

Lecture 13: limits of probabilities of nested events Kelly 2.5

13.1 The collection of all events

For (finite or) countable Ω , events are all subsets of Ω , but this does not work for $\Omega = \mathfrak{R}$.

More generally, Ω is event, E an event $\Rightarrow E^c$ an event, and E_1, E_2, \dots events $\Rightarrow \bigcup_{i=1}^{\infty} E_i$ an event.

(Such collections, closed under complements and countable unions, are called σ -fields: Kelly 1.3.)

Note $\Phi = \Omega^c$ is an event, and $\bigcap E_i = (\bigcup E_i^c)^c$ are then also events.

13.2 The events on \mathfrak{R} generated by sets $(-\infty, b]$ for all real b .

(i) First, for $a < b$, $(-\infty, a]^c \cap (-\infty, b] = (a, b]$ so we have the half-left-open intervals.

(ii) Next, $\bigcup_n (a, b - \frac{1}{n}] = (a, b)$ so we have the open intervals.

(iii) Next, $\bigcap_n (a - \frac{1}{n}, b] = [a, b]$ so we have the closed intervals.

(iv) Next, if $a = b$ in (iii), we have isolated points $\{b\}$.

(v) Finally, taking countable unions of these, we have all countable sets.

Sets generated by countable unions and intersections of intervals, are the *Borel sets* (Kelly 1.3), and make up the set of events for a real-valued (discrete or continuous) random variable.

13.3 Increasing and decreasing nested sets

(i) A_1, A_2, A_3, \dots are nested increasing sets if $A_1 \subset A_2 \subset A_3 \subset \dots$. Then $\bigcup_1^n A_i = A_n$ and $\bigcap_1^n A_i = A_1$.

(ii) A_1, A_2, A_3, \dots are nested decreasing sets if $A_1 \supset A_2 \supset A_3 \supset \dots$. Then $\bigcup_1^n A_i = A_1$ and $\bigcap_1^n A_i = A_n$.

Examples: Kelly 2.5.1, 2.5.2

1. Increasing: $A_n = (-\infty, x - \frac{1}{n}]$. $\lim_{n \rightarrow \infty} A_n = (-\infty, x)$.

2. Decreasing: $A_n = (-\infty, x + \frac{1}{n})$ or $A_n = (-\infty, x + \frac{1}{n}]$. $\lim_{n \rightarrow \infty} A_n = (-\infty, x]$.

3. Decreasing: A_n is event of no successes in n tries. Then $\lim_{n \rightarrow \infty} A_n$ is event of no success ever.

13.4 Nested sets theorem; Kelly 2.5.3, 2.5.8

Theorem: Let A_1, A_2, \dots be any events in Ω .

(i) If $A_1 \subset A_2 \subset A_3 \subset \dots$, $P(A_1 \cup A_2 \cup A_3 \dots) = \lim_{n \rightarrow \infty} P(A_n)$.

(ii) If $A_1 \supset A_2 \supset A_3 \supset \dots$, $P(A_1 \cap A_2 \cap A_3 \dots) = \lim_{n \rightarrow \infty} P(A_n)$.

Proof: (i) Let $B_i = A_i \cap A_{i-1}^c$; Then B_i are disjoint and $B_1 \cup B_2 \cup \dots \cup B_n = A_1 \cup A_2 \cup \dots \cup A_n$, so $P(A_1 \cup A_2 \cup A_3 \dots) = P(B_1 \cup B_2 \cup B_3 \dots) = \sum_1^{\infty} P(B_i) = \lim_{n \rightarrow \infty} (\sum_1^n P(B_i)) = \lim_{n \rightarrow \infty} P(B_1 \cup B_2 \cup \dots \cup B_n) = \lim_{n \rightarrow \infty} P(A_n)$.

(ii) Let $D_i = A_i^c$, so from (i) $P(D_1 \cup D_2 \cup D_3 \dots) = \lim_{n \rightarrow \infty} P(D_n)$.

But $P(D_1 \cup D_2 \cup D_3 \dots) = P((A_1 \cap A_2 \cap \dots)^c) = 1 - P(A_1 \cap A_2 \cap \dots)$

and $\lim_{n \rightarrow \infty} P(D_n) = \lim_{n \rightarrow \infty} (1 - P(A_n)) = 1 - \lim_{n \rightarrow \infty} P(A_n)$.

13.5 Examples; Kelly 2.5.4 etc.

(i) In independent trials, with probability of success $p > 0$, eventually we have success with probability 1, since if A_n is event of no successes in n tries, $P(A_n) = (1 - p)^n \rightarrow 0$.

(ii) Let the probability of success on try k be p_k . Let $D_n = A_n^c$ be event of success by try n . Then $P(D_n) \leq \sum_{k=1}^n p_k$. If p_k decrease fast (e.g. $p_k = 0.1/n^2$) then $\lim P(D_n) < 1$; eventual success is not certain.

(iii) Increasing: For any random variable X ; $P(X < a) = \lim P(X \leq (a - \frac{1}{n}))$.

Increasing: For any random variable X ; $P(X > a) = \lim P(X > (a + \frac{1}{n}))$.

Decreasing: For any random variable X ; $P(X \leq a) = \lim P(X \leq (a + \frac{1}{n})) = \lim P(X < (a + \frac{1}{n}))$.

Decreasing: For any random variable X ; $P(X \geq a) = \lim P(X \geq (a - \frac{1}{n})) = \lim P(X > (a - \frac{1}{n}))$.

Lecture 14: Cumulative distribution functions Kelly 3.2

14.1 (i) Definition: For any random variable X , the *cumulative distribution function* is defined as

$$F_X(x) = P(X \leq x) \text{ for } -\infty < x < \infty.$$

(ii) For a discrete random variable with pmf $p_X(x)$, $F_X(b) = \sum_{x \leq b} p_X(x)$.

(iii) For a continuous random variable with pdf $f_X(x)$, $F_X(b) = \int_{-\infty}^b f_X(x) dx$.

(iv) For all random variables, $P(a < X \leq b) = F(b) - F(a)$

because $\{X \leq b\} = \{X \leq a\} \cup \{a < X \leq b\}$ and $\{X \leq a\} \cap \{a < X \leq b\} = \Phi$ (empty set).

14.2 Properties:

(i) F_X is a non-decreasing function: if $a < b$, then $F_X(a) \leq F_X(b)$, because $\{X \leq a\} \subset \{X \leq b\}$.

(ii) $\lim_{b \rightarrow \infty} F_X(b) = 1$, because for any increasing sequence $b_n \rightarrow \infty$, $n = 1, 2, 3, \dots$,

$\Omega = \{X < \infty\} = \cup \{X \leq b_n\}$, so $1 = P(\Omega) = \lim_{n \rightarrow \infty} P(X \leq b_n) = \lim_{n \rightarrow \infty} F_X(b_n)$.

(iii) $\lim_{b \rightarrow -\infty} F_X(b) = 0$, because for any decreasing sequence $b_n \rightarrow -\infty$, $n = 1, 2, 3, \dots$,

$\Phi = \{X = -\infty\} = \cap \{X \leq b_n\}$, so $0 = P(\Phi) = \lim_{n \rightarrow \infty} P(X \leq b_n) = \lim_{n \rightarrow \infty} F_X(b_n)$.

(iv) F_X is right-continuous. That is, for any b and any decreasing sequence b_n , $n = 1, 2, 3, \dots$, with $b_n \rightarrow b$ as $n \rightarrow \infty$, $\lim_{n \rightarrow \infty} F_X(b_n) = F_X(b)$, because $\{X \leq b\} = \cap \{X \leq b_n\}$.

Note $P(X \leq b) = P(X < b) + P(X = b)$, and $P(X < b) = \lim_{x \rightarrow b^-} F(x)$.

If X is discrete, with $P(X = b) > 0$, F_X will be discontinuous at $x = b$.

14.3 Case of continuous random variables:

For discrete random variables, $F_X(x)$ is just a set of flat (constant) pieces, with jumps in amount $P(X = x_i)$ at each possible value x_i of X . This is not very useful.

For continuous random variables, the cdf is very useful!

$$F_X(x) = P(X \leq x) = \int_{-\infty}^x f_X(w) dw \text{ so } \frac{dF_X(x)}{dx} = f_X(x).$$

That is, we get the pdf by differentiating the cdf: the cdf is often easier to consider.

Example: scaling an exponential random variable.

Suppose $f_X(x) = \lambda e^{-\lambda x}$ on $x \geq 0$, and let $Y = aX$ ($a > 0$). What is the pdf of Y ?

$$\text{First, } F_x(x) = \int_0^x \lambda e^{-\lambda w} dw = [-e^{-\lambda w}]_0^x = 1 - e^{-\lambda x} \text{ on } x \geq 0.$$

$$\text{Now, } F_Y(y) = P(Y \leq y) = P(aX \leq y) = P(X \leq y/a) = F_X(y/a) = (1 - e^{-\lambda y/a}),$$

$$\text{so } f_Y(y) = F'_Y(y) = \frac{d}{dy}(1 - e^{-\lambda y/a}) = (\lambda/a)e^{-(\lambda/a)y} \text{ on } y \geq 0.$$

That is Y is an exponential random variable with parameter λ/a .

14.4 Using the cdf to consider functions of random variables (Kelly 5.2)

Using the cdf is often the easiest way to consider functions of a random variable.

Example: Suppose X is Uniform $U(0,1)$. What is the pdf of $Y = X^3$?

$$\begin{aligned} f_X(x) &= 1, 0 \leq x \leq 1; & F_X(x) &= x, 0 \leq x \leq 1 \\ F_Y(y) &= P(Y \leq y) = P(X^3 \leq y) = P(X \leq y^{1/3}) = F_X(y^{1/3}) = y^{1/3}, 0 \leq y \leq 1 \\ f_Y(y) &= \frac{d}{dy} F_Y(y) = (1/3)y^{-2/3} 0 \leq y \leq 1 \end{aligned}$$

Lecture 15: Conditional probability for random variables

15.1 Conditioning a discrete random variable

Recall $P(X = x)$ is just an event, and $P(X \in B) = \sum_{x \in B} P(X = x)$.

So $P(X \in C | X \in B) = P(X \in B \cap C) / P(X \in B)$.

Also $P(X = x | X \in B) = P(X = x) / P(X \in B)$, provided $x \in B$.

15.2 Examples of conditioning a discrete random variable

(i) If X is Poisson, parameter 1: $P(X = x) = e^{-1} 1^x / x! = e^{-1} / x!$, $P(X \geq 2) = 1 - e^{-1} - e^{-1}$, and $P(X = x | X \geq 2) = (e^{-1} / x!) / (1 - 2e^{-1})$, for $x = 2, 3, 4, \dots$

(ii) If X is Bin(11,0.5): $P(X \text{ even}) = 1/2$ and $P(X = x | X \text{ even}) = 2P(X = x)$ if x is even, 0 otherwise.

(iii) The forgetting property of the Geometric Distribution

Suppose on each try the probability of “success” is p . Let X be the number of failures before a “success” is achieved. Then $P(X = x) = (1 - p)^x \cdot p$ for $x = 0, 1, 2, 3, \dots$ (Geometric distribution).

$P(X \geq k) = P(\text{first } k \text{ are failures}) = (1 - p)^k$ (or $P(X \geq k) = \sum_{x=k}^{\infty} (1 - p)^x \cdot p = \text{same thing}$).

$P(X \geq k + \ell | X \geq \ell) = P(X \geq k + \ell) / P(X \geq \ell) = (1 - p)^{k+\ell} / (1 - p)^\ell = (1 - p)^k = P(X \geq k)$.

15.3 Conditioning a continuous random variable

Recall $X \in B$ is an event and $P(X \in B) = \int_{x \in B} f_X(x) dx$.

So $P(X \in C | X \in B) = P(X \in B \cap C) / P(X \in B) = \int_{B \cap C} f(x) dx / \int_B f(x) dx$

15.4 Examples of conditioning a continuous random variable

(i) Example of a Uniform random variable Suppose X has p.d.f. $f(x) = 1$, $0 \leq x \leq 1$.

$P(X > 0.6 | X \leq 0.8) = P(0.6 < X \leq 0.8) / P(X \leq 0.8) = 0.2 / 0.8 = 0.25$.

(ii) Example for an exponential random variable

Suppose X has p.d.f. $f(x) = 0.5e^{-0.5x}$ on $0 < x < \infty$: $F(x) = \int^x f(w) dw = 1 - e^{-0.5x}$.

So $P(X \leq 6 | X > 2) = P(2 < X \leq 6) / P(X > 2) = (e^{-1} - e^{-3}) / e^{-1} = (1 - e^{-2}) \approx 6/7$.

(iii) The **forgetting property** of the exponential.

Suppose X has p.d.f. $f(x) = \lambda \exp(-\lambda x)$, $0 < x < \infty$.

Note $F_X(a) = P(X \leq a) = \int_0^a f(x) dx = (1 - \exp(-\lambda a))$, so $P(X > a) = \exp(-\lambda a)$. Consider

$P(X > a + b | X > a) = P(X > a + b) / P(X > a) = \exp(-\lambda(a + b)) / \exp(-\lambda a) = \exp(-\lambda b) = P(X > b)$.

15.5 Approximating discrete by continuous distributions

Note the geometric and exponential distributions both have the “forgetting” property.

In fact, geometric is just a discrete version of the exponential.

Consider a r.v. T with geometric distribution with $p = 0.02$ and also T with an exponential with rate parameter $\lambda = 0.02$.

(i) Compare $P(T \geq 50)$ under the two models.

(ii) Repeat for $p = 0.001$ (geometric) and $\lambda = 0.001$ (exponential).

(iii) Using either model (p or $\lambda = 0.02$), what is $P(T \geq 100 | T \geq 50)$?

(iv) Using either model (p or $\lambda = 0.02$), what is $P(T \leq 50 | T \leq 100)$?

(v) In (i) is it better to compare $P(T > 49.5)$? Why? (Actually not, but it could be?)