

Math is Fun & Beautiful! - Measure-theoretic Treatment of Statistics

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Kinds of fun we can enjoy with math

- [measure-theoretic treatment of probabilities 8](#)
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Notations

- sets of numbers
 - \mathbf{N} : set of natural numbers, \mathbf{Z} : set of integers, \mathbf{Q} : set of rational numbers
 - \mathbf{R} : set of real numbers, \mathbf{R}_+ : set of nonnegative real numbers, \mathbf{R}_{++} : set of positive real numbers
- sequences $\langle x_i \rangle$ and like
 - finite $\langle x_i \rangle_{i=1}^n$, infinite $\langle x_i \rangle_{i=1}^\infty$ - use $\langle x_i \rangle$ when unambiguously understood
 - similarly for other operations - $\sum x_i, \prod x_i, \cup A_i, \cap A_i, \times A_i$
 - similarly for integrals - $\int f$ for $\int_{-\infty}^\infty f$
- sets
 - \tilde{A} : complement of A , $A \sim B: A \cap \tilde{B}$, $A \Delta B: A \cap \tilde{B} \cup \tilde{A} \cap B$
 - $\mathcal{P}(A)$: set of all subsets of A
- sets in metric vector spaces
 - \bar{A} : closure of set A
 - A° : interior of set A
 - **relint**: relative interior of set A

- **bd** A : boundary of set A
- set algebra
 - $\sigma(\mathcal{A})$: σ -algebra generated by \mathcal{A} , *i.e.*, smallest σ -algebra containing \mathcal{A}
- norms in \mathbf{R}^n
 - $\|x\|_p$ ($p \geq 1$): p -norm of $x \in \mathbf{R}^n$, *i.e.*, $(|x_1|^p + \cdots + |x_n|^p)^{1/p}$
 - $\|x\|_2$: Euclidean norm
- matrices and vectors
 - a_i : i -th entry of vector a
 - A_{ij} : entry of matrix A at position (i, j) , *i.e.*, entry in i -th row and j -th column
 - $\mathbf{Tr}(A)$: trace of $A \in \mathbf{R}^{n \times n}$, *i.e.*, $A_{1,1} + \cdots + A_{n,n}$
- symmetric, positive definite, and positive semi-definite matrices
 - $\mathbf{S}^n \subset \mathbf{R}^{n \times n}$: set of symmetric matrices
 - $\mathbf{S}_+^n \subset \mathbf{S}^n$: set of positive semi-definite matrices - $A \succeq 0 \Leftrightarrow A \in \mathbf{S}_+^n$
 - $\mathbf{S}_{++}^n \subset \mathbf{S}^n$: set of positive definite matrices - $A \succ 0 \Leftrightarrow A \in \mathbf{S}_{++}^n$
- Python script-like notations (with serious abuse of notations!)

- use $f : \mathbf{R} \rightarrow \mathbf{R}$ as if it were $f : \mathbf{R}^n \rightarrow \mathbf{R}^n$, *e.g.*,

$$\exp(x) = (\exp(x_1), \dots, \exp(x_n)) \quad \text{for } x \in \mathbf{R}^n$$

or

$$\log(x) = (\log(x_1), \dots, \log(x_n)) \quad \text{for } x \in \mathbf{R}_{++}^n$$

corresponding to Python code - `numpy.exp(x)` or `numpy.log(x)` - where `x` is instance of `numpy.ndarray`, *i.e.*, numpy array

- use $\sum x$ for $\mathbf{1}^T x$ for $x \in \mathbf{R}^n$, *i.e.*

$$\sum x = x_1 + \dots + x_n$$

corresponding to Python code - `x.sum()` - where `x` is numpy array

- use x/y for $x, y \in \mathbf{R}^n$ for

$$\left[\begin{array}{ccc} x_1/y_1 & \cdots & x_n/y_n \end{array} \right]^T$$

corresponding to Python code - `x / y` - where `x` and `y` are 1-d numpy arrays

- applies to any two matrices of same dimensions

Some definitions

Definition 1. [infinitely often - i.o.] *statement, P_n , said to happen infinitely often or i.o. if*

$$(\forall N \in \mathbf{N}) (\exists n > N) (P_n)$$

Definition 2. [almost everywhere - a.e.] *statement, $P(x)$, said to happen almost everywhere or a.e. or almost surely or a.s. (depending on context) associated with measure space, (X, \mathcal{B}, μ) if*

$$\mu\{x | P(x)\} = 1$$

or equivalently

$$\mu\{x | \sim P(x)\} = 0$$

Some conventions

- for some subjects, use following conventions
 - $0 \cdot \infty = \infty \cdot 0 = 0$
 - $(\forall x \in \mathbf{R}_{++})(x \cdot \infty = \infty \cdot x = \infty)$
 - $\infty \cdot \infty = \infty$

Measure-theoretic Treatment of Probabilities

Probability Measure

Measurable functions

- denote *n-dimensional Borel sets* by \mathcal{R}^n
- for two measurable spaces, (Ω, \mathcal{F}) and (Ω', \mathcal{F}') , function, $f : \Omega \rightarrow \Omega'$ with

$$(\forall A' \in \mathcal{F}') \left(f^{-1}(A') \in \mathcal{F} \right)$$

said to be *measurable with respect to $\mathcal{F} / \mathcal{F}'$* (thus, measurable functions defined on page ?? and page ?? can be said to be measurable with respect to $\mathcal{B} / \mathcal{R}$)

- when $\Omega = \mathbf{R}^n$ in (Ω, \mathcal{F}) , \mathcal{F} is assumed to be \mathcal{R}^n , and sometimes drop \mathcal{R}^n
 - thus, *e.g.*, we say $f : \Omega \rightarrow \mathbf{R}^n$ is measurable with respect to \mathcal{F} (instead of $\mathcal{F} / \mathcal{R}^n$)
- measurable function, $f : \mathbf{R}^n \rightarrow \mathbf{R}^m$ (*i.e.*, measurable with respect to $\mathcal{R}^n / \mathcal{R}^m$), called *Borel functions*
- $f : \Omega \rightarrow \mathbf{R}^n$ is measurable with respect to $\mathcal{F} / \mathcal{R}^n$ *if and only if* every component, $f_i : \Omega \rightarrow \mathbf{R}$, is measurable with respect to $\mathcal{F} / \mathcal{R}$

Probability (measure) spaces

- set function, $P : \mathcal{F} \rightarrow [0, 1]$, defined on algebra, \mathcal{F} , of set Ω , satisfying following properties, called *probability measure* (refer to page ?? for resemblance with measurable spaces)
 - $(\forall A \in \mathcal{F})(0 \leq P(A) \leq 1)$
 - $P(\emptyset) = 0, P(\Omega) = 1$
 - $(\forall \text{ disjoint } \langle A_n \rangle \subset \mathcal{F})(P(\bigcup A_n) = \sum P(A_n))$
- for σ -algebra, \mathcal{F} , (Ω, \mathcal{F}, P) , called *probability measure space* or *probability space*
- set $A \in \mathcal{F}$ with $P(A) = 1$, called *a support of P*

Dynkin's π - λ theorem

- class, \mathcal{P} , of subsets of Ω closed under finite intersection, called *π -system*, *i.e.*,
 - $(\forall A, B \in \mathcal{P})(A \cap B \in \mathcal{P})$
- class, \mathcal{L} , of subsets of Ω containing Ω closed under complements and countable disjoint unions called *λ -system*
 - $\Omega \in \mathcal{L}$
 - $(\forall A \in \mathcal{L})(\tilde{A} \in \mathcal{L})$
 - $(\forall \text{ disjoint } \langle A_n \rangle)(\bigcup A_n \in \mathcal{L})$
- *class that is both π -system and λ -system is σ -algebra*
- *Dynkin's π - λ theorem* - for π -system, \mathcal{P} , and λ -system, \mathcal{L} , with $\mathcal{P} \subset \mathcal{L}$,

$$\sigma(\mathcal{P}) \subset \mathcal{L}$$

- for π -system, \mathcal{P} , two probability measures, P_1 and P_2 , on $\sigma(\mathcal{P})$, agreeing \mathcal{P} , agree on $\sigma(\mathcal{P})$

Limits of Events

Theorem 1. [convergence-of-events] *no for sequence of subsets, $\langle A_n \rangle$,*

$$P(\liminf A_n) \leq \liminf P(A_n) \leq \limsup P(A_n) \leq P(\limsup A_n)$$

- *for $\langle A_n \rangle$ converging to A*

$$\lim P(A_n) = P(A)$$

Theorem 2. [independence-of-smallest-sig-alg] *no for sequence of π -systems, $\langle \mathcal{A}_n \rangle$, $\langle \sigma(\mathcal{A}_n) \rangle$ is independent*

Probabilistic independence

– given probability space, (Ω, \mathcal{F}, P)

- $A, B \in \mathcal{F}$ with

$$P(A \cap B) = P(A)P(B)$$

said to be *independent*

- indexed collection, $\langle A_\lambda \rangle$, with

$$(\forall n \in \mathbf{N}, \text{ distinct } \lambda_1, \dots, \lambda_n \in \Lambda) \left(P \left(\bigcap_{i=1}^n A_{\lambda_i} \right) = \prod_{i=1}^n P(A_{\lambda_i}) \right)$$

said to be *independent*

Independence of classes of events

- indexed collection, $\langle \mathcal{A}_\lambda \rangle$, of classes of events (*i.e.*, subsets) with

$$(\forall \lambda \in \Lambda) (\langle \mathcal{A}_\lambda \rangle \text{ are independent})$$

said to be *independent*

- *for independent indexed collection, $\langle \mathcal{A}_\lambda \rangle$, with every \mathcal{A}_λ being π -system, $\langle \sigma(\mathcal{A}_\lambda) \rangle$ are independent*
- for independent (countable) collection of events, $\langle \langle A_{ni} \rangle_{i=1}^\infty \rangle_{n=1}^\infty$, $\langle \mathcal{F}_n \rangle_{n=1}^\infty$ with $\mathcal{F}_n = \sigma(\langle A_{ni} \rangle_{i=1}^\infty)$ are independent

Borel-Cantelli lemmas

- **Lemma 1. [first Borel-Cantelli]** *for sequence of events, $\langle A_n \rangle$, with $\sum P(A_n)$ converging*

$$P(\limsup A_n) = 0$$

- **Lemma 2. [second Borel-Cantelli]** *for independent sequence of events, $\langle A_n \rangle$, with $\sum P(A_n)$ diverging*

$$P(\limsup A_n) = 1$$

Tail events and Kolmogorov's zero-one law

- for sequence of events, $\langle A_n \rangle$

$$\mathcal{T} = \bigcap_{n=1}^{\infty} \sigma(\langle A_i \rangle_{i=n}^{\infty})$$

called *tail σ -algebra associated with $\langle A_n \rangle$* ; its elements are called *tail events*

- *Kolmogorov's zero-one law* - for independent sequence of events, $\langle A_n \rangle$ every event in tail σ -algebra has probability measure either 0 or 1

Product probability spaces

- for two measure spaces, (X, \mathcal{X}, μ) and (Y, \mathcal{Y}, ν) , want to find product measure, π , such that

$$(\forall A \in \mathcal{X}, B \in \mathcal{Y}) (\pi(A \times B) = \mu(A)\nu(B))$$

- *e.g.*, if both μ and ν are Lebesgue measure on \mathbf{R} , π will be Lebesgue measure on \mathbf{R}^2
- $A \times B$ for $A \in \mathcal{X}$ and $B \in \mathcal{Y}$ is *measurable rectangle*
- σ -algebra generated by *measurable rectangles* denoted by

$$\mathcal{X} \times \mathcal{Y}$$

- thus, *not* Cartesian product in usual sense
- generally *much larger* than class of measurable rectangles

Sections of measurable subsets and functions

for two measure spaces, (X, \mathcal{X}, μ) and (Y, \mathcal{Y}, ν)

- sections of measurable subsets
 - $\{y \in Y \mid (x, y) \in E\}$ is *section of E determined by x*
 - $\{x \in X \mid (x, y) \in E\}$ is *section of E determined by y*
- sections of measurable functions - for measurable function, f , with respect to $\mathcal{X} \times \mathcal{Y}$
 - $f(x, \cdot)$ is *section of f determined by x*
 - $f(\cdot, y)$ is *section of f determined by y*
- sections of measurable subsets are measurable
 - $(\forall x \in X, E \in \mathcal{X} \times \mathcal{Y}) (\{y \in Y \mid (x, y) \in E\} \in \mathcal{Y})$
 - $(\forall y \in Y, E \in \mathcal{X} \times \mathcal{Y}) (\{x \in X \mid (x, y) \in E\} \in \mathcal{X})$
- sections of measurable functions are measurable
 - $f(x, \cdot)$ is measurable with respect to \mathcal{Y} for every $x \in X$
 - $f(\cdot, y)$ is measurable with respect to \mathcal{X} for every $y \in Y$

Product measure

for two σ -finite measure spaces, (X, \mathcal{X}, μ) and (Y, \mathcal{Y}, ν)

- two functions defined below for every $E \in \mathcal{X} \times \mathcal{Y}$ are σ -finite measures
 - $\pi'(E) = \int_X \nu\{y \in Y \mid (x, y) \in E\} d\mu$
 - $\pi''(E) = \int_Y \mu\{x \in X \mid (x, y) \in E\} d\nu$
- for every measurable rectangle, $A \times B$, with $A \in \mathcal{X}$ and $B \in \mathcal{Y}$

$$\pi'(A \times B) = \pi''(A \times B) = \mu(A)\nu(B)$$

(use conventions in page 7 for extended real values)

- indeed, $\pi'(E) = \pi''(E)$ for every $E \in \mathcal{X} \times \mathcal{Y}$; let $\pi = \pi' = \pi''$
- π is
 - called *product measure* and denoted by $\mu \times \nu$
 - σ -finite measure
 - *only* measure such that $\pi(A \times B) = \mu(A)\nu(B)$ for every measurable rectangle

Fubini's theorem

- suppose two σ -finite measure spaces, (X, \mathcal{X}, μ) and (Y, \mathcal{Y}, ν) - define
 - $X_0 = \{x \in X \mid \int_Y |f(x, y)| d\nu < \infty\} \subset X$
 - $Y_0 = \{y \in Y \mid \int_X |f(x, y)| d\mu < \infty\} \subset Y$
- *Fubini's theorem* - for nonnegative measurable function, f , following are measurable with respect to \mathcal{X} and \mathcal{Y} respectively

$$g(x) = \int_Y f(x, y) d\nu, \quad h(y) = \int_X f(x, y) d\mu$$

and following holds

$$\int_{X \times Y} f(x, y) d\pi = \int_X \left(\int_Y f(x, y) d\nu \right) d\mu = \int_Y \left(\int_X f(x, y) d\mu \right) d\nu$$

- for f , (not necessarily nonnegative) integrable function with respect to π
 - $\mu(X \setminus X_0) = 0, \nu(Y \setminus Y_0) = 0$
 - g and h are finite measurable on X_0 and Y_0 respectively
 - (above) equalities of *double integral* holds

Random Variables

Random variables

- for probability space, (Ω, \mathcal{F}, P) ,
- measurable function (with respect to $\mathcal{F} / \mathcal{R}$), $X : \Omega \rightarrow \mathbf{R}$, called *random variable*
- measurable function (with respect to $\mathcal{F} / \mathcal{R}^n$), $X : \Omega \rightarrow \mathbf{R}^n$, called *random vector*
 - when expressing $X(\omega) = (X_1(\omega), \dots, X_n(\omega))$, X is measurable *if and only if* every X_i is measurable
 - thus, n -dimensional random vector is simply n -tuple of random variables
- smallest σ -algebra with respect to which X is measurable, called *σ -algebra generated by X* and denoted by $\sigma(X)$
 - $\sigma(X)$ consists exactly of sets, $\{\omega \in \Omega | X(\omega) \in H\}$, for $H \in \mathcal{R}^n$
 - random variable, Y , is measurable with respect to $\sigma(X)$ *if and only if* exists measurable function, $f : \mathbf{R}^n \rightarrow \mathbf{R}$ such that $Y(\omega) = f(X(\omega))$ for all ω , *i.e.*, $Y = f \circ X$

Probability distributions for random variables

- probability measure on \mathbf{R} , $\mu = PX^{-1}$, *i.e.*,

$$\mu(A) = P(X \in A) \text{ for } A \in \mathcal{R}$$

called *distribution* or *law* of random variable, X

- function, $F : \mathbf{R} \rightarrow [0, 1]$, defined by

$$F(x) = \mu(-\infty, x] = P(X \leq x)$$

called *distribution function* or *cumulative distribution function (CDF)* of X

- Borel set, S , with $P(S) = 1$, called *support*
- random variable, its distribution, its distribution function, said to be *discrete* when has *countable* support

Probability distribution of mappings of random variables

- for measurable $g : \mathbf{R} \rightarrow \mathbf{R}$,

$$(\forall A \in \mathcal{R}) \left(\mathbf{Prob} (g(X) \in A) = \mathbf{Prob} \left(X \in g^{-1}(A) \right) = \mu(g^{-1}(A)) \right)$$

hence, $g(X)$ has distribution of μg^{-1}

Probability density for random variables

- Borel function, $f : \mathbf{R} \rightarrow \mathbf{R}_+$, satisfying

$$(\forall A \in \mathcal{R}) \left(\mu(A) = P(X \in A) = \int_A f(x) dx \right)$$

called *density* or *probability density function (PDF)* of random variable

- above is equivalent to

$$(\forall a < b \in \mathbf{R}) \left(\int_a^b f(x) dx = P(a < X \leq b) = F(b) - F(a) \right)$$

(refer to statement on page [12](#))

- note, though, F does not need to differentiate to f everywhere; only f required to integrate properly
- if F does differentiate to f and f is continuous, *fundamental theorem of calculus* implies f indeed is density for F

Probability distribution for random vectors

- (similarly to random variables) probability measure on \mathbf{R}^n , $\mu = PX^{-1}$, *i.e.*,

$$\mu(A) = P(X \in A) \text{ for } A \in \mathcal{B}^k$$

called *distribution* or *law* of random vector, X

- function, $F : \mathbf{R}^k \rightarrow [0, 1]$, defined by

$$F(x) = \mu S_x = P(X \preceq x)$$

where

$$S_x = \{\omega \in \Omega \mid X(\omega) \preceq x\} = \{\omega \in \Omega \mid X_i(\omega) \leq x_i\}$$

called *distribution function* or *cumulative distribution function (CDF)* of X

- (similarly to random variables) random vector, its distribution, its distribution function, said to be *discrete* when has *countable* support

Marginal distribution for random vectors

- (similarly to random variables) for measurable $g : \mathbf{R}^n \rightarrow \mathbf{R}^m$

$$(\forall A \in \mathcal{R}^m) \left(\mathbf{Prob} (g(X) \in A) = \mathbf{Prob} \left(X \in g^{-1}(A) \right) = \mu(g^{-1}(A)) \right)$$

hence, $g(X)$ has distribution of μg^{-1}

- for $g_i : \mathbf{R}^n \rightarrow \mathbf{R}$ with $g_i(x) = x_i$

$$(\forall A \in \mathcal{R}) (\mathbf{Prob} (g(X) \in A) = \mathbf{Prob} (X_i \in A))$$

- measure, μ_i , defined by $\mu_i(A) = \mathbf{Prob} (X_i \in A)$, called *(i-th) marginal distribution of X*
- for μ having density function, $f : \mathbf{R}^n \rightarrow \mathbf{R}_+$, density function of marginal distribution is

$$f_i(x) = \int_{\mathcal{R}^{n-1}} f(x_{-i}) d\mu_{-i}$$

where $x_{-i} = (x_1, \dots, x_{i-1}, x_{i+1}, \dots, x_n)$ and similarly for $d\mu_{-i}$

Independence of random variables

- random variables, X_1, \dots, X_n , with independent σ -algebras generated by them, said to be *independent*

(refer to page 15 for independence of collections of subsets)

- because $\sigma(X_i) = X_i^{-1}(\mathcal{R}) = \{X_i^{-1}(H) | H \in \mathcal{R}\}$, independent *if and only if*

$$(\forall H_1, \dots, H_n \in \mathcal{R}) \left(P(X_1 \in H_1, \dots, X_n \in H_n) = \prod P(X_i \in H_i) \right)$$

i.e.,

$$(\forall H_1, \dots, H_n \in \mathcal{R}) \left(P \left(\bigcap X_i^{-1}(H_i) \right) = \prod P \left(X_i^{-1}(H_i) \right) \right)$$

Equivalent statements of independence of random variables

- for random variables, X_1, \dots, X_n , having μ and $F : \mathbf{R}^n \rightarrow [0, 1]$ as their distribution and CDF, with each X_i having μ_i and $F_i : \mathbf{R} \rightarrow [0, 1]$ as its distribution and CDF, following statements are *equivalent*
 - X_1, \dots, X_n are independent
 - $(\forall H_1, \dots, H_n \in \mathcal{R}) (P(\bigcap X_i^{-1}(H_i)) = \prod P(X_i^{-1}(H_i)))$
 - $(\forall H_1, \dots, H_n \in \mathcal{R}) (P(X_1 \in H_1, \dots, X_n \in H_n) = \prod P(X_i \in H_i))$
 - $(\forall x \in \mathbf{R}^n) (P(X_1 \leq x_1, \dots, X_n \leq x_n) = \prod P(X_i \leq x_i))$
 - $(\forall x \in \mathbf{R}^n) (F(x) = \prod F_i(x_i))$
 - $\mu = \mu_1 \times \dots \times \mu_n$
 - $(\forall x \in \mathbf{R}^n) (f(x) = \prod f_i(x_i))$

Independence of random variables with separate σ -algebra

- given probability space, (Ω, \mathcal{F}, P)
- random variables, X_1, \dots, X_n , each of which is measurable with respect to each of n independent σ -algebras, $\mathcal{G}_1 \subset \mathcal{F}, \dots, \mathcal{G}_n \subset \mathcal{F}$ respectively, are independent

Independence of random vectors

- for random vectors, $X_1 : \Omega \rightarrow \mathbf{R}^{d_1}, \dots, X_n : \Omega \rightarrow \mathbf{R}^{d_n}$, having μ and $F : \mathbf{R}^{d_1} \times \dots \times \mathbf{R}^{d_n} \rightarrow [0, 1]$ as their distribution and CDF, with each X_i having μ_i and $F_i : \mathbf{R}^{d_i} \rightarrow [0, 1]$ as its distribution and CDF, following statements are *equivalent*
 - X_1, \dots, X_n are independent
 - $(\forall H_1 \in \mathcal{R}^{d_1}, \dots, H_n \in \mathcal{R}^{d_n}) (P(\bigcap X_i^{-1}(H_i)) = \prod P(X_i^{-1}(H_i)))$
 - $(\forall H_1 \in \mathcal{R}^{d_1}, \dots, H_n \in \mathcal{R}^{d_n}) (P(X_1 \in H_1, \dots, X_n \in H_n) = \prod P(X_i \in H_i))$
 - $(\forall x_1 \in \mathbf{R}^{d_1}, \dots, x_n \in \mathbf{R}^{d_n}) (P(X_1 \preceq x_1, \dots, X_n \preceq x_n) = \prod P(X_i \preceq x_i))$
 - $(\forall x_1 \in \mathbf{R}^{d_1}, \dots, x_n \in \mathbf{R}^{d_n}) (F(x_1, \dots, x_n) = \prod F_i(x_i))$
 - $\mu = \mu_1 \times \dots \times \mu_n$
 - $(\forall x_1 \in \mathbf{R}^{d_1}, \dots, x_n \in \mathbf{R}^{d_n}) (f(x_1, \dots, x_n) = \prod f_i(x_i))$

Independence of infinite collection of random vectors

- infinite collection of random vectors for which every finite subcollection is independent, said to be *independent*

- for independent (countable) collection of random vectors, $\langle \langle X_{ni} \rangle_{i=1}^{\infty} \rangle_{n=1}^{\infty}$, $\langle \mathcal{F}_n \rangle_{n=1}^{\infty}$ with $\mathcal{F}_n = \sigma(\langle X_{ni} \rangle_{i=1}^{\infty})$ are independent

Probability evaluation for two independent random vectors

Theorem 3. [Probability evaluation for two independent random vectors] *for independent random vectors, X and Y , with distributions, μ and ν , in \mathbf{R}^n and \mathbf{R}^m respectively*

$$\left(\forall B \in \mathcal{R}^{n+m} \right) \left(\mathbf{Prob}((X, Y) \in B) = \int_{\mathbf{R}^n} \mathbf{Prob}((x, Y) \in B) d\mu_X \right)$$

and

$$\left(\forall A \in \mathcal{R}^n, B \in \mathcal{R}^{n+m} \right) \left(\mathbf{Prob}(X \in A, (X, Y) \in B) = \int_A \mathbf{Prob}((x, Y) \in B) d\mu_X \right)$$

Sequence of random variables

Theorem 4. [squence of random variables] *for sequence of probability measures on \mathcal{R} , $\langle \mu_n \rangle$, exists probability space, (X, Ω, P) , and sequence of independent random variables in \mathbf{R} , $\langle X_n \rangle$, such that each X_n has μ_n as distribution*

Expected values

Definition 3. [expected values] for random variable, X , on (Ω, \mathcal{F}, P) , integral of X with respect to measure, P

$$\mathbf{E} X = \int X dP = \int_{\Omega} X(\omega) dP$$

called **expected value of X**

- $\mathbf{E} X$ is
 - always defined for nonnegative X
 - for general case
 - defined, or
 - X has an expected value if either $\mathbf{E} X^+ < \infty$ or $\mathbf{E} X^- < \infty$ or both, in which case, $\mathbf{E} X = \mathbf{E} X^+ - \mathbf{E} X^-$
- X is integrable *if and only if* $\mathbf{E} |X| < \infty$
- limits
 - if $\langle X_n \rangle$ is dominated by integral random variable or they are uniformly integrable, $\mathbf{E} X_n$ converges to $\mathbf{E} X$ if X_n converges to X in probability

Markov and Chebyshev's inequalities

Inequality 1. [Markov inequality] for random variable, X , on (Ω, \mathcal{F}, P) ,

$$\mathbf{Prob}(X \geq \alpha) \leq \frac{1}{\alpha} \int_{X \geq \alpha} X dP \leq \frac{1}{\alpha} \mathbf{E} X$$

for nonnegative X , hence

$$\mathbf{Prob}(|X| \geq \alpha) \leq \frac{1}{\alpha^n} \int_{|X| \geq \alpha} |X|^n dP \leq \frac{1}{\alpha^n} \mathbf{E} |X|^n$$

for general X

Inequality 2. [Chebyshev's inequality] as special case of Markov inequality,

$$\mathbf{Prob}(|X - \mathbf{E} X| \geq \alpha) \leq \frac{1}{\alpha^2} \int_{|X - \mathbf{E} X| \geq \alpha} (X - \mathbf{E} X)^2 dP \leq \frac{1}{\alpha^2} \mathbf{Var} X$$

for general X

Jensen's, Hölder's, and Lyapunov's inequalities

Inequality 3. [Jensen's inequality] for random variable, X , on (Ω, \mathcal{F}, P) , and convex function, φ

$$\varphi(\mathbf{E} X) \mathbf{Prob}(X \geq \alpha) \leq \frac{1}{\alpha} \int_{X \geq \alpha} X dP \leq \frac{1}{\alpha} \mathbf{E} X$$

Inequality 4. [Holder's inequality] for two random variables, X and Y , on (Ω, \mathcal{F}, P) , and $p, q \in (1, \infty)$ with $1/p + 1/q = 1$

$$\mathbf{E} |XY| \leq (\mathbf{E} |X|^p)^{1/p} (\mathbf{E} |Y|^q)^{1/q}$$

Inequality 5. [Lyapunov's inequality] for random variable, X , on (Ω, \mathcal{F}, P) , and $0 < \alpha < \beta$

$$(\mathbf{E} |X|^\alpha)^{1/\alpha} \leq (\mathbf{E} |X|^\beta)^{1/\beta}$$

- note Hölder's inequality implies Lyapunov's inequality

Maximal inequalities

Theorem 5. [Kolmogorov's zero-one law] *if $A \in \mathcal{F} = \bigcap_{n=1}^{\infty} \sigma(X_n, X_{n+1}, \dots)$ for independent $\langle X_n \rangle$,*

$$\mathbf{Prob}(A) = 0 \vee \mathbf{Prob}(A) = 1$$

– define $S_n = \sum X_i$

Inequality 6. [Kolmogorov's maximal inequality] *for independent $\langle X_i \rangle_{i=1}^n$ with $\mathbf{E} X_i = 0$ and $\mathbf{Var} X_i < \infty$ and $\alpha > 0$*

$$\mathbf{Prob}(\max S_i \geq \alpha) \leq \frac{1}{\alpha} \mathbf{Var} S_n$$

Inequality 7. [Etemadi's maximal inequality] *for independent $\langle X_i \rangle_{i=1}^n$ and $\alpha > 0$*

$$\mathbf{Prob}(\max |S_i| \geq 3\alpha) \leq 3 \max \mathbf{Prob}(|S_i| \geq \alpha)$$

Moments

Definition 4. [moments and absolute moments] for random variable, X , on (Ω, \mathcal{F}, P) , integral of X with respect to measure, P

$$\mathbf{E} X^n = \int x^n d\mu = \int x^n dF(x)$$

called k -th moment of X or μ or F , and

$$\mathbf{E} |X|^n = \int |x|^n d\mu = \int |x|^n dF(x)$$

called k -th absolute moment of X or μ or F

- if $\mathbf{E} |X|^n < \infty$, $\mathbf{E} |X|^k < \infty$ for $k < n$
- $\mathbf{E} X^n$ defined only when $\mathbf{E} |X|^n < \infty$

Moment generating functions

Definition 5. [moment generating function] for random variable, X , on (Ω, \mathcal{F}, P) , $M : \mathbf{C} \rightarrow \mathbf{C}$ defined by

$$M(s) = \mathbf{E} \left(e^{sX} \right) = \int e^{sx} d\mu = \int e^{sx} dF(x)$$

called **moment generating function of X**

- n -th derivative of M with respect to s is $M^{(n)}(s) = \frac{d^n}{ds^n} F(s) = \mathbf{E} \left(X^n e^{sX} \right) = \int x^n e^{sx} d\mu$
- thus, n -th derivative of M with respect to s at $s = 0$ is n -th moment of X

$$M^{(n)}(0) = \mathbf{E} X^n$$

- for independent random variables, $\langle X_i \rangle_{i=1}^n$, moment generating function of $\sum X_i$

$$\prod M_i(s)$$

Convergence of Random Variables

Convergences of random variables

Definition 6. [convergence with probability 1] *random variables, $\langle X_n \rangle$, with*

$$\mathbf{Prob}(\lim X_n = X) = P(\{\omega \in \Omega \mid \lim X_n(\omega) = X(\omega)\}) = 1$$

said to converge to X with probability 1 and denoted by $X_n \rightarrow X$ a.s.

Definition 7. [convergence in probability] *random variables, $\langle X_n \rangle$, with*

$$(\forall \epsilon > 0) (\lim \mathbf{Prob}(|X_n - X| > \epsilon) = 0)$$

said to converge to X in probability

Definition 8. [weak convergence] *distribution functions, $\langle F_n \rangle$, with*

$$(\forall x \text{ in domain of } F) (\lim F_n(x) = F(x))$$

said to converge weakly to distribution function, F , and denoted by $F_n \Rightarrow F$

Definition 9. [converge in distribution] When $F_n \Rightarrow F$, associated random variables, $\langle X_n \rangle$, said to **converge in distribution** to X , associated with F , and denoted by $X_n \Rightarrow X$

Definition 10. [weak convergence of measures] for measures on $(\mathbf{R}, \mathcal{R})$, $\langle \mu_n \rangle$, associated with distribution functions, $\langle F_n \rangle$, respectively, and measure on $(\mathbf{R}, \mathcal{R})$, μ , associated with distribution function, F , we denote

$$\mu_n \Rightarrow \mu$$

if

$$(\forall A = (-\infty, x] \text{ with } x \in \mathbf{R}) (\lim \mu_n(A) = \mu(A))$$

- indeed, if above equation holds for $A = (-\infty, x)$, it holds for many other subsets

Relations of different types of convergences of random variables

Proposition 1. [relations of convergence of random variables] *convergence with probability 1 implies convergence in probability, which implies $X_n \Rightarrow X$, i.e.*

$X_n \rightarrow X$ a.s., i.e., X_n converge to X with probability 1

$\Rightarrow X_n$ converge to X in probability

$\Rightarrow X_n \Rightarrow X$, i.e., X_n converge to X in distribution,

Necessary and sufficient conditions for convergence of probability

X_n converge in probability

if and only if

$$(\forall \epsilon > 0) (\mathbf{Prob} (|X_n - X| > \epsilon \text{ i.o.}) = \mathbf{Prob} (\limsup |X_n - X| > \epsilon) = 0)$$

if and only if

$$(\forall \text{ subsequence } \langle X_{n_k} \rangle) \left(\exists \text{ its subsequence } \langle X_{n_{k_l}} \rangle \text{ converging to } f \text{ with probability } 1 \right)$$

Necessary and sufficient conditions for convergence in distribution

$X_n \Rightarrow X$, i.e., X_n converge in distribution

if and only if

$F_n \Rightarrow F$, i.e., F_n converge weakly

if and only if

$(\forall A = (-\infty, x] \text{ with } x \in \mathbf{R}) (\lim \mu_n(A) = \mu(A))$

if and only if

$(\forall x \text{ with } \mathbf{Prob}(X = x) = 0) (\lim \mathbf{Prob}(X_n \leq x) = \mathbf{Prob}(X \leq x))$

Strong law of large numbers

– define $S_n = \sum_{i=1}^n X_i$

Theorem 6. [strong law of large numbers] *for sequence of independent and identically distributed (i.i.d.) random variables with finite mean, $\langle X_n \rangle$*

$$\frac{1}{n} S_n \rightarrow \mathbf{E} X_1$$

with probability 1

- strong law of large numbers also called *Kolmogorov's law*

Corollary 1. [strong law of large numbers] *for sequence of independent and identically distributed (i.i.d.) random variables with $\mathbf{E} X_1^- < \infty$ and $\mathbf{E} X_1^+ = \infty$ (hence, $\mathbf{E} X = \infty$)*

$$\frac{1}{n} S_n \rightarrow \infty$$

with probability 1

Weak law of large numbers

– define $S_n = \sum_{i=1}^n X_i$

Theorem 7. [weak law of large numbers] *for sequence of independent and identically distributed (i.i.d.) random variables with finite mean, $\langle X_n \rangle$*

$$\frac{1}{n} S_n \rightarrow \mathbf{E} X_1$$

in probability

- because convergence with probability 1 implies convergence in probability (Proposition 1), strong law of large numbers implies weak law of large numbers

Normal distributions

– assume probability space, (Ω, \mathcal{F}, P)

Definition 11. [normal distributions] *Random variable, $X : \Omega \rightarrow \mathbf{R}$, with*

$$(A \in \mathcal{R}) \left(\mathbf{Prob}(X \in A) = \frac{1}{\sqrt{2\pi}\sigma} \int_A e^{-(x-c)^2/2} d\mu \right)$$

where $\mu = PX^{-1}$ for some $\sigma > 0$ and $c \in \mathbf{R}$, called **normal distribution** and denoted by $X \sim \mathcal{N}(c, \sigma^2)$

– note $\mathbf{E} X = c$ and $\mathbf{Var} X = \sigma^2$

– called **standard normal distribution** when $c = 0$ and $\sigma = 1$

Multivariate normal distributions

– assume probability space, (Ω, \mathcal{F}, P)

Definition 12. [multivariate normal distributions] *Random variable, $X : \Omega \rightarrow \mathbf{R}^n$, with*

$$(A \in \mathcal{R}^n) \left(\mathbf{Prob}(X \in A) = \frac{1}{\sqrt{(2\pi)^n} \sqrt{\det \Sigma}} \int_A e^{-(x-c)^T \Sigma^{-1} (x-c)/2} d\mu \right)$$

where $\mu = PX^{-1}$ for some $\Sigma \succ 0 \in \mathbf{S}_{++}^n$ and $c \in \mathbf{R}^n$, called (*n-dimensional*) normal distribution, and denoted by $X \sim \mathcal{N}(c, \Sigma)$

– note that $\mathbf{E} X = c$ and covariance matrix is Σ

Lindeberg-Lévy theorem

– define $S_n = \sum^n X_i$

Theorem 8. [Lindeberg-Levy theorem] *for independent random variables, $\langle X_n \rangle$, having same distribution with expected value, c , and same variance, $\sigma^2 < \infty$, $(S_n - nc)/\sigma\sqrt{n}$ converges to standard normal distribution in distribution, i.e.,*

$$\frac{S_n - nc}{\sigma\sqrt{n}} \Rightarrow N$$

where N is standard normal distribution

– Theorem 8 implies

$$S_n/n \Rightarrow c$$

Limit theorems in \mathbf{R}^n

Theorem 9. [equivalent statements to weak convergence] *each of following statements are equivalent to weak convergence of measures, $\langle \mu_n \rangle$, to μ , on measurable space, $(\mathbf{R}^k, \mathcal{R}^k)$*

- $\lim \int f d\mu_n = \int f d\mu$ for every bounded continuous f
- $\limsup \mu_n(C) \leq \mu(C)$ for every closed C
- $\liminf \mu_n(G) \geq \mu(G)$ for every open G
- $\lim \mu_n(A) = \mu(A)$ for every μ -continuity A

Theorem 10. [convergence in distribution of random vector] *for random vectors, $\langle X_n \rangle$, and random vector, Y , of k -dimension, $X_n \Rightarrow Y$, i.e., X_n converge to Y in distribution if and only if*

$$\left(\forall z \in \mathbf{R}^k \right) \left(z^T X_n \Rightarrow z^T Y \right)$$

Central limit theorem

– assume probability space, (Ω, \mathcal{F}, P) and define $\sum^n X_i = S_n$

Theorem 11. [central limit theorem] *for random variables, $\langle X_n \rangle$, having same distributions with $\mathbf{E} X_n = c \in \mathbf{R}^k$ and positive definite covariance matrix, $\Sigma \succ 0 \in \mathcal{S}_k$, i.e., $\mathbf{E}(X_n - c)(X_n - c)^T = \Sigma$, where $\Sigma_{ii} < \infty$ (hence $\Sigma \prec MI_n$ for some $M \in \mathbf{R}_{++}$ due to Cauchy-Schwarz inequality),*

$(S_n - nc)/\sqrt{n}$ converges in distribution to Y

where $Y \sim \mathcal{N}(0, \Sigma)$

(proof can be found in [Proof 1](#))

Convergence of random series

- for independent $\langle X_n \rangle$, probability of $\sum X_n$ converging is either 0 or 1
- below characterize two cases in terms of distributions of individual X_n – XXX: diagram

Theorem 12. [convergence with probability 1 for random series] for independent $\langle X_n \rangle$ with $\mathbf{E} X_n = 0$ and $\mathbf{Var} X_n < \infty$

$$\sum X_n \text{ converges with probability 1}$$

Theorem 13. [convergence conditions for random series] for independent $\langle X_n \rangle$, $\sum X_n$ converges with probability 1 if and only if they converges in probability

– define truncated version of X_n by $X_n^{(c)}$, i.e., $X_n I_{|X_n| \leq c}$

Theorem 14. [convergence conditions for truncated random series] *for independent $\langle X_n \rangle$,*

$\sum X_n$ *converge with probability 1*

if all of $\sum \mathbf{Prob}(|X_n| > c)$, $\sum \mathbf{E}(X_n^{(c)})$, $\sum \mathbf{Var}(X_n^{(c)})$ converge for some $c > 0$

Selected Proofs

Selected proofs

- **Proof 1.** (Proof for “central limit theorem” on page 54)

Let $Z_n(t) = t^T(X_n - c)$ for $t \in \mathbf{R}^k$ and $Z(t) = t^T Y$. Then $\langle Z_n(t) \rangle$ are independent random variables having same distribution with $\mathbf{E} Z_n(t) = t^T(\mathbf{E} X_n - c) = 0$ and

$$\mathbf{Var} Z_n(t) = \mathbf{E} Z_n(t)^2 = t^T \mathbf{E}(X_n - c)(X_n - c)^T t = t^T \Sigma t$$

Then by Theorem 8 $\sum^n Z_i(t)/\sqrt{nt^T \Sigma t}$ converges in distribution to standard normal random variable. Because $\mathbf{E} Z(t) = 0$ and $\mathbf{Var} Z(t) = t^T \mathbf{E} Y Y^T t = t^T \Sigma t$, for $t \neq 0$, $Z(t)/\sqrt{t^T \Sigma t}$ is standard normal random variable. Therefore $\sum^n Z_i(t)/\sqrt{nt^T \Sigma t}$ converges in distribution to $Z/\sqrt{t^T \Sigma t}$ for every $t \neq 0$, thus, $\sum^n Z_i(t)/\sqrt{n} = t^T(\sum^n X_i - nc)/\sqrt{n}$ converges in distribution to $Z(t) = t^T Y$ for every $t \in \mathbf{R}$. Then Theorem 10 implies $(S_n - nc)/\sqrt{n}$ converges in distribution to Y . ■

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ZZ-todo

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