Introduction to Random Processes Probability Review 1

Probability Review

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Sigma-algebras and probability spaces

Conditional probability, total probability, Bayes’ rule

Independence

Random variables

Discrete random variables

Continuous random variables

Expected values

Joint probability distributions

Joint expectations
An event is something that happens

A random event has an uncertain outcome

⇒ The probability of an event measures how likely it is to occur

Example

I’ve written a student’s name in a piece of paper. Who is she/he?

Event: Student x’s name is written in the paper

Probability: \( P(x) \) measures how likely it is that x’s name was written

Probability is a measurement tool

⇒ Mathematical language for quantifying uncertainty
Sigma-algebra

- **Given a sample space or universe** $S$
  - **Ex:** All students in the class $S = \{x_1, x_2, \ldots, x_N\}$ ($x_n$ denote names)

- **Def:** An **outcome** is an element or point in $S$, e.g., $x_3$

- **Def:** An **event** $E$ is a subset of $S$
  - **Ex:** $\{x_1\}$, student with name $x_1$
  - **Ex:** Also $\{x_1, x_4\}$, students with names $x_1$ and $x_4$
  
  $\Rightarrow$ Outcome $x_3$ and event $\{x_3\}$ are different, the latter is a set

- **Def:** A **sigma-algebra** $\mathcal{F}$ is a collection of events $E \subseteq S$ such that
  1. The empty set $\emptyset$ belongs to $\mathcal{F}$: $\emptyset \in \mathcal{F}$
  2. Closed under complement: If $E \in \mathcal{F}$, then $E^c \in \mathcal{F}$
  3. Closed under countable unions: If $E_1, E_2, \ldots \in \mathcal{F}$, then $\bigcup_{i=1}^{\infty} E_i \in \mathcal{F}$

- $\mathcal{F}$ is a set of sets
Examples of sigma-algebras

Example
- No student and all students, i.e., \( \mathcal{F}_0 := \{\emptyset, S\} \)

Example
- Empty set, women, men, everyone, i.e., \( \mathcal{F}_1 := \{\emptyset, \text{Women, Men, } S\} \)

Example
- \( \mathcal{F}_2 \) including the empty set \( \emptyset \) plus
  - All events (sets) with one student \( \{x_1\}, \ldots, \{x_N\} \) plus
  - All events with two students \( \{x_1, x_2\}, \{x_1, x_3\}, \ldots, \{x_1, x_N\}, \{x_2, x_3\}, \ldots, \{x_2, x_N\}, \ldots \)
    - \( \{x_{N-1}, x_N\} \) plus

All events with three, four, \ldots, \( N \) students

\( \Rightarrow \mathcal{F}_2 \) is known as the power set of \( S \), denoted \( 2^S \)
Axioms of probability

- Define a function $P(E)$ from a sigma-algebra $\mathcal{F}$ to the real numbers

- $P(E)$ qualifies as a probability if
  - **A1)** Non-negativity: $P(E) \geq 0$
  - **A2)** Probability of universe: $P(S) = 1$
  - **A3)** Additivity: Given sequence of disjoint events $E_1, E_2, \ldots$

\[
P\left(\bigcup_{i=1}^{\infty} E_i\right) = \sum_{i=1}^{\infty} P(E_i)
\]

⇒ Disjoint (mutually exclusive) events mean $E_i \cap E_j = \emptyset$, $i \neq j$

⇒ Union of countably infinite many disjoint events

- Triplet $(S, \mathcal{F}, P(\cdot))$ is called a **probability space**
Consequences of the axioms

- Implications of the axioms A1)-A3)
  - Impossible event: \( P(\emptyset) = 0 \)
  - Monotonicity: \( E_1 \subset E_2 \Rightarrow P(E_1) \leq P(E_2) \)
  - Range: \( 0 \leq P(E) \leq 1 \)
  - Complement: \( P(E^c) = 1 - P(E) \)
  - Finite disjoint union: For disjoint events \( E_1, \ldots, E_N \)
    \[
    P \left( \bigcup_{i=1}^{N} E_i \right) = \sum_{i=1}^{N} P(E_i)
    \]
  - Inclusion-exclusion: For any events \( E_1 \) and \( E_2 \)
    \[
    P(E_1 \cup E_2) = P(E_1) + P(E_2) - P(E_1 \cap E_2)
    \]
Let's construct a probability space for our running example

- Universe of all students in the class $S = \{x_1, x_2, \ldots, x_N\}$
- Sigma-algebra with all combinations of students, i.e., $\mathcal{F} = 2^S$
- Suppose names are equiprobable $\Rightarrow P(\{x_n\}) = 1/N$ for all $n$
  $\Rightarrow$ Have to specify probability for all $E \in \mathcal{F}$ $\Rightarrow$ Define $P(E) = \frac{|E|}{|S|}$

Q: Is this function a probability?
  $\Rightarrow$ A1): $P(E) = \frac{|E|}{|S|} \geq 0 \checkmark$ $\Rightarrow$ A2): $P(S) = \frac{|S|}{|S|} = 1 \checkmark$
  $\Rightarrow$ A3): $P\left(\bigcup_{i=1}^{N} E_i\right) = \frac{|\bigcup_{i=1}^{N} E_i|}{|S|} = \sum_{i=1}^{N} \frac{|E_i|}{|S|} = \sum_{i=1}^{N} P(E_i) \checkmark$

- The $P(\cdot)$ just defined is called uniform probability distribution
Conditional probability, total probability, Bayes’ rule

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Consider events $E$ and $F$, and suppose we know $F$ occurred.

Q: What does this information imply about the probability of $E$?

**Def:** Conditional probability of $E$ given $F$ is (need $P(F) > 0$)

$$P(E \mid F) = \frac{P(E \cap F)}{P(F)}$$

⇒ In general $P(E \mid F) \neq P(F \mid E)$

**Renormalize** probabilities to the set $F$
- Discard a piece of $S$
- May discard a piece of $E$ as well

For given $F$ with $P(F) > 0$, $P(\cdot \mid F)$ satisfies the axioms of probability.
The name I wrote is male. What is the probability of name $x_n$?

Assume male names are $F = \{x_1, \ldots, x_M\}$ \Rightarrow $P(F) = \frac{M}{N}$

If name $x_n$ is male, $x_n \in F$ and we have for event $E = \{x_n\}$

$$P(E \cap F) = P(\{x_n\}) = \frac{1}{N}$$

\Rightarrow Conditional probability is as you would expect

$$P(E \mid F) = \frac{P(E \cap F)}{P(F)} = \frac{1/N}{M/N} = \frac{1}{M}$$

If name is female $x_n \notin F$, then $P(E \cap F) = P(\emptyset) = 0$

\Rightarrow As you would expect, then $P(E \mid F) = 0$
Law of total probability

- Consider event $E$ and events $F$ and $F^c$
  - $F$ and $F^c$ form a partition of the space $S$ ($F \cup F^c = S, F \cap F^c = \emptyset$)
- Because $F \cup F^c = S$ cover space $S$, can write the set $E$ as
  \[ E = E \cap S = E \cap [F \cup F^c] = [E \cap F] \cup [E \cap F^c] \]
- Because $F \cap F^c = \emptyset$ are disjoint, so is $[E \cap F] \cap [E \cap F^c] = \emptyset$
  \[ \Rightarrow P(E) = P([E \cap F] \cup [E \cap F^c]) = P(E \cap F) + P(E \cap F^c) \]
- Use definition of conditional probability
  \[ P(E) = P(E \mid F)P(F) + P(E \mid F^c)P(F^c) \]
- Translate conditional information $P(E \mid F)$ and $P(E \mid F^c)$
  \[ \Rightarrow \text{Into unconditional information } P(E) \]
Law of total probability (continued)

- In general, consider (possibly infinite) partition $F_i, \ i = 1, 2, \ldots$ of $S$
- Sets are disjoint $\Rightarrow F_i \cap F_j = \emptyset$ for $i \neq j$
- Sets cover the space $\Rightarrow \bigcup_{i=1}^{\infty} F_i = S$

As before, because $\bigcup_{i=1}^{\infty} F_i = S$ cover the space, can write set $E$ as

$$E = E \cap S = E \cap \left[ \bigcup_{i=1}^{\infty} F_i \right] = \bigcup_{i=1}^{\infty} [E \cap F_i]$$

Because $F_i \cap F_j = \emptyset$ are disjoint, so is $[E \cap F_i] \cap [E \cap F_j] = \emptyset$. Thus

$$P(E) = P \left( \bigcup_{i=1}^{\infty} [E \cap F_i] \right) = \sum_{i=1}^{\infty} P(E \cap F_i) = \sum_{i=1}^{\infty} P(E \mid F_i)P(F_i)$$
Consider a probability class in some university

⇒ Seniors get an A with probability (w.p.) 0.9, juniors w.p. 0.8
⇒ An exchange student is a senior w.p. 0.7, and a junior w.p. 0.3

Q: What is the probability of the exchange student scoring an A?

Let $A =$ “exchange student gets an A,” $S$ denote senior, and $J$ junior
⇒ Use the law of total probability

\[
P(A) = P(A \, | \, S)P(S) + P(A \, | \, J)P(J)
\]

\[
= 0.9 \times 0.7 + 0.8 \times 0.3 = 0.87
\]
Bayes’ rule

- From the definition of conditional probability

\[ P(E \mid F)P(F) = P(E \cap F) \]

- Likewise, for \( F \) conditioned on \( E \) we have

\[ P(F \mid E)P(E) = P(F \cap E) \]

- Quantities above are equal, giving Bayes’ rule

\[ P(E \mid F) = \frac{P(F \mid E)P(E)}{P(F)} \]

- Bayes’ rule allows time reversion. If \( F \) (future) comes after \( E \) (past),

  ⇒ \( P(E \mid F) \), probability of past \( E \) having seen the future \( F \)

  ⇒ \( P(F \mid E) \), probability of future \( F \) having seen past \( E \)

- Models often describe future \( \mid \) past. Interest is often in past \( \mid \) future
Bayes’ rule example

Consider the following partition of my email

- \(E_1\) = “spam” w.p. \(P(E_1) = 0.7\)
- \(E_2\) = “low priority” w.p. \(P(E_2) = 0.2\)
- \(E_3\) = “high priority” w.p. \(P(E_3) = 0.1\)

Let \(F\) = “an email contains the word free”

- From experience know \(P(F \mid E_1) = 0.9\), \(P(F \mid E_2) = P(F \mid E_3) = 0.01\)

I got an email containing “free”. What is the probability that it is spam?

Apply Bayes’ rule

\[
P(E_1 \mid F) = \frac{P(F \mid E_1)P(E_1)}{P(F)} = \frac{P(F \mid E_1)P(E_1)}{\sum_{i=1}^{3} P(F \mid E_i)P(E_i)} = 0.995
\]

⇒ Law of total probability very useful when applying Bayes’ rule
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Def: Events $E$ and $F$ are independent if $P(E \cap F) = P(E)P(F)$

⇒ Events that are not independent are dependent

According to definition of conditional probability

$$P(E \mid F) = \frac{P(E \cap F)}{P(F)} = \frac{P(E)P(F)}{P(F)} = P(E)$$

⇒ Intuitive, knowing $F$ does not alter our perception of $E$

⇒ $F$ bears no information about $E$

⇒ The symmetric is also true $P(F \mid E) = P(F)$

Whether $E$ and $F$ are independent relies strongly on $P(\cdot)$

Avoid confusing with disjoint events, meaning $E \cap F = \emptyset$

Q: Can disjoint events with $P(E) > 0$, $P(F) > 0$ be independent? No
Independence example

- Wrote one name, asked a friend to write another (possibly the same)

- Probability space \((S, \mathcal{F}, P(\cdot))\) for this experiment
  - \(S\) is the set of all pairs of names \([x_n(1), x_n(2)]\), \(|S| = N^2\)
  - Sigma-algebra is cartesian product \(\mathcal{F} = 2^S \times 2^S\)
  - Define \(P(E) = \frac{|E|}{|S|}\) as the uniform probability distribution

- Consider the events \(E_1 = \text{‘I wrote } x_1'\) and \(E_2 = \text{‘My friend wrote } x_2'\)
  **Q:** Are they independent? Yes, since
  \[
P(E_1 \cap E_2) = P\left(\{(x_1, x_2)\}\right) = \frac{|\{(x_1, x_2)\}|}{|S|} = \frac{1}{N^2} = P(E_1)P(E_2)
  \]

- **Dependent** events: \(E_1 = \text{‘I wrote } x_1'\) and \(E_3 = \text{‘Both names are male’} \)
Independence for more than two events

- **Def:** Events $E_i$, $i = 1, 2, \ldots$ are called **mutually independent** if

$$P \left( \bigcap_{i \in I} E_i \right) = \prod_{i \in I} P(E_i)$$

for every finite subset $I$ of at least two integers.

- **Ex:** Events $E_1$, $E_2$, and $E_3$ are mutually independent if all the following hold

$$P(E_1 \cap E_2 \cap E_3) = P(E_1)P(E_2)P(E_3)$$
$$P(E_1 \cap E_2) = P(E_1)P(E_2)$$
$$P(E_1 \cap E_3) = P(E_1)P(E_3)$$
$$P(E_2 \cap E_3) = P(E_2)P(E_3)$$

- If $P(E_i \cap E_j) = P(E_i)P(E_j)$ for all $(i, j)$, the $E_i$ are **pairwise independent**

  ⇒ Mutual independence → pairwise independence. **Not the other way**
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Random variable (RV) definition

- **Def:** RV $X(s)$ is a **function** that assigns a value to an outcome $s \in S$
  
  $\Rightarrow$ Think of RVs as measurements associated with an experiment

**Example**

- Throw a ball inside a $1m \times 1m$ square. Interested in ball position
- **Uncertain outcome** is the place $s$ where the ball falls
- Random variables are $X(s)$ and $Y(s)$ position coordinates

- RV probabilities inferred from probabilities of underlying outcomes

\[
P(X(s) = x) = P\left(\{s \in S : X(s) = x\}\right)
\]

\[
P(X(s) \in (-\infty, x]) = P\left(\{s \in S : X(s) \in (-\infty, x]\}\right)
\]
Example 1

- Throw coin for head ($H$) or tails ($T$). Coin is fair $P(H) = 1/2$, $P(T) = 1/2$. Pay $1$ for $H$, charge $1$ for $T$. Earnings?

- Possible outcomes are $H$ and $T$

- To measure earnings define RV $X$ with values

$$X(H) = 1, \quad X(T) = -1$$

- Probabilities of the RV are

$$P(X = 1) = P(H) = 1/2,$$
$$P(X = -1) = P(T) = 1/2$$

⇒ Also have $P(X = x) = 0$ for all other $x \neq \pm 1$
Example 2

- Throw 2 coins. Pay $1 for each $H$, charge $1$ for each $T$. Earnings?
- Now the possible outcomes are $HH$, $HT$, $TH$, and $TT$
- To measure earnings define RV $Y$ with values
  
  \[ Y(HH) = 2, \quad Y(HT) = 0, \quad Y(TH) = 0, \quad Y(TT) = -2 \]

- Probabilities of the RV are
  
  \[
  P(Y = 2) = P(HH) = 1/4, \\
  P(Y = 0) = P(HT) + P(TH) = 1/2, \\
  P(Y = -2) = P(TT) = 1/4
  \]
About Examples 1 and 2

- RVs are easier to manipulate than events

- Let $s_1 \in \{H, T\}$ be outcome of coin 1 and $s_2 \in \{H, T\}$ of coin 2
  \[ Y(s_1, s_2) = X_1(s_1) + X_2(s_2) \]

- Throw $N$ coins. Earnings? Enumeration becomes cumbersome

- Alternatively, let $s_n \in \{H, T\}$ be outcome of $n$-th toss and define
  \[ Y(s_1, s_2, \ldots, s_n) = \sum_{n=1}^{N} X_n(s_n) \]
  \[ \Rightarrow \text{ Will usually abuse notation and write } Y = \sum_{n=1}^{N} X_n \]
Example 3

- Throw a coin until landing heads for the first time. \( P(H) = p \)
- Number of throws until the first head?

- Outcomes are \( H \), \( TH \), \( TTH \), \( TTTH \), \ldots Note that \(|S| = \infty\)
  \[ \Rightarrow \text{Stop tossing after first } H \text{ (thus } THT \text{ not a possible outcome)} \]

- Let \( N \) be a RV counting the number of throws
  \[ \Rightarrow N = n \text{ if we land } T \text{ in the first } n - 1 \text{ throws and } H \text{ in the } n\text{-th} \]

\[
P(N = 1) = P(H) = p
P(N = 2) = P(TH) = (1 - p)p
\]

\[
\vdots
P(N = n) = P(TT \ldots TH) = (1 - p)^{n-1}p
\]

\[n - 1 \text{ tails}\]
Example 3 (continued)

- From A2) we should have \( P(S) = \sum_{n=1}^{\infty} P(N = n) = 1 \)

- Holds because \( \sum_{n=1}^{\infty} (1 - p)^{n-1} \) is a geometric series

\[
\sum_{n=1}^{\infty} (1 - p)^{n-1} = 1 + (1 - p) + (1 - p)^2 + \ldots = \frac{1}{1 - (1 - p)} = \frac{1}{p}
\]

- Plug the sum of the geometric series in the expression for \( P(S) \)

\[
\sum_{n=1}^{\infty} P(N = n) = p \sum_{n=1}^{\infty} (1 - p)^{n-1} = p \times \frac{1}{p} = 1 \checkmark
\]
Indicator function

- The indicator function of an event is a random variable
- Let \( s \in S \) be an outcome, and \( E \subset S \) be an event

\[
\mathbb{I}\{E\}(s) = \begin{cases} 
1, & \text{if } s \in E \\
0, & \text{if } s \notin E 
\end{cases}
\]

⇒ Indicates that outcome \( s \) belongs to set \( E \), by taking value 1

Example

- Number of throws \( N \) until first H. Interested on \( N \) exceeding \( N_0 \)
  ⇒ Event is \( \{N : N > N_0\} \). Possible outcomes are \( N = 1, 2, \ldots \)
  ⇒ Denote indicator function as \( \mathbb{I}_{N_0} = \mathbb{I}\{N : N > N_0\} \)

- Probability \( P(\mathbb{I}_{N_0} = 1) = P(N > N_0) = (1 - p)^{N_0} \)
  ⇒ For \( N \) to exceed \( N_0 \) need \( N_0 \) consecutive tails
  ⇒ Doesn’t matter what happens afterwards
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Discrete RV takes on, at most, a countable number of values

Probability mass function (pmf) \( p_X(x) = P(X = x) \)
- If RV is clear from context, just write \( p_X(x) = p(x) \)

- If \( X \) supported in \( \{x_1, x_2, \ldots\} \), pmf satisfies
  1. \( p(x_i) > 0 \) for \( i = 1, 2, \ldots \)
  2. \( p(x) = 0 \) for all other \( x \neq x_i \)
  3. \( \sum_{i=1}^{\infty} p(x_i) = 1 \)
- Pmf for “throw to first heads” \( (p = 0.3) \)

Cumulative distribution function (cdf)

\[
F_X(x) = P(X \leq x) = \sum_{i : x_i \leq x} p(x_i)
\]

\( \Rightarrow \) Staircase function with jumps at \( x_i \)
- Cdf for “throw to first heads” \( (p = 0.3) \)
Bernoulli

- A trial/experiment/bet can succeed w.p. $p$ or fail w.p. $q := 1 - p$
  \[ \Rightarrow \text{Ex: coin throws, any indication of an event} \]

- **Bernoulli** $X$ can be 0 or 1. Pmf is $p(x) = p^x q^{1-x}$

- Cdf is

  \[
  F(x) = \begin{cases} 
  0, & x < 0 \\
  q, & 0 \leq x < 1 \\
  1, & x \geq 1 
  \end{cases}
  \]

\[
\text{pmf (} p = 0.4) \quad \text{cdf (} p = 0.4) 
\]
Count number of Bernoulli trials needed to register first success

⇒ Trials succeed w.p. $p$

Number of trials $X$ until success is geometric with parameter $p$

Pmf is $p(x) = p(1-p)^{x-1}$

One success after $x-1$ failures, trials are independent

Cdf is $F(x) = 1 - (1-p)^x$

Recall $P(X > x) = (1-p)^x$; or just sum the geometric series

pmf ($p = 0.3$)

cdf ($p = 0.3$)
Count number of successes $X$ in $n$ Bernoulli trials

$\Rightarrow$ Trials succeed w.p. $p$

Number of successes $X$ is binomial with parameters $(n, p)$. Pmf is

$$p(x) = \binom{n}{x} p^x (1 - p)^{n-x} = \frac{n!}{(n-x)! x!} p^x (1 - p)^{n-x}$$

$\Rightarrow$ $X = x$ for $x$ successes ($p^x$) and $n - x$ failures ($(1 - p)^{n-x}$).

$\Rightarrow$ $\binom{n}{x}$ ways of drawing $x$ successes and $n - x$ failures

pmf $(n = 9, \ p = 0.4)$

cdf $(n = 9, \ p = 0.4)$
Let $Y_i, i = 1, \ldots, n$ be Bernoulli RVs with parameter $p$ \\
$\Rightarrow Y_i$ associated with independent events

Can write binomial $X$ with parameters $(n, p)$ as $\Rightarrow X = \sum_{i=1}^{n} Y_i$

Example

Consider binomials $Y$ and $Z$ with parameters $(n_Y, p)$ and $(n_Z, p)$ \\
$\Rightarrow Q$: Probability distribution of $X = Y + Z$?

Write $Y = \sum_{i=1}^{n_Y} Y_i$ and $Z = \sum_{i=1}^{n_Z} Z_i$, thus \\
$$X = \sum_{i=1}^{n_Y} Y_i + \sum_{i=1}^{n_Z} Z_i$$

$\Rightarrow X$ is binomial with parameter $(n_Y + n_Z, p)$
Counts of rare events (radioactive decay, packet arrivals, accidents)

Usually modeled as Poisson with parameter $\lambda$ and pmf

$$p(x) = e^{-\lambda} \frac{\lambda^x}{x!}$$

Q: Is this a properly defined pmf? Yes

Taylor’s expansion of $e^x = 1 + x + x^2/2 + \ldots + x^i/i! + \ldots$. Then

$$P(S) = \sum_{i=0}^{\infty} p(i) = e^{-\lambda} \sum_{i=0}^{\infty} \frac{\lambda^i}{i!} = e^{-\lambda}e^\lambda = 1 \checkmark$$

pmf ($\lambda = 4$)  

cdf ($\lambda = 4$)
Poisson approximation of binomial

- $X$ is binomial with parameters $(n, p)$
- Let $n \to \infty$ while maintaining a constant product $np = \lambda$
  - If we just let $n \to \infty$ number of successes diverges. Boring
- Compare with Poisson distribution with parameter $\lambda$
  - $\lambda = 5$, $n = 6, 8, 10, 15, 20, 50$
This is, in fact, the motivation for the definition of a Poisson RV.

Substituting $p = \lambda/n$ in the pmf of a binomial RV

$$p_n(x) = \frac{n!}{(n-x)!x!} \left( \frac{\lambda}{n} \right)^x \left( 1 - \frac{\lambda}{n} \right)^{n-x}$$

$$= \frac{n(n-1)\ldots(n-x+1)}{n^x} \frac{\lambda^x (1 - \lambda/n)^n}{x! (1 - \lambda/n)^x}$$

$\Rightarrow$ Used factorials’ defs., $(1 - \lambda/n)^{n-x} = \frac{(1-\lambda/n)^n}{(1-\lambda/n)^x}$, and reordered terms

In the limit, red term is $\lim_{n \to \infty} (1 - \lambda/n)^n = e^{-\lambda}$

Black and blue terms converge to 1. From both observations

$$\lim_{n \to \infty} p_n(x) = 1 \frac{\lambda^x}{x!} \frac{e^{-\lambda}}{1} = e^{-\lambda} \frac{\lambda^x}{x!}$$

$\Rightarrow$ Limit is the pmf of a Poisson RV
Closing remarks

- Binomial distribution is motivated by counting successes
- The Poisson is an approximation for large number of trials $n$
  - Poisson distribution is more tractable (compare pmfs)
- Sometimes called “law of rare events”
  - Individual events (successes) happen with small probability $p = \lambda/n$
  - Aggregate event (number of successes), though, need not be rare
- Notice that all four RVs seen so far are related to “coin tosses”
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Continuous RVs, probability density function

- Possible values for continuous RV $X$ form a dense subset $\mathcal{X} \subseteq \mathbb{R}$
  \[ \Rightarrow \text{Uncountably infinite number of possible values} \]

- Probability density function (pdf) $f_{X}(x)$ is such that for any subset $\mathcal{X} \subseteq \mathbb{R}$
  \[ P(X \in \mathcal{X}) = \int_{\mathcal{X}} f_{X}(x) \, dx \]
  \[ \Rightarrow \text{Will have } P(X = x) = 0 \text{ for all } x \in \mathcal{X} \]

- Cdf defined as before and related to the pdf
  \[ F_{X}(x) = P(X \leq x) = \int_{-\infty}^{x} f_{X}(u) \, du \]
  \[ \Rightarrow P(X \leq \infty) = F_{X}(\infty) = \lim_{x \to \infty} F_{X}(x) = 1 \]
More on cdfs and pdfs

- When the set $X = [a, b]$ is an interval of $\mathbb{R}$

  $$P(X \in [a, b]) = P(X \leq b) - P(X \leq a) = F_X(b) - F_X(a)$$

- In terms of the pdf it can be written as

  $$P(X \in [a, b]) = \int_a^b f_X(x) \, dx$$

- For small interval $[x_0, x_0 + \delta x]$, in particular

  $$P(X \in [x_0, x_0 + \delta x]) = \int_{x_0}^{x_0 + \delta x} f_X(x) \, dx \approx f_X(x_0) \delta x$$

  ⇒ Probability is the “area under the pdf” (thus “density”)

- Another relationship between pdf and cdf is

  $$\frac{\partial F_X(x)}{\partial x} = f_X(x)$$

  ⇒ Fundamental theorem of calculus ("derivative inverse of integral")
Model problems with equal probability of landing on an interval \([a, b]\)

Pdf of uniform RV is \(f(x) = 0\) outside the interval \([a, b]\) and

\[
f(x) = \frac{1}{b-a}, \quad \text{for } a \leq x \leq b
\]

Cdf is \(F(x) = (x - a)/(b - a)\) in the interval \([a, b]\) (0 before, 1 after)

Prob. of interval \([\alpha, \beta]\) \(\subseteq [a, b]\) is \(\int_{\alpha}^{\beta} f(x)dx = (\beta - \alpha)/(b - a)\)

\(\Rightarrow\) Depends on interval’s width \(\beta - \alpha\) only, not on its position

\begin{align*}
\text{pdf (} a = -1, \ b = 1) \\
\end{align*}

\begin{align*}
\text{cdf (} a = -1, \ b = 1)
\end{align*}
Exponential

- Model duration of phone calls, lifetime of electronic components
- Pdf of exponential RV is

\[ f(x) = \begin{cases} \lambda e^{-\lambda x}, & x \geq 0 \\ 0, & x < 0 \end{cases} \]

⇒ As parameter \( \lambda \) increases, “height” increases and “width” decreases
- Cdf obtained by integrating pdf

\[ F(x) = \int_{-\infty}^{x} f(u) \, du = \int_{0}^{x} \lambda e^{-\lambda u} \, du = -e^{-\lambda u} \bigg|_0^x = 1 - e^{-\lambda x} \]

pdf (\( \lambda = 1 \))

![Pdf Graph]

cdf (\( \lambda = 1 \))

![Cdf Graph]
Normal / Gaussian

- Model randomness arising from large number of random effects

- Pdf of normal RV is

\[ f(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-(x-\mu)^2/2\sigma^2} \]

⇒ \( \mu \) is the mean (center), \( \sigma^2 \) is the variance (width)

⇒ 0.68 prob. between \( \mu \pm \sigma \), 0.997 prob. in \( \mu \pm 3\sigma \)

⇒ Standard normal RV has \( \mu = 0 \) and \( \sigma^2 = 1 \)

- Cdf \( F(x) \) cannot be expressed in terms of elementary functions

\[
\begin{align*}
\text{pdf } (\mu = 0, \sigma^2 = 1) \\
\text{cdf } (\mu = 0, \sigma^2 = 1)
\end{align*}
\]
Expected values

Sigma-algebras and probability spaces

Conditional probability, total probability, Bayes’ rule

Independence

Random variables

Discrete random variables

Continuous random variables

Expected values

Joint probability distributions

Joint expectations
Expected values

- We are asked to summarize information about a RV in a single value
  ⇒ What should this value be?

- If we are allowed a description with a few values
  ⇒ What should they be?

- Expected (mean) values are convenient answers to these questions

- **Beware:** Expectations are condensed descriptions
  ⇒ They overlook some aspects of the random phenomenon
  ⇒ Whole story told by the probability distribution (cdf)
Definition for discrete RVs

- Discrete RV $X$ taking on values $x_i, i = 1, 2, \ldots$ with pmf $p(x)$

- **Def:** The expected value of the discrete RV $X$ is

  $$
  \mathbb{E}[X] := \sum_{i=1}^{\infty} x_i p(x_i) = \sum_{x:p(x)>0} x p(x)
  $$

- Weighted average of possible values $x_i$. Probabilities are weights

- Common average if RV takes values $x_i, i = 1, \ldots, N$ equiprobably

  $$
  \mathbb{E}[X] = \sum_{i=1}^{N} x_i p(x_i) = \sum_{i=1}^{N} x_i \frac{1}{N} = \frac{1}{N} \sum_{i=1}^{N} x_i
  $$
Expected value of Bernoulli and geometric RVs

Ex: For a Bernoulli RV \( p(x) = p^x q^{1-x} \), for \( x \in \{0, 1\} \)

\[
\mathbb{E}[X] = 1 \times p + 0 \times q = p
\]

Ex: For a geometric RV \( p(x) = p(1 - p)^{x-1} = pq^{x-1} \), for \( x \geq 1 \)

- Note that \( \frac{\partial q^x}{\partial q} = xq^{x-1} \) and that derivatives are linear operators

\[
\mathbb{E}[X] = \sum_{x=1}^{\infty} xpq^{x-1} = p \sum_{x=1}^{\infty} \frac{\partial q^x}{\partial q} = p \frac{\partial}{\partial q} \left( \sum_{x=1}^{\infty} q^x \right)
\]

- Sum inside derivative is geometric. Sums to \( q/(1 - q) \), thus

\[
\mathbb{E}[X] = p \frac{\partial}{\partial q} \left( \frac{q}{1 - q} \right) = \frac{p}{(1 - q)^2} = \frac{1}{p}
\]

- Time to first success is inverse of success probability. Reasonable
Expected value of Poisson RV

**Ex:** For a Poisson RV $p(x) = e^{-\lambda}(\lambda^x/x!)$, for $x \geq 0$

- First summand in definition is 0, pull $\lambda$ out, and use $x/x! = 1/(x-1)!$

$$
\mathbb{E}[X] = \sum_{x=0}^{\infty} xe^{-\lambda} \frac{\lambda^x}{x!} = \lambda e^{-\lambda} \sum_{x=1}^{\infty} \frac{\lambda^{x-1}}{(x-1)!}
$$

- Sum is Taylor’s expansion of $e^\lambda = 1 + \lambda + \lambda^2/2! + \ldots + \lambda^x/x!$

$$
\mathbb{E}[X] = \lambda e^{-\lambda} e^\lambda = \lambda
$$

- Poisson is limit of binomial for large number of trials $n$, with $\lambda = np$

  $\Rightarrow$ Counts number of successes in $n$ trials that succeed w.p. $p$

- Expected number of successes is $\lambda = np$

  $\Rightarrow$ Number of trials $\times$ probability of individual success. Reasonable
Definition for continuous RVs

- Continuous RV $X$ taking values on $\mathbb{R}$ with pdf $f(x)$

- **Def:** The expected value of the continuous RV $X$ is

$$\mathbb{E}[X] := \int_{-\infty}^{\infty} xf(x) \, dx$$

- Compare with $\mathbb{E}[X] := \sum_{x:p(x)>0} xp(x)$ in the discrete RV case

- Note that the integral or sum are assumed to be well defined
  ⇒ Otherwise we say the expectation does not exist
Ex: For a normal RV add and subtract $\mu$, separate integrals

$$\mathbb{E}[X] = \frac{1}{\sqrt{2\pi}\sigma} \int_{-\infty}^{\infty} xe^{-\frac{(x-\mu)^2}{2\sigma^2}} \, dx$$

$$= \frac{1}{\sqrt{2\pi}\sigma} \int_{-\infty}^{\infty} (x + \mu - \mu)e^{-\frac{(x-\mu)^2}{2\sigma^2}} \, dx$$

$$= \mu \frac{1}{\sqrt{2\pi}\sigma} \int_{-\infty}^{\infty} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \, dx + \frac{1}{\sqrt{2\pi}\sigma} \int_{-\infty}^{\infty} (x - \mu)e^{-\frac{(x-\mu)^2}{2\sigma^2}} \, dx$$

- First integral is 1 because it integrates a pdf in all $\mathbb{R}$
- Second integral is 0 by symmetry. Both observations yield

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

- The mean of a RV with a symmetric pdf is the point of symmetry
Expected value of uniform and exponential RVs

**Ex:** For a uniform RV $f(x) = 1/(b - a)$, for $a \leq x \leq b$

\[
E[X] = \int_{-\infty}^{\infty} x f(x) \, dx = \int_{a}^{b} \frac{x}{b - a} \, dx = \frac{b^2 - a^2}{2(b - a)} = \frac{(a + b)}{2}
\]

- Makes sense, since pdf is symmetric around midpoint $(a + b)/2$

**Ex:** For an exponential RV (non symmetric) integrate by parts

\[
E[X] = \int_{0}^{\infty} x \lambda e^{-\lambda x} \, dx
\]

\[
= -xe^{-\lambda x} \bigg|_{0}^{\infty} + \int_{0}^{\infty} e^{-\lambda x} \, dx
\]

\[
= -xe^{-\lambda x} \bigg|_{0}^{\infty} - \frac{e^{-\lambda x}}{\lambda} \bigg|_{0}^{\infty} = \frac{1}{\lambda}
\]
Expected value of a function of a RV

- Consider a function $g(X)$ of a RV $X$. Expected value of $g(X)$?
- $g(X)$ is also a RV, then it also has a pmf $p_{g(x)}(g(x))$

$$
\mathbb{E}[g(X)] = \sum_{g(x): p_{g(x)}(g(x)) > 0} g(x) p_{g(x)}(g(x))
$$

⇒ Requires calculating the pmf of $g(X)$. There is a simpler way

Theorem

Consider a function $g(X)$ of a discrete RV $X$ with pmf $p_X(x)$. Then

$$
\mathbb{E}[g(X)] = \sum_{i=1}^{\infty} g(x_i) p_X(x_i)
$$

- Weighted average of functional values. No need to find pmf of $g(X)$
- Same can be proved for a continuous RV

$$
\mathbb{E}[g(X)] = \int_{-\infty}^{\infty} g(x) f_X(x) \, dx
$$
Consider a linear function (actually affine) \( g(X) = aX + b \)

\[
\mathbb{E}[aX + b] = \sum_{i=1}^{\infty} (ax_i + b)p_X(x_i)
\]

\[
= \sum_{i=1}^{\infty} ax_i p_X(x_i) + \sum_{i=1}^{\infty} bp_X(x_i)
\]

\[
= a \sum_{i=1}^{\infty} x_i p_X(x_i) + b \sum_{i=1}^{\infty} p_X(x_i)
\]

\[
= a \mathbb{E}[X] + b1
\]

Can interchange expectation with additive/multiplicative constants

\[
\mathbb{E}[aX + b] = a\mathbb{E}[X] + b
\]

⇒ Again, the same holds for a continuous RV
Let $X$ be a RV and $\mathcal{X}$ be a set

$$
\mathbb{I} \{X \in \mathcal{X}\} = \begin{cases} 
1, & \text{if } x \in \mathcal{X} \\
0, & \text{if } x \notin \mathcal{X}
\end{cases}
$$

Expected value of $\mathbb{I} \{X \in \mathcal{X}\}$ in the discrete case

$$
E[\mathbb{I} \{X \in \mathcal{X}\}] = \sum_{x:\text{$p_X(x)>0$}} \mathbb{I} \{x \in \mathcal{X}\} p_X(x) = \sum_{x \in \mathcal{X}} p_X(x) = P(X \in \mathcal{X})
$$

Likewise in the continuous case

$$
E[\mathbb{I} \{X \in \mathcal{X}\}] = \int_{-\infty}^{\infty} \mathbb{I} \{x \in \mathcal{X}\} f_X(x) \, dx = \int_{x \in \mathcal{X}} f_X(x) \, dx = P(X \in \mathcal{X})
$$

Expected value of indicator RV = Probability of indicated event

$\Rightarrow$ Recall $E[X] = p$ for Bernoulli RV (it “indicates success”)
Moments, central moments and variance

Def: The $n$-th moment ($n \geq 0$) of a RV is

$$\mathbb{E}[X^n] = \sum_{i=1}^{\infty} x_i^n p(x_i)$$

Def: The $n$-th central moment corrects for the mean, that is

$$\mathbb{E}\left[(X - \mathbb{E}[X])^n\right] = \sum_{i=1}^{\infty} (x_i - \mathbb{E}[X])^n p(x_i)$$

0-th order moment is $\mathbb{E}[X^0] = 1$; 1-st moment is the mean $\mathbb{E}[X]$

2-nd central moment is the variance. Measures width of the pmf

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

Ex: For affine functions

$$\text{var}[aX + b] = a^2 \text{var}[X]$$
Variance of Bernoulli and Poisson RVs

**Ex:** For a Bernoulli RV $X$ with parameter $p$, $\mathbb{E}[X] = \mathbb{E}[X^2] = p$

$\Rightarrow \text{var}[X] = \mathbb{E}[X^2] - \mathbb{E}^2[X] = p - p^2 = p(1 - p)$

**Ex:** For Poisson RV $Y$ with parameter $\lambda$, second moment is

$$
\mathbb{E}[Y^2] = \sum_{y=0}^{\infty} y^2 e^{-\lambda} \frac{\lambda^y}{y!} = \sum_{y=1}^{\infty} y \frac{e^{-\lambda} \lambda^y}{(y - 1)!} \\
= \sum_{y=1}^{\infty} (y - 1) \frac{e^{-\lambda} \lambda^y}{(y - 1)!} + \sum_{y=1}^{\infty} \frac{e^{-\lambda} \lambda^y}{(y - 1)!} \\
= e^{-\lambda} \lambda^2 \sum_{y=2}^{\infty} \frac{\lambda^{y-2}}{(y - 2)!} + e^{-\lambda} \lambda \sum_{y=1}^{\infty} \frac{\lambda^{y-1}}{(y - 1)!} \\
= e^{-\lambda} \lambda^2 e^\lambda + e^{-\lambda} \lambda e^\lambda = \lambda^2 + \lambda
$$

$\Rightarrow \text{var}[Y] = \mathbb{E}[Y^2] - \mathbb{E}^2[Y] = \lambda^2 + \lambda - \lambda^2 = \lambda$
Joint probability distributions

Sigma-algebras and probability spaces

Conditional probability, total probability, Bayes’ rule

Independence

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Want to study problems with more than one RV. Say, e.g., $X$ and $Y$

- Probability distributions of $X$ and $Y$ are not sufficient
  \[ F_{X,Y}(x, y) = P(X \leq x, Y \leq y) \]

- If $X$, $Y$ clear from context omit subindex to write $F_{X,Y}(x, y) = F(x, y)$

- Can recover $F_X(x)$ by considering all possible values of $Y$
  \[ F_X(x) = P(X \leq x) = P(X \leq x, Y \leq \infty) = F_{X,Y}(x, \infty) \]

  \[ \Rightarrow F_X(x) \text{ and } F_Y(y) = F_{X,Y}(\infty, y) \text{ are called marginal cdfs} \]
Consider discrete RVs \( X \) and \( Y \)

\( X \) takes values in \( \mathcal{X} := \{x_1, x_2, \ldots\} \) and \( Y \) in \( \mathcal{Y} := \{y_1, y_2, \ldots\} \)

**Joint pmf** of \((X, Y)\) defined as

\[
p_{XY}(x, y) = P(X = x, Y = y)
\]

Possible values \((x, y)\) are elements of the Cartesian product \( \mathcal{X} \times \mathcal{Y} \)

\[
(x_1, y_1), (x_1, y_2), \ldots, (x_2, y_1), (x_2, y_2), \ldots, (x_3, y_1), (x_3, y_2), \ldots
\]

**Marginal pmf** \( p_X(x) \) obtained by summing over all values of \( Y \)

\[
p_X(x) = P(X = x) = \sum_{y \in \mathcal{Y}} P(X = x, Y = y) = \sum_{y \in \mathcal{Y}} p_{XY}(x, y)
\]

\( \Rightarrow \) Likewise \( p_Y(y) = \sum_{x \in \mathcal{X}} p_{XY}(x, y) \). **Marginalize by summing**
Consider continuous RVs $X$, $Y$. Arbitrary set $A \in \mathbb{R}^2$

Joint pdf is a function $f_{XY}(x, y) : \mathbb{R}^2 \rightarrow \mathbb{R}^+$ such that

$$P((X, Y) \in A) = \int\int_A f_{XY}(x, y) \, dx \, dy$$

Marginalization. There are two ways of writing $P(X \in \mathcal{X})$

$$P(X \in \mathcal{X}) = P(X \in \mathcal{X}, Y \in \mathbb{R}) = \int_{X \in \mathcal{X}} \int_{-\infty}^{+\infty} f_{XY}(x, y) \, dy \, dx$$

⇒ Definition of $f_X(x) \Rightarrow P(X \in \mathcal{X}) = \int_{X \in \mathcal{X}} f_X(x) \, dx$

Lipstick on a pig (same thing written differently is still same thing)

$$\Rightarrow f_X(x) = \int_{-\infty}^{+\infty} f_{XY}(x, y) \, dy, \quad f_Y(y) = \int_{-\infty}^{+\infty} f_{XY}(x, y) \, dx$$
Example

- Consider two Bernoulli RVs $B_1, B_2$, with the same parameter $p$
  - Define $X = B_1$ and $Y = B_1 + B_2$

- The pmf of $X$ is
  \[ p_X(0) = 1 - p, \quad p_X(1) = p \]

- Likewise, the pmf of $Y$ is
  \[ p_Y(0) = (1 - p)^2, \quad p_Y(1) = 2p(1 - p), \quad p_Y(2) = p^2 \]

- The joint pmf of $X$ and $Y$ is
  \[ p_{XY}(0, 0) = (1 - p)^2, \quad p_{XY}(0, 1) = p(1 - p), \quad p_{XY}(0, 2) = 0 \]
  \[ p_{XY}(1, 0) = 0, \quad p_{XY}(1, 1) = p(1 - p), \quad p_{XY}(1, 2) = p^2 \]
Random vectors

- For convenience often arrange RVs in a vector
  ⇒ Prob. distribution of vector is joint distribution of its entries

- Consider, e.g., two RVs $X$ and $Y$. Random vector is $\mathbf{X} = [X, Y]^T$

- If $X$ and $Y$ are discrete, vector variable $\mathbf{X}$ is discrete with pmf
  \[ p_\mathbf{X}(\mathbf{x}) = p_\mathbf{X}([x, y]^T) = p_{XY}(x, y) \]

- If $X$, $Y$ continuous, $\mathbf{X}$ continuous with pdf
  \[ f_\mathbf{X}(\mathbf{x}) = f_\mathbf{X}([x, y]^T) = f_{XY}(x, y) \]

- Vector cdf is  ⇒ $F_\mathbf{X}(\mathbf{x}) = F_\mathbf{X}([x, y]^T) = F_{XY}(x, y)$

- In general, can define $n$-dimensional RVs $\mathbf{X} := [X_1, X_2, \ldots, X_n]^T$
  ⇒ Just notation, definitions carry over from the $n = 2$ case
Joint expectations

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Joint expectations

- RVs \( X \) and \( Y \) and function \( g(X, Y) \). Function \( g(X, Y) \) also a RV

- Expected value of \( g(X, Y) \) when \( X \) and \( Y \) discrete can be written as

\[
\mathbb{E}[g(X, Y)] = \sum_{x,y: p_{XY}(x,y) > 0} g(x, y) p_{XY}(x, y)
\]

- When \( X \) and \( Y \) are continuous

\[
\mathbb{E}[g(X, Y)] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} g(x, y) f_{XY}(x, y) \, dx \, dy
\]

\( \Rightarrow \) Can have more than two RVs and use vector notation

Ex: Linear transformation of a vector RV \( X \in \mathbb{R}^n \): \( g(X) = a^T X \)

\( \Rightarrow \mathbb{E}[a^T X] = \int_{\mathbb{R}^n} a^T x f_X(x) \, dx \)
Expected value of a sum of random variables

- Expected value of the sum of two continuous RVs

\[
E[X + Y] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} (x + y) f_{XY}(x, y) \, dx \, dy
\]

\[
= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x f_{XY}(x, y) \, dx \, dy + \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} y f_{XY}(x, y) \, dx \, dy
\]

- Remove \( x \) (\( y \)) from innermost integral in first (second) summand

\[
E[X + Y] = \int_{-\infty}^{\infty} x \left( \int_{-\infty}^{\infty} f_{XY}(x, y) \, dy \right) \, dx + \int_{-\infty}^{\infty} y \left( \int_{-\infty}^{\infty} f_{XY}(x, y) \, dx \right) \, dy
\]

\[
= \int_{-\infty}^{\infty} x f_X(x) \, dx + \int_{-\infty}^{\infty} y f_Y(y) \, dy
\]

\[
= E[X] + E[Y]
\]

\[\Rightarrow\] Used marginal expressions

- Expectation \(\leftrightarrow\) summation \(\Rightarrow\) \(E \left[ \sum_i X_i \right] = \sum_i E[X_i]\)
Expected value is a linear operator

Combining with earlier result \( E[aX + b] = aE[X] + b \) proves that

\[
E[a_X X + a_Y Y + b] = a_X E[X] + a_Y E[Y] + b
\]

Better yet, using vector notation (with \( a \in \mathbb{R}^n, X \in \mathbb{R}^n, b \) a scalar)

\[
E[a^T X + b] = a^T E[X] + b
\]

Also, if \( A \) is an \( m \times n \) matrix with rows \( a_1^T, \ldots, a_m^T \) and \( b \in \mathbb{R}^m \) a vector with elements \( b_1, \ldots, b_m \), we can write

\[
E[AX + b] = \begin{pmatrix}
E[a_1^T X + b_1] \\
E[a_2^T X + b_2] \\
\vdots \\
E[a_m^T X + b_m]
\end{pmatrix} = \begin{pmatrix}
a_1^T E[X] + b_1 \\
a_2^T E[X] + b_2 \\
\vdots \\
a_m^T E[X] + b_m
\end{pmatrix} = A E[X] + b
\]

Expected value operator can be interchanged with linear operations
Independence of RVs

- Events $E$ and $F$ are independent if $P(E \cap F) = P(E)P(F)$

- **Def:** RVs $X$ and $Y$ are independent if events $X \leq x$ and $Y \leq y$ are independent for all $x$ and $y$, i.e.

\[
P(X \leq x, Y \leq y) = P(X \leq x)P(Y \leq y)
\]

⇒ By definition, equivalent to $F_{XY}(x,y) = F_X(x)F_Y(y)$

- For discrete RVs equivalent to analogous relation between pmfs

\[
p_{XY}(x,y) = p_X(x)p_Y(y)
\]

- For continuous RVs the analogous is true for pdfs

\[
f_{XY}(x,y) = f_X(x)f_Y(y)
\]

- Independence $\iff$ Joint distribution factorizes into product of marginals
**Sum of independent Poisson RVs**

- **Independent** Poisson RVs $X$ and $Y$ with parameters $\lambda_x$ and $\lambda_y$

- **Q:** Probability distribution of the sum RV $Z := X + Y$?

- $Z = n$ only if $X = k$, $Y = n - k$ for some $0 \leq k \leq n$
  (use independence, Poisson pmf, rearrange terms, binomial theorem)

\[
p_Z(n) = \sum_{k=0}^{n} P(X = k, Y = n - k) = \sum_{k=0}^{n} P(X = k) P(Y = n - k)
\]

\[
= \sum_{k=0}^{n} e^{-\lambda_x} \frac{\lambda_x^k}{k!} e^{-\lambda_y} \frac{\lambda_y^{n-k}}{(n-k)!} = \frac{e^{-(\lambda_x + \lambda_y)}}{n!} \sum_{k=0}^{n} \frac{n!}{(n-k)!k!} \lambda_x^k \lambda_y^{n-k}
\]

\[
= \frac{e^{-(\lambda_x + \lambda_y)}}{n!} (\lambda_x + \lambda_y)^n
\]

- $Z$ is Poisson with parameter $\lambda_z := \lambda_x + \lambda_y$

  $\Rightarrow$ **Sum of independent Poissons is Poisson** (parameters added)
Binomial RVs count number of successes in \( n \) Bernoulli trials

**Ex:** Let \( X_i, \ i = 1, \ldots, n \) be \( n \) independent Bernoulli RVs

- Can write binomial \( X = \sum_{i=1}^{n} X_i \) ⇒ \( \mathbb{E}[X] = \sum_{i=1}^{n} \mathbb{E}[X_i] = np \)

- Expected nr. successes = nr. trials × prob. individual success
  - Same interpretation that we observed for Poisson RVs

**Ex:** Dependent Bernoulli trials. \( Y = \sum_{i=1}^{n} X_i \), but \( X_i \) are not independent

- Expected nr. successes is still \( \mathbb{E}[Y] = np \)
  - Linearity of expectation does not require independence
  - \( Y \) is not binomial distributed
**Theorem**

For independent RVs $X$ and $Y$, and arbitrary functions $g(X)$ and $h(Y)$:

$$
E[g(X)h(Y)] = E[g(X)]E[h(Y)]
$$

*The expected value of the product is the product of the expected values*

- Can show that $g(X)$ and $h(Y)$ are also independent. *Intuitive*

**Ex:** Special case when $g(X) = X$ and $h(Y) = Y$ yields

$$
E[XY] = E[X]E[Y]
$$

- Expectation and product can be interchanged if RVs are independent
- Different from interchange with linear operations (*always possible*)
Proof.

- Suppose $X$ and $Y$ continuous RVs. Use definition of independence

\[
\mathbb{E}[g(X)h(Y)] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} g(x)h(y)f_{XY}(x, y) \, dx \, dy
\]

\[
= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} g(x)h(y)f_X(x)f_Y(y) \, dx \, dy
\]

- Integrand is product of a function of $x$ and a function of $y$

\[
\mathbb{E}[g(X)h(Y)] = \int_{-\infty}^{\infty} g(x)f_X(x) \, dx \int_{-\infty}^{\infty} h(y)f_Y(y) \, dy
\]

\[
= \mathbb{E}[g(X)] \mathbb{E}[h(Y)]
\]
Let $X_n, n = 1, \ldots, N$ be independent with $\mathbb{E}[X_n] = \mu_n$, $\text{var}[X_n] = \sigma^2_n$.

Q: Variance of sum $X := \sum_{n=1}^N X_n$?

Notice that mean of $X$ is $\mathbb{E}[X] = \sum_{n=1}^N \mu_n$. Then

\[
\text{var}[X] = \mathbb{E} \left[ \left( \sum_{n=1}^N X_n - \sum_{n=1}^N \mu_n \right)^2 \right] = \mathbb{E} \left[ \left( \sum_{n=1}^N (X_n - \mu_n) \right)^2 \right]
\]

Expand square and interchange summation and expectation

\[
\text{var}[X] = \sum_{n=1}^N \sum_{m=1}^N \mathbb{E} \left[ (X_n - \mu_n)(X_m - \mu_m) \right]
\]
Separate terms in sum. Then use independence and $\mathbb{E}(X_n - \mu_n) = 0$

$$\text{var } [X] = \sum_{n=1, n \neq m}^{N} \sum_{m=1}^{N} \mathbb{E}[(X_n - \mu_n)(X_m - \mu_m)] + \sum_{n=1}^{N} \mathbb{E}[(X_n - \mu_n)^2]$$

$$= \sum_{n=1, n \neq m}^{N} \sum_{m=1}^{N} \mathbb{E}(X_n - \mu_n)\mathbb{E}(X_m - \mu_m) + \sum_{n=1}^{N} \sigma_n^2 = \sum_{n=1}^{N} \sigma_n^2$$

If RVs are independent $\implies$ Variance of sum is sum of variances

Slightly more general result holds for independent $X_i, \ i = 1, \ldots, n$

$$\text{var } \left[ \sum_i (a_i X_i + b_i) \right] = \sum_i a_i^2 \text{var } [X_i]$$
Variance of binomial RV and sample mean

Ex: Let $X_i, i = 1, \ldots n$ be independent Bernoulli RVs

$\Rightarrow$ Recall $E[X_i] = p$ and $\text{var}[X_i] = p(1 - p)$

- Write binomial $X$ with parameters $(n, p)$ as: $X = \sum_{i=1}^{n} X_i$

- Variance of binomial then $\Rightarrow \text{var}[X] = \sum_{i=1}^{n} \text{var}[X_i] = np(1 - p)$

Ex: Let $Y_i, i = 1, \ldots n$ be independent RVs and $E[Y_i] = \mu$, $\text{var}[Y_i] = \sigma^2$

- Sample mean is $\bar{Y} = \frac{1}{n} \sum_{i=1}^{n} Y_i$. What about $E[\bar{Y}]$ and $\text{var}[\bar{Y}]$?

- Expected value $\Rightarrow E[\bar{Y}] = \frac{1}{n} \sum_{i=1}^{n} E[Y_i] = \mu$

- Variance $\Rightarrow \text{var}[\bar{Y}] = \frac{1}{n^2} \sum_{i=1}^{n} \text{var}[Y_i] = \frac{\sigma^2}{n}$ (used independence)
Covariance

- **Def:** The covariance of $X$ and $Y$ is (generalizes variance to pairs of RVs)

\[ \text{cov}(X, Y) = \mathbb{E}[(X - \mathbb{E}[X])(Y - \mathbb{E}[Y])] = \mathbb{E}[XY] - \mathbb{E}[X]\mathbb{E}[Y] \]

- If $\text{cov}(X, Y) = 0$ variables $X$ and $Y$ are said to be **uncorrelated**

- If $X, Y$ independent then $\mathbb{E}[XY] = \mathbb{E}[X]\mathbb{E}[Y]$ and $\text{cov}(X, Y) = 0$

  \[ \Rightarrow \text{Independence implies uncorrelated RVs} \]

- Opposite is **not** true, may have $\text{cov}(X, Y) = 0$ for dependent $X, Y$

  - **Ex:** $X$ uniform in $[-a, a]$ and $Y = X^2$

    \[ \Rightarrow \text{But uncorrelatedness implies independence if } X, Y \text{ are normal} \]

- If $\text{cov}(X, Y) > 0$ then $X$ and $Y$ tend to move in the same direction

  \[ \Rightarrow \text{Positive correlation} \]

- If $\text{cov}(X, Y) < 0$ then $X$ and $Y$ tend to move in opposite directions

  \[ \Rightarrow \text{Negative correlation} \]
Let $X$ be a zero-mean random signal and $Z$ zero-mean noise

$\Rightarrow$ Signal $X$ and noise $Z$ are independent

Consider received signals $Y_1 = X + Z$ and $Y_2 = -X + Z$

(I) $Y_1$ and $X$ are positively correlated ($X$, $Y_1$ move in same direction)

$$\text{cov}(X, Y_1) = \mathbb{E}[XY_1] - \mathbb{E}[X]\mathbb{E}[Y_1]$$
$$= \mathbb{E}[X(X + Z)] - \mathbb{E}[X]\mathbb{E}[X + Z]$$

$\Rightarrow$ Second term is 0 ($\mathbb{E}[X] = 0$). For first term independence of $X$, $Z$

$$\mathbb{E}[X(X + Z)] = \mathbb{E}[X^2] + \mathbb{E}[X]\mathbb{E}[Z] = \mathbb{E}[X^2]$$

$\Rightarrow$ Combining observations $\Rightarrow \text{cov}(X, Y_1) = \mathbb{E}[X^2] > 0$
(II) $Y_2$ and $X$ are **negatively correlated** ($X$, $Y_2$ move opposite direction)

- Same computations $\Rightarrow \text{cov}(X, Y_2) = -E[X^2] < 0$

(III) Can also compute correlation between $Y_1$ and $Y_2$

$$\text{cov}(Y_1, Y_2) = E[(X + Z)(-X + Z)] - E[(X + Z)]E[(-X + Z)]$$

$$= -E[X^2] + E[Z^2]$$

$\Rightarrow$ Negative correlation if $E[X^2] > E[Z^2]$ (small noise)

$\Rightarrow$ Positive correlation if $E[X^2] < E[Z^2]$ (large noise)

- Correlation between $X$ and $Y_1$ or $X$ and $Y_2$ comes from causality

- Correlation between $Y_1$ and $Y_2$ does not. **Latent variables** $X$ and $Z$

$\Rightarrow$ **Correlation does not imply causation**

Plausible, indeed commonly used, model of a communication channel
Glossary

- Sample space
- Outcome and event
- Sigma-algebra
- Countable union
- Axioms of probability
- Probability space
- Conditional probability
- Law of total probability
- Bayes’ rule
- Independent events
- Random variable (RV)
- Discrete RV
- Bernoulli, binomial, Poisson

- Continuous RV
- Uniform, Normal, exponential
- Indicator RV
- Pmf, pdf and cdf
- Law of rare events
- Expected value
- Variance and standard deviation
- Joint probability distribution
- Marginal distribution
- Random vector
- Independent RVs
- Covariance
- Uncorrelated RVs