

RICH TRANSFORMATION MODELS AND MORE

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POWER TRANSFORMATIONS TO NORMALITY
IN REGRESSION.

TRANSFORMATION PARAMETERS KNOWN.

TRANSFORMATION PARAMETERS UNKNOWN.

CONTROVERSY. WHAT CONTROVERSY?

BRILLINGER-STOKER AVERAGE DERIVATIVE
COEFFICIENTS.

TOPICS:

- 1 REGRESSION TRANSFORMATION MODELS.
- 2 YEO-JOHNSON (2000 BIOMETRIKA).
- 3 HERNANDEZ-JOHNSON (1980 JASA).
- 4 WONG TRANSFORMATIONS(1983).
- 5 KLAASSEN-WELLNER COPULA (1997).

$(\mathbf{X}_1, Y_1), \dots, (\mathbf{X}_n, Y_n)$ i.i.d $\sim (\mathbf{X}, Y)$,
 $\mathbf{X} \in R^d, Y \in R$.

$p(\mathbf{x}, y) = f(\mathbf{x})p(y|\mathbf{x})$.

RANDOM \mathbf{X} OR FIXED \mathbf{x} , "SAME" RESULT.

TRANSFORMATIONS:

$y^{(\lambda_0)}, (x_1^{(\lambda_1)}, \dots, x_d^{(\lambda_d)}) = \mathbf{x}^{(\lambda)}$.

e.g.

$$y^{(\lambda_0)} = y_{BC}^{(\lambda_0)} (\text{BoxCox}) = (y^{\lambda_0} - 1)/\lambda_0, y > 0, \lambda_0 \neq 0.$$

$$= \log y, \quad \lambda_0 = 0.$$

TRANSFORMATION MODEL:

$$Y^{(\lambda_0)} = \alpha + \beta^T \mathbf{X}^{(\lambda)} + \epsilon, \epsilon \sim \text{normal}(0, \sigma^2).$$

BOX-COX: MUST HAVE $y > 0$.

TROUBLE: WHEN $\epsilon \sim N(0, \sigma^2)$, $y \in R$.

SIGNED POWER: $\{\text{sgn}(y)|y|^\lambda - 1\}/\lambda$.

TROUBLE: CHANGES FROM CONVEX TO
CONCAVE IN y , $y \in R$. FUNNY LOOKING.

YEO-JOHNSON (2000 BIOMETRIKA)

$$y_{YJ}^{(\lambda)} = \begin{cases} \{(y + 1)^\lambda - 1\}/\lambda, & y \geq 0, \lambda \neq 0. \\ \log(1 + y), & y \geq 0, \lambda = 0. \\ -\{(-y + 1)^{2-\lambda} - 1\}/(2 - \lambda), & y < 0, \lambda \neq 2. \\ -\log(-y + 1), & y < 0, \lambda = 2. \end{cases}$$

PROPERTIES OF Y_J :

- (1) CONVEX IN y FOR $\lambda > 1$.
- (2) CONCAVE IN y FOR $\lambda < 1$.
- (3) $y_{Y_J}^{(\lambda)}$ AND ITS DERIVATIVES
 $(\partial^k / \partial \lambda^k) y_{Y_J}^{(\lambda)}$ ARE CONTINUOUS IN
 (λ, y) .
- (4) GOOD LOOKING.

HERNANDEZ JOHNSON: TRANSFORMATIONS
JASA (1980).

X =OBSERVATIONS.

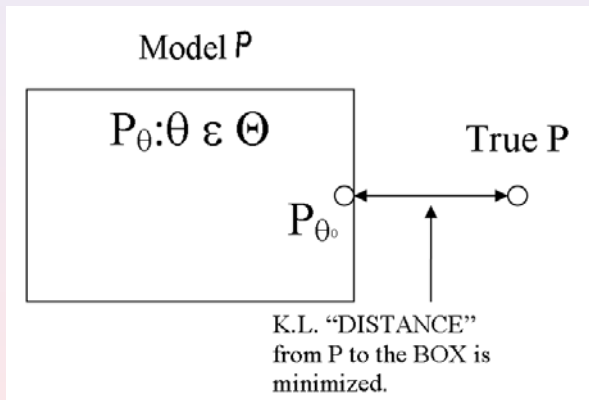
P =TRUE DISTRIBUTION OF \mathbf{X} .

$\mathcal{P} = \{P_\theta : \theta \in \Theta\}$ WORKING MODEL.

BOX AXIOMS:

- (I) \mathcal{P} IS NOT TRUE.
- (II) \mathcal{P} IS USEFUL.

THINKING INSIDE/OUTSIDE THE BOX:



DOKSUM, OZEKI, KIM, NETO. RICH VOLUME 2007.
HUBER (1967) SANDWICH FORMULA: $\text{VAR}_P(\hat{\theta})$, WHERE
 $\hat{\theta} = \text{MLE FOR } \mathcal{P}$.

DISCUSSION: WHAT IF $\mathcal{P} =$ CUBIC SPLINES
WITH 5 KNOTS AND $P =$ CUBIC SPLINE WITH
10 KNOTS?
THE MLE IS INCONSISTENT? NOT?

AWARD WINNING GENOMIC (GWAS) RESEARCHERS PHILOSOPHY:

WE PREFER SIMPLE, PROVEN, CLASSICAL
MODELS. IF WE FIND A SIGNIFICANT GENETIC
MARKER EFFECT USING A SIMPLE MODEL,
THE SIGNIFICANCE ALSO HOLDS FOR THE
TRUE MODEL PROVIDED THAT WE HAVE
INCLUDED ALL CONFOUNDING VARIABLES.
LOGISTIC REGRESSION. VALIDATION.

HERNANDEZ JOHNSON (1980) MULTIVARIATE TRANSFORMATIONS: $\theta = (\boldsymbol{\lambda}, \boldsymbol{\mu}, \Sigma)$

$(X_1^{(\lambda_1)}, \dots, X_p^{(\lambda_p)}) \sim \text{normal}(\boldsymbol{\mu}, \Sigma)$. FIX $\boldsymbol{\lambda}$,
 $(\boldsymbol{\mu}(\boldsymbol{\lambda}), \Sigma(\boldsymbol{\lambda})) = \arg \min\{d_{KL}(P, P_\theta) : \theta \in \Theta\}$.

THEN SET $\theta(\boldsymbol{\lambda}) = (\boldsymbol{\lambda}, \boldsymbol{\mu}(\boldsymbol{\lambda}), \Sigma(\boldsymbol{\lambda}))$.

$\boldsymbol{\lambda}_0 = \arg \min\{d_{KL}(P, P_{\theta(\boldsymbol{\lambda})}) : \boldsymbol{\lambda} \in R^p\}$.

$\boldsymbol{\mu}_0, \Sigma_0 = (\boldsymbol{\mu}(\boldsymbol{\lambda}_0), \Sigma(\boldsymbol{\lambda}_0))$.

P_{θ_0} IS A WORKING MODEL WHERE $\theta_0 = (\boldsymbol{\lambda}_0, \boldsymbol{\mu}_0, \Sigma_0)$.

P_{θ_0} IS NOT TRUE.

P_{θ_0} IS USEFUL.

MLE $\hat{\theta}$ of θ : REPLACE d_{KL} WITH ($-LOG LIKELIHOOD$).

REGRESSION $(Y^{(\lambda_0)}, \mathbf{X}^{(\lambda)}) \sim normal(\boldsymbol{\mu}, \boldsymbol{\Sigma})$.

REGRESS $Y^{(\lambda_0)}$ ON $\mathbf{X}^{(\lambda)}$.

ALL THE USUAL REGRESSION FORMULAS
HOLD WITH \mathbf{X} , Y REPLACED BY $\mathbf{X}^{(\hat{\lambda})}$, $Y^{(\hat{\lambda}_0)}$.

$VAR_P(\hat{\theta}) =$ SANDWICH FORMULA FOR $P \notin \mathcal{P}$.

CONTROVERSY: IF λ IS UNKNOWN, β IS A COEFFICIENT VECTOR ON AN UNKNOWN "SCALE" = $Y^{(\lambda)}$:

$$Y^{(\lambda)} = \alpha + \sum \beta_j X_j + \epsilon,$$

BRILLINGER-STOKER SOLUTION:

ADC= AVERAGE DERIVATIVE COEFFICIENT: NOTE THAT

$$E(Y|\mathbf{X}) = g(\alpha + \sum \beta_j X_j),$$

$g()$ =UNKNOWN, e.g. $g()$ COULD DEPEND ON λ .

$$E\left(\frac{\partial}{\partial X_j} E(Y|\mathbf{X})\right) = c\beta_j, \text{ WHERE } c = E(g'(\alpha + \sum \beta_j X_j)).$$

DEF: $\beta_j^{ADC} = (c\beta_j) / \sqrt{\sum (c\beta_j)^2} = \beta_j / |\beta|$.

β_j^{ADC} IS AN IDENTIFIABLE PARAMETER WHEN $g()$ (OR λ) IS UNKNOWN.

WHEN ARE THE λ KNOWN AND λ UNKNOWN CASES THE SAME?

DOKSUM AND CHI-WING WONG (1983) JASA.
CONSIDER CONTIGUOUS MODELS WHERE

$\beta_j/\sigma = \beta_{nj}/\sigma_n \rightarrow 0$ as $n \rightarrow \infty$.

SUPPOSE $Y_i^{(\lambda)} = \beta_0 + \sum_{j=1}^d \beta_j x_{ij} + \epsilon_i$,

MORE PRECISELY, SET $\theta_{ni} = \sum_{j=1}^d \beta_{nj} x_{ij}/\sigma_n$, $\text{Var}(\epsilon_i) = \sigma_n^2$,

$\Omega_n = \{\beta_n : |\theta_n| \leq K, \max |\theta_{ni}| \rightarrow 0\}$ (BICKEL–DOKSUM 1981)^c

THEN THE ASYMPTOTICS FOR THE λ KNOWN AND UNKNOWN CASE COINCIDE FOR ESTIMATION AND TESTING OF β_1, \dots, β_d . NOT FOR β_0 .

CHI-WING WONG (1983) THESIS.

$$\begin{aligned} Y_i &= \beta_0 + \sum_{j=1}^d \beta_j x_{ij}^{(\lambda_j)} + \epsilon_i \\ &= \alpha_0 + \sum_{j=1}^d \alpha_j z_{ij}^{(\lambda_j)} + \epsilon_i \end{aligned}$$

WHERE $z_{ij}^{(\lambda_j)} = [x_{ij}^{(\lambda_j)} - \bar{x}_j^{(\lambda_j)}] / SE(x_j^{(\lambda_j)})$. THE MODEL HAS BEEN REPARAMETERIZED BY STANDARDIZING THE TRANSFORMED PREDICTORS.

RESULT: IF $d=1$, THE λ , KNOWN AND UNKNOWN CASES ARE ASYMPTOTICALLY EQUIVALENT.

HERE α_0, α_1 AND λ_1 ARE ORTHOGONAL PARAMETERS IN THE SENSE OF COX AND REID, 1987 JRSS B.

IF $d > 1$, TRANSFORM $x_{ij}^{(\lambda_j)}$ TO HAVE IDENTITY SAMPLE COVARIANCE MATRIX. THE ASYMPTOTIC EQUIVALENCE OF THE λ KNOWN, UNKNOWN CASES STILL HOLDS.

HERE THE ESTIMATES OF λ ARE THE SAME IN THE STANDARDIZED AND UNSTANDARDIZED CASE. FOR ESTIMATING THE β 's, THE λ KNOWN AND UNKNOWN CASES ARE ASYMPTOTICALLY DIFFERENT EVEN THOUGH THE β 's ARE SIMPLE TRANSFORMS OF THE α 's.

THE BIVARIATE NORMAL COPULA.

$(X, Y) \sim H(x, y)$, CONTINUOUS, $X \sim F$, $Y \sim G$,
 $Z \equiv \Phi^{-1}(F(X))$, $W \equiv \Phi^{-1}(G(Y))$.

DEF:

$\mathcal{P}_C \equiv \{H : (\Phi^{-1}(F(X)), \Phi^{-1}(G(Y))) \sim N(0, 0, 1, 1, \rho)\}$

NOTE: $h_0(y) = \Phi^{-1}(G(y))$ AND

$h_1(x) = \Phi^{-1}(F(x))$ ARE NP INCREASING
TRANSFORMATIONS.

IF $F(), G()$ KNOWN, $\hat{\rho} = n^{-1} \sum Z_i W_i$ IS THE MOM
ESTIMATE.

IF $F(), G()$ UNKNOWN, REPLACE $Z_{(i)}$ WITH $E(Z_{(i)})$, $W_{(i)}$ WITH $E(W_{(i)})$. CALLED NORMAL SCORES.

FISHER-YATES 1938. GET $\hat{\rho}_{NS}$

KLAASSEN AND WELLNER (1997).

THEOREM: FOR $H \in \mathcal{P}_C$,

- (a) $\sqrt{n}(\hat{\rho}_{NS} - \rho) \rightarrow N(0, (1 - \rho^2)^2)$.
- (b) $\hat{\rho}_{NS}$ IS SEMIPARAMETRICALLY EFFICIENT.

NOTE: IF THE MODEL IS BIVARIATE NORMAL,

$$\sqrt{n}(\hat{\rho}_{MLE} - \rho) \rightarrow N(0, (1 - \rho^2)^2)$$

SPECIAL CASE: $(X, Y) \sim H(x, y)$ WITH

$$Y^{(\lambda_0)} = \beta_0 + \beta_1 X^{(\lambda_1)} + \epsilon, \text{ WHERE}$$

$(Y^{(\lambda_0)}, X^{(\lambda_1)}, \epsilon) \sim \text{NORMAL}$.

ZOU AND HALL (2002):

THE MLE OF $\rho = \text{CORR}$ WITH λ_0, λ_1
UNKNOWN HAS ASYMPTOTICALLY THE SAME
DISTRIBUTION AS THE MLE WITH λ_0, λ_1
KNOWN.

PROOF: $H \in \mathcal{P}_C$. MLE NO WORSE THAN
NORMAL SCORES.

NEED: SEMIPARAMETRIC EFFICIENCY.
⇒ PARAMETRIC EFFICIENCY.

CONSISTENT WITH WONG RESULT.
IN COX-REID LANGUAGE:
 ρ , λ_0 , and λ_1 ARE ORTHOGONAL PARAMETERS.

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