STATS310A - Lecture 7

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Contents

1 Measurable functions and random variables

Recall that a function $T : (\Omega, \mathcal{F}) \to (\Omega', \mathcal{F}')$ is *measurable* if $T^{-1}(A') \in \mathcal{F}$ for all $A' \in \mathcal{F}'$ where $T^{-1}(A') = \{\omega \in \Omega : T(\omega) \in \mathcal{A}\}$.

A *random variable* is a measurable function from $(\Omega, \mathcal{F})$ to $(\mathbb{R}, \mathcal{B})$ where $\mathcal{B}$ is the set of Borel sets.

A *random vector* is a measurable function from $(\Omega, \mathcal{F})$ to $(\mathbb{R}^k, \mathcal{B}_k)$ where $\mathcal{B}_k$ is the set of Borel subsets of $\mathbb{R}^k$.

Lemma 1. *If $Y : (\Omega, \mathcal{F}) \to \mathbb{R}^k$ is a function with coordinates $Y_i : (\Omega, \mathcal{F}) \to \mathbb{R}$, for $i = 1, \ldots, k$, then Y is a random vector if and only if Y_i is a random variable for each i.*

Proof. Suppose each Y_i is measurable then

$$\{\omega \in \Omega : Y(\omega) \le (x_1, \ldots, x_k)\} = \bigcap_{i=1}^{k} \{\omega \in \Omega : Y_i(\omega) \le x_i\} \in \mathcal{F},$$

since each set $\{\omega \in \Omega : Y_i(\omega) \le x_i\}$ is in $\mathcal{F}$ and $\mathcal{F}$ is closed under finite intersections. Since sets of the form $\{y \in \mathbb{R}^k : y \le x\}$ generate $\mathcal{B}_k$, we have that Y is measurable.

If Y is measurable, then

$$\{\omega : Y(\omega) \le x\} = \bigcup_{n=1}^{\infty} \{\omega : Y \le (n, \ldots, x, \ldots, n)\} \in \mathcal{F},$$

since Y is a random vector and $\mathcal{F}$ is closed under countable unions. The intervals $(-\infty, x]$ generate $\mathcal{B}$ and so Y_i is measurable. $\square$

Lemma 2. *If $T : \mathbb{R}^k \to \mathbb{R}^j$ is continuous, then T is Borel-measurable.*

Proof. Since T is continuous, $T^{-1}(U)$ is open for all open sets $U \subseteq \mathbb{R}^j$ and thus $T^{-1}(U)$ is Borel for all open sets $U \subseteq \mathbb{R}^j$. Since the open sets generate the Borel σ-algebra, T is measurable. $\square$

Corollary 1. *If X,Y, $(X_n)_{n=1}^{\infty}$ are random varaibles, then $X+Y$, XY, $\max\{X, Y\}$, $\sup\{X_n\}$, $\inf\{X_n\}$, $\limsup\{X_n\}$, $\liminf\{X_n\}$ are all random variables. And the set $\{\omega : \lim X_n(\omega)$ exists $\}$ is measurable.*

Proof. We can write $X + Y$ as a composition

$$\begin{aligned} \Omega \to \quad & \mathbb{R} \times \mathbb{R} \quad \to \mathbb{R} \\ \omega \mapsto & (X(\omega), Y(\omega)) \mapsto X(\omega) + Y(\omega). \end{aligned}$$

From the above lemma, $X + Y$ is measurable. The others are similar. $\square$

2 Push forwards

Definition 1. Suppose that $(\Omega, \mathcal{F}, \mu)$ is a measure space and $T : (\Omega, \mathcal{F}, \mu) \to (\Omega', \mathcal{F}')$ is measurable. We define the *push forward* of μ along T, to be the measure $\mu^{T^{-1}}$ on $(\Omega', \mathcal{F}')$ defined by

$$\mu^{T^{-1}}(A) := \mu(T^{-1}(A)) = \mu(\{\omega : T(\omega) \in A\}).$$

Note $\mu^{T^{-1}}$ is a measure. It is well defined because T is measurable. And

$$\mu^{T^{-1}}(\emptyset) = \mu(\emptyset) = 0.$$

If $A \subseteq B$, then $T^{-1}(A) \subseteq T^{-1}(B)$ and so

$$\mu^{T^{-1}}(A) = \mu(T^{-1}(A)) \leq \mu(T^{-1}(B)) = \mu^{T^{-1}}(B).$$

If $\{A_i\}_{i=1}^{\infty}$ are disjoint, then $\{T^{-1}(A_i)\}_{i=1}^{\infty}$ are disjoint and so

$$\begin{aligned} \mu^{T^{-1}}\left(\bigcup_{i=1}^{\infty} A_i\right) &= \mu\left(T^{-1}\left(\bigcup_{i=1}^{\infty} A_i\right)\right) \\ &= \mu\left(\bigcup_{i=1}^{\infty} T^{-1}(A_i)\right) \\ &= \sum_{i=1}^{\infty} \mu(T^{-1}(A_i)) \\ &= \sum_{i=1}^{\infty} \mu^{T^{-1}}(A_i). \end{aligned}$$

Lebesgue's mistake/a warning: If $U \subseteq \mathbb{R}^2$ is a Borel set, then the projections of U are not necessarily Borel sets.

3 Haar measure

Let $O_n = \{M \in \mathbb{R}^{n^2} : M^T M = I_n\}$ be the orthogonal group. The group O_n has an invariant probability ν which we call Haar measure. That is for all measurable $A \subseteq O_n$ and $m \in O_n$, $\nu(m \cdot A) = \nu(A)$. What is this measure?

3.1 One answer

We will give a recipe for drawing $M \in O_n$ from ν. To start let $Z_{i,j} \sim N(0,1)$ be independent for $1 \leq i, j \leq n$. Let $Z = (Z_{i,j})_{i,j=1}^n$ and apply Gram-Schmidt to Z to get a matrix $M \in O_n$.

3.2 A more mathematical answer

We know that $\Phi(x) = \int_{-\infty}^x \exp(-t^2/2)dt$ is a distribution. Define on $\mathbb{R}^{n^2}$

$$F(x_{1,1}, x_{1,2}, \ldots, x_{n,n}) = \prod_{i,j=1}^n \Phi(x_{i,j}).$$

One can check that this defines a probabilities distribution μ on $\mathbb{R}^{n^2}$. Define a function $T : \mathbb{R}^{n^2} \to O_n$ given by given a matriz Z, apply Gram-Schmidt to Z to get $M \in O_n$. Finally define $\nu := \mu^{T^{-1}}$ to be the push forward of μ along T.

4 Independence

Definition 2. If $\{X_i\}_{i \in I}$ is a collection of random varaibles, then we define the σ*-algebra generated by* $\{X_i\}_{i \in I}$ to be

$$\sigma(X_i, i \in I) := \sigma\left(\{X_i^{-1}((a,b]) : i \in I, a, b \in \mathbb{R}\right).$$

Definition 3. Two random variables X, Y are *independent* if $\sigma(X)$ and $\sigma(Y)$ are independent. That is equivalently,

$$\mathbb{P}(X \leq x, Y \leq y) = \mathbb{P}(X \leq x)\mathbb{P}(Y \leq y),$$

for all $x, y \in \mathbb{R}$. Yet another equivalent statement is that for all $A, B \subseteq \mathbb{R}$ Borel

$$\mathbb{P}(X \in A, Y \in B) = \mathbb{P}(X \in A)\mathbb{P}(Y \in B).$$

5 Constructing random variables

How do we pick from F where F is a univariate probability distribution? We first pick U which is uniformly distributed on $[0,1]$ and then we define $T : [0,1] \to \mathbb{R}$ by

$$T(u) = \inf\{x \in \mathbb{R} : T(x) \geq u\}.$$

Then $\mathbb{P}(T(U) \leq x) = F(x)$.

Example 1. Consider the case when

$$F(x) = \begin{cases} 0 & \text{if } x \leq 0, \\ 1 - e^{-x} & \text{if } x > 0. \end{cases}$$

Let $u = 1 - e^{-x}$, then $x = -\log(1-u)$. Define $T : (0,1) \to \mathbb{R}$ by $T(u) = -\log(1-u)$ and $X = T(U)$ where U is uniform on $(0,1)$. Then if $x > 0$,

$$\begin{aligned} \mathbb{P}(X \leq x) &= \mathbb{P}(-\log(1-U) \leq x) \\ &= \mathbb{P}(-x \leq \log(1-U)) \\ &= \mathbb{P}(e^{-1} \leq 1 - U) \\ &= \mathbb{P}(U \leq 1 - e^{-x}) \\ &= 1 - e^{-x}. \end{aligned}$$

Another good example if when X is discrete. Say $X = a_i$ with probability p_i. Then the above construction divides $[0,1]$ into intervals A_i of length p_i. Then if U lies in A_i, then we set $T(U)$ to be a_i. Thus $T(U)$ and X have the same distribution.

6 Maxima

Let $X_1, \ldots, X_n$ be independent random variables with distribution

$$\mathbb{P}(X_i \leq x) = F(x).$$

Define $M_n = \max\{X_i : i = 1, \ldots, n\}$. Then

$$\mathbb{P}(M_n \leq x) = \mathbb{P}\left(\bigcap_{i=1}^{n} \{X_i \leq x\}\right) = \prod_{i=1}^{n} \mathbb{P}(X_i \leq x) = F(x)^n.$$

What happens as $n \to \infty$? Suppose that $F(x) = 1 - e^{-x}$. Then $\mathbb{P}(M_n < x) = (1 - e^{-x})^n$. We are interested in what happens when $n \to \infty$. Let $x = \log(n) + y$, then

$$\mathbb{P}(M_n \leq x) = \left(1 - \frac{e^{-y}}{n}\right)^n \sim e^{-e^{-y}}.$$

Then function $F(y) = e^{-e^{-y}}$, $y \in \mathbb{R}$ is a distribution function and is called the standard Gumble distribution.

Definition 4. We say that a sequence of distributions F_n *converges in distribution* to a distribution F if

$$F_n(x) \to F(x),$$

for all x such that F is continuous at x.

Why do we only restrict to x at which F is continuous? Consider the following example: X_n is a point mass at $1 + \frac{1}{n}$ and X is a point mass at 1. Then

$$F_n(x) = \begin{cases} 0 & \text{if } x < 1 + 1/n, \\ 1 & \text{if } x \geq 1 + 1/n, \end{cases}$$

and

$$F(x) = \begin{cases} 0 & \text{if } x < 1, \\ 1 & \text{if } x \geq 1. \end{cases}$$

Thus $F_n(x) \to F(x)$ if and only if $x \neq 1$. Thus in the definition of convergence in distribution we do not worry about the points at which F is not continuous.

We can now say that $M_n - \log(n)$ converges in distribution to a Gumble distribution.

Now lets consider the maximum of Gaussians. Let $X_1, \ldots, X_n \sim N(0,1)$. We know that

$$\mathbb{P}(M_n \leq x) = (\Phi(x))^n = e^{n\log(\Phi(x))} = e^{n\log(1-(1-\Phi(x)))}.$$

We will use the approximation $\log(1-y) \sim -y$ is $y \to 0$. We also have (homework problem)

$$\frac{x}{1+x^2}\exp^{-x^2/2} \leq \int_x^\infty \exp(-t^2/2) \leq \frac{1}{x}\exp^{-x^2/2}.$$

Thus we can say $1 - \Phi(x) \sim \frac{1}{\sqrt{2\pi}}\frac{e^{-x^2/2}}{x}$. Thus for n large

$$\mathbb{P}(M_n \leq x) \sim e^{-n\frac{e^{-x^2}}{\sqrt{2\pi}x}}.$$

Let $x = \sqrt{2\log(n) - \log(\log(n)) + y}$, so $x \sim \sqrt{2\log(n) + y}$, then

$$\mathbb{P}(M_n \leq \sqrt{2\log(n) - \log(\log(n)) + y}) \sim e^{-\frac{e^{-y/2}}{\sqrt{2\pi}}},$$

another Gumble distribution. We can not always perform these sorts of calculations. There are distributions such that $\lim \mathbb{P}\left(\frac{M_n - a_n}{b_n} \leq x\right)$ does not exist for any choice of a_n, b_n. Discrete distributions such as the geometric or Poission ditributions tend to show this behaviour. Be careful when looking at the limiting behaviour of the maxima of discrete random variables.