

Probability and Random Processes - 3rd ed. Grimmett and Stirzaker (2001)

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1 Events and their probabilities

- Sample space - A set Ω of all possible outcomes of an experiment
- σ -field - A collection \mathcal{F} of subsets of Ω with
 - $\emptyset \in \mathcal{F}$
 - $A \in \mathcal{F} \Rightarrow A^c \in \mathcal{F}$
 - $A_1, A_2, \dots \in \mathcal{F} \Rightarrow \bigcup_{i=1}^{\infty} A_i \in \mathcal{F}$
- Probability measure \mathbb{P} on (Ω, \mathcal{F}) - A function $\mathbb{P} : \mathcal{F} \rightarrow [0, 1]$ with
 - $\mathbb{P}(\emptyset) = 0, \mathbb{P}(\Omega) = 1$
 - $A_1, A_2, \dots \in \mathcal{F}$ and $\forall i \neq j, A_i \cap A_j = \emptyset \Rightarrow \mathbb{P}(\bigcup_{i=1}^{\infty} A_i) = \sum_{i=1}^{\infty} \mathbb{P}(A_i)$
- Probability space - A triple $(\Omega, \mathcal{F}, \mathbb{P})$ comprising a set Ω , a σ -field \mathcal{F} , and a probability measure \mathbb{P} on (Ω, \mathcal{F})
- Conditional probability that event A occurs given that event B occurs
 - $\mathbb{P}(A|B) = \frac{\mathbb{P}(A \cap B)}{\mathbb{P}(B)}, \mathbb{P}(B) > 0$
- Lemma - B_1, B_2, \dots a partition of Ω with $\mathbb{P}(B_i) > 0$ for all $i \Rightarrow$
 - $\mathbb{P}(A) = \sum_{i=1}^n \mathbb{P}(A|B_i)\mathbb{P}(B_i)$
- Independent events $\{A_i : i \in I\}$
 - $\mathbb{P}(\cap_{i \in J} A_i) = \prod_{i \in J} \mathbb{P}(A_i)$ for all finite $J \subset I$

2 Random variables and their distributions

- Random variable (\mathcal{F} -measurable function) - A function $X : \Omega \rightarrow \mathbb{R}$ with
 - $\{\omega \in \Omega : X(\omega) \leq x\} \in \mathcal{F}$ for each $x \in \mathbb{R}$
- Distribution function of a random variable X - A function $F : \mathbb{R} \rightarrow [0, 1]$ given by
 - $F(x) = \mathbb{P}(X \leq x)$
- Discrete random variable - A random variable X taking values in some countable subset $\{x_1, x_2, \dots\}$ of \mathbb{R} and has (probability) mass function $f : \mathbb{R} \rightarrow [0, 1]$ given by
 - $f(x) = \mathbb{P}(X = x)$
- Continuous random variable - A random variable X with distribution function expressible as
 - $F(x) = \int_{-\infty}^x f(u) du, x \in \mathbb{R}$
 - $f : \mathbb{R} \rightarrow [0, \infty)$ is called the (probability) density function of X
- Joint distribution function of a random vector $\mathbf{X} = \{X_1, X_2, \dots, X_n\}$ on the probability space $(\Omega, \mathcal{F}, \mathbb{P})$ is the function $F_{\mathbf{X}} : \mathbb{R} \rightarrow [0, 1]$ given by
 - $F_{\mathbf{X}}(\mathbf{x}) = \mathbb{P}(\mathbf{X} \leq \mathbf{x}), \text{ for } \mathbf{x} \in \mathbb{R}^n$
 - $\mathbf{x} \leq \mathbf{y} \iff x_i \leq y_i \text{ for } i \in \{1, \dots, n\}$

3 Discrete random variables

- Independent discrete random variables - Events $\{X = x\}$ and $\{Y = y\}$ are independent
- Expected value of discrete random variable X with mass function f
 - $\mathbb{E}(X) = \sum_{x: f(x) > 0} x f(x),$
 - where this sum is absolutely convergent so that the order of the terms is irrelevant
- Lemma - If X has mass function f , and $g : \mathcal{R} \rightarrow \mathcal{R}$ then
 - $\mathbb{E}(g(X)) = \sum_x g(x) f(x),$
 - where this sum is absolutely convergent
- k th moment m_k of X
 - $m_k = \mathbb{E}(X^k)$
 - $\sigma_k = \mathbb{E}((X - m_1)^k)$ (k th central moment)

- Theorem - The expectation operator \mathbb{E} has the property
 - $a, b \in \mathbb{R} \Rightarrow \mathbb{E}(aX + bY) = a\mathbb{E}(X) + b\mathbb{E}(Y)$
- Joint distribution function $F : \mathbb{R}^2 \rightarrow [0, 1]$, and mass function $f : \mathbb{R}^2 \rightarrow [0, 1]$, of discrete random variables X and Y
 - $F(x, y) = \mathbb{P}(X \leq x \text{ and } Y \leq y)$
 - $f(x, y) = \mathbb{P}(X = x \text{ and } Y = y)$
- Lemma - Discrete random variables X and Y are independent if and only if
 - $f_{X,Y}(x, y) = f_X(x)f_Y(y)$, or
 - $f_{X,Y}(x, y) = g(x)h(y)$, for all $x, y \in \mathbb{R}$
- Conditional distribution function $F_{Y|X}(\cdot|x)$, and conditional (probability) mass function $f_{Y|X}(\cdot|x)$, of Y given $X = x$
 - $F_{Y|X}(y|x) = \mathbb{P}(Y \leq y|X = x)$
 - $f_{Y|X}(y|x) = \mathbb{P}(Y = y|X = x)$,
 - $\mathbb{P}(X = x) > 0$
- Conditional expectation of Y given X
 - $\mathbb{E}(Y|X) = \sum_y y f_{Y|X}(y|X)$
 - $\mathbb{E}_X(\mathbb{E}(Y|X)) = \mathbb{E}(Y)$
- Sum of random variables - X and Y independent \Rightarrow
 - $\mathbb{P}(X + Y = z) = f_{X+Y}(z) = (f_X * f_Y)(z)$
 - $= \sum_x f_X(x)f_Y(z - x) = \sum_y f_X(z - y)f_Y(y)$
 - $f_X * f_Y$ is the convolution of the mass functions of X and Y

4 Continuous random variables

- Independent continuous random variables X and Y
 - $\{X \leq x\}$ and $\{Y \leq y\}$ are independent events for all $x, y \in \mathbb{R}$
- Expectation of a continuous random variable X with density function f
 - $\mathbb{E}X = \int_{-\infty}^{\infty} xf(x)dx$
 - whenever this integral exists
- Theorem - X and $g(X)$ continuous random variables
 - $\mathbb{E}(g(X)) = \int_{-\infty}^{\infty} g(x)f(x)dx$

- Joint distribution function $F : \mathbb{R}^2 \rightarrow [0, 1]$, and density function $f : \mathbb{R}^2 \rightarrow [0, \infty)$, of continuous random variables X and Y
 - $F(x, y) = \mathbb{P}(X \leq x, Y \leq y)$
 - $F(x, y) = \int_{v=-\infty}^y \int_{u=-\infty}^x f(u, v) du dv$
 - for each $x, y \in \mathbb{R}$
- Conditional distribution function $F_{Y|X}(\cdot|x)$, and conditional (probability) density function $f_{Y|X}(\cdot|x)$, of continuous random variable Y given $X = x$
 - $F_{Y|X}(y|x) = \int_{-\infty}^y \frac{f(x, v)}{f_X(x)} dv$,
 - $\mathbb{P}(Y|X = x)$ does not exist because $\mathbb{P}(X = x) = 0$,
 - $f_{Y|X}(y|x) = \frac{f(x, y)}{f_X(x)}$,
 - $f_X(x) > 0$
- Conditional expectation of Y given X
 - $\mathbb{E}(Y|X) = \int_{-\infty}^{\infty} y f_{Y|X}(y|X) dy$,
 - $\mathbb{E}_X(\mathbb{E}(Y|X)) = \mathbb{E}(Y)$
- Theorem (Change of variables)
 - $g : \mathbb{R}^n \rightarrow \mathbb{R}$,
 - $T : (x_1, x_2) \in A \subseteq D \subseteq \mathbb{R}^2 \rightarrow (y_1, y_2) \in B \subseteq R \subseteq \mathbb{R}^2$ one-to-one, and
 - $J(y_1, y_2)$ the determinant of the matrix of first-order partial derivatives of its inverse (both matrix and determinant called the Jacobian)
 - \Rightarrow
 - $\int \int_A g(x_1, x_2) dx_1 dx_2 = \int \int_B g(x_1(y_1, y_2), x_2(y_1, y_2)) |J(y_1, y_2)| dy_1 dy_2$
- Corollary - X_1, X_2 joint density function f and $(Y_1, Y_2) = T(X_1, X_2) \Rightarrow$
 - $f_{Y_1, Y_2}(y_1, y_2) = f(x_1(y_1, y_2), x_2(y_1, y_2)) |J(y_1, y_2)|$,
 - if $(y_1, y_2) \in R$, and 0 otherwise.
- Sum of random variables - X and Y independent \Rightarrow
 - $f_{X+Y}(z) = (f_X * f_Y)(z)$
 - $= \int_{-\infty}^{\infty} f_X(x) f_Y(z - x) dx = \int_{-\infty}^{\infty} f_X(z - y) f_Y(y) dy$
 - $f_X * f_Y$ is the convolution of the mass functions of X and Y