Recall from 1

Model \( f(y; \theta) \)

Data \( y^0 \)

\[ L(\theta) = \text{cf}(y^0; \theta) \]

What is \( y^0 \) (one-sided? 2-sided? Conf. Why?)

\[ p(\theta) = F(y^0; \theta) \]

"left of \( y^0 \) (scalar)

\[ \text{Conditions?} \]

\[ \theta = \tilde{\theta}_\beta = \tilde{p}(\beta; y) \]

[\( \tilde{\theta}_\beta \) covers \( \theta \) with prob \( \beta \)]

Simulations

If \( y \) from \( f(y; \theta) \) then \( p(\theta; y) \sim U(0,1) \)

Bayes

\[ B(\theta) = \int \pi(\theta) L^0(\theta) \, d\theta \]

where \( \pi(\theta) \) is some sensible prior

\[ \pi(\theta) : \text{mathematical/default/refer} \]

\[ \pi(\theta): \text{opinion/subjective?} \]

\[ \pi(\theta): \text{describe live (objective)} \]

Should these be used to present an analysis? If so, just put in parallel with data?

Basic ++++

 Likelihood

\[ l(\theta) = \log L(\theta) \]

\[ S^2 R = \pm \text{sgr}(\theta - \theta_1) [2(e - t)] \sim N(0, 1) \]

1st order

Issues LHC quantile,

\[ p(\theta) \sim \text{Conf for } (\theta, \infty) \]

\[ \tilde{\theta}_\beta \text{ in Conf Quantile at level } \beta \]

Some curve
1. Recall from 2
   - Poisson ($\theta$) $\geq \theta$ 0
   - Normal ($\theta, \sigma^2$) $\theta \geq \theta$

2. Confidence
   - Invert a pivot $p \sim N(\theta, \sigma^2)$
   - Invert "general pivot" Target on $Y(\theta)$

3. Neyman Diagram
   - $A(\theta) = $ Full $\theta$
   - $A = $
   - $C(y) = $

4. What is $\theta$? Notation
   - Meaning
Ex 1

Normal \( (\theta, \sigma^2) \) \( y^* \)

\[
\beta = \Phi(z) \quad \text{p-value}
\]

\[
z = \Phi^{-1}(\beta) \quad \text{q-value}
\]

\[
\hat{\theta}_\beta = y^* - \sigma \cdot z_\beta
\]

Different view

Quantile

\[
\beta = \int_{-\infty}^{y^*/\sigma} \frac{1}{\sqrt{2\pi}} e^{-\frac{(y^* - \theta)^2}{2\sigma^2}} d\theta
\]

\[
\beta = \Phi(\frac{y^* - \theta}{\sigma}) = \Phi(z)
\]

If asymmetric, it matters

\[
\hat{\theta}_\beta = y^* - \sigma \cdot z_\beta
\]

Same

\[
\Phi(\frac{y^* - \theta}{\sigma}) = \int_{-\infty}^{y^*/\sigma} \frac{1}{\sqrt{2\pi}} e^{-\frac{(y^* - \theta)^2}{2\sigma^2}} d\theta
\]

\[
\text{Quantile with } \hat{\beta} \text{ has } \beta \text{ post.}
\]
Ex 3

Bayes Choice of $m(e)$

Data yo

$f(y; e)$

$y = f(y; e)$

when equal

$p(e) = F(y; e)$

$	heta = \hat{\theta}$

p-quantile

Conf. = p-quantile

Integrate density

$\theta = \text{inverse of } F(\theta) = \beta$

$P(\beta)$

Quantile

Bayes posterior

Quantile

Beare posterior

$\theta$ = mean

$P(\theta)$

wt quantile

Mean

$P(y; e)$

Moment

Ex 3

Stock Inc

1958

Lindley

Insight: Good $m(e)$

Pr in day: - concentrate

Examines what "outside" posterior mean

Allows us to "outside" bell curve & shift
Confidence and Posterior: Case \( F(y_j; \theta) \) Stochastically independent

1. \( F(y_j; \theta) \sim U(0, 1) \) [Call this Coord by Coord]

2. Notation: \( F_y(y_j; \theta) = \frac{\partial}{\partial y} \)

(HOL; Bardenforff-Pilke; Nielsen; Daniels & Coxe BN)

\( F_\theta(y_j; \theta) = \frac{\partial}{\partial \theta} F(y_j; \theta) \)

Concentration & History? (helps) \( \cdots \) (Bayesian “L”)

(No-No!)
Confidence and Posterior: Case $F(y; \theta)$ Stochastically inc.

1. $F(y; \theta) \sim U(0, 1)$

2. Notation: $F_y(y; \theta) = \frac{d}{dy}$

\[ p\text{-value} = p(\theta) = \int_{-\infty}^{y^*} F_y(y; \theta) \, dy = F(y^*; \theta) = \int_{\theta}^{\infty} -F_{\theta}(y^*; \theta) \, d\theta \]

\[ s\text{-value} = s(\theta) = \int_{\theta}^{\infty} \pi(\theta) F_y(y^*; \theta) \, d\theta \]

\[ \theta \]

\[ = 0 \]

\[ \frac{dfc_{\theta}}{dx} y = -\infty + \infty \]

\[ F(0, \theta) \begin{cases} y & -\infty + \infty \end{cases} \]

\[ \frac{dfc_{\theta}}{x y} \theta = -\infty + \infty \]

Equal

\[ \int_{-\infty}^{\infty} -F_{\theta}(y^*; \theta) \, d\theta = \text{Integration under } \pi(\theta) \]

\[ \text{NoNo!} \]
Confidence and Posterior: Case $F(y; \theta)$ Stochastically inc

1. $F(y; \theta) \sim U(0,1)$

2. Notation: $F_y(y; \theta) = \frac{d}{dy}$

$p$-value = $p(\theta) = \int_{y^0}^{\infty} F_y(y; \theta) dy = F(y^0; \theta) = \int_{\theta}^{\infty} F_\theta(y^0; \theta) d\theta$

$s$-value = $s(\theta) = \int_\theta^{\infty} \pi(\theta) F_y(y^0; \theta) d\theta$

Likelhood

$\pi(\theta) F_y(y^0; \theta) = -F_\theta(y^0; \theta)$

$\Rightarrow \pi(\theta) = \frac{-F_\theta(y^0; \theta)}{F_y(y^0; \theta)}$

Deriv of quantile $y$ of $\theta$

$p(\theta)$ has repetition properties repeatable

If equals Integrants same

What happens at $y^0$ if different $\neq \theta$? Velocity $\influence_{\theta \neq \theta}$ NB
Differentiate \( y \neq \Theta \) at \( y^0 \) and now at \( \Theta^0 \).

\[ \frac{df}{d\Theta} \]

R quantile

\[ R \]

\[ y = y(\Theta, u) \] quantile fn.

\[ y = y(\theta, u) \]

Free pan change what happens

\[ \frac{\partial y(\theta, u)}{\partial \theta} \]

"What effect \( \Theta \) in at date?"

Gwe: \( f: \) Constraining HQL
\( B: \) Default \( q_{10} \)

Held-freed? Cond Pvalue.
p-value: When data is N(θ, σ^2) (θ, ∞) has cmf level p/2 (θ ≤ 0) \[ θ \]

Objective: Can extra model info go beyond SLR? [or Wald?]

Can higher and default priors be found?

Give O(n^-1) Bayes Priors

Values

Benefits

Prior into

1, 2, 3, 7, 8.

O Bayes

Objective

Default: Inf Prior "Objective, like f"

Default

AIC Inf Prior

Bayes

SLR, Wald, Score

Printout

Calculation & Better

Need? Get better

Results

O(n^1/2) O(n^-1) O(n^3/2)

Definite mechanics

Why HO2? Why HOB? Higher accuracy!!

Calculation procedure

Where is coming from??

247.pdf in documents
Scalar case: HOL allows "inject" into complicated $\mathbb{R}^n$ Model + regularity $y^0$

$L^0(\theta)$ = How much prob (under $\theta$)

near/at $y^0$ = primitive $\Rightarrow$ B

$
\begin{align*}
&f(\theta) \\
&f(y^0, \theta) \rightarrow \text{paradigm.}
\end{align*}
$

$P(\theta)$ = Past model

$B$: Must have to use a data dependent $\theta$

$y^0$: Dependent

Joke: Fun

Also see CJS 2008+
Scalar $\theta$: How does $\theta$ affect model near data under $\theta$ change?

Radical? Peter McCullough at U Chic B/15858 Local Duffy

So there was sufficient structure.

[Also vector case]

Why not see what happens when I change data $y$.

$y = y(p; \theta)$, a quantile

$\frac{dy}{d\theta}(y_{0;0})$
Scalar $\theta$

$L^0(\theta) = cf(y^0; \theta) \quad l(\theta) = \log L^0(\theta)$

$l(\theta)$

$l_\theta(\theta) = \text{score (obs)}$

$mle = (\hat{\theta} - \theta)$

Dep

Fund's to likelihood anal

\[ \text{Tradint: Exp. mfe} \]

\[ i(\theta) = \text{E} l_\theta(\theta; y; \theta) \]

Meaning??

\[ = \sqrt{V\{l_\theta(\theta; y; \theta)\}} \]

HOL Recent data

\[ Efron &amp; Huuse 1991 \]

Use $M$ to cal $l_\theta(\hat{\theta}; y)$