Probability and Statistics II

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Contents

1 Review of Probability

1.1 Probability

- The probability measure P for each event A defined on sample space Ω satisfies the following properties:
  - $P(A)$ is non-negative and $0 \leqslant P(A) \leqslant 1$.
  - $P(A) = 0$ when A is empty.
  - $P(A) = 1$ when A is the entire sample space Ω.
  - P is countably additive.

1.2 Expectation

- Expected value/mean/average of r.v. X is defined as
  - $\mathbb{E}[X] = \int_{-\infty}^{\infty} x f(x) \, \mathrm{d}x$, when X is continuous;
  - $\mathbb{E}[X] = \sum_i x_i P(X = x_i)$, when X is discrete.
- Expectation is a ***linear operator***: Let X and Y are two r.v.s., then $\mathbb{E}[aX + bY + c] = a\mathbb{E}[X] + b\mathbb{E}[Y] + c$.

1.3 Indicator function

- If A is any event, define the ***indicator function*** of A, I_A to be the r.v. for all $s \in \Omega$,

$$I_A(s) = \begin{cases} 1, s \in A \\ 0, s \notin A \end{cases}.$$

Example 1.1. We are rolling a dice and $A = \{2, 4, 6\}$.

X	1	2	3	4	5	6
I_A	0	1	0	1	0	1

Therefore, $\mathbb{E}[I_A] = \frac{1}{6}(0 + 1 + 0 + 1 + 0 + 1) = \frac{1}{2} = P(A)$.

1.4 Law of large number (LLN)

- Let $X_1, X_2, ..., X_i$ be a sequence of independent r.v.s. with $\mathbb{E}[X_i] = \mu$. Let $\overline{X}_n = \frac{1}{n} \sum\limits_{i=1}^{n} X_i$. Then $\overline{X}_n \xrightarrow{P} \mu$ as $n \to \infty$, i.e.,

$$\forall \varepsilon > 0, \lim_{n \to \infty} P(|\overline{X} - \mu| > \varepsilon) = 0.$$

  ○ In naive words: Sample mean approaches the population mean as the sample size increases.

1.5 Central limit theorem (CLT)

- Suppose $X_1, X_2, ...$ is an i.i.d. sequence of r.v.s. each having finite mean μ and finite variance σ^2. Let $\overline{X}_n = \frac{1}{n}$, then as $n \to \infty, \overline{X}_n \xrightarrow{D} \mathcal{N}(\mu, \frac{\sigma^2}{n})$ or

$$\frac{\overline{X}_n - \mu}{\frac{\sigma}{\sqrt{n}}} \xrightarrow{D} \mathcal{N}(0, 1).$$

  ○ In naive words: A r.v. can follow some distribution with mean μ and variance σ^2. If we pick a fixed number of samples n and calculate the sample mean repeatedly, then those sample means will have a Normal distribution with mean μ and variance $\frac{\sigma^2}{n}$.

1.6 Linear combination of Normal variables

- Let $X_i \sim \mathcal{N}(\mu_i, \sigma_i^2)$ where $i = 1, 2, ..., n$. Let Y be a linear combination of all the X_i's with

$$Y = a_1 X_1 + \cdots + a_n X_n + b = \sum_{i=1}^{n} a_i X_i + b,$$

  where $a_i, b \in \mathbb{R}$. Then $Y \sim \mathcal{N}\left(\sum\limits_{i=1}^{n} a_i \mu_i + b, \sum\limits_{i=1}^{n} a_i^2 \sigma_i^2\right)$.

  Example 1.2. Let $X_1 \sim \mathcal{N}(10, 2), X_2 \sim \mathcal{N}(20, 3), Y = 0.4X_1 + 0.6X_2$. Then $Y \sim \mathcal{N}(16, 1.4)$.

1.7 Z and χ^2 distribution

- Standard normal/$\mathcal{N}(0,1)/Z$ distribution: If $X \sim \mathcal{N}(\mu, \sigma^2)$, then $\frac{X-\mu}{\sigma} \sim \mathcal{N}(0,1)$.
- χ^2 distribution: Let $U = Z^2$, then $U \sim \chi^2_{(1)}$.
  - Additive property: If $X \sim \chi^2_{(m)}, Y \sim \chi^2_{(n)}$, then $X + Y \sim \chi^2_{(m+n)}$.
  - If $X \sim \chi^2_{(m)}$, then $\mathbb{E}[X] = m$.

1.8 t and F distribution

- t distribution: Let $Z \sim \mathcal{N}(0,1)$ and $U \sim \chi^2_{(m)}$ be independent, then $\frac{Z}{\sqrt{U/m}} \sim t_{(m)}$.
- F distribution: Let $X \sim \chi^2_{(m)}, Y \sim \chi^2_{(n)}$ be independent, then $\frac{X/m}{Y/n} \sim F_{(m,n)}$.

2 Data Collection

2.1 Population and sample

- ***Population*** is a collection of all the subjects that have something in common.
- ***Sample*** is a subset of the population.

  ○ We use the sample to make inference about the unknown characteristics of our population.

  ○ The sample should be representative.

2.2 Parameter and statistic

- ***Parameter*** is a characteristic (summary) of the population. For example, mean (μ), standard deviation (σ), etc.

  ○ We use θ to represent the parameter(s) of population. For example, $X \sim \mathcal{N}(\mu, \sigma^2), \theta$ stands for both μ and σ.

- ***Statistic*** is any summary of the sample. For example, sample total ($\sum X_i$), etc.

  ○ When a statistic is used to estimate a parameter, it is called an estimator. For example, S is an estimator of σ.

  ○ $T(X)$ is used to represent a statistic/estimator. For example, if we are dealing with sample mean, then $T(X) = \overline{X}$.

  ○ When we have observed a sample and calculate the value of an estimator, then that numerical value is called the estimate and we use lowercase letters to represent.

Parameter (θ)	Estimator (T)	Estimate (t)
μ	$\overline{X}$	$\overline{x}$
Unknown constant	Random variable	Known constant

2.3 Finite populations

- Let π represent individual subjects in a finite population Π. For each π, we have a real valued quantity $X(\pi)$.

- The ***population CDF***,

$$F_X(x) = \frac{|\{\pi | X(\pi) \leqslant x\}|}{N},$$

where $N = |\Pi|$. Or,

$$F_X(x) = \frac{1}{N} \sum I_{(-\infty,x]}(X(\pi)) = \mathbb{E}[I_{(-\infty,x]}(X(\pi))].$$

  ◦ In naive words: $F_X(x)$ is the proportion of elements in the population with their X measurement less or equal to x.

2.4 Infinite populations

- We use probability distributions to represent the population. Informally, we can think it as a limiting distribution of a finite population of size N when $N \to \infty$.

2.5 Simple random sampling

- With replacement:

  ◦ Every subject of the population will have the same probability $\frac{1}{N}$ of being selected in the sample in each draw.

  ◦ Samples are independent.

- Without replacement:

  ◦ Not independent.

  ◦ If $N \to \infty, n << N$, where n is the sample size: $P(B) = \frac{1}{N}, P(B|A) = \frac{1}{N-1}$. But for a large N and $n << N$, $P(B) \approx P(B|A)$, then samples are independent.

2.6 Empirical CDF

- Suppose we select a sample $\{\pi_1, ..., \pi_n\} \subset \Pi$, we can approximate the population CDF F_X by the ***empirical CDF***

$$\widehat{F}_X(x) = \frac{\{|\pi_i | X(\pi_i) \leqslant x, i = 1, ..., n|\}}{n} = \frac{1}{n} \sum_{i=1}^{n} I_{(-\infty,x]}(X(\pi_i)).$$

- Assuming independence, then by LLN,

$$\frac{1}{n}\sum_{i=1}^{n} I_{(-\infty,x]}(X(\pi_i)) \xrightarrow{P} \mathbb{E}[I_{(-\infty,x]}(X(\pi_i))] = P(I_{(-\infty,x]}(X(\pi_i)))$$
$$= P(X(\pi_i) \leqslant x) = F_X(x).$$

2.7 Density histogram

- Suppose we have continuous variable X and can group X into intervals given by $(h_1, h_2], ..., (h_{m-1}, h_m]$. The ***density histogram function***

$$h_X(x) = \begin{cases} \frac{|\{\pi | X(\pi) \in (h_i, h_{i+1}]\}|}{N(h_{i+1}-h_i)}, & x \in (h_i, h_{i+1}] \\ 0, & \text{otherwise} \end{cases}.$$

  ○ In naive words: In density histogram, the height of each of the bar is the relative frequency, divided by the corresponding length of the interval.

  ○ When the interval lengths $(h_{i+1} - h_i)$ gets smaller and N gets bigger, we get a smooth function.

2.8 Quantile/Percentile for population

- For $p \in [0, 1]$, the pth quantile (100pth percentile) x_p, for the distribution with CDF F_X, is defined to be the ***smallest number*** x_p satisfying $p \leqslant F_X(x_p)$.

  ○ When F_X is strictly increasing and continuous, x_p satisfies $F_X(x_p) = p$.

  ○ When X is discrete, $F_X(x_p) = p$ may not have a solution.

- Estimating quantiles: Suppose the sample is $(x_1, ..., x_n)$ and after ordering we have $x_{(1)} < \cdots < x_{(n)}$, $x_{(i)}$ is the $(\frac{i}{n})$th quantile of the empirical distribution because $\widehat{F}_X(x_{(i)}) = \frac{i}{n}$. The sample pth quantile is x_p whenever $\frac{i-1}{n} < p \leqslant \frac{i}{n}$.

  ○ Linear interpolation: $\widetilde{x}_p = x_{(i-1)} + n(x_{(i)} - x_{(i-1)})(p - \frac{i-1}{n})$.

Proof. We have $\frac{\widetilde{x}_p - x_{(i-1)}}{np-(i-1)} = \frac{x_{(i)} - x_{(i-1)}}{i-(i-1)}$.
Therefore, $\widetilde{x}_p = x_{(i-1)} + n(x_{(i)} - x_{(i-1)})(p - \frac{i-1}{n})$. □

Example 2.1. -2.1 -0.3 0.4 1.2 1.5 2.1 2.2 3.3 4.0 5.0
First quantile = $Q_1 = \widetilde{x}_{0.25} = x_{(2)} + 10(x_{(3)} - x_{(2)})(0.25 - \frac{2}{10}) = 0.05$
Third quantile = $Q_3 = \widetilde{x}_{0.75} = x_{(7)} + 10(x_{(8)} - x_{(7)})(0.75 - \frac{7}{10}) = 2.75$
Inter quantile range = $IQR = Q_3 - Q_1 = 2.7$

- Median/Second quantile: We can use linear interpolation formula or

$$Q_2 = \widetilde{x}_{0.5} = \begin{cases} x_{(\frac{n+1}{2})}, & n \text{ is odd} \\ \frac{1}{2}(x_{(\frac{n}{2})} + x_{(\frac{n}{2}+1)}), & n \text{ is even} \end{cases}.$$

2.9 Boxplot

- Draw a box using Q_1 and Q_3 as the sides and Q_2 as a line inside the box.
- Lower limit= $Q_1 - 1.5 \cdot IQR$, Upper limit= $Q_3 + 1.5 \cdot IQR$.
- ***Adjacent values*** are the ***two extreme data points*** that falls within the lower and upper limit.
- ***Whiskers*** are the vertical lines from the quantiles to the adjacent values.
- Values beyond the adjacent values are plotted with $*$ and called outliers.
- If the variable is categorical, we use ***bar charts***. Categories on x-axis and proportions on y-axis.

2.10 Choice of summary measures

- Choice of summary measures based on the skewness of the distribution
  - Mean and s.d. when distribution is symmetric.
  - Median and IQR when distribution is skewed.

3 Point Estimation

3.1 Type of inference

- Estimation:

  ○ Point estimation: Based on the sample observations, calculating a particular value as an estimate of the parameter.

  ○ Interval estimation: Calculating a range of values that is likely to contain θ.

- Hypothesis testing: Based on the sample, assess whether a hypothetical value θ_0 is a plausible value of the θ or not.

3.2 Method of moments estimation

- Let $X_1, ..., X_n$ be i.i.d. r.v.s. and let the kth ***population moment*** $\mu_k = \mathbb{E}[X^k]$, kth ***sample moment*** $\widehat{\mu}_k = \frac{1}{n}\sum_{i=1}^{n} X_i^k$.

- We use $\widehat{\mu}_k$ as an estimator of μ_k.

  Example 3.1. $X_1, ..., X_n \overset{\text{i.i.d.}}{\sim} \text{Poisson}(\lambda)$. Find the method of moments estimator of λ.

  Solution. We have $\lambda = \mathbb{E}[X] = \mu$, then $\widehat{\lambda} = \frac{1}{n}\sum_{i=1}^{n} X_i = \overline{X}$.

  Example 3.2. $X_1, ..., X_n \overset{\text{i.i.d.}}{\sim} \mathcal{N}(\mu, \sigma^2)$. Find the method of moments estimator of μ and σ^2.

  Solution. We have $\mu = \mathbb{E}[X], \sigma^2 = \mathbb{E}[X^2] - (\mathbb{E}[X])^2$ and thus

$$\widehat{\mu} = \frac{1}{n}\sum_{i=1}^{n} X_i = \overline{X},$$

  and

$$\widehat{\sigma}^2 = \frac{1}{n}\sum_{i=1}^{n} X_i^2 - (\overline{X})^2 = \frac{1}{n}\sum_{i=1}^{n} X_i^2 - \frac{1}{n}n(\overline{X})^2 = \frac{1}{n}\sum_{i=1}^{n}(X_i - \overline{X})^2.$$

- Summary of method:

  ◦ Express the lower order population moment(s) in terms of the parameter(s).

  ◦ Invert the expression(s) to express the parameter(s) in terms of the population moment(s).

  ◦ Replace the population moment(s) using the sample moment(s).

3.3 Maximum likelihood estimation

- Suppose $X_1, ..., X_n$ has a joint density or mass function $f(x_1, ..., x_n|\theta)$ and we observe sample $X_1 = x_1, ..., X_n = x_n$. The ***likelihood function*** of $\theta, L(\theta) = f(x_1, ..., x_n|\theta)$.

  ◦ If X follows a discrete distribution, it gives the ***probability of observing the sample*** as a function of θ.

- If $X_1, ..., X_n$ are i.i.d. then $L(\theta) = \prod_{i=1}^{n} f_\theta(x_i)$.

  ◦ $L(\theta)$ is not a PDF or PMF of θ.

  ◦ Likelihood introduces a belief ordering on parameter space Ω. If $L(\theta_1) > L(\theta_2)$, the data is more likely to come from f_{θ_1} than f_{θ_2}.

  ◦ The value $L(\theta)$ is very small for every value of θ, so often we are interested in the ***likelihood ratio*** $\frac{L(\theta_1)}{L(\theta_2)}$.

- Maximum likelihood estimation (MLE): If we are interested in a point estimation of θ, a sensible choice will be to pick $\widehat{\theta}$ that maximizes $L(\theta)$, i.e., $L(\widehat{\theta}) \geqslant L(\theta), \forall\theta \in \Omega$.

  ◦ Computation for MLE:

  * ***Log-Likelihood function***

$$l(\theta) = \ln(L(\theta)) = \ln\left(\prod_{i=1}^{n} f_\theta(x_i)\right) = \sum_{i=1}^{n} \ln(f_\theta(x_i)).$$

Since $\ln x$ is an injective increasing function of $x > 0$, then $L(\widehat{\theta}) \geqslant L(\theta), \forall\theta \in \Omega$ iff $l(\widehat{\theta}) \geqslant l(\theta)$.

  * Solve $\frac{\partial l(\theta)}{\partial\theta} = 0$ and $\widehat{\theta}$ is the solution.

∗ Check if $\frac{\partial^2 l(\theta)}{\partial \theta^2}\Big|_{\theta=\widehat{\theta}} < 0$.

Example 3.3. $X_1, ..., X_n \overset{\text{i.i.d.}}{\sim}$ Poisson(λ). Find the MLE of λ.

Solution. We have $f(x) = \frac{e^{-\lambda}\lambda^x}{x!}$ and thus

$$L(\lambda) = \frac{e^{-n\lambda}\lambda^{\sum\limits_{i=1}^{n} x_i}}{\prod\limits_{i=1}^{n} x_i!}.$$

Therefore, $l(\lambda) = -n\lambda + \ln\lambda \sum\limits_{i=1}^{n} x_i + C$. Let $\frac{\partial l(\lambda)}{\partial \lambda} = 0$, we have $\widehat{\lambda} = \frac{1}{n}\sum\limits_{i=1}^{n} x_i = \overline{x}$.

◦ Properties of MLE:

∗ MLE is not unique.

∗ MLE may not exists.

∗ The likelihood may not always be differentiable. For example, $X_1, ..., X_n \overset{\text{i.i.d.}}{\sim}$ Unif$[0, \theta]$, $\widehat{\theta} = \max\{x_1, ..., x_n\}$.

∗ Invariance property of MLE: Let $\widehat{\theta}$ be the MLE of θ and $\psi(\theta)$ be any injective function of θ defined on Ω, then $\psi(\widehat{\theta})$ is the MLE of $\psi(\theta)$.

3.4 Sampling distribution of an estimator

- An estimator (T) is a r.v. and if we repeat the sampling procedure and keep calculating T for each set of sample and finally draw a density histogram based on the T values, we get the sampling distribution of T.

- Assume $X_1, ..., X_n$ is an i.i.d. sequence of r.v.s., each having finite mean μ and finite variance σ^2, then

$$\begin{aligned}\mathbb{E}[\overline{X}] &= \mathbb{E}[\frac{1}{n}X_1 + \cdots + \frac{1}{n}X_n] = \frac{1}{n}\mathbb{E}[X_1] + \cdots + \frac{1}{n}\mathbb{E}[X_n] \\ &= \frac{1}{n}n\mu = \mu,\end{aligned}$$

and

$$\begin{aligned}\mathrm{Var}[\overline{X}] &= \mathrm{Var}[\frac{1}{n}X_1 + \cdots + \frac{1}{n}X_n] = \mathrm{Var}[\frac{1}{n}X_1] + \cdots + \mathrm{Var}[\frac{1}{n}X_n] \\ &= \frac{1}{n^2}\mathrm{Var}[X_1] + \cdots + \frac{1}{n^2}\mathrm{Var}[X_n] = \frac{1}{n^2}n\sigma^2 = \frac{\sigma^2}{n}.\end{aligned}$$

Besides, $\mathrm{SE}(\overline{X}) = \frac{\sigma}{\sqrt{n}}$. (***Standard error*** is the standard deviation of an estimator)

◦ $\overline{X}$ is a linear combination of $X_1, ..., X_n$.

◦ $\mathbb{E}[\overline{X}] = \mu$ and $\mathrm{Var}[\overline{X}] = \frac{\sigma^2}{n}$ are regardless of the distribution of X.

3.5 Measuring quality of an estimator

- Let $\psi(\theta)$ be any real valued function of θ, suppose T is an estimator of $\psi(\theta)$. The most commonly used measurement of ***accuracy*** of an estimator is ***mean squared error***, $\mathrm{MSE}_\theta(T) = \mathbb{E}_\theta[(T - \psi(\theta))^2]$.

  ◦ The smaller the value of $\mathrm{MSE}_\theta(T)$, the more concentrated the sampling distribution of T is about the value $\psi(\theta)$.

  ◦ Since the true value of θ is unknown, often we evaluate the $\mathrm{MSE}_\theta(T)$ at $\theta = \widehat{\theta}$.

- $\mathrm{MSE}_\theta(T) = \mathrm{Var}_\theta[T] + (\mathbb{E}_\theta[T] - \psi(\theta))^2$.

  Proof.

  $$\begin{aligned}&\mathrm{MSE}_\theta(T) = \mathbb{E}_\theta[(T - \psi(\theta))^2] = \mathbb{E}_\theta[(T - \mathbb{E}_\theta[T] + \mathbb{E}_\theta[T] - \psi(\theta))^2] \\ &= \mathbb{E}_\theta[(T - \mathbb{E}_\theta[T])^2] + \mathbb{E}_\theta[(\mathbb{E}_\theta[T] - \psi(\theta))^2] + 2\mathbb{E}_\theta[(T - \mathbb{E}_\theta[T])(\mathbb{E}_\theta[T] - \psi(\theta))].\end{aligned}$$

  We know

  $$\begin{aligned}\mathbb{E}_\theta[(T - \mathbb{E}_\theta[T])(\mathbb{E}_\theta[T] - \psi(\theta))] &= \mathbb{E}_\theta[T - \mathbb{E}_\theta[T]](\mathbb{E}_\theta[T] - \psi(\theta)) \\ &= (\mathbb{E}_\theta[T] - \mathbb{E}_\theta[T])(\mathbb{E}_\theta[T] - \psi(\theta)) = 0.\end{aligned}$$

  Besides, $\mathbb{E}_\theta[(T - \mathbb{E}_\theta[T])^2] = \mathrm{Var}_\theta[T]$, and thus $\mathrm{MSE}_\theta(T) = \mathrm{Var}_\theta[T] + (\mathbb{E}_\theta[T] - \psi(\theta))^2$. □

3.6 Unbiasedness

- The bias of an estimator T of $\psi(\theta)$ is given by $\mathbb{E}_\theta[T] - \psi(\theta)$.

- When the bias of an estimator is zero, it is called unbiased, i.e., T is unbiased estimator of $\psi(\theta)$ when $\mathbb{E}_\theta[T] = \psi(\theta)$. In other words, T is unbiased if $\psi(\theta)$ is the mean of the sampling distribution of T.

- $\mathrm{MSE}_\theta(T) = \mathrm{Var}_\theta[T] + (\mathrm{Bias}(T))^2$.

  ◦ For unbiased estimators, $\mathrm{MSE}_\theta(T) = \mathrm{Var}_\theta[T]$.

  ◦ If all the other properties are similar, then an unbiased estimator is preferred over a biased estimator.

4 Sampling Distribution of S^2

4.1 Sample variance (S^2)

- Population variance: $\sigma^2 = \mathbb{E}[(X-\mu)^2]$, where $\mu = \mathbb{E}[X]$. If we have equally likely N data points in population, $\sigma^2 = \frac{1}{N}\sum\limits_{i=1}^{N}(X_i-\mu)^2$.

- $\sum\limits_i (X_i-\mu)^2 = \sum\limits_i (X_i-\overline{X})^2 + n(\overline{X}-\mu)^2$.

  Proof. We have

$$\begin{aligned}\sum_i (X_i-\mu)^2 &= \sum_i (X_i-\overline{X}+\overline{X}-\mu)^2 \\ &= \sum_i (X_i-\overline{X})^2 + \sum_i (\overline{X}-\mu)^2 + 2\sum_i (X_i-\overline{X})(\overline{X}-\mu) \\ &= \sum_i (X_i-\overline{X})^2 + n(\overline{X}-\mu)^2 + 2(\overline{X}-\mu)\sum_i (X_i-\overline{X}).\end{aligned}$$

  We know

$$\sum_i (X_i-\overline{X}) = \sum_i X_i - n\overline{X} = n\overline{X}-n\overline{X} = 0.$$

  Therefore,

$$\sum_i (X_i-\mu)^2 = \sum_i (X_i-\overline{X})^2 + n(\overline{X}-\mu)^2. \quad \square$$

  $\square$

- Biased and unbiased estimator of σ^2: We have $\sum\limits_i (X_i-\overline{X})^2 = \sum\limits_i (X_i-\mu)^2 - n(\overline{X}-\mu)^2$, then we take expectation on both sides and have

$$\begin{aligned}\mathbb{E}\left[\sum_i (X_i-\overline{X})^2\right] &= \mathbb{E}\left[\sum_i (X_i-\mu)^2\right] - \mathbb{E}\left[n(\overline{X}-\mu)^2\right] \\ &= \sum_i \mathbb{E}[(X_i-\mu)^2] - n\mathbb{E}[(\overline{X}-\mu)^2] \\ &= \sum_i \mathrm{Var}[X_i] - n\mathrm{Var}[\overline{X}] \\ &= \sum_i \sigma^2 - n\frac{\sigma^2}{n} = (n-1)\sigma^2.\end{aligned}$$

Therefore, $\mathbb{E}\left[\frac{1}{n}\sum_i (X_i-\overline{X})^2\right]=\frac{n-1}{n}\sigma^2, \mathbb{E}\left[\frac{1}{n-1}\sum_i (X_i-\overline{X})^2\right]=\sigma^2$, i.e., $\frac{1}{n}\sum_i (X_i-\overline{X})^2$ is a biased estimator of σ^2, $\frac{1}{n-1}\sum_i (X_i-\overline{X})^2$ is an unbiased estimator of σ^2.

○ For Normal distribution, both method of moments and MLE gives $\frac{1}{n}\sum_i (X_i-\overline{X})^2$ as an estimator of σ^2.

○ $\frac{n-1}{n}\to 1$ as $n\to\infty$, i.e., for large n both estimators will produce similar estimate.

○ We choose $S^2=\frac{1}{n-1}\sum_{i=1}^{n}(X_i-\overline{X})^2$.

4.2 Sampling distribution of S^2 under Normal distribution

- Though the expression of S^2 contains $\overline{X}$, they are independent. Besides, we can see a relation between S^2 and χ^2 distribution.

Theorem 4.1. Suppose $X_1,...,X_n \overset{\text{i.i.d.}}{\sim} \mathcal{N}(\mu,\sigma^2), \overline{X}=\frac{1}{n}\sum_{i=1}^{n}X_i, S^2=\frac{1}{n-1}\sum_{i=1}^{n}(X_i-\overline{X})^2$, then $\overline{X}\perp S^2$, and $\frac{(n-1)S^2}{\sigma^2}\sim\chi^2_{(n-1)}$.

Proof.

Lemma 1. Suppose $X_1,...,X_n \overset{\text{i.i.d.}}{\sim} \mathcal{N}(\mu,\sigma^2), U$ and V are two different linear combinations of the $X_i, \mathrm{cov}[U,V]=0$ iff $U\perp V$.

We know $\overline{X}=\frac{1}{n}X_1+\cdots+\frac{1}{n}X_n, X_1-\overline{X}=(1-\frac{1}{n})X_1-\frac{1}{n}X_2-\cdots-\frac{1}{n}X_n$.

Besides, $\mathrm{cov}[\overline{X},X_1-\overline{X}]=\mathrm{cov}[\overline{X},X_1]-\mathrm{cov}[\overline{X},\overline{X}]=\frac{\sigma^2}{n}-\frac{\sigma^2}{n}=0$. Similarly, $\mathrm{cov}[\overline{X},X_i-\overline{X}]=0,\forall i=1,...,n$.

By the Lemma, we know $\overline{X}\perp X_i-\overline{X}$, and thus

$$\overline{X}\perp\frac{1}{n-1}\sum_{i=1}^{n}(X_i-\overline{X})^2=S^2.$$

Since $\sum_i (X_i - \mu)^2 = \sum_i (X_i - \overline{X})^2 + n(\overline{X} - \mu)^2$, then

$$\frac{\sum_i (X_i - \mu)^2}{\sigma^2} = \frac{\sum_i (X_i - \overline{X})^2}{\sigma^2} + \frac{n(\overline{X} - \mu)^2}{\sigma^2},$$

i.e.,

$$\sum_i \left(\frac{X_i - \mu}{\sigma}\right)^2 = \frac{(n-1)S^2}{\sigma^2} + \left(\frac{\overline{X} - \mu}{\sigma/\sqrt{n}}\right)^2.$$

Since $X_i \sim \mathcal{N}(\mu, \sigma^2)$, then $\frac{X_i - \mu}{\sigma} \sim \mathcal{N}(0,1)$, and $\sum_i \left(\frac{X_i - \mu}{\sigma}\right)^2 \sim \chi^2_{(n)}$.

Since $\overline{X} \sim \mathcal{N}\left(\mu, \frac{\sigma^2}{n}\right)$, and $\sum_i \left(\frac{\overline{X} - \mu}{\sigma/\sqrt{n}}\right)^2 \sim \chi^2_{(1)}$. Besides, we have $S^2 \perp \overline{X}$, and therefore, we have

$$(1-2t)^{-\frac{n}{2}} = M_{\frac{(n-1)S^2}{\sigma^2}}(t) \cdot (1-2t)^{-\frac{1}{2}},$$

i.e, $M_{\frac{(n-1)S^2}{\sigma^2}}(t) = (1-2t)^{-\frac{n-1}{2}}$, and thus $\frac{(n-1)S^2}{\sigma^2} \sim \chi^2_{(n-1)}$. $\square$

- The mean of a χ^2 distribution is its df, then by theorem, we have $\mathbb{E}\left[\frac{(n-1)S^2}{\sigma^2}\right] = n-1$, i.e., $\mathbb{E}[S^2] = \sigma^2$. Hence, S^2 is an unbiased estimator for σ^2 under Normal distribution.

- An example of cov $= 0 \nRightarrow$ independence.

  Example 4.1. $X \sim \mathcal{N}(0,1), Y = X^2, X$ and Y are dependent. However,

  $$\text{cov}[X,Y] = \mathbb{E}[XY] - \mathbb{E}[X]\mathbb{E}[Y] = \mathbb{E}[X^3] - \mathbb{E}[X]\mathbb{E}[X^2] = \mathbb{E}[X^3] = 0.$$

4.3 $\frac{\overline{X}-\mu}{S/\sqrt{n}} \sim t_{(n-1)}$

- We know $\frac{\overline{X}-\mu}{\sigma/\sqrt{n}} \sim \mathcal{N}(0,1)$, $\frac{(n-1)S^2}{\sigma^2} \sim \chi^2_{(n-1)}$, and $\overline{X} \perp S^2$, then

$$\frac{\frac{\overline{X}-\mu}{\sigma/\sqrt{n}}}{\sqrt{\frac{(n-1)S^2}{\sigma^2}/(n-1)}} = \frac{\frac{\overline{X}-\mu}{\sigma/\sqrt{n}}}{S/\sigma} = \frac{\overline{X}-\mu}{S/\sqrt{n}} \sim t_{(n-1)}.$$

4.4 $\chi^2_{(m)}$

- $\chi^2_{(m)} \sim \text{Gamma}\left(\frac{m}{2}, \frac{1}{2}\right)$.
    - Gamma distribution: $f(x) = \frac{\lambda^\alpha}{\Gamma(\alpha)} x^{\alpha-1} e^{-\lambda x}$.
- $\frac{\chi^2_{(m)}}{m} = \frac{1}{m}(Z_1^2 + \cdots + Z_m^2) = \frac{1}{m}\sum\limits_{i=1}^{m} Z_i^2,$ where $Z_i \sim \mathcal{N}(0,1)$. By LLN,

$$\frac{1}{m}\sum_{i=1}^{m} Z_i^2 \xrightarrow{P} \mathbb{E}[Z_i^2] = 1,$$

  as $m \to \infty$.
- $t_{(m)} \xrightarrow{D} Z$, as $m \to \infty$.

5 Properties of an Estimator: Consistency, Efficiency and Sufficiency

6 Interval Estimation

6.1 Confidence interval

- An interval $C(X_1, ..., X_n) = (l(X_1, ..., X_n), u(X_1, ..., X_n))$ is a γ***-confidence interval*** for $\psi(\theta)$ if $P_\theta[\psi(\theta) \in C(X_1, ..., X_n)] \geqslant \gamma, \forall \theta \in \Omega. \gamma$ represents the confidence level of the interval.

  ◦ In naive words: We want two numbers which will have at least γ chance of containing the true parameter.

6.2 CI for parameters of Normal distribution

6.2.1 CI for μ with σ^2 known

- We know $\frac{\overline{X}-\mu}{\sigma/\sqrt{n}} \sim \mathcal{N}(0,1)$, we can write

$$P\left[k_1 \leqslant \frac{\overline{X}-\mu}{\sigma/\sqrt{n}} \leqslant k_2\right] \geqslant \gamma \Rightarrow P\left[\overline{X} - k_2\frac{\sigma}{\sqrt{n}} \leqslant \mu \leqslant \overline{X} - k_1\frac{\sigma}{\sqrt{n}}\right] \geqslant \gamma.$$

- k_1 and k_2 are quantiles of $\mathcal{N}(0,1)$ s.t. $P[k_1 \leqslant Z \leqslant k_2] \geqslant \gamma$.

- The sampling distribution is unimodal and symmetric around the mode, the middle γ part gives the shortest interval and thus $z_{\frac{1-\gamma}{2}}$ and $z_{\frac{1+\gamma}{2}}$ are preferred as the value of k_1 and k_2. For example, if $\gamma = 0.95, k_1 = z_{0.025} = -1.96, k_2 = z_{0.975} = 1.96$.

- For $X_1, ..., X_n \overset{\text{i.i.d}}{\sim} \mathcal{N}(\mu, \sigma^2)$ with σ^2 known, the γ-CI of μ is

$$\left[\overline{X} - z_{\frac{1+\gamma}{2}}\frac{\sigma}{\sqrt{n}}, \overline{X} + z_{\frac{1+\gamma}{2}}\frac{\sigma}{\sqrt{n}}\right].$$

6.2.2 CI for μ with σ^2 unknown

- When σ^2 is unknown, we use S^2 as an estimator of σ^2 and we have $\frac{\overline{X}-\mu}{S/\sqrt{n}} \sim t_{(n-1)}$.

- For $X_1, ..., X_n \overset{\text{i.i.d}}{\sim} \mathcal{N}(\mu, \sigma^2)$ with σ^2 unknown, the γ-CI of μ is

$$\left[\overline{X} - t_{\frac{1+\gamma}{2}(n-1)}\frac{S}{\sqrt{n}}, \overline{X} + t_{\frac{1+\gamma}{2}(n-1)}\frac{S}{\sqrt{n}}\right],$$

  where $t_{\frac{1+\gamma}{2}(n-1)}$ is the $\frac{1+\gamma}{2}$ quantile of a $t_{(n-1)}$ distribution.

6.2.3 CI for σ^2

- We know $\frac{(n-1)S^2}{\sigma^2} \sim \chi^2_{(n-1)}$, we can write

$$P\left[\chi^2_{\frac{1-\gamma}{2}(n-1)} \leqslant \frac{(n-1)S^2}{\sigma^2} \leqslant \chi^2_{\frac{1+\gamma}{2}(n-1)}\right] \geqslant \gamma \Rightarrow P\left[\frac{(n-1)S^2}{\chi^2_{\frac{1+\gamma}{2}(n-1)}} \leqslant \sigma^2 \leqslant \frac{(n-1)S^2}{\chi^2_{\frac{1-\gamma}{2}(n-1)}}\right] \geqslant \gamma.$$

- For $X_1, ..., X_n \overset{\text{i.i.d}}{\sim} \mathcal{N}(\mu, \sigma^2)$, the γ-CI of σ^2 is $\left[\frac{(n-1)S^2}{\chi^2_{\frac{1+\gamma}{2}(n-1)}} \leqslant \sigma^2 \leqslant \frac{(n-1)S^2}{\chi^2_{\frac{1-\gamma}{2}(n-1)}}\right]$.

- Remark:
  - ○ χ^2 is not a symmetric distribution (at least for lower df).
  - ○ The shape of χ^2 depends on its df.
  - ○ Using $\chi^2_{\frac{1+\gamma}{2}(n-1)}$ and $\chi^2_{\frac{1-\gamma}{2}(n-1)}$ as two ends may not result in the shortest length.

6.3 CI for mean of a non-Normal distribution using CLT

- The γ-CI of μ is $\left[\overline{X} - z_{\frac{1+\gamma}{2}}\frac{\sigma}{\sqrt{n}}, \overline{X} + z_{\frac{1+\gamma}{2}}\frac{\sigma}{\sqrt{n}}\right]$, σ^2 may be unknown.
  - ○ If σ^2 is unknown, we can use MLE to calculate SE $= \frac{\sigma}{\sqrt{n}}$.

Example 6.1. CI for λ when data follows Poisson(λ).

Solution. By CLT, $\frac{\overline{X}-\lambda}{\sqrt{\lambda/n}} \xrightarrow{D} \mathcal{N}(0,1)$, where SE($\overline{X}$) $= \sqrt{\frac{\lambda}{n}}$. We know $\overline{X}$ is the MLE of λ, then the estimated SE $= \sqrt{\frac{\overline{X}}{n}}$. Thus, the γ-CI for λ is $\left[\overline{X} - z_{\frac{1+\gamma}{2}}\sqrt{\frac{\overline{X}}{n}}, \overline{X} + z_{\frac{1+\gamma}{2}}\sqrt{\frac{\overline{X}}{n}}\right]$.

6.4 Interpreting CI

- For z and t interval, the sample mean $\overline{X}$ is the midpoint of the lower and upper bound.

- Width of the interval = Upper bound$-$Lower bound. Half of the width is known as the ***margin of error*** (ME). CI: $[\overline{X} \pm \text{ME}]$.
  - $\gamma \uparrow \Rightarrow$ Width of the interval $\uparrow$.
  - σ or $s \uparrow \Rightarrow$ Width of the interval $\uparrow$.
  - $n \uparrow \Rightarrow$ Width of the interval $\downarrow$.
- Interpretation: If we keep taking samples (infinite times) and keep constructing γ-CIs, in $100\gamma\%$ of the cases, our CIs will capture the true value of the parameter.

7 Test of Hypothesis

7.1 Types of hypothesis

- ***Null hypothesis***$/H_0$: The hypothesis that we want to test.
- ***Alternative hypothesis***$/H_A/H_1$: The alternative values of the parameter of interest.
    - ○ Often this is what we are trying to prove as a researcher.
- ***Simple hypothesis***: When a hypothesis involves only a single value from the parameter space.
- ***Composite hypothesis***: When a hypothesis involves more than one values from the parameter space.
- In practice, often we test ***simple null*** hypothesis against ***composite alternative*** hypothesis.

7.2 Two approaches of hypothesis testing

7.2.1 Critical region approach

- Due to uncertainty, often we reject H_0 even though it could be true. We assign a preferably small predefined probability of making this mistake and call it ***level of significance***, denoted by α.
- ***Test statistic***, $T(X)$, is a quantity that simultaneously serves few purposes:
    - ○ It summarizes the sample data through an estimator.
    - ○ When H_0 is true, it has a known distribution.
    - ○ Under that distribution, it is possible to find some areas that has probability α.
- ***Critical region***, $R_\alpha(T)$, is a region of the distribution of the test statistic s.t. we will reject H_0 if $T(X) \in R_\alpha(T)$. We need $P[T(X) \in R_\alpha(T)|H_0 \text{ is true}] = \alpha$.

- Testing $H_0 : \mu = \mu_0$ when $X_i \overset{\text{i.i.d.}}{\sim} \mathcal{N}(\mu, \sigma^2)$ with σ^2 known:
  - ○ $H_0 : \mu = \mu_0$.
  - ○ $T = \frac{\overline{X}-\mu}{\sigma/\sqrt{n}}$.
  - ○ If H_0 is true, then $\frac{\overline{X}-\mu_0}{\sigma/\sqrt{n}} \sim \mathcal{N}(0,1)$.
  - ○ Rejection region: $\left(-\infty, z_{\frac{\alpha}{2}}\right) \cup \left(z_{1-\frac{\alpha}{2}}.\infty\right)$.
  - ○ We reject H_0 if $\frac{\overline{X}-\mu_0}{\sigma/\sqrt{n}} < z_{\frac{\alpha}{2}}$ or $\frac{\overline{X}-\mu_0}{\sigma/\sqrt{n}} > z_{1-\frac{\alpha}{2}}$.

  ○ Intuition: We reject the null hypothesis when the test statistic falls in the lower probability area of the distribution under the null. In naive words: If μ_0 is the true mean, then $\overline{X}$ should not be too far from μ_0.

  ○ Note: We never say we accept H_0. We failed to prove that H_0 is wrong $\not\Rightarrow H_0$ is right.

- Testing $H_0 : \mu = \mu_0$ when $X_i \overset{\text{i.i.d.}}{\sim} \mathcal{N}(\mu, \sigma^2)$ with σ^2 unknown:
  - ○ $T = \frac{\overline{X}-\mu_0}{S/\sqrt{n}} \sim t_{(n-1)}$.
  - ○ Rejection region: $\left(-\infty, t_{\frac{\alpha}{2}(n-1)}\right) \cup \left(t_{1-\frac{\alpha}{2}(n-1)}\right)$.

- Testing $H_0 : \sigma^2 = \sigma_0^2$ when $X_i \overset{\text{i.i.d.}}{\sim} \mathcal{N}(\mu, \sigma^2)$:
  - ○ $T = \frac{(n-1)S^2}{\sigma_0^2} \sim \chi^2_{(n-1)}$.
  - ○ $R_\alpha(T) = \left(-\infty, \chi^2_{\frac{\alpha}{2}(n-1)}\right) \cup \left(\chi^2_{1-\frac{\alpha}{2}(n-1)}\right)$.

7.2.2 $p-$value approach

- $p-$value: It is the smallest level of significance at which H_0 would be rejected based on the observed data. Also, it is the probability of observing the result as or more extreme than that actually observed if H_0 is true. In naive words: p-value suggests how surprising the observed sample is if we assume H_0 to be true.
  - ○ Conventionally, we compare p-value to $0.01, 0.05$ or 0.1.
  - ○ If $p-$value is less than a predefined cut-off, we reject H_0.

- For z-test, $p-$value $= 2\left[1 - \Phi\left(\left|\frac{\overline{X}-\mu_0}{\sigma/\sqrt{n}}\right|\right)\right]$.
- For t-test, $p-$value $= 2\left[1 - G\left(\left|\frac{\overline{X}-\mu_0}{S/\sqrt{n}}\right|\right)\right]$, where G is the CDF of a $t_{(n-1)}$ distribution.

7.3 Type-1, 2 error and power of a test

- Definition
  - $P[\text{Type} - 1 \text{ error}] = \alpha = P[\text{Reject } H_0 | H_0 \text{ is true}]$.
  - $P[\text{Type} - 2 \text{ error}] = \beta = P[\text{Fail to reject } H_0 | H_0 \text{ is false}]$.
  - Power of a test $= 1 - \beta = P[\text{Reject } H_0 | H_0 \text{ is false}]$.
- Graph analysis: Suppose we are testing two simple hypotheses, $H_0 : \mu = 1, H_1 : \mu = 4$, and there are no other options. The area shaded in red is type-1 error and in cyan is type-2 error.

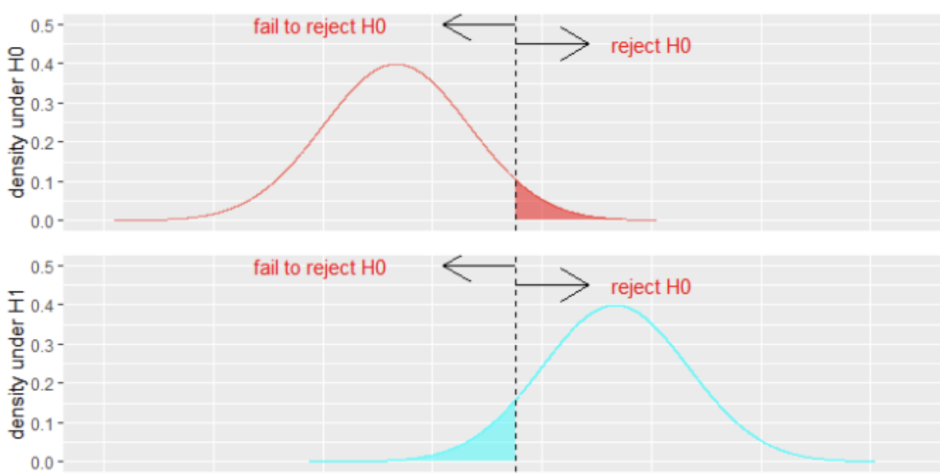

Figure 7.1: $H_0 : \mu = 1, H_1 : \mu = 4$.

Example 7.1. Suppose we have $\mathcal{N}(\mu, \sigma^2)$ populations with unknown μ and $\sigma = 3$. We want to test $H_0 : \mu = 1, H_1 : \mu = 4$ at $\alpha = 0.05, n = 9$. Calculate β and $1 - \beta$.

Solution. We have $\text{SE}(\overline{X}) = \frac{\sigma}{\sqrt{n}} = 1$.

Therefore, under $H_0, \overline{X} \sim \mathcal{N}(1, 1)$ and under $H_1, \overline{X} \sim \mathcal{N}(4, 1)$. Hence, $R_\alpha = \frac{\overline{X}-1}{1} > z_{0.95} \Rightarrow \overline{X} > 2.645$.

Therefore,

$$1 - \beta = P[\overline{X} > 2.645 | H_1] = P\left[\frac{\overline{X} - 4}{1} > \frac{2.645 - 1}{1}\right] = 0.912,$$

and $\beta = 1 - 0.912 = 0.088$.

7.4 Test of hypothesis using CI

- Let $\alpha = 1 - \gamma$. Constructing a γ level CI for μ and checking whether μ_0 is inside or note is equivalent of testing the hypothesis of $\mu = \mu_0$ at $(1 - \gamma)$ level of significant.

8 Likelihood Ratio Test and Comparing Two Populations

8.1 Likelihood ratio test (LRT)

- General definition: Suppose we are testing $H_0 : \theta \in \Omega_0, H_1 : \theta \in \Omega_1$. Let $L(\theta)$ represents the likelihood function. The generalized likelihood ratio is defined as $\Lambda^* = \frac{\max_{\theta \in \Omega_0} L(\theta)}{\max_{\theta \in \Omega_1} L(\theta)}$. A small value of Λ^* provides evidence against H_0.

- Special case: $\Lambda = \frac{\max_{\theta \in \Omega_0} L(\theta)}{\max_{\theta \in \Omega} L(\theta)} = \frac{\max_{\theta \in \Omega_0} L(\theta)}{L(\widehat{\theta})}$, where $\widehat{\theta}$ is MLE of θ.

  ∘ If $\widehat{\theta} \in \Omega_0$, then $\Lambda = 1 \Rightarrow$ we will not reject H_0.

  ∘ If $\widehat{\theta} \notin \Omega_0$. we look for the most likely θ value in Ω_0 and check if it does a good enough job as it is done by the MLE.

  ∘ Λ value closer to 0 will provide evidence against H_0.

Theorem 8.1. Let $p = \dim \Omega$ be the number of free parameters in the whole parameter space, $d = \dim \Omega_0$ be the number of free parameters under the null, then we have $-2 \ln \Lambda \xrightarrow{P} \chi^2_{(p-d)}$, when H_0 is true.

Example 8.1. $(X_1, ..., X_n) \overset{\text{i.i.d.}}{\sim} \mathcal{N}(\mu, \sigma_0^2)$. Test $H_0 : \mu = \mu_0$ at level of significance α.

Solution. We have $L(\mu) = (2\pi\sigma_0^2)^{-\frac{n}{2}} \exp\left[-\frac{1}{2\sigma_0^2} \sum (X_i - \mu)^2\right]$.

Under $H_0, L(\mu_0) = (2\pi\sigma_0^2)^{-\frac{n}{2}} \exp\left[-\frac{1}{2\sigma_0^2} \sum (X_i - \mu_0)^2\right]$.

We know $L(\mu)$ is maximized at $\overline{X}$ and thus

$$L(\widehat{\mu}) = (2\pi\sigma_0^2)^{-\frac{n}{2}} \exp\left[-\frac{1}{2\sigma_0^2} \sum (X_i - \overline{X})^2\right].$$

Therefore,

$$\begin{aligned}\Lambda = \frac{L(\mu_0)}{L(\widehat{\mu})} &= \exp\left[-\frac{1}{2\sigma_0^2}\left(\sum (X_i - \mu_0)^2 - \sum (X_i - \overline{X})^2\right)\right] \\ &= \exp\left[-\frac{1}{2\sigma_0^2} n(\overline{X} - \mu_0)^2\right].\end{aligned}$$

Besides, $p = 1, d = 0$ and thus

$$-2\ln\Lambda = \frac{1}{\sigma_0^2}n(\overline{X} - \mu_0)^2 = \left(\frac{\overline{X} - \mu_0}{\sigma_0/\sqrt{n}}\right)^2 \sim \chi^2_{(1)}.$$

We reject H_0 if $-2\ln\Lambda > \chi^2_{1-\alpha(1)}$.

- LRT for non-Normal distribution: LRT allows us to test hypothesis for non-Normal distributions since all we need is the likelihood function evaluated at θ_0 and $\widehat{\theta}$.

  Example 8.2. Suppose $X_i \sim \text{Exp}(\theta), \mathbb{E}[X] = \theta$. We test $H_0 : \theta = 60, H_1 : \theta \neq 60$. Besides, $n = 100, \overline{x} = 75$.

  Solution. (Method 1) $L(\theta) = \frac{1}{\theta^n}\exp\left[-\frac{1}{\theta}\sum_{i=1}^{n} X_i\right]$ and the MLE is $\overline{X}$. Therefore, $\Lambda = \left(\frac{\overline{X}}{\theta_0}\right)^n \exp\left[n(1 - \frac{\overline{X}}{\theta_0})\right]$ and thus

  $$-2\ln\Lambda = -2n\left(\ln\overline{X} - \ln\theta_0 + 1 - \frac{\overline{X}}{\theta_0}\right) \sim \chi^2_{(1)}.$$

  Since $\theta_0 = 60, n = 100, \overline{x} = 75$, then $-2\ln\Lambda = 5.37 > \chi^2_{0.95(1)} = 3.84$. Thus we reject H_0 at $\alpha = 0.05$.

  (Method 2) If H_0 is true, then $-2\ln\Lambda \sim \chi^2_{(1)}$ and $p-$value $= P(\chi^2_{(1)} > 5.37) = 0.02$.

8.2 Constructing CI using LRT

- Under $H_0, -2\ln\Lambda \xrightarrow{D} \chi^2_{(p-d)}$, we reject H_0 if $-2\ln\Lambda > \chi^2_{1-\alpha(p-d)}$. Conversely, we will fail to reject if $-2\ln\Lambda < \chi^2_{1-\alpha(p-d)}$. Thus, $(1-\alpha)$ level CI for θ is the interval of θ values for which $-2\ln\Lambda < \chi^2_{1-\alpha(p-d)}$, i.e., $L(\theta) > L(\widehat{\theta})\exp\left[-\frac{\chi^2_{1-\alpha(p-d)}}{2}\right]$.

8.3 Comparing two independent Normal population

8.3.1 Equality of two variances

- Suppose we have two independent Normal samples $X_1, ..., X_n \sim \mathcal{N}(\mu_X, \sigma_X^2)$ and $Y_1, ..., Y_m \sim \mathcal{N}(\mu_Y, \sigma_Y^2)$. We want to test $H_0 : \sigma_X^2 = \sigma_Y^2$, and $H_1 : \sigma_X^2 \neq \sigma_Y^2$.

- We have $\frac{(n-1)S_X^2}{\sigma_X^2} \sim \chi^2_{(n-1)}$, $\frac{(m-1)S_Y^2}{\sigma_Y^2} \sim \chi^2_{(m-1)}$ and thus

$$\frac{S_X^2/\sigma_X^2}{S_Y^2/\sigma_Y^2} \sim F_{(n-1,m-1)}.$$

  Under H_0, we have $\frac{S_X^2}{S_Y^2} \sim F_{(n-1,m-1)}$.

- The rejection region is $\left(-\infty, F_{\frac{\alpha}{2}(n-1,m-1)}\right) \cup \left(F_{1-\frac{\alpha}{2}(n-1,m-1)}, \infty\right)$.

8.3.2 Equality of two means with variances known

- We want to test $H_0 : \mu_X = \mu_Y$, which is same to test $H_0 : \mu_X - \mu_Y = 0$.

- We have $\overline{X} \sim \mathcal{N}(\mu_X, \frac{\sigma_X^2}{n}), \overline{Y} \sim \mathcal{N}(\mu_Y, \frac{\sigma_Y^2}{m})$ and thus

$$\frac{(\overline{X} - \overline{Y}) - (\mu_X - \mu_Y)}{\sqrt{\frac{\sigma_X^2}{n} + \frac{\sigma_Y^2}{m}}} \sim \mathcal{N}(0, 1).$$

  Under H_0, we have

$$\frac{\overline{X} - \overline{Y}}{\sqrt{\frac{\sigma_X^2}{n} + \frac{\sigma_Y^2}{m}}} \sim \mathcal{N}(0, 1).$$

- The $(1-\alpha)$ level CI is $\left[(\overline{X} - \overline{Y}) \pm z_{1-\frac{\alpha}{2}}\sqrt{\frac{\sigma_X^2}{n} + \frac{\sigma_Y^2}{m}}\right]$ and check if 0 is inside or not. Or, the rejection region is $\left(-\infty, z_{\frac{\alpha}{2}}\right) \cup \left(z_{1-\frac{\alpha}{2}}, \infty\right)$. Or, calculate the $p-$value.

- If $\sigma_X = \sigma_Y = \sigma$, then under H_0, we have $\frac{\overline{X}-\overline{Y}}{\sigma\sqrt{\frac{1}{n}+\frac{1}{m}}} \sim \mathcal{N}(0, 1)$.

8.3.3 Equality of two means with variances unknown

- Suppose $\sigma_X = \sigma_Y = \sigma$.
- We have $\frac{\overline{X}-\overline{Y}}{\sigma\sqrt{\frac{1}{n}+\frac{1}{m}}} \sim \mathcal{N}(0,1)$, and

$$\begin{aligned}\frac{(n-1)S_X^2}{\sigma^2} + \frac{(m-1)S_Y^2}{\sigma^2} &= \frac{1}{\sigma^2}[(n-1)S_X^2 + (m-1)S_Y^2] \\ &\sim \chi^2_{(n-1)} + \chi^2_{(n-1)} = \chi^2_{(n+m-2)}.\end{aligned}$$

Therefore,

$$\frac{\frac{\overline{X}-\overline{Y}}{\sigma\sqrt{\frac{1}{n}+\frac{1}{m}}}}{\sqrt{\frac{1}{\sigma^2}[(n-1)S_X^2 + (m-1)S_Y^2]/(n+m-2)}} \sim t_{(n+m-2)},$$

i.e.,

$$\frac{\overline{X}-\overline{Y}}{S_p\sqrt{\frac{1}{n}+\frac{1}{m}}} \sim t_{(n+m-2)},$$

where $S_p^2 = \frac{(n-1)S_X^2+(m-1)S_Y^2}{n+m-2}$ is called the ***pooled sample variance***.

8.4 Comparing two population means (paired data)

- In many practical setting, the samples are paired and thus the observations are not independent.
- We want to test $H_0: \mu_X - \mu_Y = 0, H_1: \mu_X - \mu_Y \neq 0$.
  - ◦ If we use $\overline{X}-\overline{Y}$, $\text{Var}[\overline{X}-\overline{Y}]$ will contain a covariance term.
  - ◦ To simplify, define $D = X - Y \Rightarrow \mu_D = \mu_X - \mu_Y$, and thus

$$\frac{\overline{D}}{S_D/\sqrt{n}} \sim t_{(n-1)}.$$

8.5 Comparing two populations using LRT

- Suppose we have two independent Normal samples: $X_1, , X_n \sim \mathcal{N}(\mu_X, \sigma_X^2)$ and $Y_1, , Y_m \sim \mathcal{N}(\mu_Y, \sigma_Y^2)$, where σ_X^2 and σ_Y^2 are known. We want to test $H_0: \mu_X = \mu_Y$ by LRT.

$\circ$ We have two unknown parameters μ_X, μ_Y. Under H_0, $\mu_X = \mu_Y = \mu$, then we have one unknown parameter.

$\circ$ We have

$$L(\mu_X, \mu_Y) = (2\pi\sigma_X^2)^{-\frac{n}{2}} \exp\left[-\frac{1}{2\sigma_X^2}\sum_{i=1}^{n}(X_i - \mu_X)^2\right](2\pi\sigma_Y^2)^{-\frac{n}{2}} \exp\left[-\frac{1}{2\sigma_Y^2}\sum_{i=1}^{n}(Y_i - \mu_Y)^2\right],$$

and $\widehat{\mu}_X = \overline{X}, \widehat{\mu}_Y = \overline{Y}$.

$\circ$ Under H_0, we have

$$L(\mu) = (2\pi\sigma_X^2)^{-\frac{n}{2}} \exp\left[-\frac{1}{2\sigma_X^2}\sum_{i=1}^{n}(X_i - \mu)^2\right](2\pi\sigma_Y^2)^{-\frac{n}{2}} \exp\left[-\frac{1}{2\sigma_Y^2}\sum_{i=1}^{n}(Y_i - \mu)^2\right],$$

and to find the MLE of μ, we have

$$l(\mu) = C - \frac{1}{2\sigma_X^2}\sum(X_i - \mu)^2 - \frac{1}{2\sigma_Y^2}\sum(Y_j - \mu)^2.$$

Hence,

$$\partial_\mu l = \frac{1}{\sigma_X^2}\sum(X_i - \mu) + \frac{1}{\sigma_Y^2}\sum(Y_j - \mu) = \frac{1}{\sigma_X^2}(n\overline{X} - n\mu) + \frac{1}{\sigma_Y^2}(m\overline{Y} - m\mu).$$

Let $\partial_\mu l = 0$, we have

$$\widehat{\mu} = \frac{\frac{1}{\sigma_X^2/n}}{\frac{1}{\sigma_X^2/n} + \frac{1}{\sigma_X^2/m}}\overline{X} + \frac{\frac{1}{\sigma_Y^2/m}}{\frac{1}{\sigma_X^2/n} + \frac{1}{\sigma_Y^2/m}}\overline{Y}.$$

$\circ$ Hence, $-2\ln\Lambda = -2\ln\frac{L(\widehat{\mu})}{L(\widehat{\mu}_X, \widehat{\mu}_Y)}$ and under $H_0, -2\ln\Lambda \sim \chi^2_{(1)}$.

8.6 Numerical example

Example 8.3. $(4, 10, 10, 4, 6, 8, 8, 3, 4, 4) \overset{\text{i.i.d.}}{\sim} \text{Pois}(\lambda)$. Test $H_0 : \lambda = 5$.

Solution. (Method 1) $L(\lambda) = \frac{e^{-n\lambda}\lambda^{\sum x_i}}{\prod x_i!}$. Since $n = 10, \lambda_0 = 5, \widehat{\lambda} = \overline{x} = 6.1$, then we have

$$\Lambda = \frac{e^{-50}5^{61}}{e^{-61}(6.1)^{61}} = 0.3231, -2\ln\Lambda = 2.2598.$$

Since $\chi^2_{0.95(1)} = 3.841459, -2\ln\Lambda < \chi^2_{0.95(1)}$, then we fail to reject H_0.

(Method 2) If H_0 is true, then $-2\ln\Lambda \sim \chi^2_{(1)}$. Thus, $p-$value $= P[\chi^2_{(1)} > 2.2598] = 0.13 > 0.05$.

Example 8.4. (Rice, pp.425, B) $\overline{x}_A = 80.02, \overline{x}_B = 79.98, s_{x_A} = 0.024, s_{x_B} = 0.031$, and σ_A, σ_B are unknown.

Solution. We have $s_p^2 = \frac{12(0.024)^2+7(0.031)^2}{19}, s_p\sqrt{\frac{1}{n}+\frac{1}{m}} = 0.012$.

The test statistic is $T = 3.3333, t_{0.975(19)} = 2.093$. Since $T > t_{0.975(19)}$, we reject H_0. The 95% CI for $\mu_{x_A} - \mu_{x_B}$ is $\left[(\overline{x}_A - \overline{x}_B \pm t_{0.975(19)}s_p\sqrt{\frac{1}{n}+\frac{1}{m}})\right] = [0.015, 0.065]$.

Example 8.5. (Week 8 slide, pp. 32) Let X and Y represent the before and after measurements of 10 participants. Check whether the drink changes the blood sugar level or not.

Solution. We have $\overline{d} = 4.47, s_d = 3.545106$.

The test statistic is $T = \frac{\overline{d}}{s_d/\sqrt{n}} = 3.987294, t_{0.975(9)} = 2.262$. Since $T > t_{0.975(9)}$, we reject H_0. Besides, the rejection region is $(-\infty, -2.262) \cup (2.262, \infty)$.

9 Model Checking

9.1 χ^2 goodness of fit test

- The test is used to assess whether or not a ***categorical random variable*** W, which takes finite values $\{1, 2, ..., k\}$, has a specified probability measure P.

  ∘ When we have discrete r.v. which takes infinitely many values, we partition the possible values into k categories.

  ∘ When we have a continuous r.v., we partition the real line into k sub-intervals.

  Naturally, the counts of these k categories form a ***multinomial distribution***.

- Let $X_1, ..., X_k$ be the observed counts of category $1, 2, ..., k$ respectively. We can write $(X_1, ..., X_k) \sim \text{Multinomial}(n, p_1, ..., p_k)$.

  Besides, $\mathbb{E}[X_i] = np_i, \text{Var}[X_i] = np_i(1 - p_i)$. The test statistic T is $X^2 = \sum_{i=1}^{k} \frac{(X_i - np_i)^2}{np_i} \xrightarrow{D} \chi^2_{(k-1)}$. Or we can say

$$X^2 = \sum_{i=1}^{k} \frac{(\text{Observed count of } i - \text{Expected count of } i)^2}{\text{Expected count of } i} \xrightarrow{D} \chi^2_{(k-1)}.$$

  Proof. (For the simple case, i.e., $k = 2$)

  We have

$$\begin{aligned} X^2 &= \sum_{i=1}^{2} \frac{(X_i - np_i)^2}{np_i} = \frac{(X_1 - np_1)^2}{np_1} + \frac{(X_2 - np_2)^2}{np_2} \\ &= \frac{(X_1 - np_1)^2}{np_1} + \frac{(n - X_1 - n(1 - p_1))^2}{np_2} = \frac{(X_1 - np_1)^2}{np_1} + \frac{(X_1 - np_1)^2}{np_2} \\ &= \frac{(X_1 - np_1)^2}{n} \left(\frac{1}{p_1} + \frac{1}{p_2} \right) = \left(\frac{X_1 - np_1}{\sqrt{np_1p_2}} \right)^2 \xrightarrow{D} \chi^2_{(1)}. \end{aligned}$$

  □

∘ It is recommended to ensure that $\mathbb{E}[X_i] = np_i \geqslant 1, \forall i$.

Example 9.1. Suppose we have 10000 random numbers generated from a Uniform[0, 1] distribution. After dividing them into 10 equal length bins, we test if these numbers look uniform or not.

i	1	2	3	4	5	6	7	8	9	10
x_i	993	1044	1061	1021	1017	973	975	965	996	955

Solution. If the numbers are really from a Uniform[0, 1] distribution then expected counts for each cell is $10000 \cdot \frac{1}{10} = 1000$, so we have

i	1	2	3	4	5	6	7	8	9	10
x_i	993	1044	1061	1021	1017	973	975	965	996	955
$\widehat{x}_i$	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000

The test statistic is $X^2 = \frac{(993-1000)^2}{1000} + \cdots + \frac{(955-1000)^2}{1000} = 11.056$. The p-value is 0.27189, and thus we fail to reject the statement that these number are from a Uniform[0, 1] distribution. In naive words, they look uniform.

The code for p-value is:

```
1 - pchisq(11.056, 9)
```

Example 9.2. Suppose life-lengths of light bulbs (Y_i) follows an Exponential(β), where β is unknown. We have the partitions as

$$(0, 1], (1, 2], (2, 3], (3, \infty).$$

Based on the sample of size $n = 30$, the observed counts are 5, 16, 8, 1. We test H_0 : The true model is Exponential(β).

Solution. First, we find the MLE for β. If the life-lengths of the 30 bulbs are available, then

$$L(\beta) = \beta^{30} \exp\left[-\beta \sum y_i\right] \Rightarrow \widehat{\beta} = \frac{1}{\overline{y}}.$$

If all we have is the counts of Y_i's that fall into those four partitions, we can define

$$L(\beta) = (1 - e^{-\beta})^2 (e^{-\beta} - e^{-2\beta})^{16} (e^{-2\beta} - e^{-3\beta})^8 (e^{-3\beta})^1,$$

where $(1-e^{-\beta}) = P(Y_i \in (0,1])$, similarly the other terms. For instance,

$$p_2 = \int_1^2 \beta e^{-\beta x} \, \mathrm{d}x = e^{-\beta} - e^{-2\beta}.$$

Thus, we have $\widehat{\beta} = 0.603535$, and

$$\begin{aligned} p_1 &= 0.453125, \\ p_2 &= 0.247803, \\ p_3 &= 0.135517, \\ p_4 &= 0.163555. \end{aligned}$$

The expected counts are $13.59375, 7.43409, 4.06551, 4.90665$, respectively.

Hence, the test statistic is $X^2 = \frac{(5-13.59375)^2}{13.59375} + \cdots = 22.22$. The p-value is 0.000015, and thus we reject H_0, i.e., we have strong evidence that Exponential(β) is not the true model for these data.

The code for p-value is:

```
1 - pchisq(22.22, 2)
```

9.2 Discrepancy statistic

- Suppose $(X_1, ..., X_n)$ is believed to be from f_θ with $\theta \in \Omega$. ***Discrepancy statistic***, $D(X)$ is a function that takes the samples observations and maps it to $\mathbb{R}$. It measures the deviation from the model under consideration. A large value of $D(X)$ implies a deviation has occurred.

  ∘ In test of hypothesis sense, we asses whether $D(X)$ lies in the region of low probability of its distribution when the model is correct.

  ∘ Restriction: When the model is correct, D must have a single distribution, i.e., the distribution of D cannot depend on θ.

◦ A statistic D whose distribution under the model does not depend upon θ is called ***ancillary***, i.e., if $(X_1, ..., X_n) \sim f_\theta$, then $D(X)$ has the same distribution for every $\theta \in \Omega$.

∗ Being ancillary does not mean D can be used as a discrepancy statistic.

∗ If D is constant, then it is ancillary, but not useful for model checking.

Example 9.3. Suppose $(X_1, ..., X_n) \sim \mathcal{N}(\mu, \sigma_0^2)$, X_i's are independent. Define $R_i = X_i - \overline{X}$. For instance,

$$X_1 - \overline{X} = X_1 - \frac{1}{n}(X_1 + \cdots + X_n) = (1 - \frac{1}{n})X_1 - \frac{1}{n}X_2 - \cdots - \frac{1}{n}X_n.$$

Thus,

$$\mathbb{E}[X_1 - \overline{X}] = \mathbb{E}[X_1] - \mathbb{E}[\overline{X}] = \mu - \mu = 0,$$

and

$$\begin{aligned}
&\mathrm{Var}[X_1 - \overline{X}] = \mathrm{cov}(X_1 - \overline{X}, X_1 - \overline{X}) \\
&= \mathrm{cov}((1 - \frac{1}{n})X_1 - \frac{1}{n}X_2 - \cdots - \frac{1}{n}X_n, (1 - \frac{1}{n})X_1 - \frac{1}{n}X_2 - \cdots - \frac{1}{n}X_n) \\
&= (1 - \frac{1}{n})\sigma_0^2,
\end{aligned}$$

Therefore, $R_i \sim \mathcal{N}(0, (1 - \frac{1}{n})\sigma_0^2)$. The discrepancy statistic

$$D(R) = \frac{1}{\sigma_0^2}\sum_{i=1}^{n} R_i^2 = \frac{1}{\sigma_0^2}\sum_{i=1}^{n}(X_i - \overline{X})^2 = \frac{(n-1)S^2}{\sigma_0^2} \sim \chi^2_{(n-1)}$$

If $D(r)$ represent the observed value of D based on the current sample then, then we can calculate the p-value.

9.3 Residual and quantile/probability plots

- Residual plot: Since $R_i \sim \mathcal{N}(0, (1 - \frac{1}{n}\sigma_0^2))$, we can define ***standardized residual***

$$r_i^* = \frac{x_i - \overline{x}}{\sqrt{(1 - \frac{1}{n}\sigma_0^2)}}.$$

If the true model is $\mathcal{N}(\mu, \sigma_0^2)$, then our expectation is that r_i^*'s will behave like values from a $\mathcal{N}(0, 1)$.

- ∘ Plotting $r_1^*, ..., r_n^*$ against $(1, ..., n)$.
- ∘ The points should be clustered around zero.
- ∘ The points should lie in (-3, 3).
- ∘ They should look random (should not depict any pattern).

Example 9.4. Points in Figure 9.2 satisfies the conditions above. Some of points in Figure 9.3 are outside (-3, 3), indicating longer tail. Most of points in Figure 9.4 are on positive side, indicating right skewed.

- Quantile/Probability plots: Suppose (X_i) is believed to be from $\mathcal{N}(\mu, \sigma^2)$. Let $X_{(i)}$ represent the i-th order statistic. We have

$$\mathbb{E}[X_{(i)}] = \mu + \sigma \cdot \Phi^{-1}\left(\frac{i}{n+1}\right),$$

where Φ^{-1} is the inverse CDF of $\mathcal{N}(0, 1)$.

Let x_j correspond to the oder statistic $x_{(i)}$, then $\Phi^{-1}\left(\frac{i}{n+1}\right)$ is the ***Normal score*** of x_j. If we plot the points $\left(x_{(i)}, \Phi^{-1}\left(\frac{i}{n+1}\right)\right)$, they should lie approximately on a straight line with intercept μ and slope σ.

Example 9.5. Suppose we want to assess whether or not the following data set can be considered a sample of sample of size $n = 10$ from some Normal distribution:

2.00 0.28 0.47 3.33 1.66 8.17 1.18 4.15 6.43 1.77

The order statistics and associated Normal scores are

i	1	2	3	4	5
$x_{(i)}$	0.28	0.47	1.18	1.66	1.77
$\Phi^{-1}\left(\frac{i}{n+1}\right)$	-1.34	-0.91	-0.61	-0.35	-0.12

i	6	7	8	9	10
$x_{(i)}$	2.00	3.33	4.15	6.43	8.17
$\Phi^{-1}\left(\frac{i}{n+1}\right)$	0.11	0.34	0.60	0.90	1.33

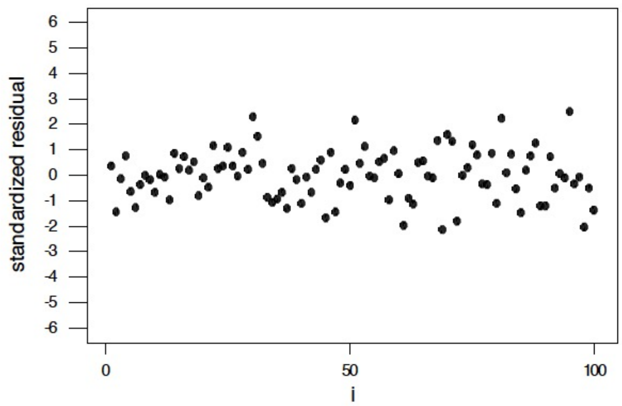

Figure 9.2: A plot of the standardized residuals for a sample of 100 from an $\mathcal{N}(0, 1)$ distribution.

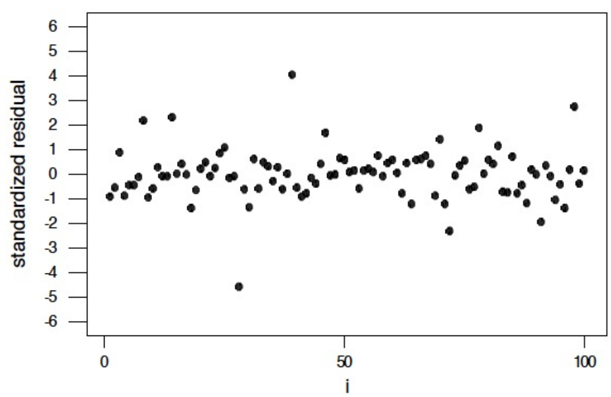

Figure 9.3: A plot of the standardized residuals for a sample of 100 from $X = (\sqrt{3})^{-1}Z$, where $Z \sim t_{(3)}$.

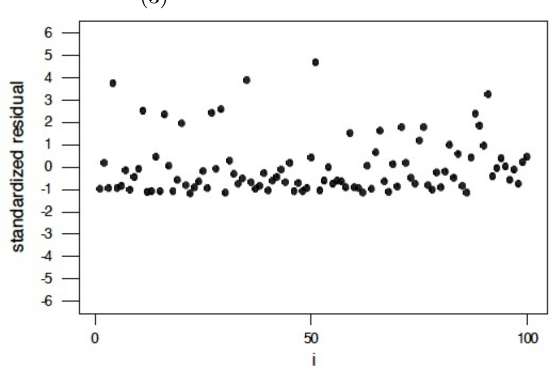

Figure 9.4: A plot of the standardized residuals for a sample of 100 from an Exponential(1) distribution.