NTHU STAT 5230, 2025

Lecture Notes

$P_{\mathbf{x}} = \underline{average} \text{ of all } \underline{P_{\mathbf{x}}} \oplus \underline{E}(\underline{y}) = \sum_{i} \underline{E}(\underline{s}_{i}) = \sum_{i} \{ \underline{E}[\underline{E}(\underline{s}_{i} \underline{\pi}_{i})] \} = \underline{l} \times \underline{mp} = \underline{np} \leftarrow (\underline{cf.} p. 3.40) $
$\underbrace{\operatorname{Sampling}}_{\text{sampling}} \operatorname{clusters} \qquad \qquad$
$\underbrace{Var(\underline{\mathbf{y}})}_{cf} = \sum_{i} \{ E[m\pi_{i}(1-\underline{\pi}_{i})] + Var(m\underline{\pi}_{i}) \} \underbrace{Var(\underline{\mathbf{y}})}_{y \sim binomial} $
$\frac{Y - N(xB, 1)}{Y - N(xB, 1)} = l \times \{mp - m[\tau^2 p(1-p) + p^2] + m^2 \tau^2 p(1-p)\}$
$ \underbrace{F - \text{test}}_{F - \text{test}} \xrightarrow{\chi^2 \text{test}} \underbrace{\left[\frac{m[a] + \sigma^2 \times 1}{2} - \frac{m[a] + \sigma^2 \times 1}{2} \right]}_{F - \text{test}} \xrightarrow{\pi} \underbrace{\left[1 + (m-1)\tau^2 \right] n p(1-p)}_{F - \text{test}} \xrightarrow{\pi} \underbrace{\left[1 + (m-1)\tau^2 \right] n p(1-p)}_{F - \text{test}} \xrightarrow{\pi} \underbrace{\left[1 + (m-1)\tau^2 \right] n p(1-p)}_{F - \text{test}} \xrightarrow{\pi} \underbrace{\left[1 + (m-1)\tau^2 \right] n p(1-p)}_{F - \text{test}} \xrightarrow{\pi} \underbrace{\left[1 + (m-1)\tau^2 \right] n p(1-p)}_{F - \text{test}} \xrightarrow{\pi} \underbrace{\left[1 + (m-1)\tau^2 \right] n p(1-p)}_{F - \text{test}} \xrightarrow{\pi} \underbrace{\left[1 + (m-1)\tau^2 \right] n p(1-p)}_{F - \text{test}} \xrightarrow{\pi} \underbrace{\left[1 + (m-1)\tau^2 \right] n p(1-p)}_{F - \text{test}} \xrightarrow{\pi} \underbrace{\left[1 + (m-1)\tau^2 \right] n p(1-p)}_{F - \text{test}} \xrightarrow{\pi} \underbrace{\left[1 + (m-1)\tau^2 \right] n p(1-p)}_{F - \text{test}} \xrightarrow{\pi} \underbrace{\left[1 + (m-1)\tau^2 \right] n p(1-p)}_{F - \text{test}} \xrightarrow{\pi} \underbrace{\left[1 + (m-1)\tau^2 \right] n p(1-p)}_{F - \text{test}} \xrightarrow{\pi} \underbrace{\left[1 + (m-1)\tau^2 \right] n p(1-p)}_{F - \text{test}} \xrightarrow{\pi} \underbrace{\left[1 + (m-1)\tau^2 \right] n p(1-p)}_{F - \text{test}} \xrightarrow{\pi} \underbrace{\left[1 + (m-1)\tau^2 \right] n p(1-p)}_{F - \text{test}} \xrightarrow{\pi} \underbrace{\left[1 + (m-1)\tau^2 \right] n p(1-p)}_{F - \text{test}} \xrightarrow{\pi} \underbrace{\left[1 + (m-1)\tau^2 \right] n p(1-p)}_{F - \text{test}} \xrightarrow{\pi} \underbrace{\left[1 + (m-1)\tau^2 \right] n p(1-p)}_{F - \text{test}} \xrightarrow{\pi} \underbrace{\left[1 + (m-1)\tau^2 \right] n p(1-p)}_{F - \text{test}} \xrightarrow{\pi} \underbrace{\left[1 + (m-1)\tau^2 \right] n p(1-p)}_{F - \text{test}} \xrightarrow{\pi} \underbrace{\left[1 + (m-1)\tau^2 \right] n p(1-p)}_{F - \text{test}} \xrightarrow{\pi} \underbrace{\left[1 + (m-1)\tau^2 \right] n p(1-p)}_{F - \text{test}} \xrightarrow{\pi} \underbrace{\left[1 + (m-1)\tau^2 \right] n p(1-p)}_{F - \text{test}} \xrightarrow{\pi} \underbrace{\left[1 + (m-1)\tau^2 \right] n p(1-p)}_{F - \text{test}} \xrightarrow{\pi} \underbrace{\left[1 + (m-1)\tau^2 \right] n p(1-p)}_{F - \text{test}} \xrightarrow{\pi} \underbrace{\left[1 + (m-1)\tau^2 \right] n p(1-p)}_{F - \text{test}} \xrightarrow{\pi} \underbrace{\left[1 + (m-1)\tau^2 \right] n p(1-p)}_{F - \text{test}} \xrightarrow{\pi} \underbrace{\left[1 + (m-1)\tau^2 \right] n p(1-p)}_{F - \text{test}} \xrightarrow{\pi} \underbrace{\left[1 + (m-1)\tau^2 \right] n p(1-p)}_{F - \text{test}} \xrightarrow{\pi} \underbrace{\left[1 + (m-1)\tau^2 \right] n p(1-p)}_{F - \text{test}} \xrightarrow{\pi} \underbrace{\left[1 + (m-1)\tau^2 \right] n p(1-p)}_{F - \text{test}} \xrightarrow{\pi} \underbrace{\left[1 + (m-1)\tau^2 \right] n p(1-p)}_{F - \text{test}} \xrightarrow{\pi} \underbrace{\left[1 + (m-1)\tau^2 \right] n p(1-p)}_{F - \text{test}} \xrightarrow{\pi} \underbrace{\left[1 + (m-1)\tau^2 \right] n p(1-p)}_{F - \text{test}} \xrightarrow{\pi} \underbrace{\left[1 + (m-1)\tau^2 \right] n p(1-p)}_{F - \text{test}} \xrightarrow{\pi} \underbrace{\left[1 + (m-1)\tau^2 \right] n p(1-p)}_{F - \text{test}} \xrightarrow{\pi} \underbrace{\left[1 + (m-1)\tau^2 \right] n p(1-p)}_{F - \text{test}} \xrightarrow{\pi} \underbrace{\left[1 + (m-1)\tau^2 \right] n p(1-p)}_{F - \text{test}} \xrightarrow{\pi} \left[1 + (m-1)\tau^2 \right] n p(1-$
$Y \sim N(xB, \sigma^2 I)$ Overdispersion cannot arise when $n=1$ (sparse case) $g_{m=1}$
Vor(4) 3/26 Violation of independence assumption can cause Check 2 Z's from
= $\sum_{u} \overline{v_{or}(z_u)}$ = <u>over-dispersion</u> , e.g., <u>response</u> has a <u>common</u> <u>in U_{P} 3-39</u> [M]
+2 $\sum (\sigma(z_u, z_v))$ cause, say a disease is influenced by genes, the $E(z_u, z_v) = E[z_u, z_v] = E[z_u, z_v]$
$responses will tend to be positively contracted responses (z_u = 1)$
$\underline{\sigma}^{2} = \frac{\nabla \alpha r(3x)}{n_{x}P_{x}(1-P_{x})} \begin{bmatrix} \frac{1}{2} \\ \frac{1}{2} \\ \frac{1}{2} \end{bmatrix}$ survival probability of an animal may be increased $\frac{2u=0}{2P(z_{11}=1)}$
$x & constant over \\ x & cr. (\Delta)$ by the death of others, i.e., negatively correlated $zr. (\Delta)$
• Q: how to model overdispersion and do analysis? Check * in addition to mean structure
Note Introduce one additional dispersion parameter $\underline{\sigma}^2$, i.e., $\underline{4}$ $\underline{2}$ $\underline{2}$ $\underline{2}$ $\underline{1}$ 1
a like $Var(\underline{y}_{\mathbf{x}}) = \underline{\sigma}^2 \times n_{\mathbf{x}} \underline{p}_{\mathbf{x}} (1 - p_{\mathbf{x}}) \Leftarrow \text{notice its similarity to linear model}$ defined by $\underline{g}^{-1}(\underline{y}_{\mathbf{x}}) = \underline{E}(\underline{y}_{\mathbf{x}})/\underline{n_{\mathbf{x}}} \xrightarrow{\mathbf{x}} \mathbf{often include under-dispersion} \xrightarrow{\mathbf{x}} \underline{\sigma}^2 < 1$
(standard binomial case $\Rightarrow \underline{\sigma^2=1}$; over-dispersion $\Rightarrow \underline{\sigma^2>1}$)
For a model S, $\underline{\sigma}^2$ can be estimated using $\hat{\sigma}^2_{C} = \frac{\chi^2_{C}}{\sqrt{k-p}}$
For a model S , σ^2 can be estimated using $\hat{\sigma}_S^2 = \frac{X_S^2}{M_{p, 3-41}} = \frac{\chi_S^2}{M_{p, 3-41$
For a model S , σ^2 can be estimated using $\hat{\sigma}_{S}^2 = \frac{\chi_{S}^2}{\frac{M}{2}} = \chi_{$
For a model S , σ^2 can be estimated using $\hat{\sigma}_S^2 = \frac{X_S^2}{(k - p)} = \frac{M_{DS}^2}{(k - p)}$ When $2 = \sum_{l=1}^{2} B_l R_l = D_s = \frac{X_S^2}{2} = \sum_i (\underline{r_{LS}^2})^2 \stackrel{\text{cf}}{\leftarrow} RSS \text{ in } \underline{LM} \rightarrow \underline{\sigma}_S^2 = \frac{X_S^2}{(k - p)} = \frac{M_{DS}^2}{(k - p)}$ Nis large. (using deviance D in place of X^2 is not very recom- using D_s (using deviance D in place of X^2 is not very recom- using D_s (using deviance D may be inconsistent for sparse data) check W_{p}3-14 \rightarrow D/(B-p) might not converge to $\sigma^2 = 1$ as $B \rightarrow \infty = 1$ Fatimation of B is unoffected since $F(\alpha)$ (is = 1. $\sigma^2 = 1$) (rationale • IRWLS only need
For a model S , σ^2 can be estimated using $\hat{\sigma}_{S'}^2 = \frac{X_S^2}{X_S^2} + \frac{M_{P,341}}{X_S^2} = \frac{S_{P,1}^2}{X_S^2} + \frac{S_{P,341}}{D_S} + \frac{S_{P,341}}{D_S} + \frac{S_{P,341}}{D_S} = \frac{S_{P,1}^2}{X_S^2} + \frac{S_{P,341}}{D_S} + $
For a model S, σ^2 can be estimated using $\hat{\sigma}_S^2 = X_S^2 / (\frac{k}{k} - p)$ When $2 = \sum_{\beta=1}^{p} \beta_{\beta} \beta_{\beta} - D_s \sum_{x=1}^{p} X_s^2 = \sum_i (\underline{r_i} s)^2 + \underline{c} + RSS in \underline{L}M - \underline{r} + \underline{\sigma} + \underline{r} + \underline{r} + \underline{r} + \underline{\sigma} + \underline{r} + \underline{r} + \underline{\sigma} + \underline{r} + $
For a model S , σ^2 can be estimated using $\hat{\sigma}_S^2 = X_S^2 / (\frac{k}{k} - p)^{-1}$ When $2 = \sum_{\ell=1}^{n} \underline{\beta}_{\ell} \underline{R}_{\ell} - \underline{D}_{S} \underline{s} X_{s}^{2} = \sum_{i} (\underline{r}_{i,s}^{2})^{2} \underbrace{\epsilon}_{s} \underline{R}SS \text{ in } \underline{L}M^{-1} - \underline{\sigma}_{S}^{2} = X_S^2 / (\frac{k}{k} - p)^{-1}$ When $2 = \sum_{\ell=1}^{n} \underline{\beta}_{\ell} \underline{R}_{\ell} - \underline{D}_{S} \underline{s} X_{s}^{2} = \sum_{i} (\underline{r}_{i,s}^{2})^{2} \underbrace{\epsilon}_{s} \underline{R}SS \text{ in } \underline{L}M^{-1} - \underline{\sigma}_{S}^{2} = X_S^2 / (\frac{k}{k} - p)^{-1}$ When $2 = \sum_{\ell=1}^{n} \underline{\beta}_{\ell} \underline{R}_{\ell} - \underline{D}_{S} \underline{s} X_{s}^{2} = \sum_{i} (\underline{r}_{i,s}^{2})^{2} \underbrace{\epsilon}_{s} \underline{R}SS \text{ in } \underline{L}M^{-1} - \underline{\sigma}_{S}^{2} \underline{s} X_{S}^{2} / (\frac{k}{k} - p)^{-1}$ When $2 = \sum_{\ell=1}^{n} \underline{\beta}_{\ell} \underline{R}_{\ell} \underline{e}_{\ell}$ $D_{s} \underline{s} X_{s}^{2} = \sum_{i} (\underline{r}_{i,s}^{2})^{2} \underbrace{\epsilon}_{s} \underline{R}SS \text{ in } \underline{L}M^{-1} - \underline{\sigma}_{S}^{2} \underline{s} X_{S}^{2} - \underline{r}_{S}^{2} / (\frac{k}{k} - p)^{-1}$ With low $2 = \sum_{i,j} \underline{\beta}_{i,j} \underline{R}_{i,j} \underline{r}_{i,j$
For a model S , σ^2 can be estimated using $\hat{\sigma}_S^2 = X_S^2/(k - p)$ When $2 = \sum_{\theta=1}^{2} \beta_{\theta} R_{\theta} - D_{s} \sum X_s^2 = \sum_i (\underline{r_{i,s}})^2 \cdot \underline{c^{c_{s}}} RSS in \underline{LM} - \underline{c^{c_{s}}}^2 = X_S^2/(k - p)$ When $2 = \sum_{\theta=1}^{2} \beta_{\theta} R_{\theta} - D_{s} \sum X_s^2 = \sum_i (\underline{r_{i,s}})^2 \cdot \underline{c^{c_{s}}} RSS in \underline{LM} - \underline{c^{c_{s}}}^2 = X_S^2/(k - p)$ (using deviance D in place of X^2 is not very recom- using D_s mended as D may be inconsistent for sparse data) (heck Up 3-U - D(g-p) might not converge to $\sigma^2 = 1$ as $\beta \to \infty q^2$ is not $2 = 1$ as $\beta \to \infty q^2$ is not $2 = 1$. (mLE) Estimation of β is unaffected since $E(y_x) = n_x g^2(2_x)$ is not changed (Why? Note that y_x is not $= n_x g^2(2_x)$ is not changed (Why? Note that y_x is not $= n_x g^2(2_x)$ $= \sqrt{[g^2 n_x B_x(1-B_x)]} = [g^2 n_x B_x(1-B_x)$
For a model S , σ^2 can be estimated using $\hat{\sigma}_S^2 = X_S^2 / (\frac{k}{k} - p)^{-1}$ When $2 = \sum_{a=1}^{a} \underline{\beta} \underline{g} \underline{R} \underline{e} - D_S \underline{s} \underline{X} \underline{s} = \sum_i (\underline{r}_{i,s})^2 \underbrace{\epsilon^{cs}} \underline{R} \underline{S} \underline{S} \text{ in } \underline{L} \underline{M} - \underline{s}^2 = X_S^2 / (\frac{k}{k} - p)^{-1}$ Ris large. (using deviance D in place of X^2 is not very recom- using D_S mended as D may be inconsistent for sparse data) check UMp 3-14 - $D(\underline{g} - p)$ might not converge to $\underline{\sigma}^2 = 1$ as $\underline{g} \to 2 \underline{\sigma}^2$ for $\underline{R} \underline{S} \underline{S}$ only need mean $\underline{g} \underline{S} \underline{S} - \underline{S} \underline{S} - \underline{S} \underline{S} - \underline{S} \underline{S} \underline{S} \underline{S} \underline{S} \underline{S} \underline{S} \underline{S}$
For a model S , σ^2 can be estimated using $\hat{\sigma}_S^2 = X_S^2/(\underline{k} - \underline{p})^{-1}$ When $2 = \sum_{k=1}^{p} \underline{\beta}_k \underline{R}_k - \underline{D}_s \underline{\hat{x}} X_s^2 = \underline{\Sigma}_i (\underline{r}_{ks})^2 + \underline{C}_k \underline{R}SS in \underline{L}M^{-1} - \underline{\sigma}_S^2 = X_S^2/(\underline{k} - \underline{p})^{-1}$ Mislonge (using deviance \underline{D} in place of X^2 is not very recom- using deviance \underline{D} in place of X^2 is not very recom- using deviance \underline{D} in place of X^2 is not very recom- using ΔS mended as D may be inconsistent for sparse data) check $\underline{W}_3 + \underline{W}_{-1} \cdot \underline{D}_{(\underline{k} - \underline{p})}$ might not converge to $\underline{\sigma}^2 = 1$ as $\underline{R} \to \infty e^{-1}$ MLE E Estimation of β is unaffected since $E(\underline{y}_x) = \underline{n}_x \underline{g}'(\underline{2}x)$ is not changed (Why? Note that \underline{y}_x is not $= n_x \underline{g}'(\underline{2}x)$ \sim binomial so that likelihood is different $-\underline{q}_x \underline{g}'(\underline{2}x)$ $= \sqrt{\underline{L}} \underline{c}^2 \cdot \underline{G}^2 \cdot \underline{L}^T \cdot \underline{W} \cdot \underline{X}^{-1}$ and $\underline{Var}(\hat{\beta}) = \hat{\sigma}^2 (X^T \cdot \underline{W} \cdot X)^{-1}$ $= \sum_{i=n_x} \underline{G}^2 \cdot (X^T \cdot \underline{W} \cdot X)^{-1}$ and $\underline{Var}(\hat{\beta}) = \hat{\sigma}^2 (X^T \cdot \underline{W} \cdot X)^{-1}$ $= \sum_{i=n_x} \underline{G}^2 \cdot \underline{M} \cdot \underline{K}^{-1}$ $= \sum_{i=n_x} \underline{G}^2 \cdot \underline{M} \cdot \underline{K}^{-1}$ $= \sum_{i=n_x} \underline{G}^2 \cdot \underline{K} \cdot \underline{K} \cdot \underline{K}^{-1}$ $= \sum_{i=n_x} \underline{G}^2 \cdot \underline{K} \cdot \underline{K}^{-1}$ $= \sum_{i=n_x} \underline{G}^2 \cdot \underline{K} \cdot \underline{K} \cdot \underline{K}^{-1}$ $= \sum_{i=n_x} \underline{G}^2 \cdot \underline{K} \cdot \underline{K}^{-1}$ $= \sum_{i=n_x} \underline{G}^2 \cdot \underline{K} \cdot \underline{K} \cdot \underline{K}^{-1}$ $= \sum_{i=n_x} \underline{G}^2 \cdot \underline{K} \cdot \underline{K} \cdot \underline{K}^{-1}$ $= \sum_{i=n_x} \underline{G}^2 \cdot \underline{K} \cdot \underline{K}$
For a model S , σ^2 can be estimated using $\hat{\sigma}_S^2 = \frac{X_S^2}{X_S^2} \frac{ \mathbf{f} _{\mathbf{x}} _{\mathbf{x}}^2}{ \mathbf{x} _{\mathbf{x}}^2} \frac{ \mathbf{f} _{\mathbf{x}}^2}{ \mathbf{x} _{\mathbf{x}}^2}} \frac{ \mathbf{f} \mathbf{x} \mathbf{x} \mathbf{x} $
For a model S , σ^2 can be estimated using $\hat{\sigma}_S^2 = X_S^2/(k - p)$ $T_S = \sum_{k=1}^{p} \beta_k R_k - D_S = X_S^2 = \sum_i (\underline{r_L S})^2 - \underline{c}^2 RSS in LM - \underline{\sigma}_S^2 = X_S^2/(k - p)$ $T_S = \sum_{k=1}^{p} \beta_k R_k - D_S = \sum_i (\underline{r_L S})^2 - \underline{c}^2 RSS in LM - \underline{\sigma}_S^2 = X_S^2/(k - p)$ $T_S = \sum_{k=1}^{p} \beta_k R_k - D_S = \sum_i (\underline{r_L S})^2 - \underline{c}^2 RSS in LM - \underline{\sigma}_S^2 = X_S^2/(k - p)$ $T_S = \sum_{k=1}^{p} (using deviance D in place of X^2 is not very recom- T_S = \sum_{k=1}^{p} (\underline{h}_{S-p}) might not converge to \underline{s}^2 = 1 as \underline{h} \to \infty e^{-1}T_S = \sum_{k=1}^{p} (\underline{h}_{S-p}) might not converge to \underline{s}^2 = 1 as \underline{h} \to \infty e^{-1}T_S = \sum_{k=1}^{p} (\underline{h}_{S-p}) might not converge to \underline{s}^2 = 1 as \underline{h} \to \infty e^{-1}T_S = \sum_{k=1}^{p} (\underline{h}_{S-p}) might not converge to \underline{s}^2 = 1 as \underline{h} \to \infty e^{-1}T_S = \sum_{k=1}^{p} (\underline{h}_{S-p}) might not converge to \underline{s}^2 = 1 as \underline{h} \to \infty e^{-1}T_S = \sum_{k=1}^{p} (\underline{h}_{S-p}) might not converge to \underline{s}^2 = 1 as \underline{h} \to \infty e^{-1}T_S = \sum_{k=1}^{p} (\underline{h}_{S-p}) might not converge to \underline{s}^2 = 1 as \underline{h} \to \infty e^{-1}T_S = \sum_{k=1}^{p} (\underline{h}_{S-p}) might not converge to \underline{s}^2 = 1 as \underline{h} \to \infty e^{-1}T_S = \sum_{k=1}^{p} (\underline{h}_{S-p}) might not converge to \underline{s}^2 = 1 as \underline{h} \to \infty e^{-1}T_S = \sum_{k=1}^{p} (\underline{h}_{S-p}) might not converge to \underline{s}^2 = 1 as \underline{h} \to \infty e^{-1}T_S = \sum_{k=1}^{p} (\underline{h}_{S-p}) might not converge to \underline{s}^2 = 1 as \underline{h} \to \infty e^{-1}T_S = \sum_{k=1}^{p} (\underline{h}_{S-p}) might not converge to \underline{s}^2 = 1 as \underline{h} \to \infty e^{-1}T_S = \sum_{k=1}^{p} (\underline{h}_{S-p}) and T_S = \underline{h}_{S-1} and T_S = \underline{h}_{$
For a model S , σ^2 can be estimated using $\hat{\sigma}_S^2 = X_S^2/(k-p)^{(k-p)}$ $T = \Sigma_{p_1}^{p_1} \underline{\beta_p} \underline{R_e} - D_S \underline{a} X_S^2 = \Sigma_i (T_{i,S}^{p_2})^{4c} RSS in \underline{LM} - \underline{\sigma}_S^2 = X_S^2/(k-p)^{(k-p)}$ $n_is large.$ (using deviance D in place of X^2 is not very recom- using deviance D in place of X^2 is not very recom- (using deviance D) = nay be inconsistent for sparse data) $check U_{p_3} - U_{p_1}^{(p_2)} = \underline{m_i} \underline{p_i} + \underline{\sigma}_i + \underline{\sigma}_i^{(p_1)} = \underline{\sigma}_i \underline{p}_i^{(p_1)} + \underline{\sigma}_i^{(p_2)} + \underline{\sigma}_i^{(p_1)} + \underline{\sigma}_i^{(p_2)} + $
For a model S , σ^2 can be estimated using $\hat{\sigma}_S^2 = X_S^2/(k-p)$ when $2 = \sum_{a=1}^{a} \underline{\beta}_{a} \underline{\beta}_{a} \underbrace{\alpha}_{a} \underbrace{D_{s}}_{a} \underbrace{X_{s}^{2}}_{a} = \underbrace{\Sigma_{i}}(r_{i}^{a}s)^{2} \underbrace{x_{s}^{c}}_{a} \underline{RSS} in \underline{LM}_{a} \underbrace{\sigma}_{S}^{2} = \underbrace{X_{S}^{2}/(k-p)}_{a} \underbrace{T_{a}}_{a} \underbrace{T_{a}}_{a$
For a model S , σ^2 can be estimated using $\hat{\sigma}_S^2 = X_S^2/(\frac{k}{k} - p)$ when $2 = \sum_{k=1}^{a} \underline{\beta}_k \underline{R}_k - D_s \underline{\hat{s}} \times \underline{\hat{s}} = \underline{\Sigma}_i (\underline{r}_{is}^*)^2 \underline{\hat{s}}^* \underline{R}_s SS in \underline{L}_{is} - \underline{\hat{\sigma}}_S^2} - X_S^2/(\frac{k}{k} - p)$ using D_s (using deviance D in place of X^2 is not very recom- using D_s mended as D may be inconsistent for sparse data) check U_k 3 W - D_k (\underline{\beta}_{-p}) might not converge to $\underline{\sigma}^2 - \underline{I}$ as $\underline{\beta} \to \underline{\sigma}^2 + 1$ ($\underline{M}_{-s} = \underline{N}_{-s}^2 - \underline{I}_{-s} = I$

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Lecture Notes

Alternative approaches to over-dispersion more flexible than dispersion p. 3-42
is known beta-binomial method (Williams, 1982; Crowder, 1978)
(cf. dispersion - quasi-likelihood: specify only how the mean and variance
of the response are connected to covariates1st moment - 2nd moment -
$\frac{B_{x} \sim beta(d_{x}, B_{x})}{E(\mathcal{J}_{x}) = \underline{n}_{x} \left(\underbrace{\alpha_{x}}{\partial x + B_{x}} \right) \left[B_{x}^{*} \left[\underbrace{\alpha_{x}}{\partial x + B_{x}} \right] \left[B_{x}^{*} \left(\underbrace{\alpha_{x}}{\partial x + B_{x}} \right) \right] \left[B_{x}^{*} \left(\underbrace{\alpha_{x}}{\partial x + B_{x}} \right) \right] \left[B_{x}^{*} \left(\underbrace{\alpha_{x}}{\partial x + B_{x}} \right) \right] \left[B_{x}^{*} \left(\underbrace{\alpha_{x}}{\partial x + B_{x}} \right) \right] \left[B_{x}^{*} \left(\underbrace{\alpha_{x}}{\partial x + B_{x}} \right) \right] \left[B_{x}^{*} \left(\underbrace{\alpha_{x}}{\partial x + B_{x}} \right) \right] \left[B_{x}^{*} \left(\underbrace{\alpha_{x}}{\partial x + B_{x}} \right) \right] \left[B_{x}^{*} \left(\underbrace{\alpha_{x}}{\partial x + B_{x}} \right) \right] \left[B_{x}^{*} \left(\underbrace{\alpha_{x}}{\partial x + B_{x}} \right) \right] \left[B_{x}^{*} \left(\underbrace{\alpha_{x}}{\partial x + B_{x}} \right) \right] \left[B_{x}^{*} \left(\underbrace{\alpha_{x}}{\partial x + B_{x}} \right) \right] \left[B_{x}^{*} \left(\underbrace{\alpha_{x}}{\partial x + B_{x}} \right) \right] \left[B_{x}^{*} \left(\underbrace{\alpha_{x}}{\partial x + B_{x}} \right) \right] \left[B_{x}^{*} \left(\underbrace{\alpha_{x}}{\partial x + B_{x}} \right) \right] \left[B_{x}^{*} \left(\underbrace{\alpha_{x}}{\partial x + B_{x}} \right) \right] \left[B_{x}^{*} \left(\underbrace{\alpha_{x}}{\partial x + B_{x}} \right) \right] \left[B_{x}^{*} \left(\underbrace{\alpha_{x}}{\partial x + B_{x}} \right) \right] \left[B_{x}^{*} \left(\underbrace{\alpha_{x}}{\partial x + B_{x}} \right) \right] \left[B_{x}^{*} \left(\underbrace{\alpha_{x}}{\partial x + B_{x}} \right) \right] \left[B_{x}^{*} \left(\underbrace{\alpha_{x}}{\partial x + B_{x}} \right) \right] \left[B_{x}^{*} \left(\underbrace{\alpha_{x}}{\partial x + B_{x}} \right) \right] \left[B_{x}^{*} \left(\underbrace{\alpha_{x}}{\partial x + B_{x}} \right) \right] \left[B_{x}^{*} \left(\underbrace{\alpha_{x}}{\partial x + B_{x}} \right) \right] \left[B_{x}^{*} \left(\underbrace{\alpha_{x}}{\partial x + B_{x}} \right) \right] \left[B_{x}^{*} \left(\underbrace{\alpha_{x}}{\partial x + B_{x}} \right) \right] \left[B_{x}^{*} \left(\underbrace{\alpha_{x}}{\partial x + B_{x}} \right) \right] \left[B_{x}^{*} \left(\underbrace{\alpha_{x}}{\partial x + B_{x}} \right) \right] \left[B_{x}^{*} \left(\underbrace{\alpha_{x}}{\partial x + B_{x}} \right) \right] \left[B_{x}^{*} \left(\underbrace{\alpha_{x}}{\partial x + B_{x}} \right) \right] \left[B_{x}^{*} \left(\underbrace{\alpha_{x}}{\partial x + B_{x}} \right) \right] \left[B_{x}^{*} \left(\underbrace{\alpha_{x}}{\partial x + B_{x}} \right) \right] \left[B_{x}^{*} \left(\underbrace{\alpha_{x}}{\partial x + B_{x}} \right) \right] \left[B_{x}^{*} \left(\underbrace{\alpha_{x}}{\partial x + B_{x}} \right) \right] \left[B_{x}^{*} \left(\underbrace{\alpha_{x}}{\partial x + B_{x}} \right) \right] \left[B_{x}^{*} \left(\underbrace{\alpha_{x}}{\partial x + B_{x}} \right) \right] \left[B_{x}^{*} \left(\underbrace{\alpha_{x}}{\partial x + B_{x}} \right) \right] \left[B_{x}^{*} \left(\underbrace{\alpha_{x}}{\partial x + B_{x}} \right) \right] \left[B_{x}^{*} \left(\underbrace{\alpha_{x}}{\partial x + B_{x}} \right) \right] \left[B_{x}^{*} \left(\underbrace{\alpha_{x}}{\partial x + B_{x}} \right) \right] \left[B_{x}^{*} \left(\underbrace{\alpha_{x}}{\partial x + B_{x}} \right) \right] \left[B_{x}^{*} \left(\underbrace{\alpha_{x}}{\partial x + B_{x}} \right) \right] \left[B_{x}^{*} \left(\underbrace{\alpha_{x}}{\partial x + B_{x}} \right) \right] \left[B_{x}^{*} \left(\underbrace{\alpha_{x}}{\partial x + B_{x}} \right) \right] \left[B_{x}^{*} \left(\underbrace{\alpha_{x}}{\partial x +$
$\frac{d_x}{d_x} = \frac{\partial u}{\partial x} \left(\frac{\partial u}{\partial x} \right) = \frac{\partial u}{\partial x} \left(\frac{\partial u}{\partial x} \right) \left(\frac{\partial u}{\partial x} + \frac{\partial u}{\partial x} \right) \left(\frac{\partial u}{\partial x} + \frac{\partial u}{\partial x} + \frac{\partial u}{\partial x} \right) $ $(use them to define a function working as (use the section of the sectio$
★ Reading: Faraway (2006, 1^{st} ed.), 2.11 $-p_{*}^{*}$ $- \ge 1$
[1Np 3-19] Matched Case-Control Studies — Recall 1. blocking in DOE
• 0: In a case-control study, how should we choose the city's black area
controls if there exist some confounding variables W, son) vs. 2-sample t
deal say age and sex, that may affect the outcome in Lock factor in DOE, i.e.,
Win addition to the risk factors X? - covariates of but should be considered
analysis Approach 1: record and include confounding in design and analysis.
ANCOVA ^{SE} variables as covariates in GLM analysis Interact is model 2 Pacell To LM
deal with (however, we may not be interested in the true: Y=XiBi+XiBi+XiBi+XiBi+XiBi+XiBi+XiBi+XiBi
Win data (nowever, we may <u>not be interested</u> in the <u>may cause a large number of</u>
Approach 2: confounding variables are Sparse data
blocked cfi availation and the design Recall. In paired t comparison
design explicitly adjusted for in the design block effect removed >
$\stackrel{\text{design}}{\leftarrow} \text{explicitly adjusted for in the design} \xrightarrow{\leftarrow} \text{block effect removed} \Rightarrow \\ \stackrel{\text{design}}{\leftarrow} Matched case-control design (MCCD): match each case with one p. 3-43}$
 ▲esign explicitly adjusted for in the design → ▲ Matched case-control design (MCCD): match each case with one p. 3-43 or more controls that have the same or similar values of some set
 design explicitly adjusted for in the design → block effect removed. Matched case-control design (MCCD): match each case with one p. 3-43 or more controls that have the same or similar values of some set of potential confounding variables. A group of a case and its having same value of W
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 ✓ • Matched case-control design (MCCD): match each case with one p. 3-43 or more controls that have the same or similar values of some set of potential confounding variables. A group of a case and its having same value of W corresponding controls is called a matched set, e.g., allows within block comparison units in a matched Set are 1st case 2st case nst case In a matched Set are 1st case 2st case nst case
$ \frac{design}{explicitly adjusted for in the design} block effect removed block effect removed $
▲ explicitly adjusted for in the design with black effect removed ★ • Matched case-control design (MCCD): match each case with one p. 343 or more controls that have the same or similar values of some set of potential confounding variables. A group of a case and its baving same corresponding controls is called a matched set, e.g., allows within black annancian in this contingency table units in a matched set are regarded as homogeneous age=20; sex=male age=20; sex=male age=20; sex=male age=20; sex=female and the same controls is called a matched set, e.g., and the same of the
★ • Matched case-control design (MCCD): match each case with one $p^{.343}$ or more controls that have the same or similar values of some set of potential confounding variables. A group of a case and its having same corresponding controls is called a matched set, e.g., allows within black comparison corresponding controls is called a matched set, e.g., allows within black comparison in this controls + age=20; sex=male+ walues of TV. check + in LNp.3-39, of risk + $\frac{D^c}{2}$ D
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 Additional controls for each case <i>Recall</i>. S.e.(𝔅)=𝔅/Int V Matched case-control design (MCCD): match each case with one p. 343 or more controls that have the same or similar values of some set of potential confounding variables. A group of a case and its having same corresponding controls is called a matched set, e.g., allows within black comprised as homogeneous age 20; sex=male about age 20; sex=female about ag
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made by S.-W. Cheng (NTHU, Taiwan)