Statistical Tools:
Is there any merit in calibration?

D.A.S. Fraser
Statistics
University of Toronto

Colloque du CRM
6 novembre 2009

references
x
http://fisher.utstat.toronto.edu/dfraser/documents/crm09.pdf
slides

Meeting earlier this year: "What was I working on?"

- Reasonable affable question.. -
- Hesitant ... offbeat Topics ..

1925   Fisher: ancillaries

85 BP   "Kind of old!"

but

Q from someone who works on:

1763   Bayes:

247 BP   "Kind of Older"

Statistics: Global language, methodology, logic ... science et al

Concepts ... disagreement ... over 250 years of ideas

Concern? ... within & without discipline?

Fraser, Reid, Wong (2004).. bounded parameters ... Physics Rev D, 69, 033002

Kendall, Stuart V2 (1961, 1979)   Two sided confidence

Stainforth et al (2007)   Phil Trans Roy Soc A 365

Economist, Aug 18 (2007) p69   "Now a new difficulty is emerging"

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Coming:

Paradigm
Original Bayes
Extended Bayes
Redirected Bayes

With linearity
" + curvature
" - curvature

graph
"Prior to analyze model"?

Wrap-up

Paradigm: $\theta | y^\circ \sim$

$\pi(\theta)\ f(y^\circ;\theta)$ Just probability theory!

Carving up experience!

All instances. Full experience.

Where do the pieces come from?

Model $f(y;\theta)$ ... Acknowledged: "performance in Appl."
... There is a "true" θ (value) in Appl.
.. after true θ there was an observed $y = y^\circ$ "temporal" order

prior $\pi(\theta)$ ... where the true θ came from!

Types*: 1) Mathematical / invariance ... Original Bayes 1763 + {Jeffreys, Bernardo, many more} *

2) frequencies / empirical ... An identified source *
.. objective *

3) subjective: views, opinions, ... of investigator +

and many variants

Here: Examine 1) Mathematical ... Default priors

& some thoughts re 2) and 3)

(*) Some terms have been co-opted for other B purposes: → "noise", "dissonance"

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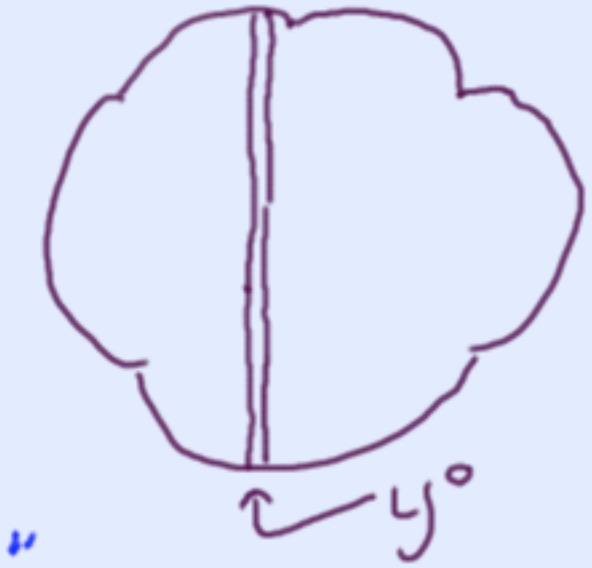

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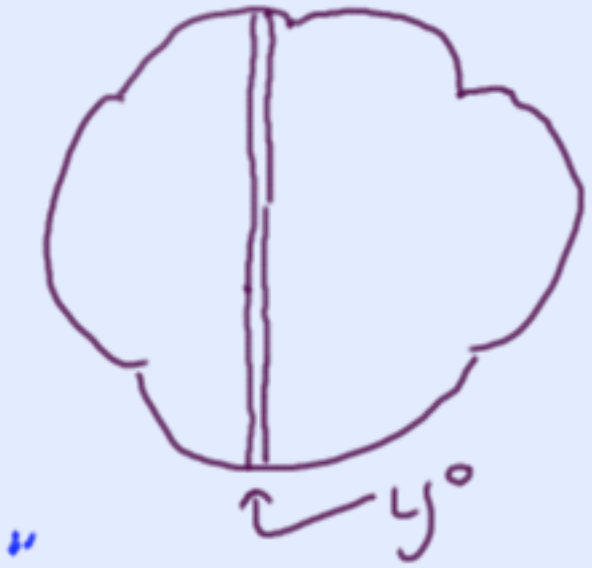

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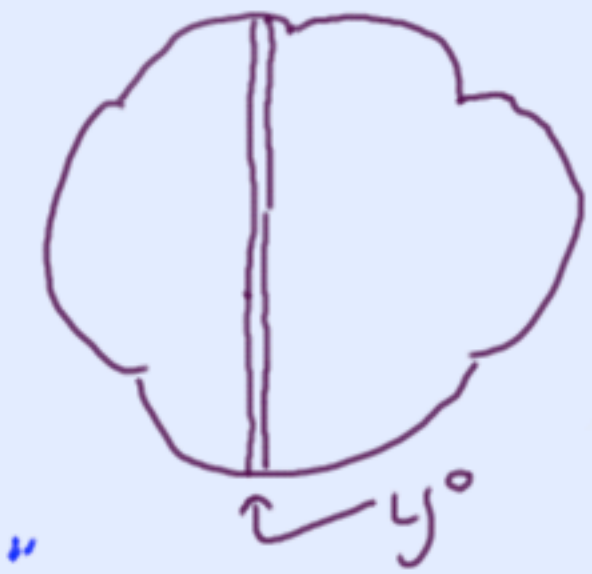

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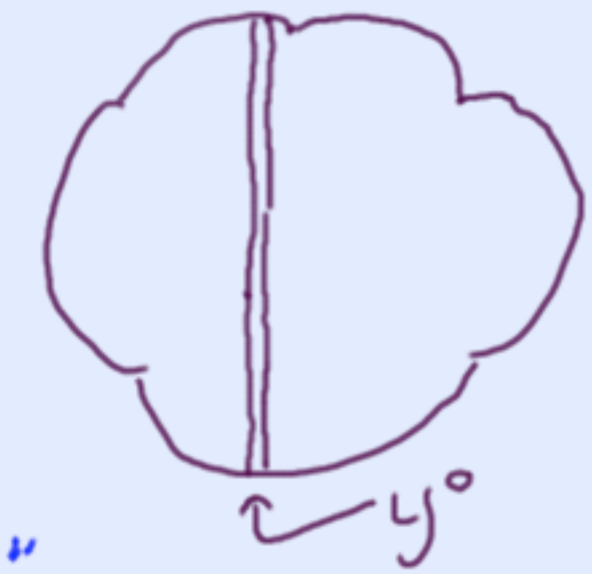

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Original Bayes Model: $f(y-\theta)$ Prior Math / Invariant $\pi(\theta)=c$

$$p(\theta) = \int_{-\infty}^{y^\circ} f(y-\theta)\,dy = \int_{-\infty}^{y^\circ-\theta} f(z)\,dz = \int_{\theta}^{\infty} f(y^\circ-\theta)\,d\theta = s(\theta)$$

Posterior pdf is $L^\circ(\theta)$
Posterior "prob" is Confidence

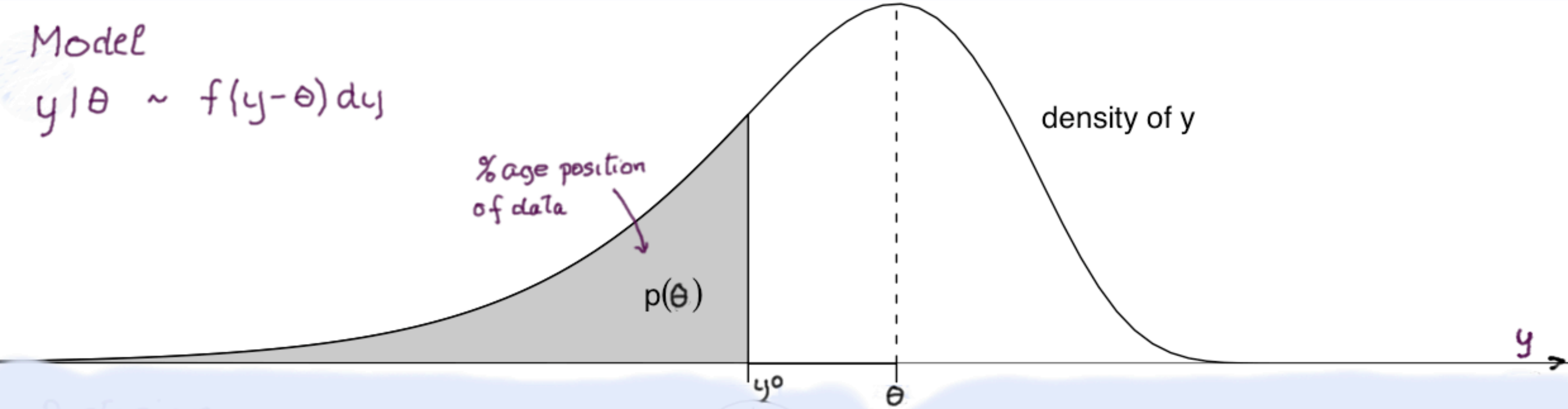
Bayes 1763 gave us: Likelihood: $L(\theta) = f(y^\circ-\theta)$ ① long before Fisher 1922
Confidence: $s(\theta)$ (upper tail) ② Fisher 1930

Substance is there .... not names, not argument

Original Bayes Model: $f(y-\theta)$ Prior Math / Invariant $\pi(\theta) = c$

Model

$y \mid \theta \sim f(y-\theta)\,dy$



Posterior

$\theta \mid y^{\circ} \sim f(y^{\circ}-\theta)\,d\theta$

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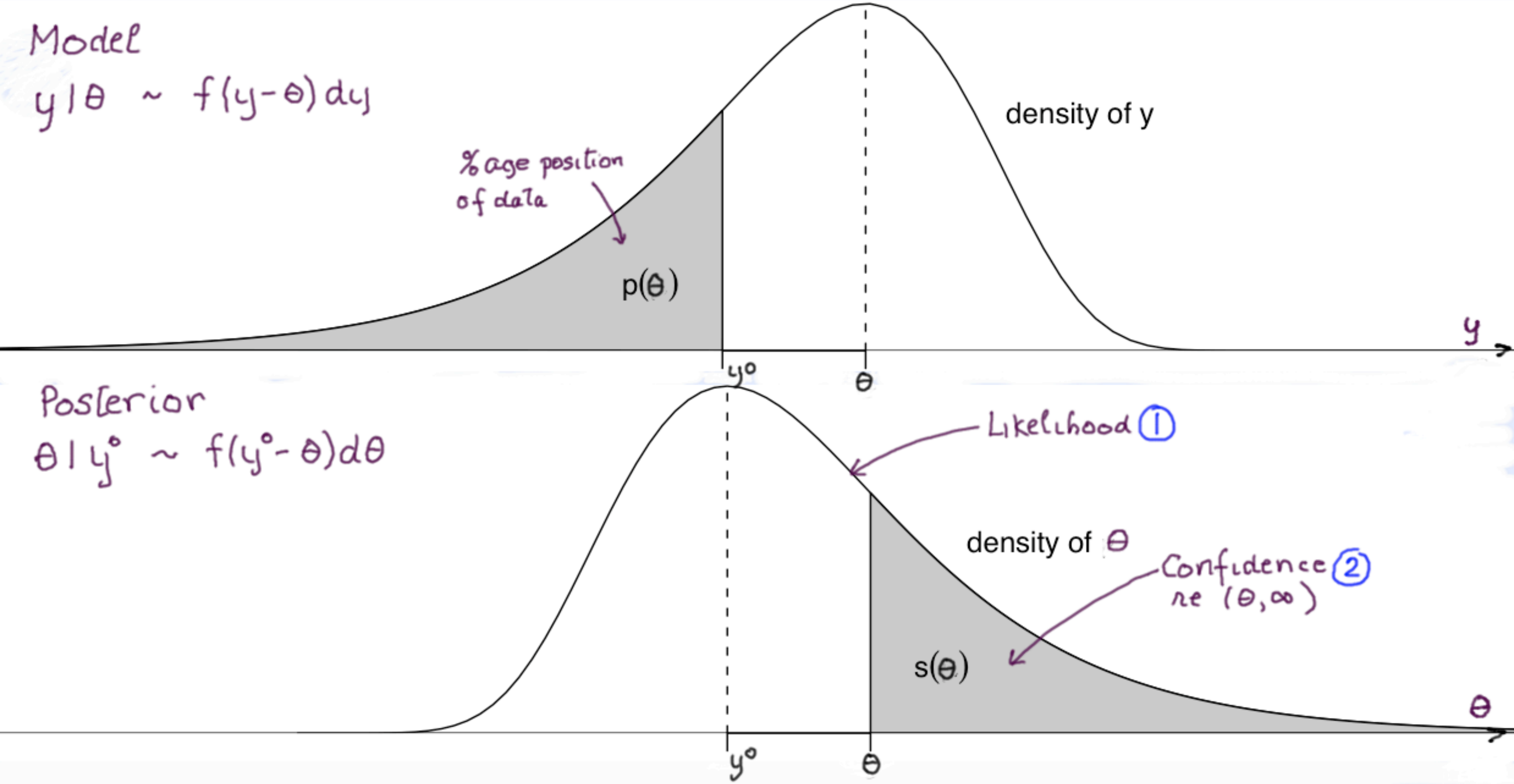

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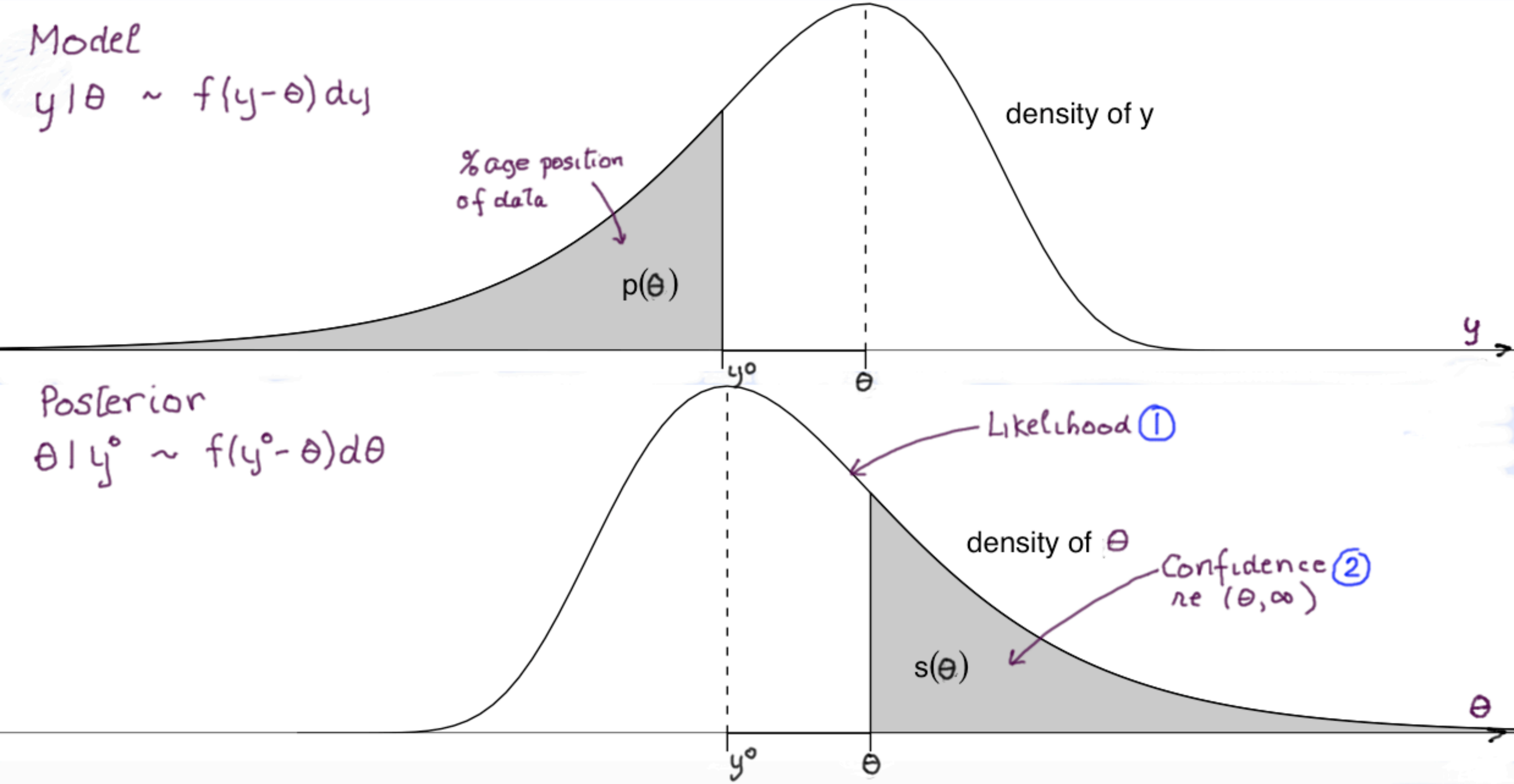

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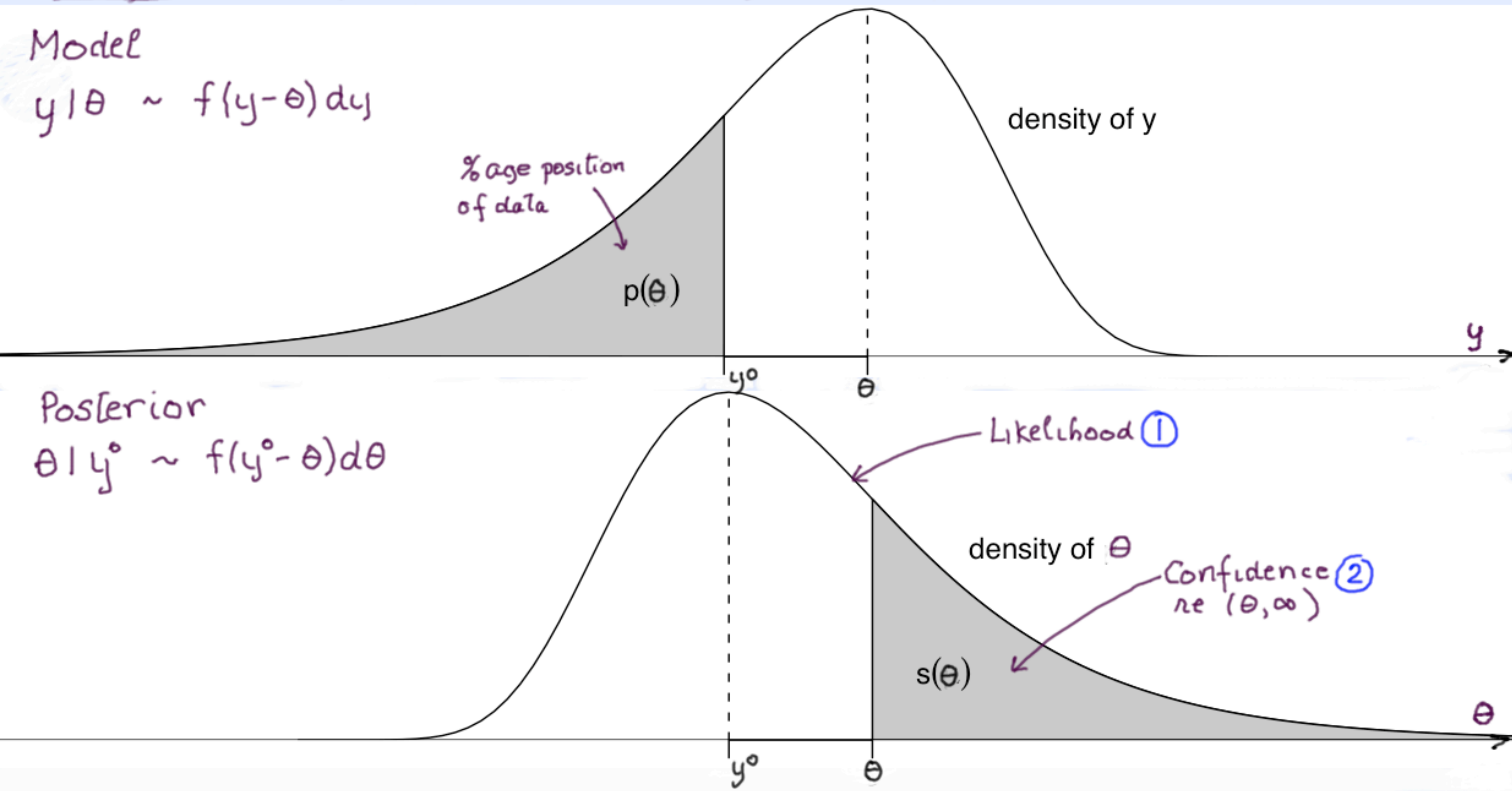

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Extended Bayes

p-value: $p(\theta) = \int_{-\infty}^{y^0} f(y;\theta)dy = F(y^0;\theta)$ = %age position of data y^0 regularity

$$= \int_\theta^\infty - F_{;\theta}(y^0;\theta)\,d\theta \qquad F_{;\theta}(y;\theta) = \frac{\partial}{\partial\theta}F(y;\theta)$$

s-value (Bayes): $s(\theta) = \int_\theta^\infty \pi(\theta)\,\underbrace{f(y^0;\theta)}_{L(\theta)}\,d\theta$

$$= \int_\theta^\infty \pi(\theta)\,F_y(y^0;\theta)\,d\theta \qquad F_y(y;\theta) = f(y;\theta)$$

If agree $\Rightarrow$ $\pi(\theta) = -\dfrac{F_{;\theta}(y^0;\theta)}{F_y(y^0;\theta)} = \dfrac{\partial y}{\partial\theta}\Big|_{y^0}$ Quantile fn $y = y(u;\theta)$ Invert $u = F(y;\theta)$

default prior $\pi(\theta) = \left|\dfrac{\partial y}{\partial\theta}\right|_{y^0}$

general: $y_1, \ldots, y_n$ $F_i(y_i;\theta)$ Invert $\underset{\sim}{y} = \underset{\sim}{y}(\underset{\sim}{u};\theta)$ Vector quantile fn. Vector p-value $\underset{\sim}{u}$

$\dfrac{\partial \underset{\sim}{y}}{\partial\theta}\Big|_{y^0} = (\underset{\sim}{v}_1(\theta), \ldots, \underset{\sim}{v}_p(\theta)) = V(\theta)$ ... like a $\underset{n\times p}{\text{design}}$ matrix ... $\underset{(\text{at } y^0)}{dy} = V(\theta)d\theta$ Curvature cf $\underset{\sim}{y} = X\theta +$

1) Default prior $= |V(\theta)|d\theta$ Data dependent ... "necessary"

F Reid Marras Yi (2009) JRSSB: revision, review $x = 239$

2) Conditioning: $\mathcal{L}(V(\hat\theta^0))$ cf $\mathcal{L}(X)$

F F Staicu (2009) Bernoulli: cond'ly accepted $x = 240$

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Vector quantile fn.
Vector p-value $\underset{\sim}{u}$

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If agree $\Rightarrow$ $\pi(\theta) = -\dfrac{F_{;\theta}(y^\circ;\theta)}{F_y(y^\circ;\theta)} = \left.\dfrac{\partial y}{\partial\theta}\right|_{y^\circ}$ Quantile fn $y = y(u;\theta)$ Invert $u = F(y;\theta)$

<u>default prior</u> $\pi(\theta) = \left|\dfrac{\partial y}{\partial\theta}\right|_{y^\circ}$

Vector quantile fn.
Vector p-value $\underset{\sim}{u}$

<u>general</u>: $y_1, \ldots, y_n$ $F_i(y_i;\theta)$ Invert $\underset{\sim}{y} = \underset{\sim}{y}(\underset{\sim}{u};\theta)$

$\left.\dfrac{\partial \underset{\sim}{y}}{\partial\theta}\right|_{y^\circ} = (\underset{\sim}{v}_1(\theta), \ldots, \underset{\sim}{v}_p(\theta)) = V(\theta)$ ... like a $\underset{n\times p}{\text{design}}$ matrix ... $\underset{(\text{at } y^\circ)}{dy} = V(\theta)\,d\theta$ cf $\underset{\sim}{y} = X\theta +$

Curvature

Data dependent ... "necessary"

↳ 1) Default prior $= |V(\theta)|\,d\theta$

F Reid Marras Yi (2009) JRSSB: revision, review $x = 239$

2) Conditioning: $\mathcal{L}(V(\hat\theta^\circ))$ cf $\mathcal{L}(X)$

F F Staicu (2009) Bernoulli: condn'ly accepted $x = 240$

Extended Bayes

regularity

p-value: $p(\theta) = \int_{-\infty}^{y^\circ} f(y;\theta)\,dy = F(y^\circ;\theta) =$ %age position of data y°

$$= \int_\theta^\infty -F_{;\theta}(y^\circ;\theta)\,d\theta \qquad F_{;\theta}(y;\theta) = \frac{\partial}{\partial\theta}F(y;\theta)$$

s-value (Bayes): $s(\theta) = \int_\theta^\infty \pi(\theta)\,\underbrace{f(y^\circ;\theta)}_{L(\theta)}\,d\theta$

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1) Default prior $= |V(\theta)|\,d\theta$ Data dependent ... "necessary"

F Reid Marras Yi (2009) JRSSB: revision, review $x = 239$

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Extended Bayes

p-value: $p(\theta) = \int_{-\infty}^{y^0} f(y;\theta)\,dy = F(y^0;\theta) =$ %age position of data y^0 regularity

$= \int_{\theta}^{\infty} -F_{;\theta}(y^0;\theta)\,d\theta$ $F_{;\theta}(y;\theta) = \frac{\partial}{\partial\theta}F(y;\theta)$

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general: $y_1,\dots,y_n$ $F_i(y_i;\theta)$ Invert $\tilde{y} = \tilde{y}(\tilde{u};\theta)$ Vector quantile fn. Vector p-value $\tilde{u}$

$\dfrac{\partial \tilde{y}}{\partial\theta}\Big|_{y^0} = (\tilde{v}_1(\theta),\dots,\tilde{v}_p(\theta)) = V(\theta)$ ... like a $\underset{n\times p}{\text{design}}$ matrix ... $dy = V(\theta)\,d\theta$ (at y^0) Curvature cf $\tilde{y} = X\theta +$

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Bayes redirected

Prior

* 1) Mathematical
2) frequencies
3) subjective:

Extended Bayes: $\pi(\theta) L(\theta) d\theta$

Mathematical prior $\times L(\theta)$
(Weighted Lebesgue)
"Invert" the density fn

Redirected Bayes: Fisher 1930 1935 Neyman 1937

upper tail dist'n fn. $s(\theta) = F(y^0; \theta)$ "Invert" the distribution function

Lindley (1958) NO! You can't do that! It's not Bayes! territory / turf

Actually: $s(\theta)$ is Bayes only if "$f(y-\theta)$" ... the original Bayes!

$\left(\frac{dy}{d\theta} = \text{constant} \Rightarrow \text{Location} \right)$

Result: Bayesians kept term probability: Lebesgue measure + Likelihood & stir gently. ?

Others (frequentists) stuck with Neyman & Confidence

But: Well known New data: "always multiply Likelihoods"

More than 1st order accuracy? ... Need more than Likelihood!

None the less: Bayes: rich exploratory use of Likelihood ... but risks
Use of term probability ... fraudulent ... we'll see!

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upper tail
dist'n fn: $s(\theta) = F(y^0; \theta)$ "Invert" the distribution function

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Two parameters: The risks!

Large sample analysis: Standardized $\begin{pmatrix} y_1 \\ y_2 \end{pmatrix} \sim \text{Normal}\left(\begin{pmatrix} \theta_1 \\ \theta_2 \end{pmatrix}, I\right)$ Standard N on The plane

Normal distn
One sigma disk

<u>Model: Normal at theta</u>

Two parameters : The risks !

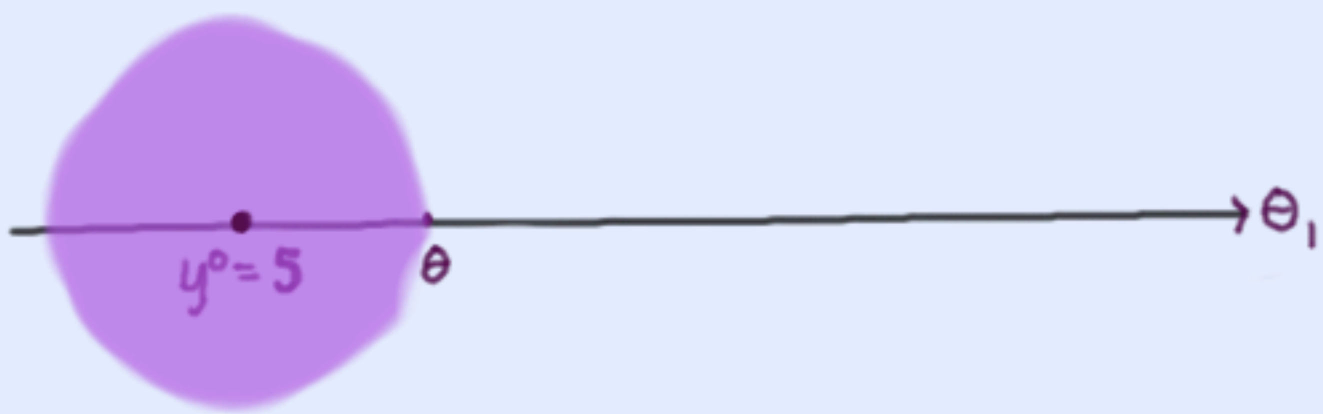
Large sample analysis : Standardized $\begin{pmatrix} y_1 \\ y_2 \end{pmatrix} \sim \text{Normal}\left(\begin{pmatrix} \theta_1 \\ \theta_2 \end{pmatrix}, I\right)$

Standard N
on the plane

Normal distn
One sigma disk

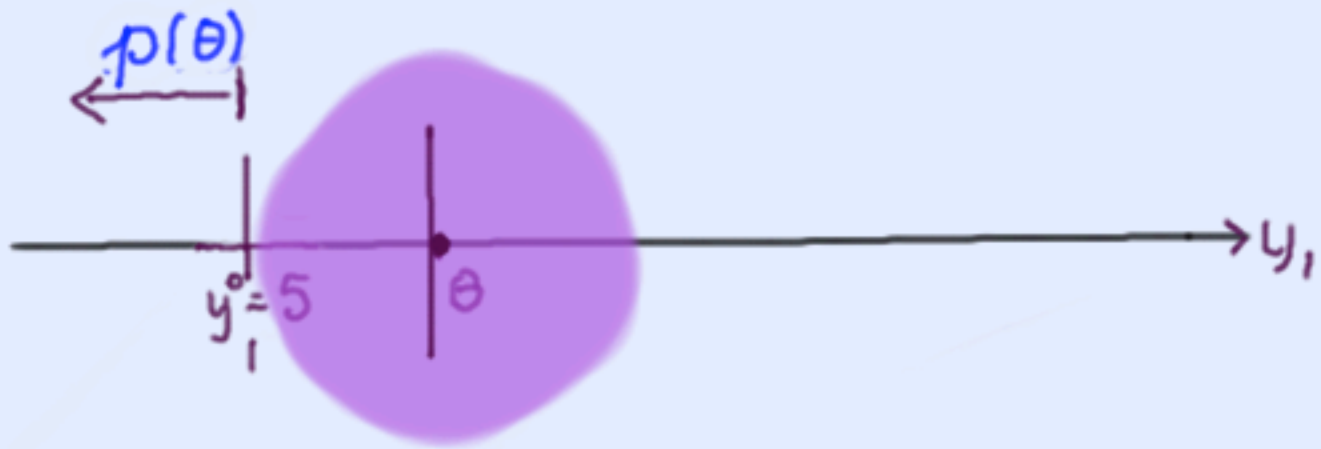
Model : Normal at theta

Bayes : Normal at data

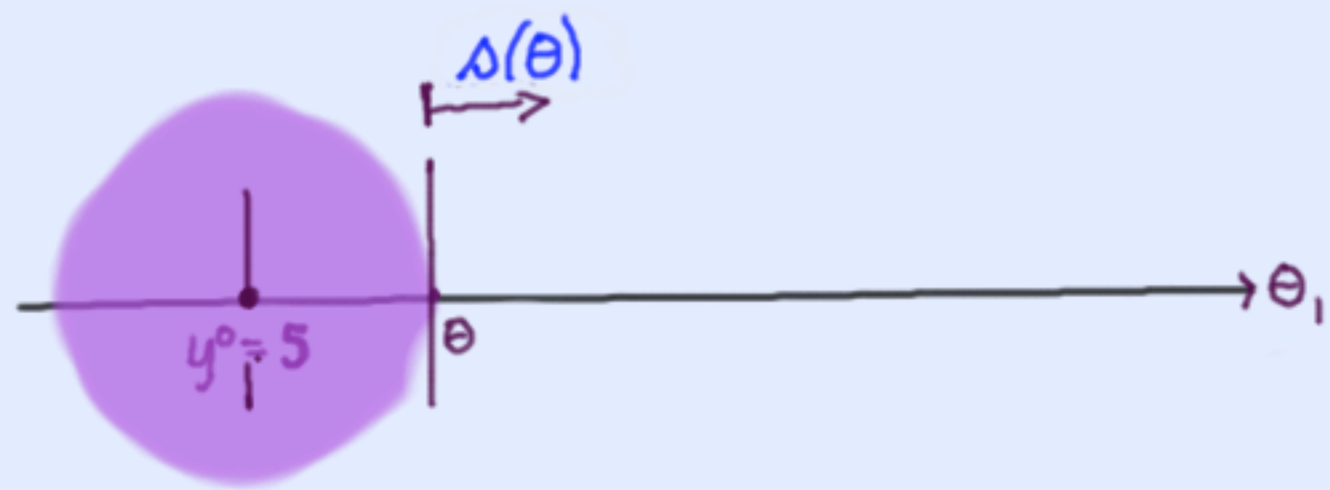


Case: Interest $\psi = \theta_1$ ... <u>linear</u>

Model: Normal at theta

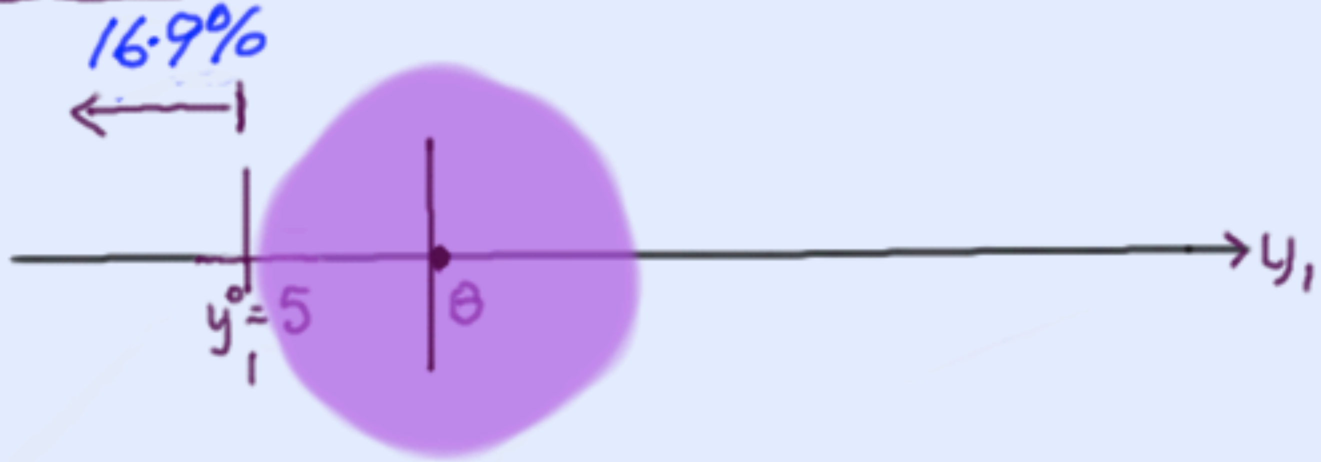


Bayes: Normal at data

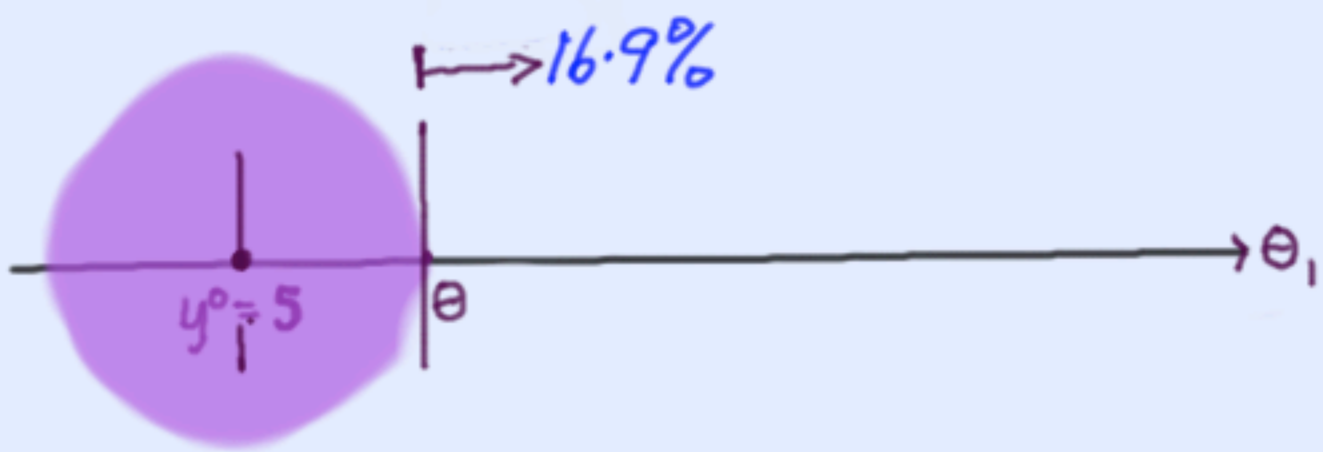


(a) Linear interest $\psi = \theta_1 = 5 + \delta$

Model : Normal at theta



Bayes : Normal at data

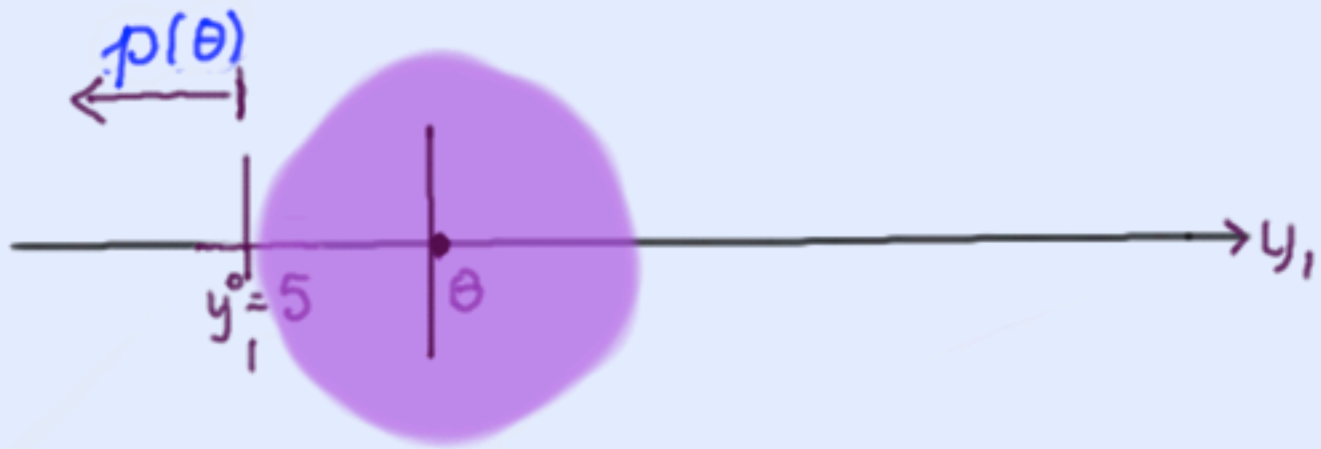


(a) Linear interest $\psi = \theta_1 = 5 + \delta$

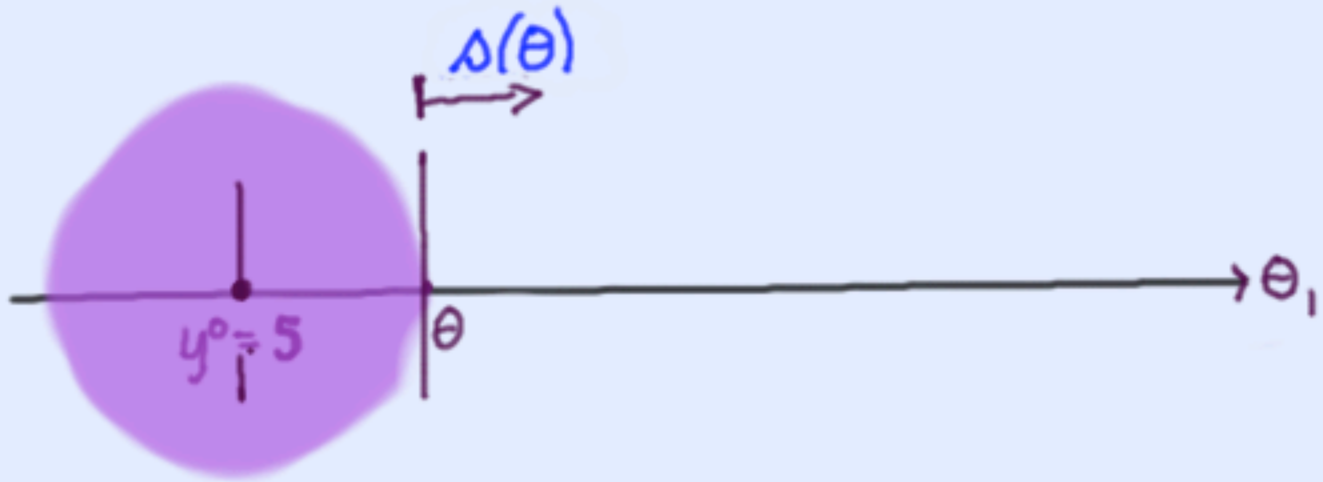
Bayes original:
$p(\theta) = s(\theta)$

$p(\theta)$	δ	$s(\theta)$
16.9 %	1	16.9 %

Model : Normal at theta



Bayes : Normal at data



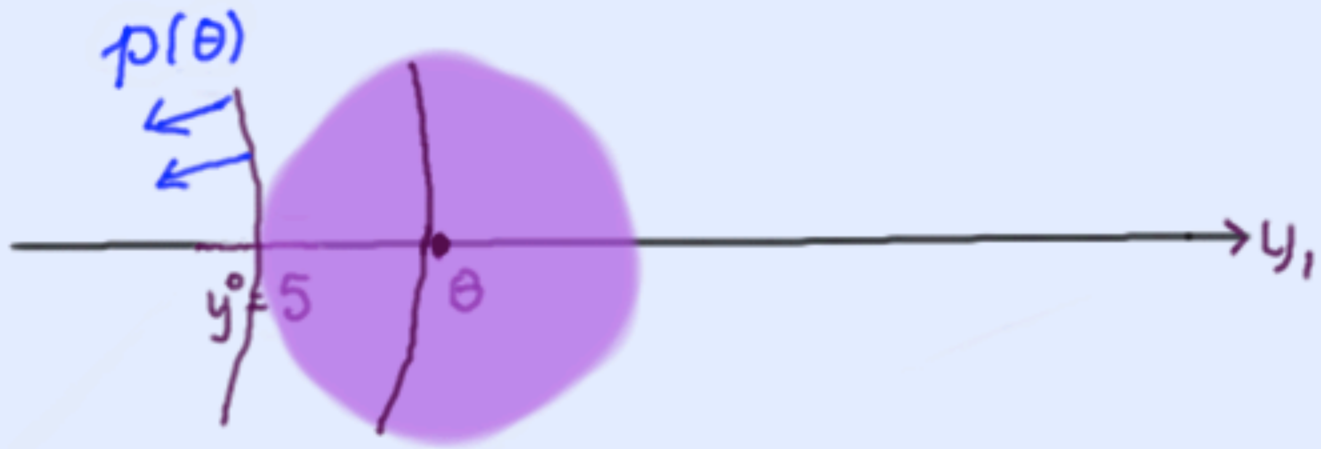
(a) Linear interest $\psi = \theta_1 = 5 + \delta$

Bayes original!
$p(\theta) = s(\theta)$

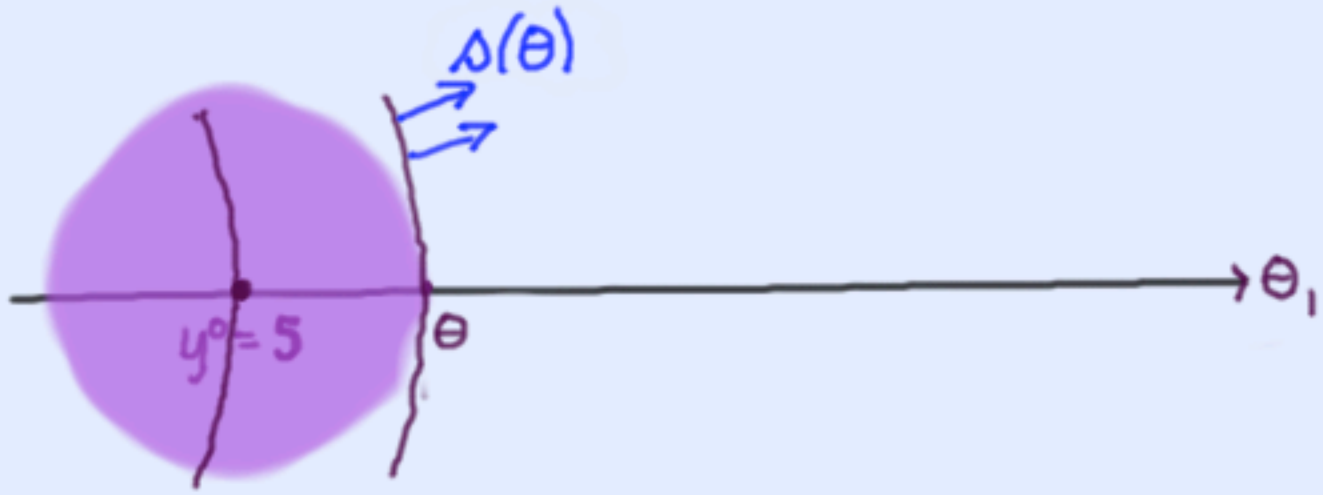
$p(\theta)$	δ	$s(\theta)$
2.3	2	2.3
16.9 %	1	16.9 %
50	0	50
83.1	-1	83.1
97.7	-2	97.7

Curved interest ψ

Model: Normal at theta



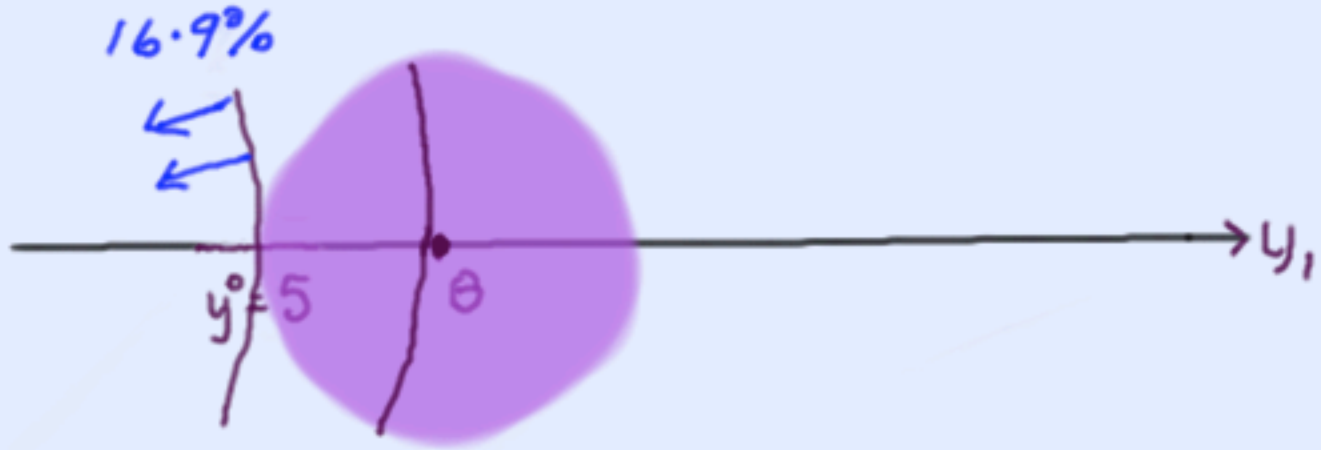
Bayes : Normal at data



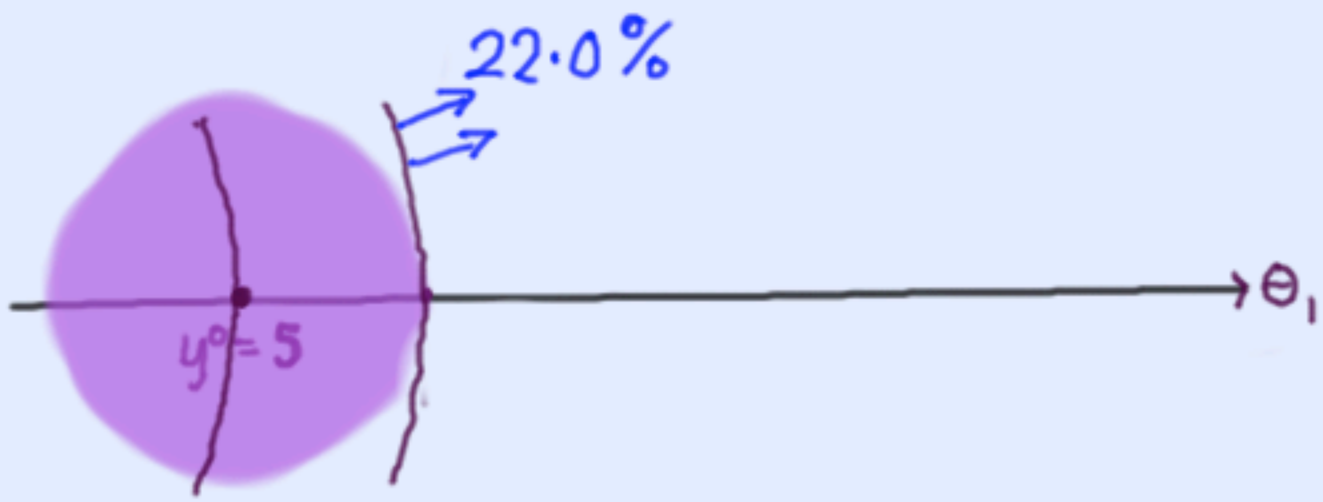
(b) Curved interest: $\psi = \theta_1 + \gamma \frac{\theta_2^2}{2}$ (locally)

Curvature $\gamma = .2$

Model: Normal at theta



Bayes: Normal at data



$s(\theta)$ larger

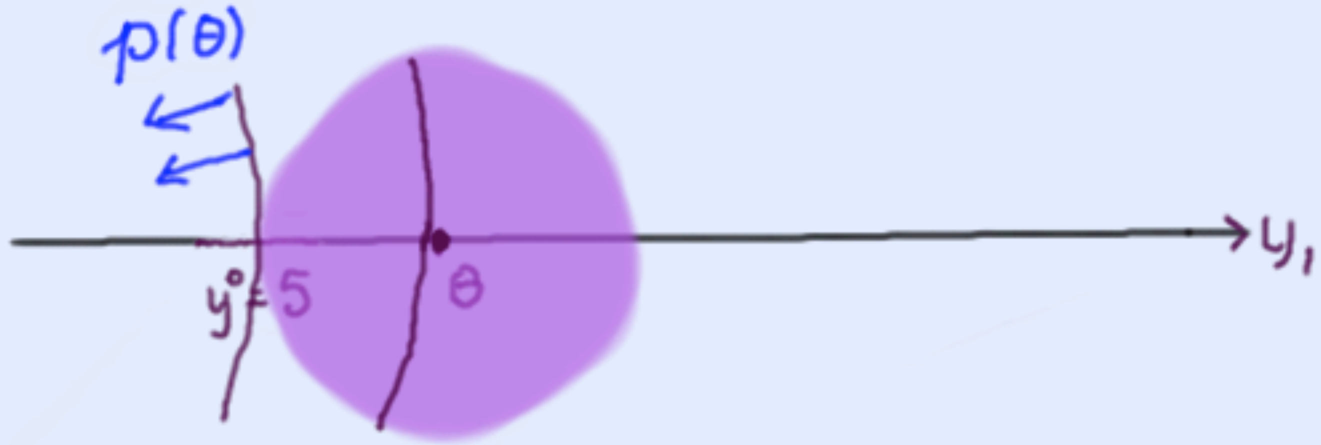
$p(\theta)$	$\delta = \theta - 5$	$s(\theta)$
16.9%	.86	22.0%

(b) Curved interest: $\psi = \theta_1 + \gamma \frac{\theta_2^2}{2}$

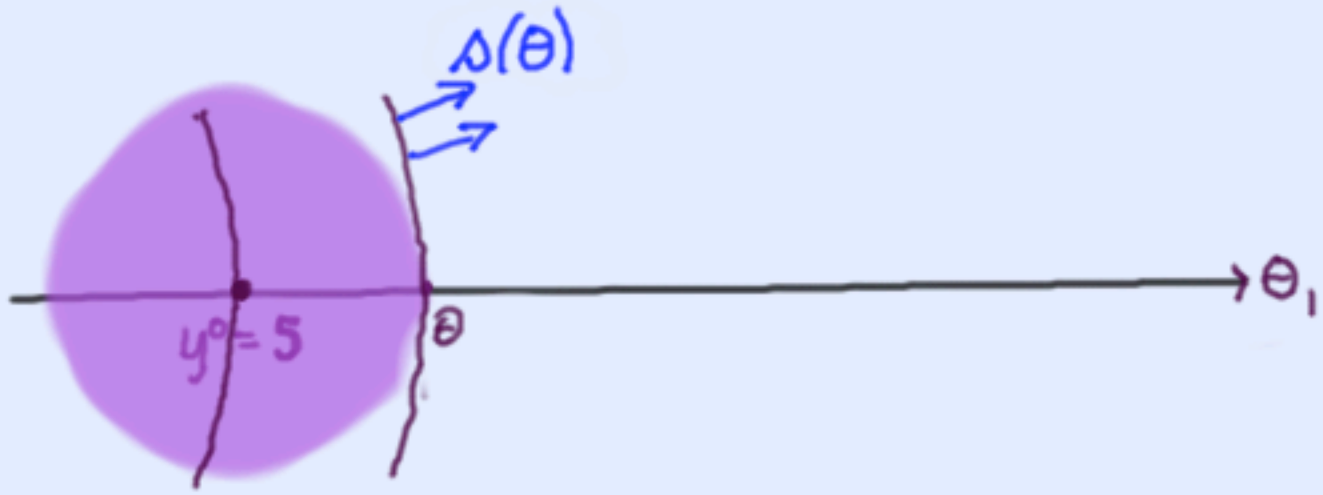
curvature $\gamma = .2$

$NC\chi^2(4^2)$ $NC\chi^2(5^2)$

Model : Normal at theta



Bayes : Normal at data



$s(\theta)$ larger

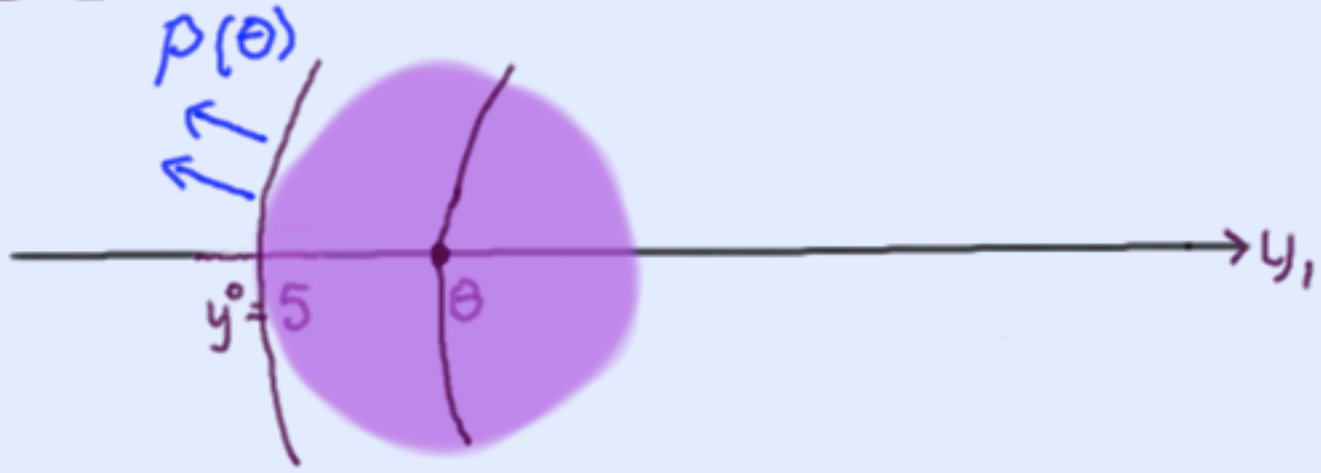
$p(\theta)$	$\delta = \theta - 5$	$s(\theta)$
2.3		3.4
16.9 %		22.0%
50		58.1
83.1		88.2
97.7		98.8
$NC\chi^2(4^2)$		$NC\chi^2(5^2)$

(b) Curved interest: $\psi = \theta_1 + \gamma \frac{\theta_2^2}{2}$

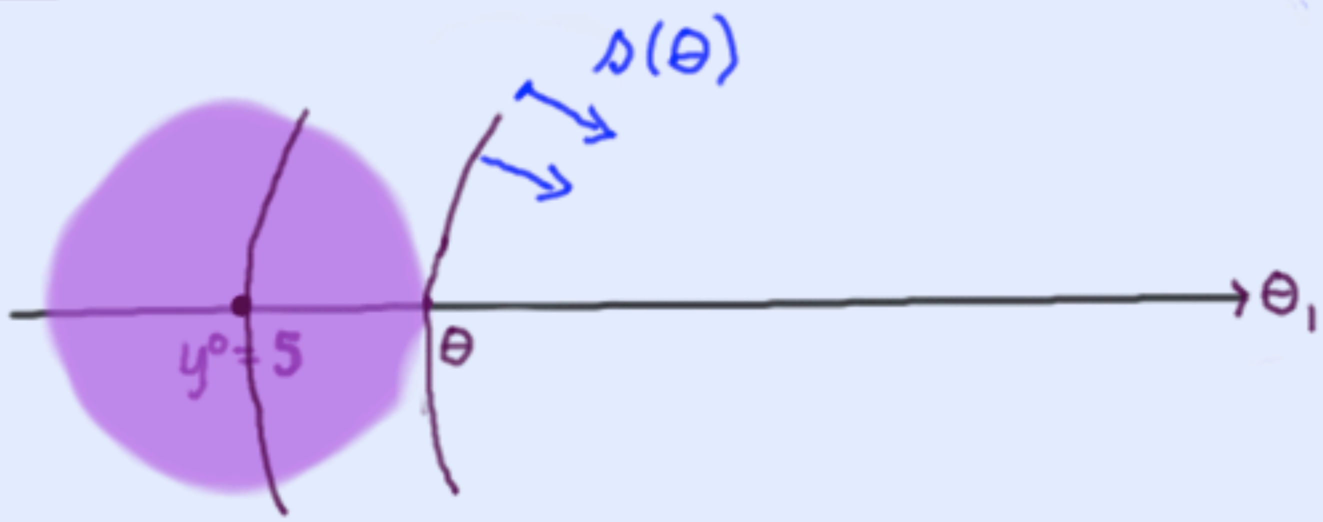
Curvature $\gamma = .2$

Curved interest ψ $\quad \gamma = -.2$

Model: Normal at theta



Bayes: Normal at data

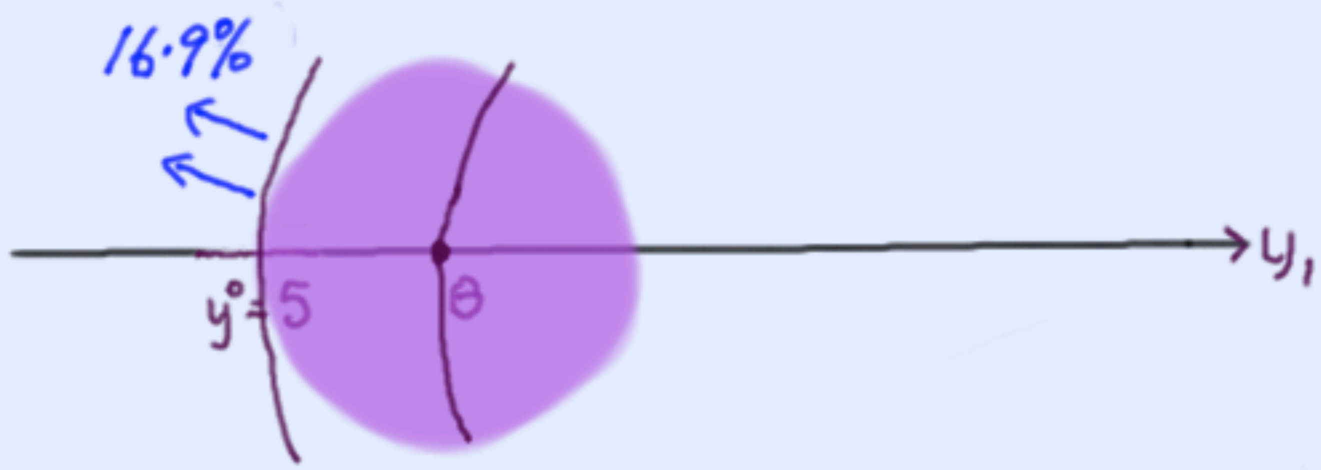


(b) Curved interest: $\psi = \theta_1 + \gamma \frac{\theta_2^2}{2}$

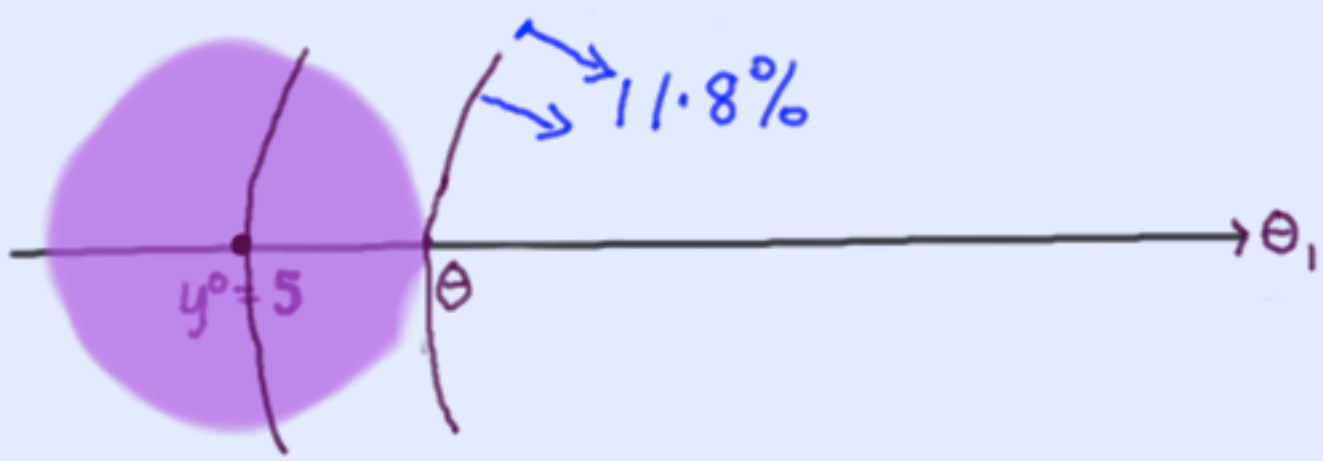
Curvature

(c) $\gamma = -.2$

Model: Normal at theta



Bayes: Normal at data



$s(\theta)$ smaller

$p(\theta)$	δ	$s(\theta)$
16.9 %	1.07	11.8 %

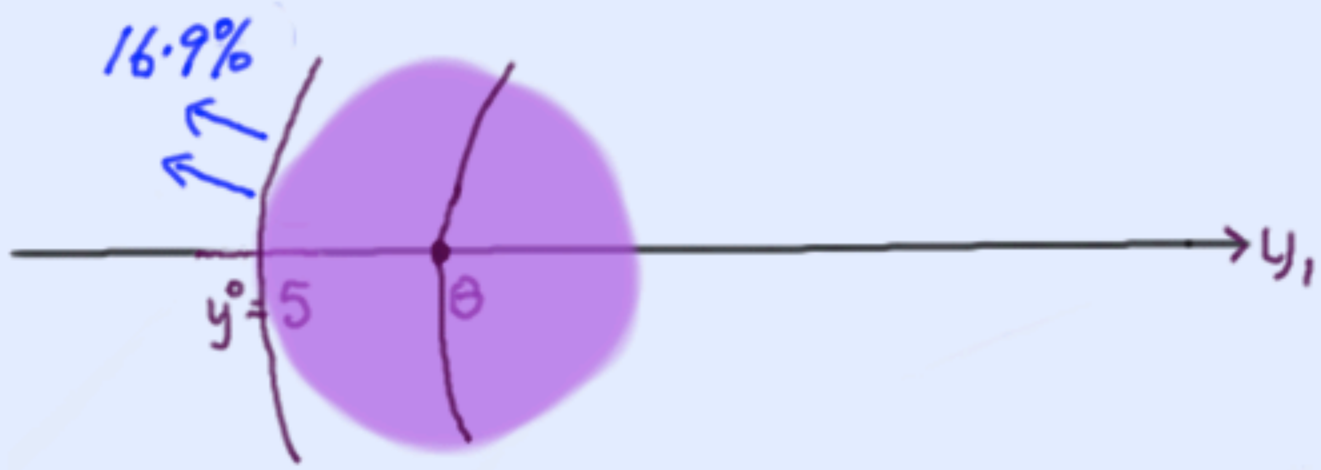
(b) Curved interest: $\psi = \theta_1 + \gamma \frac{\theta_2^2}{2}$

Curvature

(c) $\gamma = -.2$

$NC\chi^2\{(5-\delta)^2\}$ $NC\chi^2(5^2)$

Model: Normal at theta



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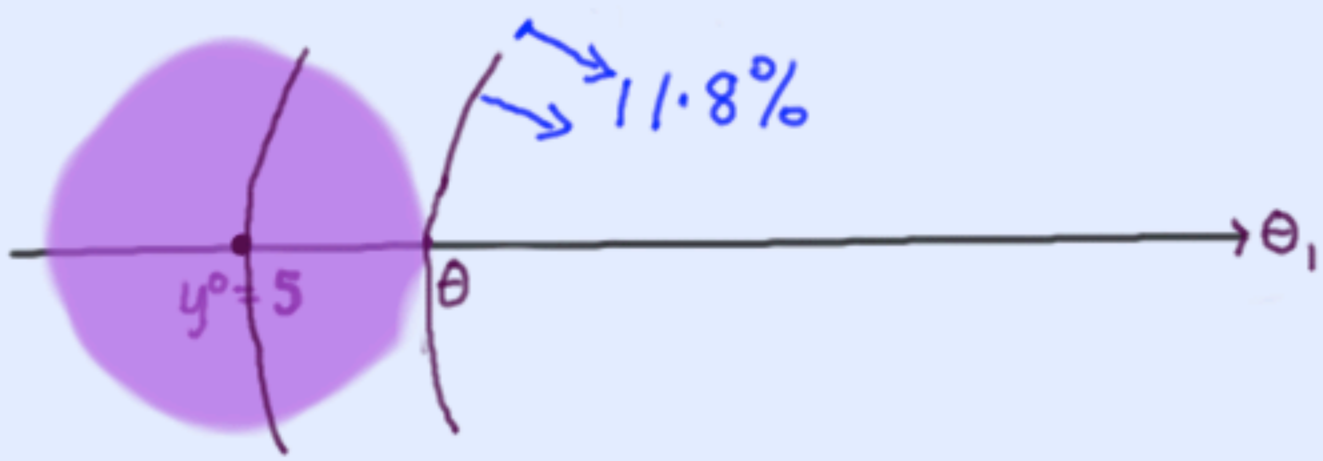


$s(\theta)$ smaller

$p(\theta)$	δ	$s(\theta)$
2.3		1.19
16.9 %	1.07	11.8 %
50		41.9
83.1		78.0
97.7		96.6

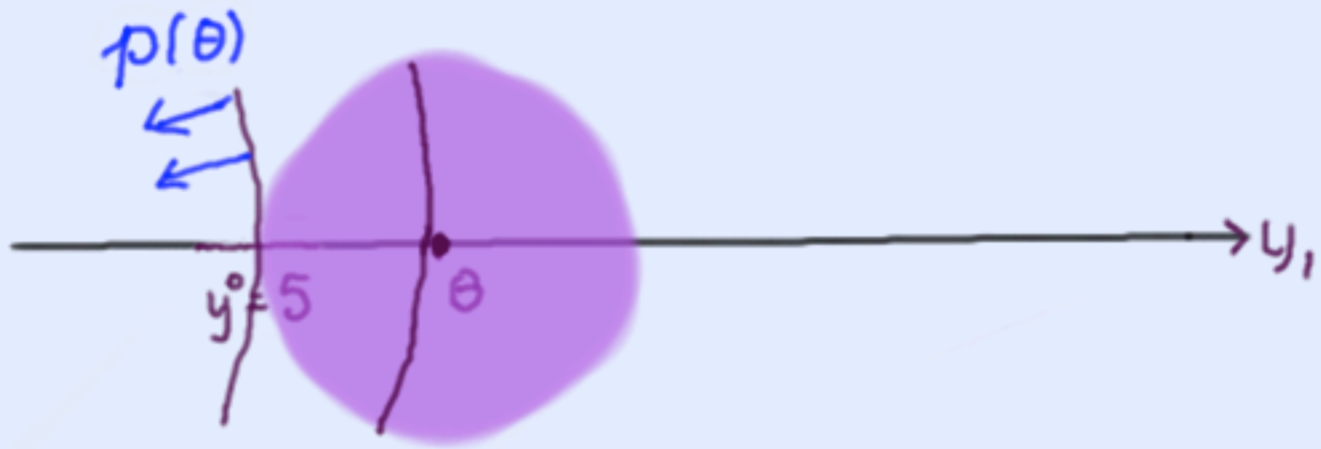
(b) Curved interest: $\psi = \theta_1 + \gamma \frac{\theta_2^2}{2}$

curvature

(c) $\gamma = -.2$

$NC\chi^2\{(5-\delta)^2\}$ $\quad NC\chi^2(5^2)$

Model: Normal at theta



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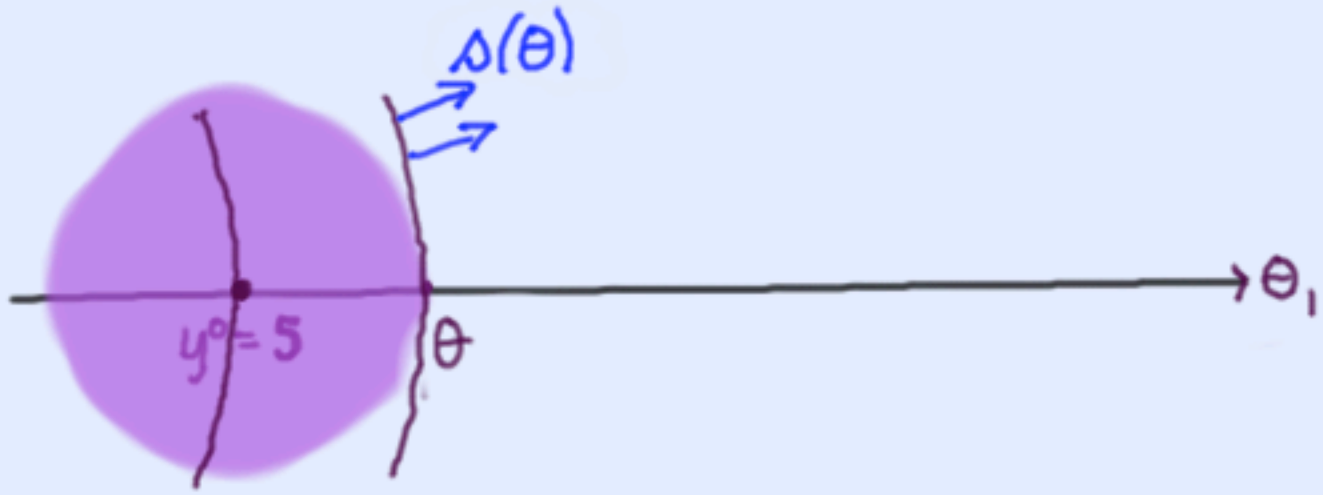
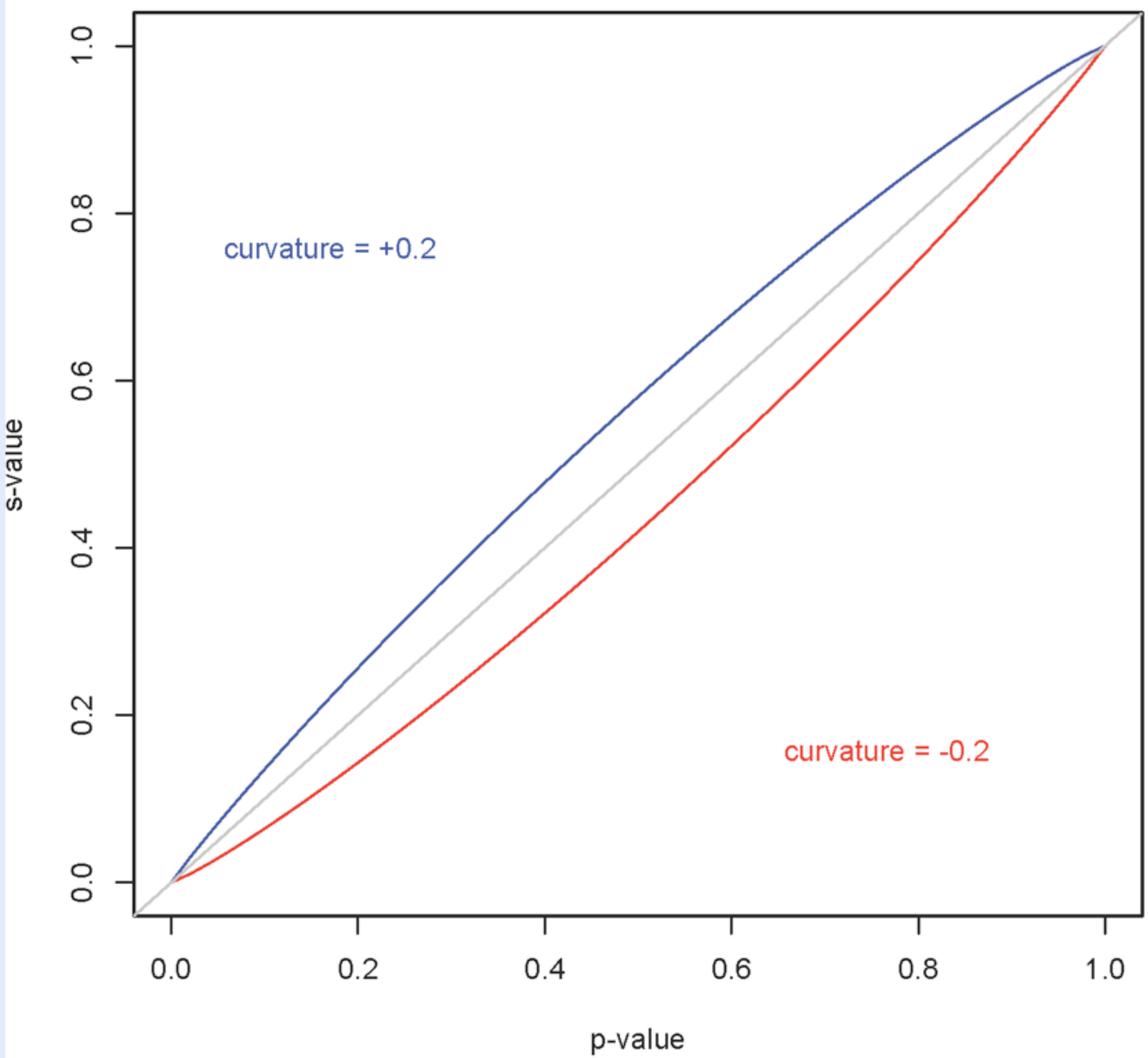


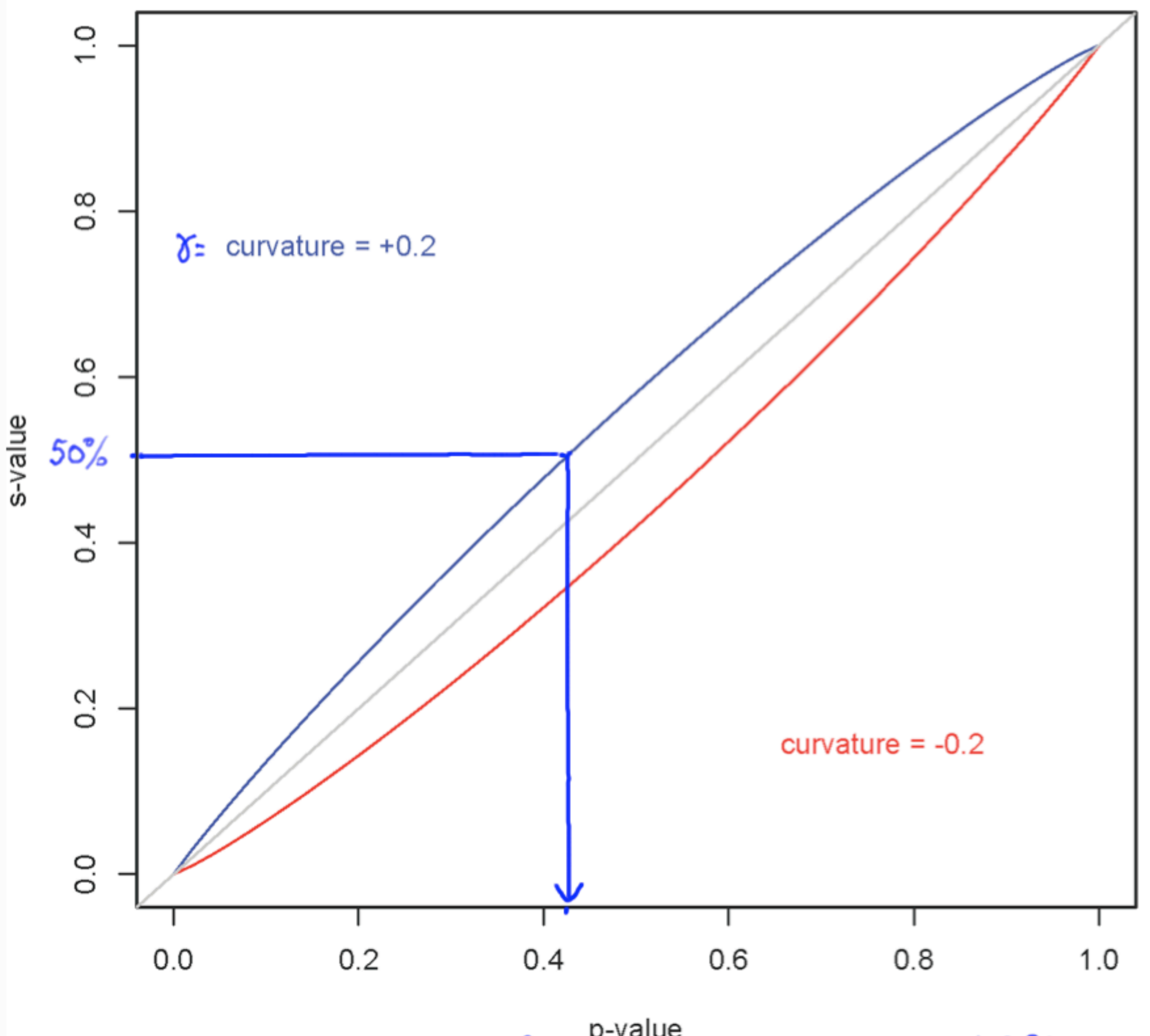
Plot $s(\theta)$ vs. $p(\theta)$

for $\gamma = -.2,\ 0,\ .2$

(b) Curved interest: $\psi = \theta_1 + \gamma \frac{\theta_2^2}{2}$

curvature $\gamma = .2$


curvature = +0.2
curvature = -0.2
s-value
p-value
0.0
0.2
0.4
0.6
0.8
1.0



If you promised 50% and you deliver 42%

Is it misrepresentation, fraud, Ponzi ?

All in (implicit) ... Dawid Stone Zidek (1973)

Parameter can be curved $\quad \Delta(\theta)$ above / below $p(\theta) \quad \{\Delta(\theta)$: weighted Lebesgue ? $\}$

Stainforth et al (2007) Phil Trans Roy Soc A 365

Economist, Aug 18 (2007) p69 "Now a new difficulty is emerging"

Model can be curved $\quad \Delta(\theta)$ above / below $p(\theta) \quad \{\Delta(\theta)$: weighted Lebesgue ? $\}$

Ex: $y \sim N \quad \theta \quad \sigma^2(\theta)$

... unless linearity ... $x = 247$

Lindley (1965) Promoted invariant priors

(1970s) Renounced improper priors

Distribution for θ ?

Evaluate ? Use β quantile $\quad \hat{\theta}_\beta(y) \quad 1-\beta \quad \beta$

Remember: y came after θ

What is "track" record ?

Ex: $y \sim N \quad \theta \quad \sigma^2(\theta)$ {No choice of prior will duplicate Confidence reliability $O(n^{-3/2})$ .... see $x = 247$

Can you Ponzi the θ's that already exist ?

If $\pi(\theta)$ ... Who said you had to use it to analyze "Model + Data" ?

Be responsible ! Report.... Model-Data inferences

and ... $\pi(\theta)$: 1) math 2) freq or 3) subj

separately for end user !

Unless ... explore (first order)

and not calibrate !

$x = 247$

<u>Parameter</u> can be <u>curved</u> $\quad \Delta(\theta) \ \begin{smallmatrix}\text{above}\\ \text{below}\end{smallmatrix} \ p(\theta) \quad \{\Delta(\theta) : \text{weighted Lebesgue?}\}$

| Stainforth et al (2007) Phil Trans Roy Soc A 365
| Economist, Aug 18 (2007) p69 "Now a new difficulty is emerging"

<u>Model</u> can be <u>curved</u> $\quad \Delta(\theta) \ \begin{smallmatrix}\text{above}\\ \text{below}\end{smallmatrix} \ p(\theta) \quad \{\Delta(\theta) : \text{weighted Lebesgue?}\}$

Ex: $y \sim N \quad \theta \quad \sigma^2(\theta)$

... unless <u>linearity</u> ... $x = 247$

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Can you <u>Ponzi</u> the θ's that already exist?

<u>If $\pi(\theta)$</u> ... Who said you <u>had</u> to use it to analyze "Model + Data"?

Be responsible! Report.... Model-Data inferences
and ... $\pi(\theta)$: 1) math 2) freq or 3) subj

separately for end user!

Unless ... <u>explore</u> (first order)
and not <u>calibrate</u>!

$x = 247$

Parameter can be curved $\quad s(\theta) \begin{matrix}\text{above}\\ \text{below}\end{matrix}\ p(\theta) \quad \{s(\theta)$: weighted Lebesgue ? $\}$

Stainforth et al (2007) Phil Trans Roy Soc A 365

Economist, Aug 18 (2007) p69 "Now a new difficulty is emerging"

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"Through the looking glass" (B)

- Images are inverted!
- but also there is curvature, distortion

  "Now a new difficulty is emerging"

- Is there any merit in calibration?

Ponzi