PH 712 Probability and Statistical Inference

Part I: Random Variable

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Probability (HMC Sec. 1.1–1.3)

- Sample space (denoted by Ω): the set of all the possible outcomes, e.g.,
 - $-\Omega = \mathbb{R}^+$ if investigating survival times of cancer patients
 - $-\Omega = \{yes, no\}$ if investigating whether a treatment is effective
- Event (denoted by capital Roman letters, e.g., A): a subset of the sample space, e.g., corresponding to the previous sample spaces,
 - (0, 10]: the survival time ≤ 10
 - {yes}: the treatment is effective
- Occurrence of event: the outcome is part of the event
- Probability (denoted by Pr): a function quantifying the occurrence likelihood of an event
 - E.g.,
 - * Pr(A): the occurrence probability of event A
 - * $Pr(A^c)$: the probability that event A does NOT occur $(A^c = \Omega \setminus A \text{ denoting the complement set of } A)$
 - * $Pr(A \cup B)$: the occurrence probability of either A or B
 - * $Pr(A \cap B)$: the occurrence probability of both A and B
 - Input: an event
 - Output: a real number (the occurrence probability of the input event)
 - Requirements:
 - * $Pr(A) \ge 0$ for any event A
 - * $Pr(\Omega) = 1$ (i.e., the sample space as a special event always occurs)
 - * (The probability of the union of mutually exclusive countably events is the sum of the probability of each event) If $\{A_n\}_{n=1}^{\infty}$ is a sequence of events with $A_{n_1} \cap A_{n_2} = \emptyset$ for all $n_1 \neq n_2$, then $\Pr(\bigcup_{n=1}^{\infty} A_n) = \sum_{n=1}^{\infty} \Pr(A_n)$
 - More properties (deduced from the above requirements):
 - $* \operatorname{Pr}(A) = 1 \operatorname{Pr}(A^c)$
 - $* \Pr(\emptyset) = 0$
 - * Pr(A) < Pr(B) if $A \subset B$
 - * $0 \le \Pr(A) \le 1$ for each A
 - * $\lim_{n\to\infty} \Pr(A_n) = \Pr(\lim_{n\to\infty} A_n) = \Pr(\bigcup_{n=1}^{\infty} A_n)$ if $\{A_n\}_{n=1}^{\infty}$ is nondecreasing (i.e., $A_1 \subset A_2 \subset \cdots$)
 - * $\lim_{n\to\infty} \Pr(A_n) = \Pr(\lim_{n\to\infty} A_n) = \Pr(\bigcap_{n=1}^{\infty} A_n)$ if $\{A_n\}_{n=1}^{\infty}$ is nonincreasing (i.e., $A_1 \supset A_2 \supset \cdots$)
 - * $\Pr(A \cup B) = \Pr(A) + \Pr(B) \Pr(A \cap B)$ for any events A and B regardless if they are disjoint or not

* $\Pr(\bigcup_{n=1}^{\infty} A_n) \leq \sum_{n=1}^{\infty} \Pr(A_n)$ for arbitrary sequence $\{A_n\}_{n=1}^{\infty}$

Conditional probability and independence (HMC Sec. 1.4)

- Conditional probability of B given A (with Pr(A) > 0): $Pr(B \mid A) = Pr(A \cap B) / Pr(A)$
 - Properties:
 - * $\Pr(B \mid A) \geq 0$
 - * Pr(A | A) = 1
 - * $\Pr(\bigcup_{n=1}^{\infty} B_n \mid A) = \sum_{n=1}^{\infty} \Pr(B_n \mid A)$ if $\{B_n\}_{n=1}^{\infty}$ are mutually exclusive
 - * (Law of total probability) $\Pr(B) = \sum_{n=1}^{N} \Pr(A_n) \Pr(B \mid A_n)$ if $\{A_n\}_{n=1}^{N}$ form a partition of Ω (i.e., $\{A_{n_1}\}_{n=1}^N$ are mutually exclusive and $\Omega = \bigcup_{n=1}^N A_n$)

 * (Bayes' theorem) $\Pr(A_i \mid B) = \Pr(A_i) \Pr(B \mid A_i) / \sum_{n=1}^N \Pr(A_n) \Pr(B \mid A_n)$ if $\{A_n\}_{n=1}^N$ form
 - a partition of Ω
- Independence between two events B and A (i.e., $B \perp A$): $\Pr(B \cap A) = \Pr(A) \Pr(B)$
 - $\Leftrightarrow B \perp A^c$
 - $\Leftrightarrow \Pr(B \mid A) = \Pr(B) \text{ (if } \Pr(A) \neq 0)$
- Mutual independence among N events A_1, \ldots, A_N : for arbitrary subset of $\{A_1, \ldots, A_N\}$, say $\{A_{n_1}, \ldots, A_{n_K}\}$ with $2 \leq K \leq N$, $\Pr(\bigcap_{k=1}^K A_{n_k}) = \prod_{k=1}^K \Pr(A_{n_k})$

HMC Ex. 1.4.31

- A French writer, Chevalier de Méré, had asked a famous mathematician, Pascal, to explain why the following two probabilities were different (the difference had been noted from playing the game many times): (1) at least one six in four independent casts of a six-sided die; (2) at least a pair of sixes in 24 independent casts of a pair of dice. From proportions it seemed to Mr. de Méré that the two probabilities should be the same. Compute the probabilities of (1) and (2).
 - Hint: Pr(no six in one cast of a die) = 5/6, Pr(no six in one cast of a pair of dice) = $(5/6)^2$, and Pr(only one six in one cast of a pair of dice) = $2 \times (1/6) \times (5/6)$.

Distribution of an RV (HMC Chp. 1.5–1.7)

- An RV: a function encoding the entries of Ω
 - Input: an entry of Ω
 - Output: a real number
 - Usage: any event may be expressed in term of
- The cumulative distribution function (cdf) of RV X, say F_X , is defined as

$$F_X(t) = \Pr(X < t), \quad t \in \mathbb{R}.$$

- $-F_X$ satisfies following three properties:
 - * (Right continuous) $\lim_{x \to t^+} F_X(x) = F_X(t)$ (p.s., $\lim_{x \to t^-} F_X(x) = \Pr(X < t)$);
 - * (Non-decreasing) $F_X(t_1) \leq F_X(t_2)$ for $t_1 \leq t_2$;
 - * (Ranging from 0 to 1) $F_X(-\infty) = 0$ and $F_X(\infty) = 1$.
- Reversely, a function satisfying the three above properties must be a cdf for certain RV.
 - * Indicating an one-to-one correspondence between the set of all the RVs and the set of all the
- Knowing the distribution of an RV ⇔ knowing the cdf

Example Lec1.1

• Given $p \in (0,1)$, suppose

$$F_X(x) = \begin{cases} 1 - (1-p)^{\lfloor x \rfloor}, & x \ge 1, \\ 0, & \text{otherwise,} \end{cases}$$

where |x| represents the integer part of real x.

- Show that F_X is a cdf. (Hint: Check all the three properties of cdf, especially the right-continuity of F at positive integers.)

Distribution of an RV (con'd)

- Discrete RV
 - RV X merely takes countably different values
 - Probability mass function (pmf): $p_X(t) = \Pr(X = t)$

 - * $F_X(t) = \sum_{x \le t} p_X(x)$ * $p_X(t) = F_X(t) \Pr(X < t) = F_X(t) \lim_{x \to t^-} F_X(x)$
 - Knowing the distribution of a discrete RV ⇔ knowing the pmf
 - Examples:
 - * Bernoulli: a discrete RV with two possible outcomes, typically coded as 0 (failure) and 1 (success).
 - · https://en.wikipedia.org/wiki/Bernoulli distribution
 - * Binomial: the number of successes in a fixed number of independent Bernoulli trials.
 - · https://en.wikipedia.org/wiki/Binomial_distribution
 - · E.g., flipping a coin 10 times and counting the number of heads.
 - * Negative binomial: the number of trials until a specified number of successes is achieved.
 - · https://en.wikipedia.org/wiki/Negative binomial distribution
 - · E.g., the number of coin flips until you get 3 heads.
 - * Geometric: the number of trials until the first success in a series of independent Bernoulli trials.
 - · https://en.wikipedia.org/wiki/Geometric_distribution
 - E.g., the number of coin flips needed until the first head appears.
 - * Hypergeometric: the number of successes in a sample drawn without replacement from a finite population.
 - · https://en.wikipedia.org/wiki/Hypergeometric distribution
 - E.g., drawing a certain number of red balls from a bag containing both red and blue balls without replacement.
 - * Poisson: the number of events that occur in a fixed interval of time or space, where events happen independently.
 - · https://en.wikipedia.org/wiki/Poisson_distribution
 - · E.g., the number of emails you receive in an hour.
 - * Uniform (the discrete version): each outcome in a finite set has an equal probability.
 - · https://en.wikipedia.org/wiki/Discrete_uniform_distribution
 - E.g., rolling a fair dice, where each of the six faces has an equal chance of landing.
- Continuous RV
 - RV X is continuous \Leftrightarrow its cdf F_X is absolutely continuous, i.e., there exists f_X such that

$$F_X(t) = \int_{-\infty}^t f_X(x) dx, \quad \forall t \in \mathbb{R}.$$

- * Probability density function (pdf): $f_X(t) = dF_X(t)/dt = \lim_{\delta \to 0^+} \Pr(t < X \le t + \delta)/\delta (\ge 0)$. * $\int_{-\infty}^{\infty} f_X(x) dx = 1$ Knowing the distribution of a continuous RV \Leftrightarrow knowing the pdf
- Examples:
 - * Uniform (the continuous version): all outcomes in a continuous range are equally likely.
 - · https://en.wikipedia.org/wiki/Uniform distribution (continuous)
 - * Normal/Gaussian (denoted by $\mathcal{N}(\mu, \sigma^2)$): the most important and widely used distributions, where data is symmetrically distributed around the mean.
 - · https://en.wikipedia.org/wiki/Normal_distribution
 - * Exponential: the time between events in a Poisson process, often used to describe waiting
 - https://en.wikipedia.org/wiki/Exponential distribution

- * Chi-squared: sum of squared standard normal RVs; arising in hypothesis testing, particularly in tests of independence and goodness of fit.
 - · https://en.wikipedia.org/wiki/Chi-squared distribution
- * Cauchy: known for its heavy tails and undefined mean and variance; used in robust statistics.
 - · https://en.wikipedia.org/wiki/Cauchy distribution
- * Weibull: a generalization of the exponential distribution, used in reliability engineering and failure time analysis.
 - · https://en.wikipedia.org/wiki/Weibull distribution
- * Log-normal: $\exp(\mathcal{N}(0,1))$; commonly used to model stock prices and other financial data.
 - · https://en.wikipedia.org/wiki/Log-normal_distribution
- * (Student's) t: used in hypothesis testing, particularly for small sample sizes.
 - · https://en.wikipedia.org/wiki/Student%27s t-distribution

Example Lec1.2

• Given $p \in (0,1)$, suppose

$$F_X(x) = \begin{cases} 1 - (1-p)^{\lfloor x \rfloor}, & x \ge 1, \\ 0, & \text{otherwise,} \end{cases}$$

where |x| represents the integer part of x.

- What is the type of X, discrete or continuous?

Support of RV (CB pp. 50 & HMC pp. 46)

- For discrete RV X with pmf p_X
 - $\text{ supp}(X) = \{ x \in \mathbb{R} : p_X(x) > 0 \}$
 - E.g., support of Binom(n, p) is $\{0, \ldots, n\}$
 - $-\int_{\operatorname{supp}(X)} f_X(x) \mathrm{d}x = 1$
- For continuous RV X with pdf f_X
 - $\text{ supp}(X) = \{ x \in \mathbb{R} : f_X(x) > 0 \}$
 - E.g., support of $\mathcal{N}(0,1)$ is \mathbb{R}
 - $-\sum_{x \in \text{supp}(X)} p_X(x) = 1$

Example Lec1.3

• Revisit F_X defined in Example Lec1.1, i.e.,

$$F_X(x) = \begin{cases} 1 - (1-p)^{\lfloor x \rfloor}, & x \ge 1, \\ 0, & \text{otherwise,} \end{cases}$$

where |x| represents the integer part of real x.

- What is the support of X?

Expectations (HMC Sec. 1.8–1.9)

- Given RV X and function g, the expectation of g(X) is $\mathrm{E}\{g(X)\}$
 - $\begin{array}{l} = \int_{-\infty}^{\infty} g(x) f_X(x) \mathrm{d}x \text{ for continuous } X \\ = \sum_{x \in \mathrm{supp}(X)} g(x) p_X(x) \text{ for discrete } X \\ \text{ Weighted average of values of } g(X) \end{array}$

 - $E\{a_1g_1(X) + a_2g_2(X)\} = a_1E\{g_1(X)\} + a_2E\{g_2(X)\}\$
- Mean of X (a.k.a. the 1st raw moment/moment about 0 of X): E(X)
- Variance of X (a.k.a. the 2nd central moment of X): $Var(X) = E\{X E(X)\}^2$

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

$$- \operatorname{Var}(aX + b) = a^2 \operatorname{Var}(X)$$

• Standard deviation of X: square root of the variance of X

Example Lec1.4

- Find the mean and variance of $X \sim \mathcal{N}(0,1)$, i.e., $f_X(x) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{x^2}{2}\right)$
- Find the mean and variance of $X \sim \mathcal{N}(\mu, \sigma^2)$ with $\mu \in \mathbb{R}$ and $\sigma \in \mathbb{R}^+$, i.e., $f_X(x) =$ $\frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right) \text{ (p.s. } X \sim \mathcal{N}(\mu, \sigma^2) \Leftrightarrow Z = (X-\mu)/\sigma \sim \mathcal{N}(0, 1))$
- Find the mean and variance of Cauchy distribution, i.e., $f_X(x) = {\pi(1+x^2)}^{-1}, x \in \mathbb{R}$

Distribution of an RV (con'd)

- Moment generating function (MGF, HMC Sec. 1.9/CB Sec. 2.3)
 - $M_X(t) = \mathbb{E}\{\exp(tX)\}\$
 - * Continuous X: $M_X(t) = \int_{-\infty}^{\infty} \exp(tx) f_X(x) dx$ * Discrete X: $M_X(t) = \sum_{u \in \text{supp}(X)} \exp(tx) p_X(x)$
 - The MGF of X is $M_X(t)$, $t \in A$, $\Leftrightarrow M_X(t)$ is finite for t in a neighborhood of 0, say A; otherwise the MGF does NOT exist or is NOT well defined.
 - $-M_{aX+b}(t) = \exp(bt)M_X(at)$
 - Knowing the distribution of an RV ⇔ knowing the MGF (if any)
 - If MGF M(t) is well-defined, then the kth raw moment is the kth-order derivative of M(t) evaluated at 0, i.e., $E(X^k) = M^{(k)}(0)$
- Characteristic function (CF, optional)
 - $-\varphi_X(t) = \mathbb{E}\{\exp(itX)\}\$

 - * Continuous X: $\varphi_X(t) = \int_{-\infty}^{\infty} \exp(itu) f_X(u) du$ * Discrete X: $\varphi_X(t) = \sum_{u \in \text{supp}(X)}^{\infty} \exp(itu) p_X(u)$
 - Always well-defined
 - $-\varphi_{aX+b}(t) = \exp(bt)\varphi_X(at)$
 - Knowing the distribution of an RV \Leftrightarrow knowing the CF

Example Lec1.5

- Find the MGF of $X \sim \mathcal{N}(\mu, \sigma^2)$ with $\mu \in \mathbb{R}$ and $\sigma \in \mathbb{R}^+$, i.e., $f_X(x) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)$
- Find the MGF of Cauchy distribution, i.e., $f_X(x) = {\pi(1+x^2)}^{-1}, x \in \mathbb{R}$

Indicator function

Given a set A, the indicator function of A is

$$\mathbf{1}_{A}(x) = \begin{cases} 1, & x \in A, \\ 0, & \text{otherwise.} \end{cases}$$

Example Lec1.6

• Revisit F_X defined in Example Lec1.1, i.e.,

$$F_X(x) = \begin{cases} 1 - (1-p)^{\lfloor x \rfloor}, & x \ge 1, \\ 0, & \text{otherwise,} \end{cases}$$

where |x| represents the integer part of x.

- Please reformulate F_X with the indicator function of $A = \{x : x \ge 1\}$.