

1 Probability and random variables

- **Probability:** S sample space (all possible states of the system), $F \subset \mathcal{P}(S)$ a σ -algebra, $P : F \rightarrow \mathbb{R}$ a measure, such that $P(S) = 1$.
- **Random variable:** $X : S \rightarrow \mathbb{R}$, such that preimages of open sets are in F (i.e. has a well defined probability).
- **Cumulative distribution function** of random variable: $F_X(t) = P(X \leq t)$.
- **Probability distribution** of random variable: g such that $F_X(t) = \sum_{x \leq t, x \in C} g(x)$.
- **Probability density function:** f such that $F_X(t) = \int_{-\infty}^t f(s)ds$.
- Two random variables have the **same distribution** if they have the same cdf.

Example: **uniform distribution:**

- S a finite interval $[a, b]$
- F : Set of Borel sets on S (sets with a well defined “length”)
- P : Borel measure (“length”) divided by $b - a$
- $X = id$.

1.1 Expectation of random variables and their functions

- X is a random variable, the **expectation** of X is $E[X] = \int_S X dP$.
- The **variance** of X is $E[(X - E[X])^2]$.
- The k -th **moment** of X is $E[X^k]$.
- The **moment generating function** of X is $E[e^{Xt}]$ (two sided Laplace transform)
- The **characteristic function** of X is $E[e^{itX}]$ (Fourier transform)

Since expectation is defined via integration, one can use the properties of integration to prove statements regarding expectation.

Example: **Chebyshev’s theorem:** $E[X] = 0$, $E[X^2] = 1$, then $P(|X| < k) \geq 1 - \frac{1}{k^2}$.
Proof:

$$1 = E[X^2] = \int_S X^2 dP \geq k^2 \int_{|X| \geq k} 1 dP = k^2(1 - P(|X| < k))$$

Example: If X has p.d.f. f_X , then $E[g(X)] = \int_{-\infty}^{\infty} g f_X dt$. We prove it when $g(X)$ is bounded via Fubini's theorem:

$$\begin{aligned} E[g(X)] &= \int_S g(X) dP \\ &= \int_{g(X) \geq 0} \int_0^{g(X)} 1 dy dP - \int_{g(X) < 0} \int_{g(X)}^0 1 dy dP \\ &= \int_0^{\infty} \int_{g^{-1}([y, \infty))} f_X(t) dt dy - \int_{-\infty}^0 \int_{g^{-1}([-\infty, y])} f_X(t) dt dy \\ &= \int_{-\infty}^{\infty} g f_X dt \end{aligned}$$

There is a multivariate version of this formula, and one can also write down $E[g(X)]$ when only the c.d.f. of X is known (via Fubini's theorem or integration by parts).

Can you write down a random variable with neither probability distribution nor p.d.f.?

Can you write down a random variable with no expectation?

1.2 Independence and conditional probability for random events

- $A, B \in \mathcal{F}$ are **independent** iff $P(A \cap B) = P(A)P(B)$.
- If $P(B) \neq 0$, $P(A \cap B) = P(B)P(A|B)$. Here $P(A|B)$ is the **conditional probability** of A when B is known to happen.

1.3 Joint distribution, marginal distribution, conditional distribution

1.3.1 Joint distribution

- X and Y are two random variables. The **joint cumulative distribution function** is $F(s, t) = P(X \leq s, Y \leq t)$.
- If $F(s, t) = \sum_{(x, y) \in C, x \leq s, y \leq t} g(s, t)$, we call g the **joint probability distribution**.
- If $F(s, t) = \int_{(-\infty, s] \times (-\infty, t]} f(x, y) dx dy$ we call f the **joint probability density function**.
- X and Y are called independent iff the joint c.d.f. is $F(x, y) = F_X(x)F_Y(y)$.
- The **covariance** between X and Y is $E[(X - E[X])(Y - E[Y])]$

Example: X and Y are two independent random variable with uniform distribution on $[0, 1]$. What is the joint distribution function of X and Y ? How about $\max(X, Y)$ and $\min(X, Y)$? What are their covariances?

1.3.2 Marginal distribution

Knowing the joint c.d.f. of X and Y , the c.d.f. of X or Y are called the **marginal cumulative distribution function**, their p.d. or p.d.f. the **marginal p.d. or marginal p.d.f.**

1.3.3 Conditional distribution

- If A is a set such that $P(Y \in A) > 0$, then the **conditional cumulative distribution function** of X is $F_{X|Y \in A}(t) = P(X \leq t | Y \in A) = P(X \leq t \cap Y \in A) / P(Y \in A)$. The **conditional p.d.f.**, **conditional p.d.** and **conditional expectation** are defined similarly.
- If $P(Y \in A) = 0$ there isn't a definition of conditional distribution that works in all cases. For example, if X, Y has joint p.d.f. $f_{X,Y}$, and the marginal p.d.f. of Y , denoted as $f_Y(y) = \int_{\mathbb{R}} f_{X,Y}(x, y) dx$, exists and is non zero at y_0 , then the conditional p.d.f. at $Y = y_0$ is defined as $f_{X|Y=y_0} = f_{X,Y}(x, y_0) / f_Y(y_0)$. The conditional c.d.f. is its integral.

Remark: The definition of conditional distribution for the case $P(Y \in A) = 0$ depends on Y and not just $Y^{-1}(A)$. For example, if $Z = Ye^X$, $f_{X|Y=0} \neq f_{X|Z=0}$.

Example: X is a random variable with uniform distribution on $[0, 1]$, $P(Y = 1 | X = p) = p$ (i.e. $P(Y = 1 | X \in A) = \int_A p dF_x(p)$), $P(Y = 0 | X = p) = 1 - p$. Find the conditional distribution of X when $Y = 1$.

When there are N random variables, $N \geq 3$, the joint/marginal/conditional distributions can be defined analogously.

2 Special probability distributions, central limit theorem

2.1 Special discrete distributions

- **Bernoulli distribution:** $f(1) = \theta$, $f(0) = 1 - \theta$.
- **Binomial distribution** (sum of iid Bernoulli): $f(x) = \binom{n}{x} \theta^x (1 - \theta)^{n-x}$, $x = 0, 1, \dots, n$.

- **Negative Binomial distribution** (waiting time for the k -th success of iid trials): $f(x) = \binom{x-1}{k-1} \theta^k (1-\theta)^{x-k}$, $x = k, k+1, \dots$. When $k = 1$ it is the **geometric distribution**.
- **Hypergeometric distribution** (randomly pick n elements at random from N elements, the number of elements picked from a fixed subset of M elements) $f(x) = \binom{M}{x} \binom{N-M}{n-x} \binom{N}{n}^{-1}$.
- **Poisson distribution** (limit of binomial as $n \rightarrow \infty$, $n\theta \rightarrow \lambda$) $f(x) = \lambda^x e^{-\lambda} / x!$.
- **Multinomial distribution** $f(x_1, \dots, x_k) = \binom{n}{x_1, \dots, x_k} \theta_1^{x_1} \dots \theta_k^{x_k}$, $\sum_i x_i = n$, $\theta_i \theta_i = 1$.
- **Multivariate Hypergeometric distribution** $f(x_1, \dots, x_k) = \prod_i \binom{M_i}{x_i} \binom{N}{n}^{-1}$. $\sum_i x_i = n$, $\sum_i M_i = N$.

2.2 Special continuous distributions

- **Uniform distribution**: $f(x) = \begin{cases} 1/(b-a) & x \in (a, b) \\ 0 & x \notin (a, b) \end{cases}$.
- **Normal distribution**: $f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$.
- **Multivariate Normal distribution**: $x \in \mathbb{R}^d$, Σ positive definite $d \times d$ symmetric matrix, $f(x) = (2\pi)^{-d/2} |\Sigma|^{-1/2} e^{-\frac{1}{2}(x-\mu)^T \Sigma^{-1} (x-\mu)}$.
- **χ^2 distribution** d : degrees of freedom. Squared sum of d normal distributions: $f(x) = \begin{cases} \frac{1}{2^{d/2} \Gamma(d/2)} x^{\frac{d-2}{2}} e^{-x/2} & x > 0 \\ 0 & x \leq 0 \end{cases}$.
- **Exponential distribution** $f(x) = \begin{cases} \frac{1}{\theta} e^{-x/\theta} & x > 0 \\ 0 & x \leq 0 \end{cases}$.
- **Gamma-distribution**: $f(x) = \begin{cases} \frac{1}{\beta^\alpha \Gamma(\alpha)} x^{\alpha-1} e^{-x/\beta} & x > 0 \\ 0 & x \leq 0 \end{cases}$.
- **Beta distribution**: (conjugate prior of Bernoulli distribution) $f(x) = \begin{cases} \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} x^{\alpha-1} (1-x)^{\beta-1} & x \in (0, 1) \\ 0 & x \notin (0, 1) \end{cases}$.

2.3 Law of Large Numbers and Central Limit Theorem

2.3.1 Convergence

- **Convergence in distribution:** cdf pointwise convergence.
- **Convergence almost surely:** $P(\lim_i X_i \neq X) = 0$.

Example: X uniform on $[0, 1]$, $Y_i = \begin{cases} 1 & \exists n \in \mathbb{Z} (X + n \in [\sum_{j=1}^i \frac{1}{j}, \sum_{j=1}^{i+1} \frac{1}{j}]) \\ 0 & \text{otherwise} \end{cases}$.

Then Y_i converges to 0 in distribution but not almost surely.

2.3.2 CLT and weak LLN

Levy's continuity theorem: If $\phi_{X_j} \rightarrow \phi_X$ pointwise, then X_j converges to X in distribution.

Weak Law of Large Numbers X_i i.i.d. with expectation μ . $S_n = \frac{1}{n} \sum_{i=1}^n X_i$. Then S_n converges to μ in distribution.

(Levy's) Central Limit Theorem X_i i.i.d. with expectation μ and variance $\sigma^2 > 0$. $Y_n = \sqrt{\frac{1}{n\sigma^2}} \sum_i (X_i - \mu)$, then Y_n converges in distribution to standard normal distribution (normal distribution with $\mu = 0$ and $\sigma^2 = 1$).

Proof of both theorems (assume X_i bounded): Taylor expansion of the characteristic function.

One can also use the continuity of moment generating function, which is the argument in the textbook.

2.3.3 Strong Law of Large Numbers

Borel-Cantelli Lemma A_i events, $i = 1, 2, \dots$, $\sum_i (A_i) < \infty$, then $P(\cap_i (\cup_{j>i} A_j)) = 0$. (the probability of infinitely many A_i happening is 0)

Proof: $P(\cap_i (\cup_{j>i} A_j)) \leq P(\cup_{j>i} A_j) \leq \sum_{j>i} P(A_j)$ which converges to 0 as $i \rightarrow \infty$.

Strong Law of Large Numbers $X_i, i = 1, 2, \dots$ i.i.d. (independent with identical distribution) and $E(X_i) = \mu$, then $Y_n = \frac{1}{n} \sum_{i=1}^n X_i$ converges a.s. to constant μ .

Proof (assume X_i bounded by M): Suppose $Var(X_i) = m$. $\sqrt{\frac{n}{m}}(Y_n - \mu)$ has expectation 0 and variance 1, so $P(|Y_n - \mu| > C\sqrt{\frac{m}{n}}) < 1/C^2$ by Chebyshev's theorem. Now let $n_k = k^4$, $C_k = k$, then $Y_{n_k} = Y_{k^4}$ converges a.s. to μ by Borel-Cantelli.

$Y_n = (\lfloor n^{1/4} \rfloor^4 Y_{\lfloor n^{1/4} \rfloor^4} + X_{\lfloor n^{1/4} \rfloor^4 + 1} + \dots + X_n) / n = Y_{\lfloor n^{1/4} \rfloor^4} + (M + |\mu|) \frac{n - \lfloor n^{1/4} \rfloor^4}{n}$.
The first term converges to μ as $n \rightarrow \infty$, and the second converges to 0.

3 Sample statistics

3.1 Some important distributions

- Standard Normal Distribution: $\mathcal{N}(0, 1)$
- $\chi^2(k)$: squared sum of k independent standard normal distribution.
- t distribution: Z standard normal, $Y \sim \chi^2(k)$, Z and Y independent, then $T = \frac{Z}{\sqrt{Y/k}}$ is said to have t -distribution with k degrees of freedom.
- F distribution: U and V independent, $U \sim \chi^2(m)$, $V \sim \chi^2(n)$, then $F = \frac{U/m}{V/n}$ is said to have F distribution with degrees of freedom m and n ,

3.2 Sample statistics

X_1, \dots, X_n i.i.d. (independent with identical distributions). Sample statistics: a random variable computed from n other random variables.

- **Sample mean:** $\bar{X} = \frac{\sum_i X_i}{n}$

$$- E[\bar{X}] = E[X_1], \text{Var}(\bar{X}) = \frac{1}{n} \text{Var}(X_1).$$

Proof:

$$E[\bar{X}] = E\left[\frac{1}{n} \sum_i X_i\right] = \frac{1}{n} \sum_i E[X_i] = E[X_1]$$

$$\text{Var}(\bar{X}) = E[(\bar{X} - E[X_1])^2] = \frac{1}{n^2} E\left[\sum_i (X_i - E[X_i])^2\right] = \frac{1}{n} \text{Var}(X_1)$$

- If $X_1 \sim \mathcal{N}(\mu, \sigma^2)$, $\bar{X} \sim \mathcal{N}(\mu, \sigma^2/n)$.

Proof: By calculation using MGF.

- If $n \rightarrow \infty$, $\sqrt{\frac{n}{\text{Var}(X_1)}}(\bar{X} - E[X_1])$ converges to standard normal by distribution.

Proof: This is just central limit theorem.

- **Sample variance:** $S^2 = \frac{1}{n-1} \sum_i (X_i - \bar{X})^2 = \frac{1}{n-1} (\sum_i X_i^2 - n\bar{X}^2)$.

$$- E[S^2] = \text{Var}(X_1).$$

Proof:

$$E[S^2] = \frac{1}{n-1} \sum_i E[(X_i - \bar{X})^2] = \frac{1}{n-1} \sum_i E\left[\left(\frac{n-1}{n} X_i - \sum_{j \neq i} \frac{1}{n} X_j\right)^2\right]$$

$$\begin{aligned}
&= \frac{1}{n-1} \sum_i \left(\frac{(n-1)^2}{n^2} E[X_i^2] + \sum_{j \neq i} \frac{1}{n^2} E[X_j^2] - \sum_{j \neq i} \frac{2n-2}{n^2} E[X_i] E[X_j] \right. \\
&\quad \left. + \sum_{j \neq i, k \neq i, j \neq k} \frac{2}{n^2} E[X_j] E[X_k] \right) \\
&= E[X_1^2] - E[X_1]^2 = \text{Var}(X_1)
\end{aligned}$$

– If $X_1 \sim \mathcal{N}(\mu, \sigma^2)$, then

* \bar{X} and S^2 are independent

Proof: Calculate joint cdf, do a change of variables.

* $\frac{(n-1)S^2}{\sigma^2} \sim \chi^2(n-1)$

Proof:

$$\frac{(n-1)S^2}{\sigma^2} + n \frac{(\bar{X} - E[X_1])^2}{\sigma^2} = \frac{1}{\sigma^2} \sum_i (X_i - E[X_1])^2 \sim \chi^2(n)$$

Now use moment generating function and the independence between S^2 and \bar{X} .

* $\frac{\bar{X} - \mu}{S/\sqrt{n}} \sim t(n-1)$.

Proof: By definition of t -distribution.

– If S_1^2 is the sample variance of n_1 i.i.d. $\mathcal{N}(\mu, \sigma^2)$ random variables Y_i , S_2^2 the sample variance of n_2 i.i.d. $\mathcal{N}(\mu', \sigma'^2)$ random variables Z_j independent from Y_i , then $\frac{S_1^2/\sigma_1^2}{S_2^2/\sigma_2^2} \sim F(n_1-1, n_2-1)$

Proof: By definition of F -distribution.

- **Order statistics** The k -th order statistics is the k -th smallest element in $\{X_i\}$, denoted as Y_k . Then, if X_1 has pdf f , then

$$\begin{aligned}
f_{Y_k}(t) &= \frac{d}{dt} F_{Y_k}(t) = \lim_{\delta \rightarrow 0} \frac{F_{Y_k}(t+\delta) - F_{Y_k}(t)}{\delta} \\
&= \lim_{\delta \rightarrow 0} \frac{1}{\delta} \binom{n}{k-1, 1, n-k} \left(\int_0^t f ds \right)^{k-1} \int_t^{t+\delta} f ds \left(\int_{t+\delta}^\infty f ds \right)^{n-k} \\
&= \frac{n!}{(k-1)!(n-k)!} \left(\int_0^t f ds \right)^{k-1} f(t) \left(\int_t^\infty f ds \right)^{n-k}
\end{aligned}$$

3.3 PDF of χ^2 -, t- and F- distributions

3.3.1 χ^2

Let X_i be iid standard normal, their joint distribution is

$$f(x_1, \dots, x_n) = (2\pi)^{-n/2} e^{-\sum_i x_i^2/2}$$

Hence the pdf of χ^2 is:

$$f_{\chi^2(n)}(r) = \frac{d}{dr} \int_{\sum_i x_i^2 \leq r} (2\pi)^{-n/2} e^{-\sum_i x_i^2/2} dx_1 \dots dx_n$$

which is easy to see must be proportional to $r^{\frac{n-2}{2}} e^{-r/2}$.

3.4 t

Let X and Y be independent with pdf: $f_X(x) = \frac{1}{\sqrt{2\pi}} e^{-x^2/2}$ and $f_Y(y) = \frac{1}{2^{d/2}\Gamma(d/2)} y^{\frac{d-2}{2}} e^{-y/2}$. Then

$$\begin{aligned} f_{t(d)}(s) &= \frac{d}{ds} P(X \leq s\sqrt{Y/d}) = \frac{d}{ds} \int_0^\infty dy \int_{-\infty}^{s\sqrt{y/d}} dx \frac{1}{\sqrt{2\pi}} e^{-x^2/2} \frac{1}{2^{d/2}\Gamma(d/2)} y^{\frac{d-2}{2}} e^{-y/2} \\ &= \int_0^\infty dy \sqrt{y/d} \frac{1}{\sqrt{2\pi}} e^{-s^2 y/2d} \frac{1}{2^{d/2}\Gamma(d/2)} y^{\frac{d-2}{2}} e^{-y/2} \end{aligned}$$

Do change of variables $z = (s^2/d + 1)y$ we get that it is proportional to $(s^2/d + 1)^{-\frac{d+1}{2}}$.

The calculation for the pdf of F is similar.

4 Point estimators and their properties

Basic setting:

- \mathcal{F} : a family of possible distributions (represented by a family of cdf, pdf, or pd)
- $\theta : \mathcal{F} \rightarrow \mathbb{R}$ population parameter
- X_1, \dots, X_n i.i.d. with distribution $F \in \mathcal{F}$
- $\hat{\theta} = \hat{\theta}(X_1, \dots, X_n)$ a function of X_i , which is an estimate of $\theta(F)$, is called a point estimate.

Example: \mathcal{F} : all distributions with an expectation, then \bar{X} is a point estimate of the expectation.

$\hat{\theta}$ is a point estimate of θ .

- The **bias** is $E[\hat{\theta}] - \theta$. $\hat{\theta}$ is called unbiased if $E[\hat{\theta}] = \theta$.
- The **variance** is $Var(\hat{\theta})$.
- $\hat{\theta}$ is called **minimum variance unbiased estimate** if it has the smallest variance among all unbiased estimates.
- $\hat{\theta}_1$ and $\hat{\theta}_2$ are two unbiased estimates, the relative efficiency is the ratio of their variance. When they are biased, one can use the mean squared error $E[(\hat{\theta} - \theta)^2]$ instead.
- $\hat{\beta}$ is called **asymptotically unbiased** if bias converges to 0 as $n \rightarrow \infty$.
- $\hat{\beta}$ is called **consistent** if $\hat{\beta}$ converges to β in distribution.

Example: Estimate of the expectation and variance of binomial distribution.

Example: Estimate t for uniform distribution on $[0, t]$.

5 Method of moments, Maximum likelihood

6 Maximum a posteriori

7 Hypothesis testing

8 Examples of hypothesis testing

9 Confidence interval

10 Linear Regression

11 ANOVA

12 Example of non parametric methods