Probability Theory

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Contents

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 ≥ 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.

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

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

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

1.2 Back to Probability

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

Example. The sample space Ω 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 Ω is a finite set, a probability P on Ω is a function: $P \colon 2^\Omega \to [0, 1]$ such that $\mathbb{P}(\varnothing) = 0$ and $\mathbb{P}(\Omega) = 1$.

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

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

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

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 outcommes, 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 consisiting 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

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

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

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 $(x_1 + \ldots + x_r)^n =$

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

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 $P : \mathcal{F} \to \mathbb{R}$ is a **probability measure** on $(\Omega, \mathcal{F})$ if

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

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

Lecture 2: More Probabiliy

1.6 Properties of Event Spaces

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

- $\mathcal{F}$ is non-empty.
- if $A \in \mathcal{F}$ then $\Omega \setminus A \in \mathcal{F}$.
- if $A_1, A_2, \ldots \in \mathcal{F}$ 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 cnsists of us taking 1 marble, replacing it, and drawing another marble. What is the sample space?

Explanation.

$$\begin{aligned}\Omega =\{&(r,r),(r,b),(r,g),\\ &(b,r),(b,g),(b,b),\\ &(g,r),(g,g),(g,b)\}.\end{aligned}$$

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 flushses 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 withdrawings 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 situatons 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 $\mathbb{P}(A\mid B)$ and defined by

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

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

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 occurence of one does not affect the other. Formally,

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

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 $\left(\frac{1}{2}\right)^3 = \frac{1}{8}$.

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.

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

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

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.

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

Lecture 3: Bayes Theorem and Random Variables

Continuing on with conditional probabiltiy 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

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

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

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

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

will then be our answer.

1.9 Bayes Theorem

Definition 21. A **partition** of Ω 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 $\{B_1, B_2, \ldots\}$ is such a parition with $\mathbb{P}(B_i) > 0$, then

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

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' Theorem to yield

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

2 Random Variables

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

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

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. $\Omega = \{1, 2, 3, \ldots, 20\}$. $|\Omega| = \binom{20}{3}$. Let our random variable $X : \Omega \to \mathbb{R}$, $X =$ 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 $p_X(i) = \frac{c\lambda^i}{i!}$, $i = 0, 1, 2\ldots$ where λ is some positive value. What is $\mathbb{P}(X = 0)$ and $\mathbb{P}(X > 2)$?

Explanation.

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

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

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

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

$$\begin{aligned}\mathbb{P}(X \leq 2) &= \mathbb{P}(X = 0) + \mathbb{P}(X = 1) + \mathbb{P}(X = 2)\\ &= e^{-\lambda}\left(1 + \lambda + \frac{\lambda^2}{2}\right).\end{aligned}$$

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

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

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.

$$\begin{aligned}\mathbb{E}(I_A) &= 0 \cdot \mathbb{P}(I_A = 0) + 1 \cdot \mathbb{P}(I_A = 1)\\ &= \mathbb{P}(I_A = 1)\\ &= \mathbb{P}(\{\omega \in \Omega : I_A(\omega) = 1\})\\ &= \mathbb{P}(\{\omega \in A\})\\ &= \mathbb{P}(A).\end{aligned}$$

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,

$$\begin{aligned}\mathbb{E}(X) &= 36 \cdot \frac{36}{120} + 40 \cdot \frac{40}{120} + 44 \cdot \frac{44}{120}\\ &= \frac{36^2 + 40^2 + 44^2}{120}\end{aligned}$$

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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 proabilities $p(x_i)$, 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

$$\begin{aligned}\mathbb{E}(g(X)) &= \sum_{x\in \operatorname{Im} X} g(x)\cdot p_X(x)\\ &= (b+l)\underbrace{\sum_{x\in \operatorname{Im} X} x\cdot p_X(x)}_{\mathbb{E}(X)}\\ &\quad - lt\underbrace{\sum_{x\in \operatorname{Im} X} p_X(x)}_{1}\\ &= (b+l)\mathbb{E}(X) - lt.\end{aligned}$$

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

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

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

Proof. We have

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

■

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

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 $\operatorname{Var}(X)$, we have $\operatorname{Var}(X) = c^2 - c^2 = 0$. ($\Rightarrow$) Suppose $\operatorname{Var}(X) = 0$. Then,

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

■

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

Definition 27. Let $X : \Omega \to \mathbb{R}$ 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 $X \sim \operatorname{Bernoulli}(p)$ 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 propotion 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 $0, 1, 2, \ldots$ is said to be a **Poisson** random variable with parameter λ 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

$$\operatorname{Var} X = \mathbb{E}(X^2) - (\mathbb{E}X)^2$$

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

such that

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

Example. Same thing, but with X as poisson.

Explanation.

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

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

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

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 threshhold.

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 $\mathbb{E}(X \mid B)$ and defined by

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

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

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

Lecture 6: Multivariate Probability

3 Multivariate Probability

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

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
$$p_{X,Y} : \mathbb{R}^2 \to [0, 1].$$
defined by
$$p_{X,Y}(x, y) \\ = \mathbb{P}(\{\omega \in \Omega : X(\omega) = x \text{ and } Y(\omega) = y\}).$$
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 dech of 52 cards. If X denotes the number of aces drawn and Y denotes the number of kings, display the join 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 proabilities, $p_1, p_2, \ldots p_r$ which sum up to one. If we let X_l denote the nubmer of the n experiments that result in outcome number i, then the probability mass function is given by
$$\mathbb{P}(X_1 = n_1, \ldots, X_r = n_r) \\ = \binom{n}{n_1, n_2, \ldots, n_r} p_1^{n_1} \cdot p_2^{n_2} \cdot \ldots \cdot p_r^{n_r}.$$

Definition 35. We have that
$$\mathbb{E}(g(X, Y)) \\ = \sum_{x \in \operatorname{Im} X} \sum_{y \in \operatorname{Im} Y} g(x, y)\mathbb{P}(X = x, Y = y).$$
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
$$\mathbb{P}(X = x, Y = y) = \mathbb{P}(X = x)\mathbb{P}(Y = y) \\ \forall x, y \in \mathbb{R}.$$

Corollary. If X is independent of itself, then X is almost surely consant.

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

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,

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

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

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

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 λ and Y has Poisson disrubtion with parameter μ, show that $X + Y$ has poisson distrubtion 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 numbesr. 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

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

Then, we have

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

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)

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

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

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

This means that

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

Example. A grove of 52 trees is araranged 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,

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

4 Probability Generating Functions

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

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

Example. The sequence given by

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

has generating function

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

Example. If $u_0, u_1, \ldots$ has generating function $U(s)$ and $v_0, v_1, \ldots$ has generating function $V(s)$, find $V(s)$ in terms of $U(s)$ when (a) $v_n = 2u_n$ and (b) $v_n = u_1 + 1$, 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: More on PGFs

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,

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

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 kth **moment** of the random variable X is the quantity $\mathbb{E}(X^k)$.

Theorem 13. The rth 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 λ has both mean and variance equal to λ.

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

$$\begin{aligned} \mathbb{E}X^2 &= \mathbb{E}[X(X-1) + X] \\ &= \mathbb{E}(X(X-1)) + \mathbb{E}X \\ &= G''_X(1) + G'_X(1). \end{aligned}$$

Which means that

$$\begin{aligned} \operatorname{Var} X &= \mathbb{E}(X^2) - (\mathbb{E}X)^2 \\ &= G''_X(1) + G'_X(1) - (G'_X(1))^2. \end{aligned}$$

Recall that $G_X(s) = e^{\lambda(s-1)}$. Note that $G'_X(1) = \lambda$, which is the expectation (mean). Also, $G''_X(1) = \lambda^2$ which means that

$$\operatorname{Var} X = \lambda^2 + \lambda - \lambda^2 = \lambda.$$

Theorem 14. Suppose we have X, Y such that

$$G_X(s) = G_Y(s).$$

This means that

$$\mathbb{P}(X = k) = \mathbb{P}(Y = k) \quad \forall k.$$

Theorem 15. If X and Y are independent random variables, then $X + Y$ has generating function

$$G_{X+Y}(s) = G_X(s) G_Y(s).$$

Proof.

$$\begin{aligned} G_{X+Y}(s) &= \mathbb{E}(s^{X+Y}) \\ &= \mathbb{E}(s^X s^Y) \\ &= \mathbb{E}(s^X)\mathbb{E}(s^Y) \qquad \text{(Independence)} \\ &= G_X(s) G_Y(s). \end{aligned}$$

■

Theorem 16. (Random sum formula) Let N and $X_1, X_2 \dots$ be independent random variables taking values in $\mathbb{Z}_{>0}$. If X_i are identically distributed with common PGF G_X, then

$$S = X_1 + X_2 + \dots + X_N.$$

has PGF

$$G_S(s) = G_N(G_X(s)).$$

Proof. Note that $G_S(t) = \mathbb{E}t^S$. Recall that for partitions E_i of Ω,

$$\mathbb{E}X = \sum_{i=1}^{\infty} \mathbb{E}(X \mid E_i)\mathbb{P}(E_i).$$

Applying that

$$G_S(t) = \mathbb{E}t^S = \mathbb{E}(t^{X_1 + X_2 + \dots + X_N}).$$

we have that

$$\begin{aligned}G_S(t) &= \sum_{n=0}^{\infty} \mathbb{E}(t^{X_1+\ldots+X_N} \mid N = k)\mathbb{P}(N = n)\\ &= \sum_{n=0}^{\infty} \mathbb{E}(t^{X_1+\ldots+X_n})\mathbb{P}(N = n)\\ &= \sum_{n=0}^{\infty} \mathbb{E}(t^{X_1})\ldots\mathbb{E}(t^{X_n})\mathbb{P}(N = n)\\ &= \sum_{n=0}^{\infty} (\mathbb{E}(t^{X_1}))^n\mathbb{P}(N = n)\\ &= \sum_{n=0}^{\infty} G_{X_1}(t)^n\mathbb{P}(N = n)\\ &= G_N(G_{X_1}(t)).\end{aligned}$$

■

Example. The hutch in the garden contains 20 pregnant rabbits. The hutch is insecure and each rabbit has a $\frac{1}{2}$ chance of escaping overnight. The next morning, each remaining rabbit gives birth to a litter, with each mother having a random number of offspring with Poisson distribution with parameter 3.

Explanation. Let S be the number of baby bunnies. We wish to compute $G_S(t)$ and $\mathbb{E}S$. Let X_i be the number of rabbits in the ith litter. Let N be the number of rabbits in the hutch the next morning. Note that N is binomial with $p = \frac{1}{2}$ and 20 trials.

Then, $S = X_1 + \ldots + X_N$. Then,

$$\begin{aligned}G_S(t) &= G_N(G_X(t))\\ &= G_N(e^{3(t-1)}).\end{aligned}$$

Also,

$$G_N(t) = \left(\frac{1}{2} + \frac{1}{2}t\right)^{20}.$$

Therefore,

$$\begin{aligned}\mathbb{E}(S) &= G_S'(1)\\ &= G_X'(1)G_N'(G_X(1))\\ &= 3e^{3(1-1)} \cdot \frac{1}{2} \cdot 20\left(\frac{1}{2} + \frac{1}{2}e^{3(1-1)}\right)^{19} \quad \text{(at } t = 1\text{)}\\ &= 3 \cdot \frac{1}{2} \cdot 20 \cdot 1 = 30.\end{aligned}$$

Lecture 10: CDFs and PDFs

Definition 40. The CDF is everything under the graph of a PDF to the left of some point t.

Theorem 17. We have for PDFs

$$\mathbb{P}(a \leq X \leq b) = \int_a^b f_X(t)dt = F_x(b) - F_x(a)$$

where F is a CDF.

Example. If X is uniformly distributed over $(0, 10)$, calculate the probability that $X < 3$, $X > 6$, and $3 < X < 8$.

Explanation. For $X < 3$, we have

$$\mathbb{P}(X < 3) = \sum_{-\infty}^{3} f_X(t)dt.$$