## Axioms of Probability

- The subject of probability is concerned with random process, a process that can have multiple outcomes.
- A probability space consists of three components.

1. A sample space $\Omega$ of all outcomes of a random process. An element of the sample space is called a simple element.
2. A family of sets $\mathcal{F}$ of allowable events. Each element of $\mathcal{F}$, called an event, is a subset of $\Omega$.
3. A probability function $\operatorname{Pr}: \mathcal{F} \rightarrow \mathbb{R}$, satisfying the following properties:
(a) For any $E \in \mathcal{F}$, we have $0 \leq \operatorname{Pr}(E) \leq 1$.
(b) $\operatorname{Pr}(\Omega)=1$.
(c) For any finite or countably infinite sequence of pairwise mutually disjoint events $E_{1}, E_{2}, E_{3}, \ldots$,

$$
\operatorname{Pr}\left(\bigcup_{i=1}^{\infty} E_{i}\right)=\sum_{i=1}^{\infty} \operatorname{Pr}\left(E_{i}\right)
$$

- Example: Consider the process of rolling two fair die. We can model the sample space as the set $\{(a, b): 1 \leq a, b \leq 6\}$. We also have $\operatorname{Pr}(\{(a, b)\})=\frac{1}{36}$ for all $(a, b)$ pairs. Now, let's look at some more interesting events:
$-\operatorname{Pr}($ sum of rolls are even $)=\frac{18}{36}=\frac{1}{2}$.
$-\operatorname{Pr}($ the first roll is equal to the second $)=\frac{6}{36}=\frac{1}{6}$.
$-\operatorname{Pr}($ the first roll is larger than the second $)=\frac{15}{36}=\frac{5}{12}$.
$-\operatorname{Pr}($ at least one roll equals 4$)=\frac{11}{36}$.
- We will be only interested in discrete probability space, the probability space where $\Omega$ is finite or countably infinite. In this case, if event $E=\left\{s_{1}, s_{2}, s_{3}, \ldots\right\}$, we have that

$$
\operatorname{Pr}(E)=\operatorname{Pr}\left(\left\{s_{1}\right\}\right)+\operatorname{Pr}\left(\left\{s_{2}\right\}\right)+\operatorname{Pr}\left(\left\{s_{3}\right\}\right)+\cdots
$$

A common special case is when $\Omega$ is finite, and every simple event has equal probability. In this case, we have that

$$
\operatorname{Pr}(E)=\frac{\#(E)}{\#(\Omega)}
$$

- Some properties of the probability functions:
- If $A \subseteq B$, then $\operatorname{Pr}(A) \leq \operatorname{Pr}(B)$.
- Union bound:

$$
\operatorname{Pr}\left(\bigcup_{i=1}^{\infty} E_{i}\right) \leq \sum_{i=1}^{\infty} \operatorname{Pr}\left(E_{i}\right)
$$

## - Inclusion-exclusion principle:

$$
\operatorname{Pr}\left(\bigcup_{i=1}^{n} E_{i}\right)=\sum_{k=1}^{n}(-1)^{k+1}\left(\sum_{\substack{S \subseteq[n] \\ \#(\bar{S})=k}} \operatorname{Pr}\left(\bigcap_{i \in S} E_{i}\right)\right) .
$$

## Conditional Probability

- The conditional probability that event $A$ occurs given that event $F$ occurs is

$$
\operatorname{Pr}(A \mid B)=\frac{\operatorname{Pr}(A \cap B)}{\operatorname{Pr}(B)}
$$

The conditional probability is defined only when $P(B) \neq 0$.

- Conditional probability satisfies all the probability axioms.
- The probability space $\Omega$ maps to $B$.
- The set of allowable events $\mathcal{F}$ maps to $\{A \cap B: A \in \mathcal{F}\}$.
- The probability function $\operatorname{Pr}(A)$ maps to $\operatorname{Pr}(A \mid B)$.
- Example: You are dealt two cards face down from a shuffled deck of 8 cards consisting of the four queens and four kings from a standard bridge deck.
- The dealer looks at both of your two cards (without showing them to you) and tells you (truthfully) that at least one card is a queen. What is the probability that you have been given two queens?

Answer: Let $A$ be the event that I get two queens, and let $B$ be the event that one card is a queen. We have that $\#(A \cap B)=\#(A)=6$, and $\#(B)=4 \times 4+6=22$, so $\operatorname{Pr}(A \mid B)=6 / 22=3 / 11$.

- What is this probability if the dealer tells you instead that at least one card is a red queen?

Answer: Let $C$ be the event that at least one card is a red queen. We have that $\#(A \cap C)=$ $1+2 \times 2=5$, and $\#(C)=12+1=13$. So, $\operatorname{Pr}(A \mid C)=5 / 13$.

- What is this probability if the dealer tells you instaed that one card is the queen of hearts?

Answer: Let $D$ be the event that one card is the queen of hearts. We have that $\#(A \cap D)=3$, and $\#(D)=7$. So $\operatorname{Pr}(A \mid D)=3 / 7$.

- Multiplication Rule: Assuming all conditioning events have positive probability, we have

$$
\operatorname{Pr}\left(\cap_{i=1}^{n} A_{i}\right)=\operatorname{Pr}\left(A_{1}\right) \operatorname{Pr}\left(A_{2} \mid A_{1}\right) \operatorname{Pr}\left(A_{3} \mid A_{1} \cap A_{2}\right) \cdots \operatorname{Pr}\left(A_{n} \mid \cap_{i=1}^{n-1} A_{i}\right) .
$$

- Example: A class consisting of 4 graduate and 12 undergraduate students is randomly divided into 4 groups of 4 . What is the probability that each group includes a graduate students?

Let us denote the four graduate students by $1,2,3$, and 4 .
Let $A_{1}=\{$ students 1 and 2 are in different group $\}$.
Let $A_{2}=\{$ students 1, 2, and 3 are in different group $\}$.
Let $A_{3}=\{$ students $1,2,3$, and 4 are in different group $\}$.
We have that

$$
\operatorname{Pr}\left(A_{3}\right)=\operatorname{Pr}\left(A_{1} \cap A_{2} \cap A_{3}\right)=\operatorname{Pr}\left(A_{1}\right) \operatorname{Pr}\left(A_{2} \mid A_{1}\right) \operatorname{Pr}\left(A_{3} \mid A_{1} \cap A_{2}\right)=\operatorname{Pr}\left(A_{1}\right) \operatorname{Pr}\left(A_{2} \mid A_{1}\right) \operatorname{Pr}\left(A_{3} \mid A_{2}\right)
$$

Now, $\operatorname{Pr}\left(A_{1}\right)=12 / 15$ because there are 12 slots out of 15 slots that student 2 can occupy. Similarly, $\operatorname{Pr}\left(A_{2} \mid A_{1}\right)=\frac{8}{14}=\frac{4}{7}$, and $\operatorname{Pr}\left(A_{3} \mid A_{2}\right)=\frac{4}{13}$. So,

$$
\operatorname{Pr}\left(A_{3}\right)=\frac{12}{15} \cdot \frac{4}{7} \cdot \frac{4}{13}
$$

- The Law of Total Probability: Let $A_{1}, A_{2}, \ldots, A_{n}$ be a partition of the sample space. Then, for any event $B$, we have

$$
\operatorname{Pr}(B)=\sum_{i=1}^{n} \operatorname{Pr}\left(A_{i}\right) \operatorname{Pr}\left(B \mid A_{i}\right)
$$

The form of this fomula that turns up very often is:

$$
\operatorname{Pr}(B)=\operatorname{Pr}(A) \operatorname{Pr}(B \mid A)+\operatorname{Pr}\left(A^{c}\right) \operatorname{Pr}\left(B \mid A^{c}\right)
$$

- Baye's Rule: Let $A_{1}, A_{2}, \ldots, A_{n}$ be a partition of the sample space. Then, for any event $B$ such that $\operatorname{Pr}(B)>0$, we have, for any $i$,

$$
\operatorname{Pr}\left(A_{i} \mid B\right)=\frac{\operatorname{Pr}\left(A_{i} \cap B\right)}{\operatorname{Pr}(B)}=\frac{\operatorname{Pr}\left(A_{i}\right) \operatorname{Pr}\left(B \mid A_{i}\right)}{\sum_{j=1}^{n} \operatorname{Pr}\left(A_{j}\right) \operatorname{Pr}\left(B \mid A_{j}\right)}
$$

Baye's rule is certainly very useful, but we will not use it much here.

## Independence

- Event $A$ is said to be independent of event $B$ if $\operatorname{Pr}(A \cap B)=\operatorname{Pr}(A) \operatorname{Pr}(B)$. This implies that, if $\operatorname{Pr}(B) \neq 0$, then $\operatorname{Pr}(A \mid B)=\operatorname{Pr}(A)$.
Similarly, we say that events $A_{1}, A_{2}, \ldots, A_{n}$ are independent if, for every subset $S$ of $\{1,2, \ldots, n\}$,

$$
\operatorname{Pr}\left(\bigcap_{i \in S} A_{i}\right)=\prod_{i \in S} \operatorname{Pr}\left(A_{i}\right) .
$$

In other words, for any subset $S$ and for any $j \notin S$,

$$
\operatorname{Pr}\left(A_{j} \mid \bigcap_{i \in S} A_{i}\right)=\operatorname{Pr}\left(A_{j}\right)
$$

- Example: An unfair coin (probability $p$ of showing heads) is tossed $n$ times. What is the probability that the number of heads will be even?

It is natural to assume that the coin tosses are independent. Let us solve a similar problem first. Let $A_{n, k}$ be the event that we get exactly $k$ heads from $n$ tosses. With some counting, we know that

$$
\operatorname{Pr}\left(A_{n, k}\right)=\binom{n}{k} p^{k}(1-p)^{n-k}
$$

Letting $E_{n}$ be the event that we get an even number of heads from $n$ tosses, we have

$$
\begin{aligned}
\operatorname{Pr}\left(E_{n}\right) & =\operatorname{Pr}\left(A_{n, 0}\right)+\operatorname{Pr}\left(A_{n, 2}\right)+\operatorname{Pr}\left(A_{n, 4}\right)+\ldots+\operatorname{Pr}\left(A_{n, 2\lfloor n / 2\rfloor}\right) \\
& =\sum_{k=0}^{\lfloor n / 2\rfloor}\binom{n}{k} p^{2 k}(1-p)^{n-2 k} .
\end{aligned}
$$

Evaluating this sum is a pain in the ass, so we should find another method. Say, let $O_{n}$ be the event that we get an odd number of heads after $n$ tosses. We have

$$
\begin{aligned}
\operatorname{Pr}\left(E_{n}\right) & =p \operatorname{Pr}\left(O_{n-1}\right)+(1-p) \operatorname{Pr}\left(E_{n-1}\right) \\
& =p\left(1-\operatorname{Pr}\left(E_{n-1}\right)\right)+(1-p) \operatorname{Pr}\left(E_{n-1}\right) \\
& =p+(1-2 p) \operatorname{Pr}\left(E_{n-1}\right)
\end{aligned}
$$

Recall that this is an inhomogeneous linear recurrence relation. The homogeneous part

$$
P\left(E_{n}\right)=(1-2 p) \operatorname{Pr}\left(E_{n-1}\right)
$$

has solution $\operatorname{Pr}\left(E_{n}\right)=\alpha(1-2 p)^{n}$. Next, we guess the solution of the inhomogeneous relation to be $\alpha(1-2 p)^{n}+\beta n+\gamma$, so

$$
\begin{aligned}
1 & =\alpha(1-2 p)^{0}+0 \cdot \beta+\gamma \\
1-p & =\alpha(1-2 p)^{1}+1 \cdot \beta+\gamma \\
p^{2}+(1-p)^{2} & =\alpha(1-2 p)^{2}+2 \cdot \beta+\gamma
\end{aligned}
$$

Solving, we have that $\alpha=\frac{1}{2}, \beta=0$, and $\gamma=\frac{1}{2}$. So,

$$
\operatorname{Pr}\left(E_{n}\right)=\frac{1+(1-2 p)^{n}}{2}
$$

## Discrete Random Variables

- A random variable $X$ on a sample space $\Omega$ is a real-valued function $X: \Omega \rightarrow \mathbb{R}$.

We are only interested in discrete random variable, random variable $X$ whose range is the integers.

- Two random variables $X$ and $Y$ are said to be independent if and only if, for pairs of integers $x, y$, it is true that

$$
\operatorname{Pr}(\{X=x\} \cap\{Y=y\})=\operatorname{Pr}(X=x) \operatorname{Pr}(Y=y) .
$$

Similarly, random variables $X_{1}, X_{2}, \ldots, X_{n}$ are independent if and only if, for any subset $I \subset$ $\{1,2, \ldots, n\}$, and for any integer value $x_{i}, i \in I$,

$$
\operatorname{Pr}\left(\bigcap_{i \in I} X_{i}=x_{i}\right)=\prod_{i \in I} \operatorname{Pr}\left(X_{i}=x_{i}\right) .
$$

- The expectation of a discrete random variable $X$, denoted by $\mathbf{E}[X]$, is given by

$$
\mathbf{E}[X]=\sum_{i \in \mathbb{Z}} i \operatorname{Pr}(X=i) .
$$

- Bernoulli Random Variable: A biased coin with probability $p$ of turning head is flipped. The Bernoulli random variable $X$ is defined to be

$$
X= \begin{cases}1, & \text { if head } \\ 0, & \text { if tail }\end{cases}
$$

So, $\operatorname{Pr}(X=1)=p, \operatorname{Pr}(X=0)=1-p$, and $\operatorname{Pr}(X=i)=0$ for other $i$. Thus, $\mathbf{E}[X]=(1-p) \cdot 0+p \cdot 1=p$.

- Binomial Random Variable: The above biased coin is flipped (independently) $n$ times, and $X$ is the number of heads. We have that, if $X_{i}$ is 1 if the $i$ th flip resulted in a head and 0 otherwise, then $X=X_{1}+X_{2}+\cdots+X_{n}$. Note that $X_{i}$ is a Bernoulli random variable for all $i$.
From a problem in the last section, we have

$$
\operatorname{Pr}(X=k)=\binom{n}{k} p^{k}(1-p)^{n-k}
$$

So,

$$
\begin{aligned}
\mathbf{E}[X] & =\sum_{k=0}^{n} k\binom{n}{k} p^{k}(1-p)^{n-k}=\sum_{k=1}^{n} k\binom{n}{k} p^{k}(1-p)^{n-k}=\sum_{k=1}^{n} k \cdot \frac{n}{k}\binom{n-1}{k-1} p^{k}(1-p)^{n-k} \\
& =n p \sum_{k=1}^{n}\binom{n-1}{k-1} p^{k-1}(1-p)^{n-k}=n p \sum_{k=0}^{n-1}\binom{n-1}{k} p^{k}(1-p)^{n-1-k}=n p .
\end{aligned}
$$

- Linearity of Expectations: If $X$ and $Y$ are two random variables, then

$$
\begin{aligned}
\mathbf{E}[X+Y] & =\sum_{i \in \mathbb{Z}} \sum_{j \in \mathbb{Z}}(i+j) \operatorname{Pr}(\{X=i\} \cap\{Y=j\}) \\
& =\sum_{i \in \mathbb{Z}} \sum_{j \in \mathbb{Z}} i \operatorname{Pr}(\{X=i\} \cap\{Y=j\})+\sum_{i \in \mathbb{Z}} \sum_{j \in \mathbb{Z}} j \operatorname{Pr}(\{X=i\} \cap\{Y=j\}) \\
& =\sum_{i \in \mathbb{Z}} i \sum_{j \in \mathbb{Z}} \operatorname{Pr}(Y=j) \operatorname{Pr}(X=i \mid Y=j)+\sum_{j \in \mathbb{Z}} j \sum_{i \in \mathbb{Z}} \operatorname{Pr}(X=i) \operatorname{Pr}(Y=j \mid X=i) \\
& =\sum_{i \in \mathbb{Z}} i \operatorname{Pr}(X=i)+\sum_{j \in \mathbb{Z}} j \operatorname{Pr}(Y=j) \\
& =\mathbf{E}[X]+\mathbf{E}[Y] .
\end{aligned}
$$

This imples that, for any random variables $X_{1}, X_{2}, \ldots, X_{n}$,

$$
\mathbf{E}\left[\sum_{i=1}^{n} X_{i}\right]=\sum_{i=1}^{n} \mathbf{E}\left[X_{i}\right] .
$$

Linearity of expectations is very powerful because it holds for any random variable.

- Example: Note that linearity of expection gives us a very easy way to calculate the expectation of the binomial random variable: because $X=X_{1}+X_{2}+\ldots+X_{n}$, we have $\mathbf{E}[X]=\mathbf{E}\left[X_{1}\right]+\cdots+\mathbf{E}\left[X_{n}\right]=n p$.
- Example: $n$ people wearing hats enter a shop. They give their hats to the door boy for safe keeping. When they leave, the door boy hands each of them a random hat. How many people get their own hats back on average?

Let $X_{i}$ be the indicator random variable (random variable that takes either 0 or 1 as its value) such that $X_{i}=1$ if person $i$ gets his hat back, and $X_{i}=0$ otherwise. We have that $\mathbf{E}\left[X_{i}\right]=1 / n$ because $i$ gets a random hat back. Now, let $X$ be the number of people who get their own hats back. We have that $X=X_{1}+X_{2}+\ldots+X_{n}$. So, $\mathbf{E}[X]=n \mathbf{E}\left[X_{1}\right]=1$.

- More properties of expectations:
- For any constant $c, \mathbf{E}[c X]=c \mathbf{E}[X]$.
- For any random variable $X$ taking only positive values, $\mathbf{E}[X]=\sum_{i \geq 1} \operatorname{Pr}(X \geq i)$.
- Geometric Random Variable: A biased coin (with probability $p$ of showing head) is flipped until the first head shows up. Let $X$ be the number of flips until it happens.
We have that $P(X=k)=(1-p)^{k-1} p$ for all $k \geq 1$. Since $X$ takes only positive values:

$$
\mathbf{E}[X]=\sum_{i \geq 1} \operatorname{Pr}(X \geq i)=1+(1-p)+(1-p)^{2}+\cdots=\frac{1}{1-(1-p)}=\frac{1}{p}
$$

- Markov's Inequality: For any positive random variable $X$, for any $a>0$,

$$
\operatorname{Pr}(X \geq a) \leq \frac{\mathbf{E}[X]}{a}
$$

