributions/Random Vectors

- **Joint probability measure:** A distribution of a D dimensional random vector $\mathbf{X} = [X_1, X_2 \dots X_D]$ is specified by a joint probability measure $(\Omega = \prod_{i=1}^D \Omega_i, \mathcal{F} = \otimes_{i=1}^D \mathcal{F}_i, P)$, where Ω_i is the outcome space for X_i and \mathcal{F}_i is the event space containing subsets of Ω_i .
 - If $\Omega_i = \mathbf{R}$ then $\Omega = \mathbf{R}^D$ and \mathcal{F} contains subsets of \mathbf{R}^D
 - $P : \mathcal{F} \rightarrow [0,1]$ assigns probabilities to subsets of \mathbf{R}^D .

Expected Values

$X \sim p(x)$  X is a random variable
with density $p(x)$

Statistics

$$\mathbb{E}[X] = \sum_x p(x) x$$

$$\mathbb{E}[X] = \int dx p(x) x$$

(distribution implied by X)

Machine Learning

$$\mathbb{E}_{p(x|y)}[f(x)] = \sum_x p(x|y) f(x)$$

$$\mathbb{E}_{p(x|y)}[f(x)] = \int dx p(x|y) f(x)$$

(explicitly define distribution)

Mean, Variance, Covariance

Mean

$$\mu_X = \mathbb{E}[X]$$

Variance

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

Covariance

$$\Sigma_{X,Y} = \text{Cov}[X, Y] = \mathbb{E}[(X - \mu_X)(Y - \mu_Y)]$$