ST520 Statistical Principles of Clinical Trials

1 Introduction

1.1 Brief Introduction to Epidemiology

- **Prevalence** of disease P(D)
- Incidence of disease: probability of getting disease during a certain time period
- Relative risk $\psi = \frac{P(D|E)}{P(D|\overline{E})}$ (easier interpretation, association not causation)
- Odds ratio $\theta = \frac{P(D|E)/\{1-P(D|E)\}}{P(D|\overline{E})/\{1-P(D|\overline{E})\}}$
- $\psi > 1 (= 1, < 1) \iff \theta > 1 (= 1, < 1)$
- For rare disease, $P(D \mid E) \approx 0$ and $P(D \mid \overline{E}) \approx 0$, then $\theta \approx \psi$
- Estimates

$$- \hat{\theta} = \frac{n_{11}n_{22}}{n_{12}n_{21}}$$

$$-\hat{V}\{\log(\hat{\theta})\} = \frac{1}{n_{11}} + \frac{1}{n_{12}} + \frac{1}{n_{21}} + \frac{1}{n_{22}}$$

$$- \hat{V}(\hat{\theta}) = \hat{\theta}^2 \left(\frac{1}{n_{11}} + \frac{1}{n_{12}} + \frac{1}{n_{21}} + \frac{1}{n_{22}} \right)$$

Cross-sectional study

• can estimate P(D), $P(D \mid E)$ and the similar type (i.e., $P(\bar{D})$, $P(D \mid \bar{E})$, and so on), ψ , θ

Longitudinal study

- Prospective
 - can estimate $P(D \mid E)$ and the similar type, ψ , θ
- Retrospective: case-control
 - can estimate $P(E \mid D)$ and the similar type, θ (ψ for rare disease)

1.2 Brief Introduction and History of Clinical Trials

2 Phase I and II clinical trials

2.1 Phases of Clinical Trials

- Phase I (toxicity and dose-finding)
- Phase II (screening and feasibility)
- Phase III (comparative study)
- Phase IV (post marketing)

2.2 Phase II clinical trials

- surrogate markers
- Example (a binary endpoint): π =the response rate
 - X =the number of responses among a random sample of n
 - $X \sim b(n,\pi)$
 - Normal approximation $p = X/n \sim N\left(\pi, \frac{\pi(1-\pi)}{n}\right)$
 - $(1-\alpha)$ confidence interval $p\pm z_{1-\alpha/2}\left\{rac{p(1-p)}{n}
 ight\}^{1/2}$
- Exact confidence interval C(X) such that $C(k) = (\pi_L(k), \pi_U(k))$

-
$$P_{\pi_L(k)}(X \ge k) = \sum_{j=k}^n \binom{n}{j} \pi_L(k)^j \{1 - \pi_L(k)\}^{n-j} = \alpha/2$$

$$- P_{\pi_U(k)}(X \le k) = \sum_{j=0}^k \binom{n}{j} \pi_U(k)^j \{1 - \pi_U(k)\}^{n-j} = \alpha/2$$

- Gehan's two-stage design
 - Stage I. (start with n_0 and a minimum acceptable response rate π_0) if no one responds, declare a failure.
 - * determine $n_0: P_{\pi}(X=0) \le (1-\pi_0)^{n_0} \le \alpha$
 - Stage II. (add $n-n_0$) count the total number of responses, calculate p and construct a CI for π .

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- * determine n: based on the precision of 95% CI using π_0 .
- The expected sample size is

$$n_0P(ext{stopping at Stage I})+nP(ext{stopping at Stage II})$$

$$= n_0P(X=0\mid\pi_0)+n\{1-P(X=0\mid\pi_0)\}=(n_0-n)(1-\pi_0)^{n_0}+n$$

- Simon's two-stage design (n_1, n, r_1, r) with $\pi_0 < \pi_1$
 - Stage I. (start with n_1) $X_1 \sim b(n_1, \pi)$ if $X_1 \leq r_1$, declare a failure.
 - Stage II. (add $n_2=n-n_1$) $X_2\sim b(n_2,\pi)$ if $X_1+X_2\leq r$, declare a failure. constraints:

*
$$P(\text{success} \mid \pi \leq \pi_0) \leq \alpha \Leftrightarrow P\{(X_1 > r_1)\&(X_1 + X_2 > r) \mid \pi = \pi_0\} \leq \alpha$$

*
$$P(\text{failure} \mid \pi \geq \pi_1) \leq \beta \Leftrightarrow P\{(X_1 > r_1) \& (X_1 + X_2 > r) \mid \pi = \pi_1\} \geq 1 - \beta$$

- Optimal design: to minimize the expected sample size

$$n_1P(ext{stopping at Stage I})+nP(ext{stopping at Stage II})$$

$$= n_1P(X_1 \leq r_1 \text{ or } X_1 > r \mid \pi_0)+nP(r_1+1 \leq X_1 \leq r \mid \pi_0).$$

3 Phase III clinical trials

3.1 Why are clinical trials needed

3.2 Issues to consider before designing a clinical trial

3.3 Ethical issues

3.4 The randomized clinical trial - hierarchical models

- To address the question of whether the results from the different studies are random samples form underlying groups with a common response rate or from groups with different underlying response rates.
- Hierarchical models for (n_i, X_i, π_i) i = 1, ..., N

- (1st)
$$\pi_1, \ldots, \pi_N \stackrel{iid}{\sim} (\mu_{\pi}, \sigma_{\pi}^2)$$

- (2rd)
$$X_i \mid n_i, \pi_i \sim b(n_i, \pi_i), i = 1, ..., N$$

- Goal is to estimate σ_{π}^2
- Law of conditional expectation: $E(X) = E\{E(X \mid Y)\}$
- Law of conditional variance: $V(X) = E\{V(X \mid Y)\} + V\{E(X \mid Y)\}$

•
$$p_i = X_i/n_i$$

-
$$E(p_i \mid \pi_i, n_i) = \pi_i$$

-
$$V(p_i \mid \pi_i, n_i) = \pi_i (1 - \pi_i) / n_i$$

$$- E(p_i) = E\{E(p_i \mid \pi_i, n_i)\} = \mu_{\pi}$$

$$-V(p_i) = E\{V(p_i \mid \pi_i, n_i)\} + V\{E(p_i \mid \pi_i, n_i)\} = E\{\pi_i(1 - \pi_i)/n_i\} + \sigma_{\pi}^2$$

•
$$\bar{p} = N^{-1} \sum_{i=1}^{N} p_i$$

•
$$s_p^2 = \frac{\sum_{i=1}^N (p_i - \bar{p})^2}{N-1}$$
: $E(s_p^2) = V(p_i)$

•
$$N^{-1} \sum_{i=1}^{N} \frac{p_i(1-p_i)}{n_i-1}$$
: $E\left\{N^{-1} \sum_{i=1}^{N} \frac{p_i(1-p_i)}{n_i-1}\right\} = E\left\{\frac{\pi_i(1-\pi_i)}{n_i}\right\}$

•
$$\hat{\sigma}_{\pi}^{2} = \left\{ \frac{\sum_{i=1}^{N} (p_{i} - \bar{p})^{2}}{N-1} \right\} - \left\{ N^{-1} \sum_{i=1}^{N} \frac{p_{i} (1 - p_{i})}{n_{i} - 1} \right\}$$
 is unbiased for σ_{π}^{2} .

$$\bullet \hat{\mu}_{\pi} = \frac{p_1 + \dots + p_N}{N}$$

4 Randomization

- Advantage of randomization: eliminate conscious and unconscious biases
- Disadvantage of randomization:
 - interference with physician patient relationship
 - resources expended in the control group

4.1 Inference

4.1.1 Design-based inference

- Sharp null hypothesis: A & B (two treatments) are exactly the same for each patient
- Test statistics: T = difference of the sample means
- ullet The distribution of test statistics is induced by the randomization \Longrightarrow the permutation distribution of T
- One-sided p-value (the alternative is "A is better than B") $P(T \ge t_{obs} \mid \text{sharp } H_0) = \frac{\# \text{of } t_i \ge t_{obs}}{\# \text{of } t_i \text{ under permutation}}$
- Two-sided p-value (the alternative is "A is different than B") $P(|T| \ge |t_{obs}| \mid \text{sharp } H_0) = \frac{\#\text{of } |t_i| \ge |t_{obs}|}{\#\text{of } t_i}$
- Remark: In the permutational distribution, we treat each individual's response as fixed. Randomness is induced by the treatment assignment mechanism.

4.1.2 Model-based inference

• The distribution of test statistics is induced by assumptions about a super-population and a probability model.

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- Statistical model:
- $Y_1, Y_2 \stackrel{iid}{\sim} N(\mu_A, \sigma^2)$
- $Y_3, Y_4 \stackrel{iid}{\sim} N(\mu_B, \sigma^2)$
- Null hypothesis: $H_0: \mu_A = \mu_B$

•
$$T = \frac{\bar{Y}_A - \bar{Y}_B}{s_p(n_A^{-1} + n_B^{-1})^{1/2}} \stackrel{H_0}{\sim} t_{n_A + n_B - 2}$$

•
$$p$$
-value= $P(t_{n_A+n_B-2} \ge t_{obs} \mid H_0)$

4.1.3 Causal inference from an experimental sample to a larger population

- Potential outcomes $Y^*(1)$ and $Y^*(2)$
- The average treatment effect is ATE= $E\{Y^*(2) Y^*(1)\}$
- $\bullet \ \ {\it Treatment indicator} \ A \in \{1,2\}$
- Observed outcome $Y = Y^*(1)I(A=1) + Y^*(2)I(A=2) = Y^*(A)$ under SUTVA
- Randomization: $A \perp \{Y^*(1), Y^*(2)\}$
 - implication $E\{Y^*(a)\}=E\{Y^*(a)\mid A=a\}=E\{Y\mid A=a\}\equiv \mu_a$ for a=1,2
 - $\mu_2 \mu_1$ is the same as ATE
 - estimator: $\bar{Y}_2 \bar{Y}_1$

4.2 Fixed allocation randomization

1. Simple randomization

- Two treatments A & B; $\Delta=\mu_2-\mu_1$; $\hat{\Delta}=\bar{Y}_2-\bar{Y}_1$
- Treatment allocation with $P(A) = \pi$
- $V(\hat{\Delta}) = \sigma^2 \left(\frac{1}{n_1} + \frac{1}{n_2} \right)$
- Advantage: easy; impossible to guess the next treatment assignment; iid
- Disadvantage: possibility of severe treatment imbalance

2. Permuted block randomization

- try to balance A & B
- fixed block size
- varying block size

- 3. Stratified randomization (permuted block randomization): see homework 3 additional question
 - The maximum imbalance between A & B is # of strata×(block size)/2
 - Advantage: treatment groups are similar; more precise estimates of treatment difference
 - Disadvantage: too many prognostic factors to form strata, very few (or even zero) patient in some strata, back to simple randomization
- Linear combination of random variables
 - Let Z_1, \ldots, Z_m be random variables, and let a_0, \ldots, a_m be constants
 - $E(a_0 + a_1 Z_1 + \ldots + a_m Z_m) = a_0 + a_1 E(Z_1) + \ldots + a_m E(Z_m)$
 - In addition, Z_1, \ldots, Z_m are mutually independent, then $V(a_0+a_1Z_1+\ldots+a_mZ_m)=a_1^2V(Z_1)+\ldots+a_m^2V(Z_m)$
 - Eg. Let $X_1, \ldots, X_n \stackrel{iid}{\sim}$ be random variables, and let a_0, \ldots, a_m be constants
 - $E(a_0 + a_1 Z_1 + \ldots + a_m Z_m) = a_0 + a_1 E(Z_1) + \ldots + a_m E(Z_m)$
 - In addition, Z_1,\ldots,Z_m are mutually independent, then $V(a_0+a_1Z_1+\ldots+a_mZ_m)=a_1^2V(Z_1)+\ldots+a_m^2V(Z_m)$
- Effect of blocking within strata on the precision of estimators
 - $Y_i = \mu + \alpha S_i + \beta X_i + \epsilon_i$, strata indicator $S_i \in \{0, 1\}$, treatment indicator $X_i \in \{0, 1\}, \epsilon_i \stackrel{iid}{\sim} (0, \sigma^2)$
 - $\hat{\Delta} = \bar{Y}_A \bar{Y}_B$
 - Under stratified randomization: $V(\hat{\Delta}) = \frac{4\sigma^2}{n}$
 - Under permuted block randomization: $V(\hat{\Delta}) = \sigma^2 \frac{4}{n}$
 - Under simple randomization: $V(\hat{\Delta})=\{\sigma^2+\alpha^2\theta(1-\theta)\}E\left(\frac{1}{n_A}+\frac{1}{n-n_A}\right)$
 - The test statistics $T=\frac{\bar{Y}_A-\bar{Y}_B}{s_p(\frac{1}{n_A}+\frac{1}{n_B})^{1/2}}$ is conservative in a stratified random design with $\alpha\neq 0$ (i.e. some strata effect)

4.3 Baseline adaptive randomization

Efron biased coin design

- Urn Model (L.J. Wei)
- Minimization method of Pocock and Simon

4.4 Response adaptive randomization

- Play-the-Winner Rule (Zelen)
- Urn Model (L.J. Wei)

5 Some additional issues in Phase III clinical trails

- Blinding and Placebos
- Ethics
- The protocol document

6 Sample Size Calculations

• Generally,
$$\begin{cases} T_n \overset{\Delta=0}{\sim} N(0,1) & \Rightarrow \text{ one-sided level-}\alpha \text{ test} \Rightarrow \text{rejection region: } T_n \geq z_\alpha \\ T_n \overset{\Delta=\Delta_A}{\sim} N(\phi(n,\Delta_A,\theta),\sigma_*^2(\Delta_A,\theta)) & \Rightarrow \text{ power: } P_{\Delta=\Delta_A}(T_n \geq z_\alpha) = 1-\beta \end{cases}$$

• Key formula for sample size calculation:

$$\phi(n, \Delta_A, \theta) = \begin{cases} Z_{\alpha} + Z_{\beta}\sigma_*(\Delta_A, \theta) \text{ for a one-sided test} \\ Z_{\alpha/2} + Z_{\beta}\sigma_*(\Delta_A, \theta) \text{ for a two-sided test} \end{cases}$$

6.1 Comparison of two means

•
$$H_0: \Delta = \mu_1 - \mu_2 \le 0 \text{ vs } H_A: \Delta > 0$$

•
$$Y_i \mid A_i = 1 \sim (\mu_1, \sigma^2), Y_i \mid A_i = 2 \sim (\mu_2, \sigma^2)$$

$$T_n = \frac{\bar{Y}_1 - \bar{Y}_2}{s_p \sqrt{\frac{1}{n_1} + \frac{1}{n_2}}}$$

$$\bullet \begin{cases}
T_n \stackrel{\Delta=0}{\sim} N(0,1) \\
T_n \stackrel{\Delta=\Delta_A}{\sim} N\left(\frac{\Delta_A}{\sigma\sqrt{\frac{1}{n_1} + \frac{1}{n_2}}}, 1\right)
\end{cases}$$

6.2 Comparison of two proportions

• Hypothesis testing: $H_0: \pi_1 \leq \pi_2 \ (\Delta = \pi_1 - \pi_2 \leq 0) \text{ vs } H_A: \pi_1 > \pi_2(\Delta > 0)$

• Data:
$$X_1 \sim b(n_1, \pi_1), X_2 \sim b(n_2, \pi_2), p_1 = \frac{X_1}{n_1}$$
 and $p_2 = \frac{X_2}{n_2}$ $(n_1 = n_2 = \frac{n}{2})$

•
$$T_1 = \frac{p_1 - p_2}{\sqrt{\bar{p}(1-\bar{p})(\frac{1}{n_1} + \frac{1}{n_2})}}, \bar{p} = \frac{X_1 + X_2}{n_1 + n_2}$$

$$\bullet \begin{cases}
T_1 \stackrel{\Delta=0}{\sim} N(0,1) \\
T_1 \stackrel{\Delta=\Delta_A}{\sim} N\left(\frac{\Delta_A}{\left\{\bar{\pi}(1-\bar{\pi})(\frac{1}{n_1} + \frac{1}{n_2})\right\}^{1/2}}, \frac{\pi_1(1-\pi_1) + \pi_2(1-\pi_2)}{2\bar{\pi}(1-\bar{\pi})}\right) \bar{\pi} = \frac{\pi_1 + \pi_2}{2}
\end{cases}$$

•
$$T_2 = \frac{p_1 - p_2}{\sqrt{\frac{p_1(1 - p_1)}{n_1} + \frac{p_2(1 - p_2)}{n_2}}}$$

$$\bullet \left\{ T_2 \overset{\Delta=0}{\sim} N(0,1) \atop T_2 \overset{\Delta=\Delta_A}{\sim} N\left(\frac{\Delta_A}{\left\{\frac{\pi_1(1-\pi_1)}{n_1} + \frac{\pi_2(1-\pi_2)}{n_2}\right\}^{1/2}}, 1\right) \right.$$

6.3 Arcsin square root transformation for proportions

•
$$X \sim b(n,\pi), p = \frac{X}{n} \implies \sin^{-1}(p^{1/2}) \sim N\left(\sin^{-1}(\pi^{1/2}), \frac{1}{4n}\right)$$

•
$$T_3 = \frac{\sin^{-1}(p_1^{1/2}) - \sin^{-1}(p_2^{1/2})}{\left(\frac{1}{4n_1} + \frac{1}{4n_2}\right)^{1/2}}$$