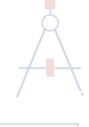


WINTER 20/21

STA.303

Review 面条









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Winter 2021 STA 303

Mixed assessment

February 19, 2021

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Review of Linear Regression

• Model:

$$y_i = \beta_0 + \beta_1 x_{1i} + \ldots + \beta_p x_{pi} + \varepsilon_i$$

- -y: response variable
- $-x_1,\ldots,x_p$: Explanatory variable/predictor
- $-\varepsilon$: Error term
- Key Assumptions:
 - Linear relationship: All the β 's enter the model in a linear way. The predictor can be in any form.

*
$$y_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i}^2 + \varepsilon_i$$

* $y_i = \beta_0 + \beta_1 \beta_2 x_{1i} + \varepsilon_i$ ×

*
$$y_i = \beta_0 + \beta_1 \beta_2 x_{1i} + \varepsilon_i \times$$

总而言之,不要让不同的 β 出现在同一项里。

- Errors are **independent** (Satisfied if observations are independent) 比如说对于这一个病人,连续测量了 100 天的体温,就不能算作是一组 independent observations.
- Errors are **normally** distributed with zero expected value, i.e., $E(\varepsilon_i) = 0$ 如果 response variable 是一个 categorical variabel, 那就不能用 linear regression 来做。
- Equal/constant variance (homoscedasticity), i.e., $var(\varepsilon_i) = \sigma^2$.

2 Common Statistical Tests

2.1 Introduction

	Parametric	Non-Parametric
主要的区别	Require distributional assumption	Purely based on data(Distribution Free)
与某组数字对比差异	One-sample t-test	Wilcoxon signed rank
两组数据之间的差异	Two-sample t-test	Mann-Whitney-U
多组数据之间的差异	One-way ANOVA	Kruskal-Wallace
配对数据之间的差异	Paired t-test	Paired Wilcoxon signed rank

这门课我们主要 focus 在 Parametric Tests 上,因为大多数时候我们对于样本都假设服从正态分布 – Normal distribution.

2.2 One-Sample t-test

- Assumptions:
 - 1. The data are continuous
 - 2. The data are normally distributed
 - 3. The sample is a simple random sample from its population. (意味着 population 里每一个个体都有相同的概率被包含在样本里,同时 random sampling 保证了 observation 之间的独立性)
- Hypotheses:

 $H_0: \mu = \text{hypothesized value}$

 $H_1: \mu \neq \text{hypothesized value}$

• Test Statistic:

$$t = \frac{\bar{x} - \text{hypothesized value}}{s/\sqrt{n}}$$

 $-\bar{x}$: sample mean

-s: sample standard deviation

Under H_0 , the test statistic follows the t-distribution with degree of freedom df = n-1.

• p-value:

p-value =
$$\Pr(|t_{n-1}| > |t|) = 2\Pr(t_{n-1} > |t|)$$

• Relationship with Linear Regression:

$$y = \beta_0 + \varepsilon$$
 (Intercept-only model)

Then,

 $H_0: \mu = \text{hypothesized value} \Leftrightarrow H_0: \beta_0 = \text{hypothesized value}$

 $H_1: \mu \neq \text{hypothesized value} \Leftrightarrow H_1: \beta_0 \neq \text{hypothesized value}$

2.3 Dummy Variables

这一部分内容是为了帮助大家理解后面介绍的多样本检验。

• Model matrix/Design matrix: Consider a multiple linear regression

$$y = X\beta + \varepsilon$$

where

$$\mathbf{y} = \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{pmatrix},$$

$$oldsymbol{eta} = egin{pmatrix} eta_0 \ eta_1 \ dots \ eta_p \end{pmatrix}, oldsymbol{arepsilon} = egin{pmatrix} arepsilon_1 \ arepsilon_2 \ dots \ arepsilon_n \end{pmatrix}$$

and

$$\mathbf{X} = \begin{pmatrix} 1 & x_{11} & \cdots & x_{1p} \\ 1 & x_{21} & \cdots & x_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ 1 & x_{n1} & \cdots & x_{np} \end{pmatrix}$$

Here, **X** is the so-called model matrix.

- Usually, if we have p predictors, we will have a $n \times (p+1)$ matrix.
- However, if one of the predictor is a categorical variable (also called factor) with k different levels. Then we may have another story.

• How R deals with factor?

- Case 1: When the predictor is numerical data, one column for each predicator.
- Case 2: When the predictor is categorical data with k levels, k-1 columns will be allocated to this predictor with meaningful names. In this case, if k > 2, the model matrix is no longer tidy.

```
> y = rnorm(6)
 #Case 1: X is numerical data
> x = rnorm(6)
 mod1 = lm(y \sim x)
> model.matrix(mod1)
  (Intercept)
1
            1 -0.36779526
               0.80742972
            1 0.31876245
            1 1.14942357
            1 -0.08720758
            1 -0.25540711
attr(,"assign")
[1] 0 1
> #Case 2: X is categorical data, suppose X have three levels ("Low", "Medium", "High")
> x = rep(c("Low", "Medium", "High"), 2)
> mod2 = lm(y\sim x)
> model.matrix(mod2)
  (Intercept) xLow xMedium
1
            1
                 1
                          1
3
                          0
attr(,"assign")
[1] 0 1 1
attr(,"contrasts")
attr(,"contrasts")$x
[1] "contr.treatment"
```

• Dummy variable

- What R is doing for a categorical variable(factor)?
 - * Drop the first level (Alphabetically), the dropped level becomes the reference level.
 - * Create dummy variables for the other levels.
- How to interpret dummy variables?
 - * 0: The observation not belongs to that level
 - * 1: The observation belongs to that level
- Why we have to drop one level?
 - * Mathematically, we have to make the model matrix \mathbf{X} an invertible matrix to get estimates of $\boldsymbol{\beta}$.
 - * Intuitively, we should have linearly independent predictors.

2.4 Two-sample t-test

- Assumptions:
 - 1. The data are continuous
 - 2. The data are normally distributed in each group
 - 3. Each group is a simple random sample from its population. Each individual in the population has an equal probability of being selected in the sample
 - 4. \star The variances for the groups are equal.
- Hypotheses:

$$H_0: \mu_1 = \mu_2$$

$$H_1: \mu_1 \neq \mu_2$$

• Test Statistic:

$$t = \frac{\bar{x}_1 - \bar{x}_2}{\sqrt{s^2 \left(\frac{1}{n_1} + \frac{1}{n_2}\right)}}$$

- $-\bar{x}_1, \bar{x}_2$: sample mean for each group
- -s: pooled sample standard deviation

$$s = \sqrt{\frac{(n_1 - 1)s_1^2 + (n_2 - 1)s_2^2}{n_1 + n_2 - 2}}$$

Under H_0 , the test statistic follows the t-distribution with degree of freedom

$$df = (n_1 - 1) + (n_2 - 1) = n_1 + n_2 - 2.$$

• p-value:

p-value =
$$\Pr(|t_{n_1+n_2-2}| > |t|) = 2\Pr(t_{n_1+n_2-2} > |t|)$$

• Relationship with Linear Regression:

$$y = \beta_0 + \beta_1 x + \varepsilon$$
 (x is a factor with two levels)

Then,

$$H_0: \mu_1 = \mu_2 \Leftrightarrow H_0: \beta_1 = 0$$

$$H_1: \mu_1 \neq \mu_2 \Leftrightarrow H_1: \beta_1 \neq 0$$

2.5 One-way ANOVA (F-test)

可以看作是 independent two-sample t-test 的延伸,用于检验多组样本 (>2) 之间的差异。

- Assumptions:
 - 1. The data are continuous
 - 2. The data are normally distributed in each group
 - 3. Each group is a simple random sample from its population. Each individual in the population has an equal probability of being selected in the sample
 - 4. \bigstar The variances for the groups are equal.
- Hypotheses:

$$H_0: \mu_1 = \mu_2 = \dots = \mu_n$$

 H_1 : at least one μ differ from the others.

• Relationship with Linear Regression:

$$y = \beta_0 + \beta_1 D_1 + \ldots + \beta_{n-1} D_{n-1} + \varepsilon$$

Here, we assume predictor x is a factor with n levels (corresponding to n different groups), therefore R will allocate n-1 dummy variables in the model.

$$H_0: \mu_1 = \mu_2 = \dots = \mu_n \Leftrightarrow H_0: \beta_1 = \beta_2 = \dots = \beta_{n-1} = 0$$

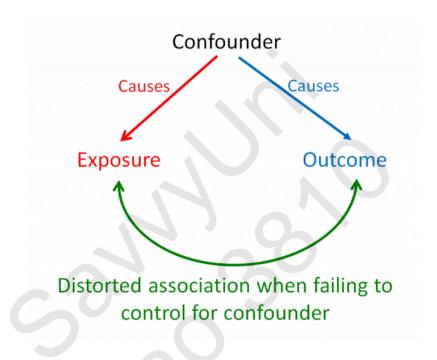
 H_1 : at least one μ differ from the others. $\Leftrightarrow H_1$: at least one β differ from 0.

所以 linear regression 里的 F-test 其实在比较的是一个 full model 和 intercept-only model 之间的 fit performance。

3 Confounding and Study Design

3.1 Confounding

• Confounder: 干扰因素, 会同时影响 dependent variable (Y) 和 independent variable (X), 忽略它的存在会使得我们得出错误的结论 (spurious association)



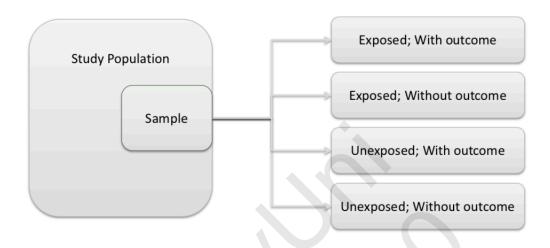
3.2 Association and causation

- Association: 相关性,来自于调查的数据或者观察到的现象 (Observational Study)。
 - Confounder 的存在可能会使得我们得出错误的 association
- Causation: 因果性, 需要严格的科学实验来得出结论 (Experimental Study)
 - 会对 confounder 进行控制,消除 confounder 的影响

3.3 Observational vs Experimental Study

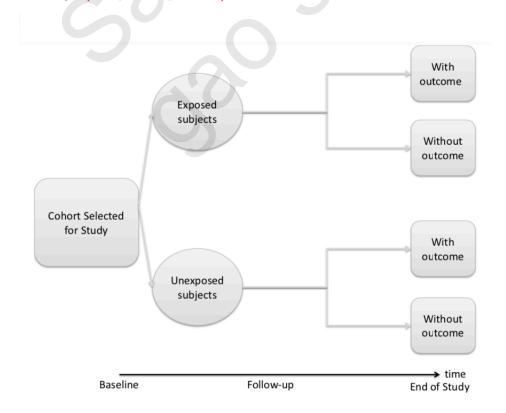
	Observational Study	Experimental Study
Methods	Survey/Cross Sectional Study Cohort Study, Case-Control Study	Randomized Control Trial
Difference	Without control over the exposure	With control over the exposure
Conclusion	Association	Causation
Limitation	Susceptible to confounding	Not always feasible (impratical/unethical/costly)

Survey/Cross-Sectional Study (Observational)



- 根据调查同时得到每一个 subject 的 exposure 和 outcome
- 样本需要有代表性, 否则会面临 selection bias

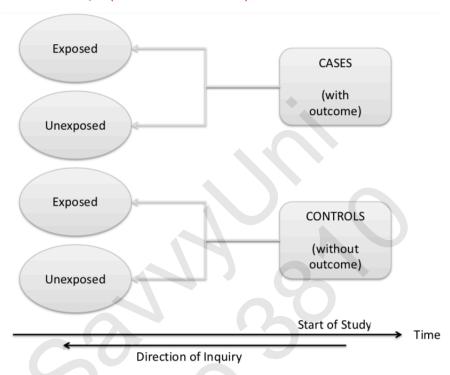
Cohort Study (Observational)



• 先按照是否有 exposure 把研究对象分成两组,跟踪调查一段时间看看是否有 outcome 出现

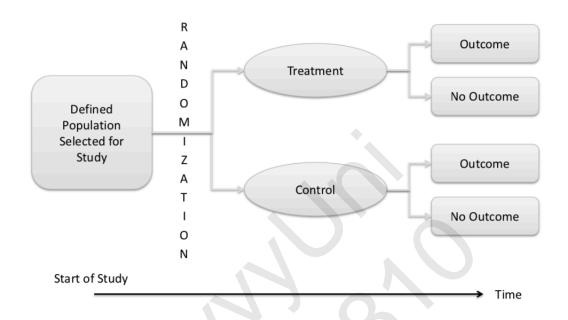
• 比较费时

Case-Control Study (Observational)



- 先按照是否有 outcome 把研究对象分成两组,回溯过去一个阶段是否存在 exposure
- 比较适合潜伏期长或者罕见的疾病

Randomized Controlled Trial (RCT) (Experimental)



- 先挑选没有 exposure 也没有 outcome 的群体, 然后随机分配是否接受 exposure。最后跟踪调查看看哪些人会出现 outcome
- 因为实验是随机分配的, 所以两个 group 之前唯一的差异就是是否存在 exposure/intervention, 其他差异都是因为偶然, 这样子就消除掉了 confounder 的影响。

4 Random Effect vs. Fixed Effect

• **Fixed effect:** 一般针对我们实验中直接想要去研究的未知参数(variable of interest)。 通常来说我们的数据里包含了这个 factor 所有可能的类别。

$$y_{ij} = \mu + \alpha_i + \varepsilon_{ij}, i = 1, \dots, a, j = 1, \dots, n$$

- $-\varepsilon_{ij} \stackrel{iid}{\sim} N(0, \sigma_{\varepsilon}^2)$
- $-\mu + \alpha_i$ denotes group mean for level i.
- Random effect: 一般存在于 correlated data 里,由于 dependence 的影响导致我们的分析存在了偏差,我们需要引入 random effect 来刻画 group 的差异。
 - 当一个 factor 有很多类别,但是数据里只包含了随机选择的一部分类别,为了避免以偏概全,我们会把它当作一个 random effect/variable
 - 通常 group 的差异对于结论的影响并不是我们直接关心的事。让我们把它放在 regression 里考虑的唯一原因是不然就<mark>违背了 independence assumption</mark>。

$$y_{ij} = \mu + \alpha_i + \varepsilon_{ij}, i = 1, \dots, a, j = 1, \dots, n$$

- $-\alpha_i \sim N(0, \sigma_\alpha^2), \varepsilon_{ij} \stackrel{iid}{\sim} N(0, \sigma^2)$
- Observations within same group share common term α_i , therefore they are correlated.
- Mixed effect: 如果一个模型里既考虑了 fixed effect 又考虑了 random effect, 那么就叫做 mixed effect model。
 - 有的时候我们甚至会考虑 interaction between fixed and random effect, 注意 interaction term 也仍然要当作一个random variable。

$$y_{ijk} = \mu + \alpha_i + b_j + (\alpha b)_{ij} + \varepsilon_{ijk}, i = 1, \dots, a, j = 1, \dots, n$$

$$-b_j \sim N(0, \sigma_b^2), (\alpha b)_{ij} \sim N(0, \sigma_{\alpha b}^2), \varepsilon_{ijk} \stackrel{iid}{\sim} N(0, \sigma^2)$$

按照老师的意思,只要涉及到 random effect model, 我们列的 model equation 不会出现 β_i 的结构。

如何区分 fixed/random effect?

- 如果是 grouping unit, 都当作 random effect, 比如说 group id/group name/group number
- 除此之外,都当作 fixed。尤其注意那些 group 的属性,都是 fixed。

如何估计 $\sigma_b^2, \sigma_{\alpha b}^2, \sigma^2$?

假设我们有 I 个 treament level (fixed effect), J 个 groups (random effect), 每一个 group 每一种 treatment repeat K 次。

• Aggregate (Main) model:

 $\texttt{Response} \sim \texttt{Treatment+Group}$

• Interaction model:

 ${\tt Response} \sim {\tt Treatment*Group}$

• Group model:

Average Response over each group ~ 1

- $\hat{\sigma}^2 \Leftarrow \text{summary(Interaction model)}\sigma2
- $\hat{\sigma}_b^2 \Leftarrow \text{summary(group model)} = \frac{1}{2} \frac{1}{2} \frac{1}{2} = \frac{1}{2} \frac{1}{2} = \frac{1}{2} \frac{1}{2} = \frac{1}{$
- $\hat{\sigma}_{\alpha b}^2 \Leftarrow \text{summary(Aggregate model)} = \frac{1}{2} \frac{1}{2} \frac{1}{2} \frac{1}{2} = \frac{1}{2} \frac{1}{2} = \frac{1}{2} \frac{1}{2} = \frac{1}{2} = \frac{1}{2} \frac{1}{2} = \frac{1}{2}$

5 Nested design vs. Crossed effect design

- Nested design: 个体嵌套于群体/组别。通常每一个组别只会接受一种 treamtnet
- Crossed effect design: 每一个个体会接受所有的 treament, 通常是个体的重复性实验。

对于 nested design 来说,考虑 group 和 treatment 之间的 interaction 没有任何意义。 因为每一个 group 里只接受一种 treatment,不存在重叠。

6 Likelihoods

- 相比于 regression, 有以下几点好处:
 - 不需要假设样本是正态分布
 - 不需要假设样本之间是独立的
- Likelihood: 表示的是在给定参数下能够获取到当前观测数据的数据可能性
- Likelihood Ratio Test: 适用于 nested model 之间的比较。通常来说会有一个 reduced model, 一个 full model。full model 里包含了所有 reduced model 里面的 parameters。

$$LRT = 2 \log \left(\frac{\max(Lik(Full\ model))}{\max(Lik(Reduced\ model))} \right)$$

- H_0 : Simpler model explains the data just as well as the more complicated
- 比较方法: 利用 likelihood ratio test
- 结论:
 - 如果 p value >0.05, no evidence against, should use the simpler model
 - 如果 p value <0.05, strong evidence against, should use the complicated model