

# Probability Theory

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**Definition 4.** The **intersection** of two sets  $A$  and  $B$  is the collection of elements that are in both  $A$  and  $B$ .

**Definition 5.** The **complement** of a set  $A$  is everything not in  $A$ .

**Definition 6.** A **finite set** is a set with finite number of elements.

**Definition 7.** The **cartesian** product of two sets  $A$  and  $B$  denoted  $A \times B$  is

$$\{(a, b) : a \in A \wedge b \in B\}.$$

Then,  $|A \times B| = |A| \cdot |B|$ .

## Lecture 1: Intro to Probability

### 1 Basics of Probability

What data do you need to specify probability? You need the **set of all outcomes**, a list of everything that could possibly occur as a consequence, and the likelihood of each event.

**Example.** For a roll of a dice, the set of all outcomes would be  $\{1, 2, 3, 4, 5, 6\}$ . The list could include things like “the result is 3”, or “the result is  $\geq 4$ ”, and the likelihood would be  $\frac{1}{6}$  for each of the results.

#### 1.1 Basics of Set Theory

**Definition 1.** A **set** is an unordered collection of elements. **Elements** are objects within sets.

**Definition 2.** A set  $A$  is a **subset** of a set  $B$  if  $a \in A \Rightarrow a \in B$

**Definition 3.** The **union** of two sets  $A$  and  $B$  is the collection of elements that are in  $A$  or  $B$ .

#### 1.2 Back to Probability

**Definition 8.** A **sample space** is the set of all possible outcomes in an experiment.

**Example.** The sample space  $\Omega$  for a coin flip is  $\{H, T\}$ .

Note that **events** are just subsets of the sample space, and **elementary events** are just elements of the sample space.

**Example.** For a dice roll:  $\Omega = \{1, 2, 3, 4, 5, 6\}$ , some events could be  $\{1, 2\}$ ,  $\{3, 6\}$ ,  $\{3\}$ . There are a total of  $2^6$  events.

**Definition 9.** If  $\Omega$  is a finite set, a probability  $P$  on  $\Omega$  is a function:  $P: 2^\Omega \rightarrow [0, 1]$  such that  $\mathbb{P}(\emptyset) = 0$  and  $\mathbb{P}(\Omega) = 1$ .

**Lemma 1.** If  $A_1, \dots, A_\alpha \subset \Omega$  are disjoint,  $\mathbb{P}(\bigcup_i A_i) = \sum_i \mathbb{P}(A_i)$ .

**Proposition 1.** Let  $A = \{a_1, a_2, \dots, a_I\}$  such that  $a_i$  are elementary events. Then,

$$\mathbb{P}(A) = \sum_{i=1}^I \mathbb{P}(\{a_i\}).$$

**Example.** For the dice roll, if  $A = \{1, 3, 5\}$ , then  $\mathbb{P}(A) = 3 \cdot \frac{1}{6} = \frac{1}{2}$ .

**Definition 10. Equiprobable outcomes:** Let's say we have the set  $\Omega = \{\omega_1, \dots, \omega_N\}$  and  $\mathbb{P}(\omega_i) = \mathbb{P}(\omega_j)$  for all  $i$  and  $j$ . Then,  $\mathbb{P}(\omega) = \frac{1}{N}$  for all  $\omega \in \Omega$  and  $\mathbb{P}(A) = \frac{|A|}{N}$ . In other words, when outcomes are probable,

$$\mathbb{P}(\text{event}) = \frac{\text{number of outcomes for that event}}{\text{number of possible outcomes}}.$$

### 1.3 Counting

Suppose 2 experiments are being performed. Let's say that experiment 1 has  $m$  possible outcomes, and experiment 2 has  $n$  possible outcomes. Then together, there are total of  $n \cdot m$  total outcomes.

**Example.** Rolling a dice and then flipping a coin, how many possible outcomes are there?

**Explanation.** You have  $6 \cdot 2 = 12$  outcomes.

**Example.** Let's say you have a college planning committee that consists of 3 freshman, 4 sophomores, 5 juniors, and 2 seniors. How many ways are there to select a subcommittee of 4 with one person from each grade?

**Explanation.** There are 4 events with 3, 4, 5, and 2 possible outcomes for each. Therefore, there are  $3 \cdot 4 \cdot 5 \cdot 2 = 120$  total subcommittees.

**Example.** How many 7-place license plates are there if the first 3 are letters and the last 4 are numbers?

**Explanation.** There are  $26^3 \cdot 10^4$  license plates.

**Definition 11.** A **permutation** is an ordering of elements in a set. The number of ways to order  $n$  elements is given by  $n!$ .

**Example.** Alex has a bunny ranch with 10 bunnies. They are going to run an obstacle course and ranked 1-10 based on completion time. How many possible rankings are there (no ties)?

**Explanation.** There are  $10!$  possible rankings.

**Example.** Assume 6 bunnies have straight ears and 4 have floppy ears. We rank the bunnies separately. How many possible rankings are there?

**Explanation.** There are  $6! \cdot 4!$  possible outcomes.

**Definition 12.** A **combination** denotes the number of ways to choose  $k$  elements from  $n$  total elements (counting subsets).

**Example.** How many ways are there to pick a 2 person team from a set of 5 people?

**Explanation.** There are  $C(5, 2) = \binom{5}{2} = \frac{5!}{2! \cdot 3!} = 10$  ways.

**Example.** How many committees consisting of 2 women and 3 men can be formed from a group of 5 women and 7 men?

**Explanation.** We have  $C(5, 2) \cdot C(7, 3)$  possible committees.

**Example.** What if two of the men do not want to serve on the committee together?

**Explanation.** The number of ways to choose the women stays the same. However, for the men we must subtract the number of committees that have both men. Therefore, we have  $C(5, 2) \cdot (C(7, 3) - C(5, 1))$  possible committees.

**Example.** How many ways can we divide a 10 person class into 3 groups, sizes 3, 3, and 4?

**Explanation.** We just have 3 events, multiplying:  $C(10, 3) \cdot C(7, 3) \cdot C(4, 4)$ .

**Definition 13.** This is known as a **multinomial**,

and is given by

$$\binom{n}{n_1, n_2, \dots, n_r} = \frac{n!}{n_1! \cdot n_2! \cdot \dots \cdot n_r!}.$$

It counts the number of ways to partition a set of size  $n$  into sets of sizes  $n_1, n_2, \dots, n_r$ .

## 1.4 Back to Probability Again

**Example.** Flip 10 fair coins. What is the likelihood of flipping 3 heads?

**Explanation.** Number of events of 3 heads is  $C(10, 3)$ . Total number of events is  $2^{10}$ . Therefore,

$$\mathbb{P}(10 \text{ heads}) = \frac{C(10, 3)}{2^{10}}.$$

In general, we have  $\sum_{k=0}^n \mathbb{P}(k \text{ heads}) = 1$ . In other words,

$$\frac{1}{2^{10}} \cdot \sum_{k=0}^{10} \binom{10}{k} = 1.$$

such that

$$\sum_{k=0}^{10} \binom{10}{k} = 2^{10}.$$

More generally,

**Definition 14.** The **binomial theorem** states that for all  $x, y \in \mathbb{R}$ ,  $n \geq 1$ ,  $n \in \mathbb{N}$ ,

$$(x + y)^n = \sum_{k=0}^n \binom{n}{k} x^k y^{n-k}.$$

**Example.** Rolling 10 dice, what is the likelihood of exactly 2 outcomes each of 1,2,3,4, 1 outcome of 6, and 1 outcome of 5.

**Explanation.** There are total  $6^{10}$  outcomes, and there are  $\binom{10}{2,2,2,2,1,1}$  desired outcomes. Therefore, the probability of this event is  $\frac{\binom{10}{2,2,2,2,1,1}}{6^{10}}$ .

**Definition 15.** The **multinomial theorem** states that  $(x_1 + \dots + x_r)^n =$

$$\sum_{n_1 + \dots + n_r = n} \binom{n}{n_1, \dots, n_r} x_1^{n_1} x_2^{n_2} \dots x_r^{n_r}.$$

## 1.5 Measure Theory

This is just a generalization of what we have seen before.

**Definition 16.** Let  $\mathcal{F} \subset 2^\Omega$  be an “event space”. A mapping  $P : \mathcal{F} \rightarrow \mathbb{R}$  is a **probability measure** on  $(\Omega, \mathcal{F})$  if

- $\mathbb{P}(A) \geq 0 \quad \forall A \in \mathcal{F}$
- $\mathbb{P}(\emptyset) = 0, \mathbb{P}(\Omega) = 1$
- If  $A_1, A_2, \dots$  are disjoint,

$$\mathbb{P}\left(\bigcup_{i=1}^{\infty} A_i\right) = \sum_{i=1}^{\infty} \mathbb{P}(A_i).$$

## Lecture 2: More Probability

### 1.6 Properties of Event Spaces

**Definition 17.** A collection  $\mathcal{F}$  of subsets of the sample space  $\Omega$  is called an **event space** if

- $\mathcal{F}$  is non-empty.
- if  $A \in \mathcal{F}$  then  $\Omega \setminus A \in \mathcal{F}$ .
- if  $A_1, A_2, \dots \in \mathcal{F}$  then  $\bigcup_{i=1}^{\infty} A_i \in \mathcal{F}$ .

**Theorem 1.** If  $A \in \mathcal{F}$ , then  $\mathbb{P}(A) + \mathbb{P}(\Omega \setminus A) = 1$

**Proof.** Notice that  $A$  and  $\Omega \setminus A$  are disjoint. And, that  $A \cup (\Omega \setminus A) = \Omega$ . Then,

$$\mathbb{P}(A \cup (\Omega \setminus A)) = \mathbb{P}(\Omega) = 1.$$

■

**Theorem 2.** If  $A, B \in \mathcal{F}$  then  $\mathbb{P}(A \cup B) + \mathbb{P}(A \cap B) = \mathbb{P}(A) + \mathbb{P}(B)$ .

**Proof.** Note that  $A \cup B = (A \setminus B) \cup (A \cap B) \cup (B \setminus A)$ . This is a union of disjoint sets, such that  $\mathbb{P}(A \cup B) = \mathbb{P}(A \setminus B) + \mathbb{P}(A \cap B) + \mathbb{P}(B \setminus A)$ . Then, we have  $\mathbb{P}(A \cup B) + \mathbb{P}(A \cap B) = \mathbb{P}(A \setminus B) + \mathbb{P}(A \cap B) + \mathbb{P}(B \setminus A) + \mathbb{P}(A \cap B)$ , of which the RHS simplifies to  $\mathbb{P}(A) + \mathbb{P}(B)$ . ■

**Theorem 3.** If  $A, B \in \mathcal{F}$ , and  $A \subseteq B$ , then  $\mathbb{P}(A) \leq \mathbb{P}(B)$ .

**Proof.** We wish to show  $A \subseteq B \Rightarrow \mathbb{P}(A) \leq \mathbb{P}(B)$ . Then,  $B = (B \setminus A) \cup (B \cap A) = (B \setminus A) \cup A$ , such that  $\mathbb{P}(B) = \mathbb{P}(B \setminus A) + \mathbb{P}(A) \geq \mathbb{P}(A)$  because  $\mathbb{P}(B \setminus A) \geq 0$ . ■

## 1.7 Examples

**Example.** What is the probability that one is dealt a full house?

**Explanation.** This is the number of ways one can get a full house, divided by the total number of poker hands (5 card). The total number of poker hands is  $\binom{52}{5}$ . The number of full houses is  $\frac{52 \cdot \binom{3}{2} \cdot 48 \cdot 3}{2!3!}$ . Another way we can count the number of full houses is  $\binom{13}{1} \cdot \binom{4}{3} \cdot \binom{12}{1} \cdot \binom{4}{2}$ . The result of the division is our answer.

**Example.** A box contains 3 marbles, 1 red 1 green and 1 blue. Consider an experiment that consists of us taking 1 marble, replacing it, and drawing another marble. What is the sample space?

**Explanation.**

$$\Omega = \{(r, r), (r, b), (r, g), (b, r), (b, g), (b, b), (g, r), (g, g), (g, b)\}.$$

**Example.** What about if we don't replace the first marble?

**Explanation.** Everything without  $(r, r), (b, b), (g, g)$ .

**Example.** What is the probability of being dealt a flush?

**Explanation.** This is just number of flushes divided by number of poker hands. The number of flushes is  $\binom{4}{1} \cdot \binom{13}{5}$ .

**Example.** What is the probability of being dealt a straight?

**Explanation.** We can do the probability of any straight, minus probability of straight flush. The number of straights is 10 number-wise. Therefore, the number of straights is  $10 \cdot (4^5 - 4)$ . The probability can be then calculated.

**Example.** An urn contains  $n$  balls. If  $k$  balls are withdrawn one at a time, what is the probability that a special ball is chosen?

**Explanation.**  $\mathbb{P}(\text{special}) = 1 - \mathbb{P}(\text{special}^c)$ . If the special ball is not chosen, it would be

$\frac{(n-1)!}{(n-k-1)!}$ . The total number of withdrawals is  $\frac{n!}{k!}$ . Then, the total probability is  $1 - \frac{n-k}{n}$ .

**Example.** If  $n$  people are present in a room, what is the prob that no two celebrate their birthday on the same date? How large must  $n$  be such that this probability is  $< \frac{1}{2}$ .

**Explanation.**  $\mathbb{P}(\text{no people with same birthday})$  is the number of no same birthday situations divided by the number of possibilities. Total possibilities is  $365^n$ . No same birthday situations is  $\mathbb{P}(365, n) = \frac{365!}{(365-n)!}$ . For the second question,  $n = 23$ .

## 1.8 Conditional Probability

**Definition 18.** If  $A, B \in \mathcal{F}$  and  $\mathbb{P}(B) > 0$  then the **conditional probability** if  $A$  given  $B$  is denoted by  $\mathbb{P}(A | B)$  and defined by

$$\mathbb{P}(A | B) = \frac{\mathbb{P}(A \cap B)}{\mathbb{P}(B)}.$$

**Theorem 4.** If  $B \in \mathcal{F}$  and  $\mathbb{P}(B) > 0$  then  $(\Omega, \mathcal{F}, \mathbb{Q})$  is a probability space where  $\mathbb{Q} : \mathcal{F} \rightarrow \mathbb{R}$  is defined by  $\mathbb{Q}(A) = \mathbb{P}(A | B)$

**Example.** Let's say a coin is flipped twice. What is the conditional probability that both flips land on heads, given that the first flip lands on heads?

**Explanation.**  $\frac{\mathbb{P}(\text{two heads} \cap \text{first heads})}{\mathbb{P}(\text{first heads})} = \frac{\mathbb{P}(\text{two heads})}{\mathbb{P}(\text{first heads})}$ . This is just  $\frac{1}{2}$ .

**Example.** What if given at least one lands on heads?

**Explanation.**  $\frac{\mathbb{P}(\text{two heads} \cap \text{at least one head})}{\mathbb{P}(\text{at least one head})} = \frac{\mathbb{P}(\text{two heads})}{\mathbb{P}(\text{at least one head})} = \frac{2}{3}$ .

**Example.** In the card game bridge, the 52 cards are dealt equally. If North and South have a total of 8 spades among them, what is the probability that East has 3 of the 5 remaining spades?

**Explanation.** No rule:  $\mathbb{P}(\text{E has 3 spades}) = \frac{\binom{5}{3} \cdot \binom{21}{10}}{\binom{26}{13}}$ .

**Theorem 5.** Probability of intersection of three sets (insert from canvas).

**Definition 19.** We call two events  $A, B$  **independent** if the occurrence of one does not affect the other. Formally,

$$\mathbb{P}(A | B) = \mathbb{P}(A) \text{ and } \mathbb{P}(B | A) = \mathbb{P}(B).$$

We can also check that  $\mathbb{P}(A \cap B) = \mathbb{P}(A) \cdot \mathbb{P}(B)$ .

**Example.** Flip three fair coins. What is likelihood that all three come up heads?

**Explanation.** With the sample space approach:  $\Omega = \{H, T\}^3$ . Of 8 total elementary events, 1 has three heads, so the probability is  $\frac{1}{8}$ .

With independence: we know that each event is independent, and all events are  $\frac{1}{2}$ , so the probability is  $(\frac{1}{2})^3 = \frac{1}{8}$ .

**Definition 20.** Independence can be expanded to more than just two events (insert from canvas). However, note that events can be pairwise independent, but may not be all together independent.

**Lemma 2.**

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

**Proof.** The RHS is the same as  $\frac{\mathbb{P}(A \cap B)}{\mathbb{P}(B)} \cdot \frac{\mathbb{P}(B)}{\mathbb{P}(A)} = \frac{\mathbb{P}(A \cap B)}{\mathbb{P}(A)} = \mathbb{P}(B | A)$ . ■

**Example.** There are  $n$  balls that are sequentially chosen without replacement from  $r$  red balls and  $b$  blue balls. Given that  $k$  of the  $n$  balls are blue, what is the conditional probability that the first chosen is blue?

**Explanation.**

$$\begin{aligned} & \mathbb{P}(\text{first is blue} | k \text{ are blue}) \\ &= \mathbb{P}(k \text{ are blue} | \text{first is blue}) \\ & \cdot \frac{\mathbb{P}(\text{first is blue})}{\mathbb{P}(k \text{ are blue})} \cdots \end{aligned}$$

## Lecture 3: Bayes Theorem and Random Variables

Continuing on with conditional probability from last time,

**Example.** A total of  $n$  balls are sequentially and randomly chosen without replacement from an urn containing  $r$  red balls and  $b$  blue balls ( $n \leq r + b$ ). Given that  $k$  of the  $n$  balls are blue, what is the conditional probability that the first ball chosen is blue?

**Explanation.** We can use Lemma 2. Then, we have

$$\mathbb{P}(\text{first blue}) = \frac{b}{r + b}$$

$$\mathbb{P}(\text{first } k \text{ are blue}) = \frac{\binom{n}{k} P(b, k) P(r, n - k)}{P(r + b, n)}.$$

$\mathbb{P}(k - 1 \text{ of remaining } n - 1 \text{ slots are blue.}) =$

$$\frac{\binom{n-1}{k-1} P(b - 1, k - 1) \cdot P(r, n - k)}{P(r + b - 1, n - 1)}.$$

$$\mathbb{P}(k - 1 \text{ of rest } n - 1 \text{ are blue}) \cdot \frac{\mathbb{P}(\text{first blue})}{\mathbb{P}(\text{first } k \text{ are blue})}.$$

will then be our answer.

### 1.9 Bayes Theorem

**Definition 21.** A **partition** of  $\Omega$  is a collection  $\{B_i : i \in I\}$  of disjoint events with union  $\bigcup_i B_i = \Omega$ .

**Theorem 6.** Let  $(\Omega, \mathcal{F}, \mathbb{P})$  be a probability space. If  $\{B_1, B_2, \dots\}$  is such a partition with  $\mathbb{P}(B_i) > 0$ , then

$$\mathbb{P}(A) = \sum_i \mathbb{P}(A | B_i) \mathbb{P}(B_i) \quad \text{for } A \in \mathcal{F}.$$

**Example.** Flip a fair coin. If heads, roll a 6-sided fair die. If tails, roll two 4-sided dice and sum the total. What is the overall likelihood of an outcome of 3?

**Explanation.** Look at the event tree, and count the probabilities. The heads case is  $\frac{1}{2} \cdot \frac{1}{6}$  and the tails case is  $\frac{1}{2} \cdot \frac{1}{8}$ . This is an informal Bayes Theorem.

**Theorem 7.** We can also rearrange Bayes' The-

orem to yield

$$\mathbb{P}(B_j | A) = \frac{\mathbb{P}(A | B_j)\mathbb{P}(B_j)}{\sum_i \mathbb{P}(A | B_i)\mathbb{P}(B_i)}.$$

## 2 Random Variables

**Definition 22.** A **random variable** on  $(\Omega, \mathbb{P})$ ,  $|\Omega| < \infty$  is a function  $X : \Omega \rightarrow \mathbb{R}$ .

**Notation.**  $\{X = a\} = \{\omega \in \Omega : X(\omega) = a\} = \dots = X^{-1}(a)$ .

**Example.** 3 balls are to be selected without replacement from an urn containing 20 balls numbered 1 to 20. What is the probability that at least one of the balls that are drawn has a number as large or larger than 17?

**Explanation.**  $\Omega = \{1, 2, 3, \dots, 20\}$ .  $|\Omega| = \binom{20}{3}$ . Let our random variable  $X : \Omega \rightarrow \mathbb{R}$ ,  $X$  = largest of the three values. Let  $E = \{X \geq 17\}$ . Then,  $\mathbb{P}(E) = 1 - \mathbb{P}(E^c) = \mathbb{P}(\text{all} < 17)$ .

$$\mathbb{P}(\text{all} < 17) = \frac{|E^c|}{|\Omega|} = \frac{\binom{16}{3}}{\binom{20}{3}}$$

$$\mathbb{P}(E) = 1 - \mathbb{P}(E^c) = 1 - \frac{\binom{16}{3}}{\binom{20}{3}}.$$

**Definition 23.**  $X$  is called **discrete** if  $\exists$  a countable set  $S \subset \mathbb{R}$  such that  $\mathbb{P}(X \in S) = 1$ .

**Definition 24.** The **probability mass function**  $p(a) = \mathbb{P}(X = a)$  is positive for most a countable number of values of  $a$ .

**Example.** The pmf of a random variable  $X$  is given by  $p_X(i) = \frac{c\lambda^i}{i!}$ ,  $i = 0, 1, 2, \dots$  where  $\lambda$  is some positive value. What is  $\mathbb{P}(X = 0)$  and  $\mathbb{P}(X > 2)$ ?

**Explanation.**

$$\sum p_X(i) = \sum_{i=0}^{\infty} \frac{c\lambda^i}{i!} = 1$$

$$\Rightarrow X = \frac{1}{\sum_{k=0}^{\infty} \frac{\lambda^k}{k!}} = e^{-\lambda}.$$

Then,  $\mathbb{P}(X = 0) = p_X(0) = \frac{c\lambda^0}{0!} = c = e^{-\lambda}$ .

Also,  $\mathbb{P}(X > 2) = 1 - \mathbb{P}(X \leq 2)$ .

$$\mathbb{P}(X \leq 2) = \mathbb{P}(X = 0) + \mathbb{P}(X = 1) + \mathbb{P}(X = 2)$$

$$= e^{-\lambda} \left( 1 + \lambda + \frac{\lambda^2}{2} \right).$$

**Definition 25.** If  $X$  is a discrete random variable, the **expectation** of  $X$  is denoted by  $\mathbb{E}(X)$  and is defined by

$$\mathbb{E}(X) = \sum_{x \in \text{Im} X} x \mathbb{P}(X = x).$$

**Example.** We say that  $I$  is an indicator variable for the event  $A$  if

$$I = \begin{cases} 1 & \text{if } A \text{ occurs} \\ 0 & \text{if } A^c \text{ occurs} \end{cases}.$$

Find  $\mathbb{E}(I)$ .

**Explanation.**

$$\mathbb{E}(I_A) = 0 \cdot \mathbb{P}(I_A = 0) + 1 \cdot \mathbb{P}(I_A = 1)$$

$$= \mathbb{P}(I_A = 1)$$

$$= \mathbb{P}(\{\omega \in \Omega : I_A(\omega) = 1\})$$

$$= \mathbb{P}(\{\omega \in A\})$$

$$= \mathbb{P}(A).$$

**Example.** A class of 120 students is driven in 3 buses to a performance, with 36, 40, and 44 students in the busees. Let  $X$  denote the number of students on the bus of a randomly chosen student. Find  $\mathbb{E}(X)$ .

**Explanation.** Note that  $\mathbb{P}(B_1) = \frac{36}{120}$ ,  $\mathbb{P}(B_2) = \frac{40}{120}$  and  $\mathbb{P}(B_3) = \frac{44}{120}$ . Then,

$$\mathbb{E}(X) = 36 \cdot \frac{36}{120} + 40 \cdot \frac{40}{120} + 44 \cdot \frac{44}{120}$$

$$= \frac{36^2 + 40^2 + 44^2}{120}$$

## Lecture 4: Random Variables and Expected Values

**Proposition 2.** If  $X$  is a discrete random variables that takes on one of the values  $x_i$ ,  $i \geq 1$ , with respective probabilities  $p(x_i)$ , then, for any

real valued function  $g$ ,

$$\mathbb{E}(g(X)) = \sum_i g(x_i) p(x_i).$$

In other words,  $g(X)$  is also a random variable.

**Proof.** Done with a change of variables. ■

**Example.** Suppose  $t$  units of a product are ordered, and  $X$  = number of units sold is a random variable. Assume a net profit of  $b$  per unit and a net loss of  $l$  per unit left unsold. Compute expected profit.

**Explanation.** Our profit function is then  $\gamma = bX - l(t - X)$ . Then,  $\mathbb{E}(\gamma) = \mathbb{E}(g(X))$  where  $g(X) = (b + l)X - lt$ . Then we have

$$\begin{aligned} \mathbb{E}(g(X)) &= \sum_{x \in \text{Im} X} g(x) \cdot p_X(x) \\ &= (b + l) \underbrace{\sum_{x \in \text{Im} X} x \cdot p_X(x)}_{\mathbb{E}(X)} \\ &\quad - lt \underbrace{\sum_{x \in \text{Im} X} p_X(x)}_1 \\ &= (b + l)\mathbb{E}(X) - lt. \end{aligned}$$

**Definition 26.** If  $X$  is a random variable with mean  $\mu$ , then the **variance** of  $X$ , denoted by  $\text{Var}(X)$  is defined by

$$\text{Var}(X) = \mathbb{E}((X - \mu)^2).$$

**Proposition 3.**  $\text{Var}(X) = \mathbb{E}(X^2) - (\mathbb{E}(X))^2$

**Proof.** We have

$$\begin{aligned} \text{Var}(X) &= \mathbb{E}((X - \mathbb{E}(X))^2) \\ &= \mathbb{E}(X^2 - 2X \cdot \mathbb{E}(X) + (\mathbb{E}(X))^2) \\ &= \mathbb{E}(X^2) - 2\mathbb{E}(X) + (\mathbb{E}(X))^2 \\ &\quad (\mathbb{E}(c) = c \text{ for constant } c) \\ &= \mathbb{E}(X^2) - (\mathbb{E}(X))^2. \end{aligned}$$

■

**Proposition 4.** If  $X$  is a discrete random variable with finitely many values, then  $\text{Var}(X) = 0 \Leftrightarrow X \equiv \mathbb{E}(X)$ .

**Proof.** ( $\Leftarrow$ ) Suppose  $X = \mathbb{E}(X)$  Then,

$$\begin{aligned} \mathbb{E}(X^2) &= \sum_{i=1}^n x_i^2 p_X(x_i) \\ &= c^2 \cdot \sum_{i=1}^n p_X(x_i) \\ &= c^2. \end{aligned}$$

Plugging both sides back into  $\text{Var}(X)$ , we have  $\text{Var}(X) = c^2 - c^2 = 0$ . ( $\Rightarrow$ ) Suppose  $\text{Var}(X) = 0$ . Then,

$$\begin{aligned} \text{Var}(X) &= \mathbb{E}[(X - \mathbb{E}(X))^2] = 0 \\ &= \underbrace{\sum_i (x_i - c)^2 \cdot p_X(x_i)}_{\text{every term} \geq 0} \\ &\Rightarrow (x_i - c)^2 \cdot p_X(x_i) = 0 \quad \forall i \Rightarrow \mathbb{E}(X) = c. \end{aligned}$$

■

Note that  $\text{Var}(X)$  is very similar to standard deviation, and it measures the spread of how far apart data is from the mean.

**Definition 27.** Let  $X : \Omega \rightarrow \mathbb{R}$  be a random variable. The **cumulative distributino function** (CDF) is defined as

$$F_X(a) = \mathbb{P}(X \leq a) = \mathbb{P}(X(\omega) \in (-\infty, a]).$$

**Definition 28.** We say  $X \sim \text{Bernoulli}(p)$  if

$$\mathbb{P}(X = 1) = p \quad \mathbb{P}(X = 0) = 1 - p \quad (p \in (0, 1)).$$

**Example.** It is known that screws produced will be defective with probability 0.1. The company sells screws in packages of 10 and gives a refund if more than 1 screw is defective. What proportion of packages must the company refund?

**Explanation.** Let  $X$  represent the number of defective screws. We wish to find  $1 - \mathbb{P}(X \leq 1)$ . This is just  $1 - \mathbb{P}(X = 0) - \mathbb{P}(X = 1)$ . Just apply the binomial formula to get your answer.

**Definition 29.** A random variable  $X$  that takes on one of the values  $0, 1, 2, \dots$  is said to be a **Poisson** random variable with parameter  $\lambda$  if for some  $\lambda > 0$

$$p(i) = \mathbb{P}(X = i) = e^{-\lambda} \left( \frac{\lambda^i}{i!} \right).$$

## Lecture 5: More Distributions

Note that the Poisson distribution can be derived from the binomial distribution with  $p = \frac{\lambda}{n}$ .

**Example.** Let  $X$  be a binomial random variable. Calculate  $\mathbb{E}[X]$  and the variance.

**Explanation.** We have

$$\begin{aligned}\mathbb{E}[X] &= \sum_{x=0}^n x \cdot \binom{n}{x} p^x \cdot q^{n-x} \\ &= \sum_{x=1}^n n \cdot \binom{n-1}{x-1} p^x q^{n-x} \\ &= np \cdot \sum_{x=1}^n \binom{n-1}{x-1} p^{x-1} q^{n-x} \\ &= np \cdot (p+q)^{n-1} \\ &= np.\end{aligned}$$

For the variance, we have

$$\begin{aligned}\text{Var } X &= \mathbb{E}(X^2) - (\mathbb{E}X)^2 \\ \mathbb{E}(X^2) &= np \cdot \sum_{x=1}^n x \cdot \binom{n-1}{x-1} p^{x-1} q^{n-x} \\ &= np \cdot \mathbb{E}(Y+1) \quad (Y \sim \text{Bin}(n-1, p)) \\ &= n \cdot p((n-1)p+1).\end{aligned}$$

such that

$$\text{Var } X = np(1-p).$$

**Example.** Same thing, but with  $X$  as poisson.

**Explanation.**

$$\begin{aligned}\mathbb{E}X &= \sum_{x=0}^{\infty} x \cdot \left( \frac{e^{-\lambda} \lambda^x}{x!} \right) \\ &= e^{-\lambda} \cdot \lambda \sum_{x=1}^{\infty} \frac{\lambda^{x-1}}{(x-1)!} \\ &= e^{-\lambda} \cdot \lambda \cdot e^{\lambda} \quad (\text{Change of vars.}) \\ &= \lambda.\end{aligned}$$

For the variance, we have

$$\begin{aligned}\mathbb{E}(X^2) &= \sum_{x=0}^{\infty} x^2 \frac{e^{-\lambda} \lambda^x}{x!} \\ &= \lambda \sum_{x=1}^{\infty} x \frac{e^{-\lambda} \lambda^{x-1}}{(x-1)!} \\ &= \lambda \sum_{y=0}^{\infty} \frac{(y+1) \cdot e^{-\lambda} \lambda^y}{y!} \\ &= \lambda \left[ \sum_{y=0}^{\infty} y \cdot \frac{e^{-\lambda} \lambda^y}{y!} + \sum_{y=0}^{\infty} \frac{e^{-\lambda} \lambda^y}{y!} \right] \\ &= \lambda(\lambda+1).\end{aligned}$$

such that

$$\text{Var } X = \lambda.$$

**Example.** If  $n$  people are present in the room, what is the probability that no two of them celebrate their birthday on the same day of the year? How large does  $n$  be such that this probability is less than  $\frac{1}{2}$ ?

**Explanation.** We compare  $\binom{n}{2}$  times. Each probability for same birthday is  $\frac{1}{365}$ . Using Poisson,

$$\mathbb{P}(X=0) = e^{-\lambda} = \exp\left(\frac{-n \cdot (n-1)}{730}\right).$$

such that  $n = 23$  is our threshold.

**Definition 30.** A **geometric distribution** is the number of independent Bernoulli trials it takes for a single success. The pmf is

$$p_X(i) = (1-p)^{i-1} \cdot p.$$

**Definition 31.** If  $X$  is a discrete random variable and  $\mathbb{P}(B) > 0$ , the **conditional expectation** of  $X$  given  $B$  is denoted by  $\mathbb{E}(X | B)$  and defined by

$$\mathbb{E}(X | B) = \sum_{x \in \text{Im } X} x \cdot \mathbb{P}(X = x | B).$$

**Definition 32.** If  $X$  is a discrete random variable and  $\{B_1, B_2, \dots\}$  is a partition of the sample space such that  $\mathbb{P}(B_i) > 0 \forall i$ , then the **partition theorem** states that

$$\mathbb{E}(X) = \sum_i \mathbb{E}(X | B_i) \mathbb{P}(B_i).$$



## Lecture 6: Multivariate Probability

### 3 Multivariate Probability

Our objective is to treat random vectors  $(X, Y_0 \in \mathbb{R}^2)$  together as

$$(X, Y) : \Omega^2 \rightarrow \mathbb{R}^2.$$

**Definition 33.** If  $X$  and  $Y$  are discrete random variables on  $(\Omega, \mathcal{F}, \mathbb{P})$ , the **joint probability mass function**  $P_{X,Y}(x, y)$  of  $X$  and  $Y$  is the function

$$p_{X,Y} : \mathbb{R}^2 \rightarrow [0, 1].$$

defined by

$$\begin{aligned} p_{X,Y}(x, y) \\ = \mathbb{P}(\{\omega \in \Omega : X(\omega) = x \text{ and } Y(\omega) = y\}). \end{aligned}$$

and abbreviated

$$p_{X,Y}(x, y) = \mathbb{P}(X = x, Y = y).$$

**Note.** The sum of all options still remains one.

**Example.** Two cards are drawn at random from a deck of 52 cards. If  $X$  denotes the number of aces drawn and  $Y$  denotes the number of kings, display the joint mass function of  $X$ , and  $Y$  in tabular form.

**Explanation.** Note that  $X = \{0, 1, 2\}, Y = \{0, 1, 2\}$ . Then, we have

	$X = 0$	$X = 1$	$X = 2$
$Y = 0$	$\frac{44}{52} \cdot \frac{43}{51}$	$\frac{\binom{4}{1} \cdot \binom{44}{1}}{\binom{52}{2}}$	$\frac{\binom{4}{2}}{\binom{52}{2}}$
$Y = 1$	$\frac{\binom{4}{1} \cdot \binom{44}{1}}{\binom{52}{2}}$	$\frac{\binom{4}{1} \cdot \binom{4}{1}}{\binom{52}{2}}$	0
$Y = 2$	$\frac{\binom{4}{2}}{\binom{52}{2}}$	0	0

Note that we can expand this past 2 dimensions.

**Definition 34.** Suppose that each of  $n$  experiments can result in any one of  $r$  possible outcomes, with probabilities,  $p_1, p_2, \dots, p_r$  which sum up to one. If we let  $X_i$  denote the number of the  $n$  experiments that result in outcome number  $i$ , then the probability mass function is given by

$$\begin{aligned} \mathbb{P}(X_1 = n_1, \dots, X_r = n_r) \\ = \binom{n}{n_1, n_2, \dots, n_r} p_1^{n_1} \cdot p_2^{n_2} \cdot \dots \cdot p_r^{n_r}. \end{aligned}$$

**Definition 35.** We have that

$$\begin{aligned} \mathbb{E}(g(X, Y)) \\ = \sum_{x \in \text{Im} X} \sum_{y \in \text{Im} Y} g(x, y) \mathbb{P}(X = x, Y = y). \end{aligned}$$

when this sum converges absolutely.

**Corollary.**

$$\mathbb{E}(aX + bY) = a\mathbb{E}(X) + b\mathbb{E}(Y).$$

**Proof.** Linearity :).

**Definition 36.** Two discrete random variables  $X$  and  $Y$  are **independent** if the pair of events  $[X = x]$  and  $[Y = y]$  are independent for all  $x, y \in \mathbb{R}$ . We write this as

$$\begin{aligned} \mathbb{P}(X = x, Y = y) &= \mathbb{P}(X = x) \mathbb{P}(Y = y) \\ \forall x, y \in \mathbb{R}. \end{aligned}$$

**Corollary.** If  $X$  is independent of itself, then  $X$  is almost surely constant.

**Proposition 5.**  $k$  random variables are independent of the product of all of them is the same as the multivariate probability of all.

**Definition 37.** The **indicator function** of an event  $A$  is the function  $\mathbb{I}_A$  defined by

$$\mathbb{I}_A(\omega) = \begin{cases} 1 & \text{if } \omega \in A \\ 0 & \text{if } \omega \notin A \end{cases}.$$

**Example.** Show that two events  $A$  and  $B$  are independent iff their indicator functions are independent random variables.

**Explanation.** Case work for the forward direction, and set construction for the second.

## Lecture 7: More Independence

**Example.** Suppose that  $n + m$  independent trials with probability of success  $p$  are performed. If  $X$  is the number of successes of the first  $n$ , and  $Y$  is the number of successes of the last  $m$ , then  $X$  and  $Y$  are independent.

**Explanation.** Look at  $p_{x,y}(X = x, Y = y)$ . We wish to show that this equals  $p_X(x) \cdot p_Y(y)$ . Let 1 be success, 0 be failure. Then,  $\Omega = \{0, 1\}^{n+m} = (a = \{0, 1\}^n, b = \{0, 1\}^m)$ . Then

$$\begin{aligned}\mathbb{P}((a, b)) &= p^{x+y} \cdot (1-p)^{m+n-(x+y)} \\ &= p^x \cdot (1-p)^{n-x} \cdot p^y \cdot (1-p)^{m-y}.\end{aligned}$$

Therefore,

$$\begin{aligned}\mathbb{P}(x, y) &= \sum_{(a,b) \in \{X=x, Y=y\}} \mathbb{P}((a, b)) \\ &= \binom{n}{x} \binom{m}{y} \underbrace{p^x (1-p)^{n-x} p^y (1-p)^{m-y}}_{\mathbb{P}((a,b))} \\ &= \binom{n}{x} p^x (1-p)^{n-x} \binom{m}{y} p^y (1-p)^{m-y} \\ &= p_X(x) \cdot p_Y(y).\end{aligned}$$

**Theorem 8.** Discrete random variables  $X, Y$  are independent iff

$$\mathbb{E}(g(X)h(Y)) = \mathbb{E}(g(X))\mathbb{E}(h(Y)).$$

**Proof.** We have that

$$\begin{aligned}\mathbb{E}(g(X)h(Y)) &= \sum_{x,y} g(x)h(y)\mathbb{P}(X = x, Y = y) \\ &= \sum_{x,y} g(x)h(y)\mathbb{P}(X = x)\mathbb{P}(Y = y) \\ &= \mathbb{E}(g(X)) + \mathbb{E}(h(Y)).\end{aligned}$$

In the other direction, assume that

$$\mathbb{E}(g(X)h(Y)) = \mathbb{E}(g(X))\mathbb{E}(h(Y)).$$

We must show that

$$p_{X,Y}(x, y) = p_X(x)p_Y(y).$$

for all real numbers  $a, b$ . Define the indicator functions

$$g(x) = \begin{cases} 1, & \text{if } x = a \\ 0 & \text{if } x \neq a \end{cases} \quad h(y) = \begin{cases} 1, & \text{if } y = b \\ 0 & \text{if } y \neq b \end{cases}.$$

Then, we have that

$$\begin{aligned}\mathbb{E}(g(X)h(Y)) &= \sum_{x,y} g(x)h(y)\mathbb{P}(X = x, Y = y) \\ &= \mathbb{P}(X = a, Y = b).\end{aligned}$$

We also have that

$$\mathbb{E}(g(X))\mathbb{E}(h(Y)) = \mathbb{P}(X = a)\mathbb{P}(Y = b).$$

Putting these two together, we have that  $X, Y$  are independent, as desired. ■

**Example.** Suppose that  $X$  has distribution given by  $\mathbb{P}(X = -1) = \mathbb{P}(X = 0) = \mathbb{P}(X = 1) = \frac{1}{3}$  and  $Y$  is given by

$$Y = \begin{cases} 0, & \text{if } X = 0 \\ 1 & \text{if } X \neq 0 \end{cases}.$$

**Explanation.** We have that  $\mathbb{E}X\mathbb{E}Y = \mathbb{E}XY$  if (not only if)  $X, Y$  independent. However,  $X$  and  $Y$  are dependent here.

$$\begin{aligned}\mathbb{E}[XY] &= \mathbb{E}[X \cdot |X|] \\ &= \frac{1}{3} \cdot -1 \cdot |-1| + \frac{1}{3} \cdot 0 \cdot |0| + \frac{1}{3} \cdot 1 \cdot |1| \\ &= 0.\end{aligned}$$

and

$$\begin{aligned}\mathbb{E}X &= \sum_x x \cdot \mathbb{P}(X = x) \\ &= -1 \cdot \frac{1}{3} + 0 \cdot \frac{1}{3} + 1 \cdot \frac{1}{3} = 0.\end{aligned}$$

and

$$\mathbb{E}Y = \mathbb{E}(|X|) = \frac{2}{3}.$$

This means that

$$\mathbb{E}XY = \mathbb{E}X\mathbb{E}Y.$$

which shows that this property is not bidirectional.

**Theorem 9.** (Convolution Formula) Set  $Z = X + Y$ ,  $X, Y$  independent. Then for all  $z \in \mathbb{R}$ ,

$$\begin{aligned}\mathbb{P}(Z = z) &= \sum_x \mathbb{P}(X = x, Y = z - x) \\ &= \sum_x \mathbb{P}(X = x)\mathbb{P}(Y = z - x).\end{aligned}$$

**Example.** If  $X$  and  $Y$  are independent discrete random variables,  $X$  having the Poisson distribution with parameter  $\lambda$  and  $Y$  has Poisson distribution with parameter  $\mu$ , show that  $X + Y$  has poisson distribution with parameter  $\lambda + \mu$ .

**Explanation.** Let  $Z = X + Y$ . Remember that

$$\mathbb{P}(X = x) = \frac{e^{-\lambda}\lambda^x}{x!} \quad \text{and} \quad \mathbb{P}(Y = y) = \frac{e^{-\mu}\mu^y}{y!}.$$

Then,

$$\begin{aligned}
\mathbb{P}(Z = z) &= \sum_{x=0}^{\infty} \mathbb{P}(X = x) \mathbb{P}(Y = z - x) \\
&= \sum_{x=0}^z \mathbb{P}(X = x) \mathbb{P}(Y = z - x) \\
&= \sum_{x=0}^z \frac{e^{-\lambda} \lambda^x}{x!} \cdot \frac{e^{-\mu} \mu^{z-x}}{(z-x)!} \\
&= \sum_{x=0}^z e^{-\lambda-\mu} \frac{1}{z!} \frac{z!}{x!(z-x)!} \cdot \lambda^x \mu^{z-x} \\
&= e^{-\lambda-\mu} \frac{1}{z!} \sum_{x=0}^z \binom{z}{x} \lambda^x \mu^{z-x} \\
&= e^{-\lambda-\mu} \frac{1}{z!} (\lambda + \mu)^z.
\end{aligned}$$

which is precisely the Poisson distribution with  $\lambda + \mu$ .

**Theorem 10.** Let  $A_1, A_2 \dots A_n$  be events. Then, we have that

$$\sum_{i=0}^n \mathbb{I}_{A_i}(\omega) = \text{number of events that } \omega \text{ occurs.}$$

**Example.** The  $2n$  seats around a circular table are numbered clockwise. Queens sit in odd numbered seats and Kings in even numbers. Let  $N$  be the number of queens sitting next to their king. Find the mean and variance of  $N$ .

**Explanation.** Let  $A_i$  be the event that the  $i$ -th pair sit together. Then,

$$N = \sum_{i=1}^n \mathbb{I}_{A_i}.$$

Note that  $\mathbb{P}(A_i) = \frac{2}{n}$ . Think of a fixed king permutation, then there are two spots out of  $n$  spots for the queen to sit. Next,

$$\begin{aligned}
\mathbb{E}N &= \mathbb{E}\left(\sum_{i=1}^n \mathbb{I}_{A_i}\right) \\
&= \sum_{i=1}^n \mathbb{E}\mathbb{I}_{A_i} \\
&= \sum_{i=1}^n \mathbb{P}(A_i) \\
&= \sum_{i=1}^n \frac{2}{n} = 2.
\end{aligned}$$

The variance calculation is more involved. Remember that

$$\text{Var}(N) = \mathbb{E}N^2 - (\mathbb{E}N)^2.$$

Then, we have

$$\begin{aligned}
\mathbb{E}(N^2) &= \mathbb{E}\left(\left[\sum_{i=1}^n \mathbb{I}_{A_i}\right]^2\right) \\
&= \mathbb{E}\left(\sum_{i=1}^n \sum_{j=1}^n \mathbb{I}_{A_i} \mathbb{I}_{A_j}\right) \\
&= \mathbb{E}\left(\sum_{i=1}^n \mathbb{I}_{A_i} \mathbb{I}_{A_i} + 2 \sum_{1 \leq i < j \leq n} \mathbb{I}_{A_i} \mathbb{I}_{A_j}\right) \\
&= \sum_{i=1}^n \mathbb{E}(\mathbb{I}_{A_i} \mathbb{I}_{A_i}) + 2 \sum_{1 \leq i < j \leq n} \mathbb{E}(\mathbb{I}_{A_i} \mathbb{I}_{A_j}) \\
&= \sum_{i=1}^n \mathbb{E}(\mathbb{I}_{A_i}) + 2 \sum_{1 \leq i < j \leq n} \mathbb{E}(\mathbb{I}_{A_i} \mathbb{I}_{A_j}) \\
&= \sum_{i=1}^n \underbrace{\mathbb{P}(A_i)}_{\frac{2}{n}} + 2 \sum_{1 \leq i < j \leq n} \mathbb{P}(A_i \cap A_j).
\end{aligned}$$

From here, we need to calculate  $\mathbb{P}(A_i \cap A_j)$ .

## Lecture 8: Generating Functions

Continuing on with the Variance calculation, we have that

**Explanation.** Note that  $\mathbb{P}(A_i \cap A_j)$  is given by (WLOG)

$$\begin{aligned}
\mathbb{P}(A_i \cap A_j) &= \mathbb{P}(A_1) \cdot \mathbb{P}(A_2 | A_1) \\
&= \frac{2}{n} \cdot \left[ \frac{1}{n-1} \frac{1}{n-1} + \frac{n-2}{n-1} \frac{2}{n-1} \right] \\
&= \frac{2}{n} \cdot \frac{2n-3}{(n-1)^2}.
\end{aligned}$$

Continuing on, we have that

$$\mathbb{E}(N^2) = n \cdot \frac{2}{n} + \frac{4}{n} \cdot \frac{2n-3}{(n-1)^2} \binom{n}{2}.$$

**Example.** My squad of bunnies have been training all summer. Each bunny is ready for the bunny mission with probability  $p$ . If I have  $n$  bunnies in the squad and need  $k$  for the mission, find  $\mathbb{E}$  of the number of  $k$ -large teams that I can form.

**Explanation.** Let  $A_i$  be the event that bunny  $i$

is ready. Then,

$$X = \sum_{i=1}^n \mathbb{I}_{A_i}.$$

counts the number of bunnies ready. We want to compute for  $X \geq k$  how many  $k$ -large teams is possible. This is just  $\binom{X}{k}$ . Note that

$$\binom{X}{k} = \sum_{1 \leq i_1 < i_2 < \dots < i_k \leq n} \mathbb{I}_{A_{i_1} \cap A_{i_2} \cap \dots \cap A_{i_k}}.$$

This means that

$$\begin{aligned} \mathbb{E} \binom{X}{k} &= \sum_{1 \leq i_1 < i_2 < \dots < i_k \leq n} \mathbb{E} \left( \mathbb{I}_{A_{i_1} \cap A_{i_2} \cap \dots \cap A_{i_k}} \right) \\ &= \sum_{1 \leq i_1 < i_2 < \dots < i_k \leq n} \mathbb{P}(A_{i_1} \cap \dots \cap A_{i_k}) \\ &= \sum_{1 \leq i_1 < i_2 < \dots < i_k \leq n} \mathbb{P}(A_{i_1}) \cdot \dots \cdot \mathbb{P}(A_{i_k}) \\ &\quad \text{(Independent)} \\ &= \sum_{1 \leq i_1 < i_2 < \dots < i_k \leq n} p^k \\ &= \binom{n}{k} p^k. \end{aligned}$$

**Example.** A grove of 52 trees is arranged in a circular fashion. If 15 chipmunks live in these trees, show that there is a group of 7 consecutive trees that together house at least 3 chipmunks.

**Explanation.** We find

$$\mathbb{E}(\text{num chipmunks that lie in 7 con. trees}) > 2.$$

In other words, if on average there are 3, then for one group there must be 3. Let  $X$  be the number of chipmunks that lie in a random tree and 6 neighbors clockwise. Let

$$X_i = \begin{cases} 1, & \text{if chipmunk } i \text{ lives in nbhd} \\ 0 & \text{otherwise.} \end{cases}$$

We know that

$$X = \sum_{i=1}^{15} X_i \quad \text{and} \quad \mathbb{E}X = \sum_{i=1}^{15} \mathbb{E}X_i.$$

Then, we have that

$$\mathbb{E}[X_i] = \mathbb{P}(X_i = 1) = \frac{7}{52}.$$

. Therefore,

$$\mathbb{E}X = 15 \cdot \frac{7}{52} = \frac{105}{52} > 2.$$

## 4 Probability Generating Functions

**Definition 38.** Consider the sequence  $u_0, u_1, u_2, \dots$  of real numbers. We can write down the **generating function** of this sequence as

$$U(s) = u_0 + u_1 s + u_2 s^2 + \dots$$

**Example.** The sequence given by

$$u_n = \begin{cases} \binom{N}{n}, & \text{if } n = 0, 1, 2, \dots, N \\ 0 & \text{otherwise} \end{cases}$$

has generating function

$$U(s) = \sum_{n=0}^N \binom{N}{n} s^n = (1+s)^N.$$

**Example.** If  $u_0, u_1, \dots$  has generating function  $U(s)$  and  $v_0, v_1, \dots$  has generating function  $V(s)$ , find  $V(s)$  in terms of  $U(s)$  when (a)  $v_n = 2u_n$  and (b)  $v_n = u_n + 1$ , and (c)  $v_n = nu_n$ .

**Explanation.** We have (a)  $2U(s)$ , (b)  $U(s) + \frac{1}{1-s}$ , and (c)  $s \cdot U'(s)$ .

## Lecture 9

**Theorem 11.** We have that  $G_X(s) = \mathbb{E}(s^X)$ .

**Proof.**

$$\begin{aligned} \mathbb{E}(s^X) &= \sum_{i=0}^{\infty} \mathbb{P}(X = i) \cdot s^i \\ &= G_X(s). \end{aligned}$$

■

**Example.** What is the PGF for  $X \equiv 0$ ?

**Explanation.** We have that  $p_i = \mathbb{P}(X = i)$ , such that  $p_0 = 1$ ,  $p_i = 0$  for all  $i > 0$ . Then,

$$\begin{aligned} \mathbb{E}(s^X) &= p_0 s^0 + \dots + p_i s^i + \dots = 1 \\ &= G_X(s). \end{aligned}$$

**Example.** What is the PGF for  $X \sim \text{Bernoulli}(p)$ ?

**Explanation.** Remember that  $p$  is the probability for success, and  $1 - p$  is the probability for failure (Binomial). We have that  $p_0 = 1 - p$  and  $p_1 = p$ . Then,

$$\begin{aligned}\mathbb{E}(s^X) &= G_X(s) = p_0 s^0 + p_1 s^1 \\ &= (1 - p) + p \cdot s.\end{aligned}$$

**Theorem 12.** Given  $X$  with geometric distribution with parameter  $p$ , we have that

$$\mathbb{P}(X = k) = pq^{k-1}.$$

where  $p + q = 1$ , and  $X$  has probability generating function

$$\frac{p}{q} \cdot \frac{1}{1 - qs}.$$

**Definition 39.** Let  $k \geq 1$ . The  $k$ th **moment** of the random variable  $X$  is the quantity  $\mathbb{E}(X^k)$ .

**Theorem 13.** The  $r$ th derivative of  $G_X(s)$  for  $s = 1$  is  $\mathbb{E}(X[X - 1] \dots [X - r + 1])$  for  $r = 1, 2, \dots$ . In other words, with  $s = 1, r = 1$  we can get  $G'_X(1) = \mathbb{E}(X)$ .

**Example.** Use the method of generating functions to show that a random variable with Poisson distribution with parameter  $\lambda$  has both mean and variance equal to  $\lambda$ .

**Explanation.** Note that  $G''(1) = \mathbb{E}(X[X - 1]) = \mathbb{E}X^2 - \mathbb{E}X$ .