Identity for Statistics:

Calibration in Statistics

D A S Fraser
Dept Statistics
Univ Toronto

May 1 2010
Fields Institute

www.utstat.utoronto.ca/dfraser/documents/fields10.pdf

What's up?

1	Statistics	1349	O
2	Identity	1763	B
3	Economist	1922	L
4	Theorem	1930	C
5	Priors	1937	N
6	Linear parameters	1958	Li
7	Curved parameters	1973	DSZ
8	Curved models	2010	
9	Calibration!		

1 Statistics: Why?

Why are we here? Statistics MANY thanks to organizers!

1 Statistics: Why?

Why are we here? Statistics

Why am I here? Dumb numbers!

MANY thanks to organizers!

The clock was set ticking long before I knew!

1 Statistics: Why?

Why are we here? Statistics

MANY thanks to organizers!

Why am I here? Dumb numbers!

The clock was set ticking long before I knew!

Came from another discipline:

- There was a book published on "probability!"

1 Statistics: Why?

Why are we here? Statistics — MANY thanks to organizers!

Why am I here? Dumb numbers! — The clock was set ticking long before I knew!

Came from another discipline?

- There was a book published on "probability!"
- Some mathematicians viewed it as profound & admired it
- " " " it as wrong & condemned it
- " " were mystified

- an aura of the 'religious' .... ?

The issues still pervade...: despite attempts to hide | "Bayes 1763"

1 Statistics: Why?

Why are we here?	Statistics	MANY thanks to organizers!
Why am I here?	Dumb numbers!	The clock was set ticking long before I knew!

Came from another discipline?

- There was a book published on "probability!"
- Some mathematicians viewed it as profound & admired it
  - " " " it as wrong & condemned it
  - " " were mystified
- an aura of the 'religious' .... ?

Why again!

The issues still pervade...: despite attempts to hide | "Bayes 1763"

1 Statistics: Why?

Why are we here? Statistics MANY thanks to organizers!

Why am I here? Dumb numbers! The clock was set ticking long before I knew!

Came from another discipline?

- There was a book published on "probability!"
- Some mathematicians viewed it as profound & admired it
- " " " it as wrong & condemned it
- " " were mystified
- an aura of the 'religious' .... ?

The issues still pervade...: despite attempts to hide | "Bayes 1763"

Jeffreys: Theory of Probability 1939

Gave fundamental extensions to Bayes 1763

Geophysicist of highest stature!

Jeffreys: Theory of Probability 1939

Gave fundamental extensions to Bayes 1763

Geophysicist of highest stature!

Vehemently against
- plate tectonics!
- continental drift!

| Iceland !
| Hawaii !

Jeffreys: Theory of Probability 1939

Gave fundamental extensions to Bayes 1763

Geophysicist of highest stature!

vehemently against
- plate tectonics
- continental drift

| Iceland !
| Hawaii !

<u>Deep</u> things involved!

<u>Beliefs</u> ... re the <u>earth</u>!
... re how to <u>think</u>!

<u>Toleration in statistics</u> ... of contradictions?

Jeffreys: Theory of Probability 1939

Gave fundamental extensions to Bayes 1763

Geophysicist of highest stature!

vehemently against - plate tectonics | Iceland!
- continental drift | Hawaii!

Deep things involved!

Beliefs ... re the earth!
... re how to think!

Toleration in statistics ... of contradictions?

... intolerable in science

What do sensible people think of "us"?

2 Identity

How do others see Statistics?

- You say you are a Statistician! ... Reactions: # ! & ...
- Used to be that way for Mathematicians (~25BP)... they fixed it!
- What can we do ?

2 Identity

How do others see Statistics?

- You say you are a Statistician! ... Reactions: # ! & ...
- Used to be that way for Mathematicians (-25BP)... they fixed it!
- What can we do ?

Not good enough to:

- say we have a tool box ... then find most tools uncalibrated!

2 Identity

How do others see Statistics?

- You say you are a Statistician! ... Reactions: # ! & ...
- Used to be that way for Mathematicians (~25BP)... they fixed it!
- What can we do ?

Not good enough to:

- say we have a tool box ... then find most tools uncalibrated!
- use our opinions ... To do the analyses!

2 Identity

How do others see Statistics?

- You say you are a Statistician! ... Reactions: # ! & ...
- Used to be that way for Mathematicians (-25BP). they fixed it!
- What can we do ?

Not good enough to:

- say we have a tool box ... then find most tools uncalibrated!
- use our opinions ... To do The analyses!
- promote contradictory tools ... then shrug:

  just "Different way of thinking"   What ?   Double talk !

2 Identity

How do others see Statistics?

- You say you are a Statistician! ... Reactions: # ! & ...
- Used to be that way for Mathematicians (-25BP).. they fixed it!
- What can we do ?

Not good enough to:

- say we have a tool box ... then find most tools uncalibrated!
- use our opinions ... to do the analyses!
- promote contradictory tools.. then shrug:

  "just Different way of thinking" What? Double talk!
- 'shoot ourselves in the foot' publicly!

2 Identity

How do others see Statistics?

- You say you are a Statistician! ... Reactions: # ! & ...
- Used to be that way for Mathematicians (-25BP).. they fixed it!
- What can we do ?

Not good enough to:

- say we have a tool box .. then find most tools uncalibrated!
- use our opinions ... To do The analyses!
- promote contradictory tools.. then shrug:

  "just Different way of thinking" What ? Double talk !

- 'shoot ourselves in the foot' publicly!
- promote a religious view of our insights!

3. The Economist 2000 sept 28

In praise of Bayes   upbeat ... "proponent's views ..."

"... value of a statistical method ... apparent .."

"... results ... easier to understand ..."

"... clinical trials ... faster"

"Not bad for an old dead white male"

Not much on: what the method is ...

"... math. rule .. how you should change .... beliefs .."

Some "f" bashing ...

Quote Larry W. .. "more a religion than a science"

"Evidently there is life in the old reverend yet."

3. The Economist 2000 Sept 28

<u>In praise of Bayes</u>   Upbeat ... "proponent's views ..."

"... value of a statistical method ... apparent .. "

"... results ... easier to understand ... "

"... clinical trials ... faster"

"Not bad for an old dead white male"

2

Not much on: What the method is ...

"... math rule .. how you should change .... beliefs .."

3

Some "f" bashing ...

Quote Larry W. .. "more a religion than a science"

4

"Evidently there is life in the old reverend yet."

5

3. The Economist 2000 sept 28

<u>In praise of Bayes</u> Upbeat ... "<u>pro</u>ponent's views ..."

"... value of a statistical method ... apparent .. "

"... results ... easier to understand ... "

"... clinical trials ... faster"

"Not bad for an old dead white male"

Not much on: What the <u>method</u> is ...

" ... <u>math. rule</u> .. how you <u>should</u> change .... beliefs .. "

3

Some "f" bashing ...

Quote Larry W. .. "more a religion than a science"

4

"Evidently there is life in the old reverend yet."

5

3. The Economist 2000 sept 28

<u>In praise of Bayes</u>   upbeat ... "<u>pro</u>ponent's views ..."

"... value of a statistical method ... apparent .."

"... results ... easier to understand ..."

"... clinical trials ... faster"

"Not bad for an old dead white male"

Not much on: What the <u>method</u> is ...

"... <u>math. rule</u> .. how you <u>should</u> change .... beliefs.."

Some "f" bashing ...

Quote Larry W. .. "more a religion than a science"

4

"Evidently there is life in the old reverend yet."

5

3. The Economist 2000 sept 28

<u>In praise of Bayes</u> upbeat ... "proponent's views ..."

"... value of a statistical method ... apparent .."

"... results ... easier to understand ..."

"... clinical trials ... faster"

"Not bad for an old dead white male"

Not much on: What the method is ...

"... math. rule .. how you should change .... beliefs .."

Some "f" bashing ...

Quote Larry W. ... "more a religion than a science"

"Evidently there is life in the old reverend yet."

3. The Economist 2000 sept 28

In praise of Bayes Upbeat ... "proponent's views ..."

"... value of a statistical method ... apparent .. "

"... results ... easier to understand ... "

"... clinical trials ... faster"

"Not bad for an old dead white male"

Not much on: What the method is ...

"... math. rule .. how you should change .... beliefs .."

Some "f" bashing ...

Quote Larry W. ... "more a religion than a science"

"Evidently there is life in the old reverend yet."

4 The Theorem

Good theorem : Two inputs $f(x)$, $f(y|x)$

One output $f(x|y)$

Incontrovertible !

An application : one of inputs is missing

So you make one up ! Do some cosmetics ...

then claim the output is valid ?

1

Even MAT 137 students can handle that !

Worse than " $\frac{0}{0}$ " !

2

Context : There was a value ... θ

" was a process $f(y;\theta)$

" was a consequent value y^0

they are all in the past !

What do we know about the value ... θ ?

3 Do we assert probability ? On what basis ?

4 The Theorem

<u>Good theorem</u> : Two inputs $f(x)$, $f(y|x)$

One output $f(x|y)$

Incontrovertible !

<u>An application</u> : <u>one</u> of inputs is <u>missing</u>

So you <u>make</u> one <u>up</u> ! Do some cosmetics...

then <u>Claim</u> the output is <u>valid</u> ?

1 Even MAT 137 students can handle that !

Worse than " $\frac{0}{0}$ " !

2

<u>Context</u> : There <u>was</u> a <u>value</u> ... θ

" <u>was</u> a <u>process</u> $f(y;\theta)$

" <u>was</u> a consequent <u>value</u> y°

they are all in the <u>past</u> !

What do we know about the <u>value</u> ... θ ?

3 Do we assert <u>probability</u> ? On what basis ?

4 The Theorem

Good theorem : Two inputs $f(x)$, $f(y|x)$

One output $f(x|y)$

Incontrovertible !

An application : one of inputs is missing

So you make one up ! Do some cosmetics ...

then claim the output is valid ?

Even MAT 137 students can handle that !

Worse than "$\frac{0}{0}$" !

Context : There was a value ... θ

" was a process $f(y;\theta)$

" was a consequent value y°

they are all in the past !

What do we know about the value ... θ ?

Do we assert probability ? On what basis ?

4 The Theorem

Good theorem : Two inputs $f(x)$, $f(y|x)$
One output $f(x|y)$
Incontrovertible !

An application : one of inputs is missing
So you make one up ! Do some cosmetics...
then claim the output is valid ?
Even MAT 137 students can handle that !
Worse than "$\frac{0}{0}$" !

Context : There was a value... θ
" was a process $f(y;\theta)$
" was a consequent value y^0
they are all in the past !
What do we know about the value... θ ?

Do we assert probability ? On what basis ?

5 Types of Prior $\pi(\theta)$

$$\boxed{\pi(\theta)} \longrightarrow \theta \qquad \boxed{f(y;\theta)} \longrightarrow y^{\circ}$$

5 Types of Prior $\pi(\theta)$

$$\boxed{\pi(\theta)} \longrightarrow \theta \quad \boxed{f(y;\theta)} \longrightarrow y^{\circ}$$

Not Bayes!
Name?

$\pi(\cdot)$		
1. <u>Real</u>	<u>Known</u> <u>random</u> source for the θ	- - - - - - - - -

5 Types of Prior $\pi(\theta)$

$$\boxed{\pi(\theta)} \longrightarrow \theta \qquad \boxed{f(y;\theta)} \longrightarrow y^{o}$$

Not "Bayes!"
Name?

$\pi(\cdot)$		
1. <u>Real</u>	<u>Known</u> <u>random</u> source for the θ	- - - - - - - - -
2. <u>Opinion</u>	Your betting <u>instincts</u>	<u>Subjective</u> ← opinion

5 Types of Prior $\pi(\theta)$

$$\boxed{\pi(\theta)} \longrightarrow \theta \qquad \boxed{f(y;\theta)} \longrightarrow y^{o}$$

Not Bayes! Name?

$\pi(\cdot)$		
1. Real	Known random source for the θ	- - - - - - - - -
2. Opinion	Your betting instincts	Subjective $\leftarrow$ opinion
3. Convenient	Hope for something useful	Default

Is "Bayes!"

5 Types of Prior $\pi(\theta)$

$$\boxed{\pi(\theta)} \longrightarrow \theta \quad \boxed{f(y;\theta)} \longrightarrow y^{\circ}$$

Not Bayes! Name?

$\pi(\cdot)$		
1. Real	Known random source for the θ	- - - - - - - - -
2. Opinion	Your betting instincts	Subjective ← opinion
3. Convenient	Hope for something useful	Default

"Is Bayes!"

Does the Theorem apply to Application?

Case 1. Yes!

Case 3. No! ... but things 'sort of work'

5 Types of Prior $\pi(\theta)$

$$\boxed{\pi(\theta)} \longrightarrow \theta \qquad \boxed{f(y;\theta)} \longrightarrow y^{\circ}$$

Not Bayes! Name?

$\pi(\cdot)$

1. Real — Known random source for the θ — - - - - - - - - -
2. Opinion — Your betting instincts — Subjective ← opinion
3. Convenient — Hope for something useful — Default

Is "Bayes!"

Does the Theorem apply to Application?

Case 1. Yes!

Case 3. No! ... but things 'sort of work'

It is "Approximate confidence"

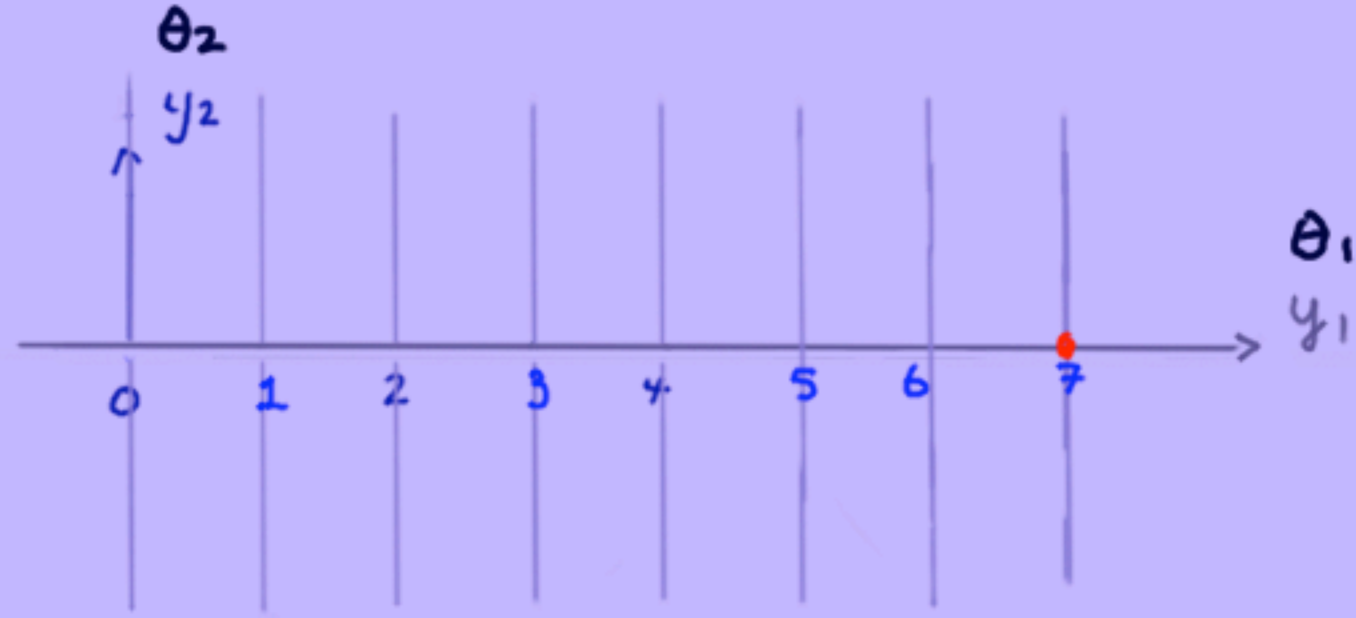
Laplace liked the answers!

... after all | $y = X\beta + \sigma z$
β, σ linear!

6 Linearity : $N(\theta; I)$ on R^2: Contours of Interest $\psi(\theta) = \theta_1$

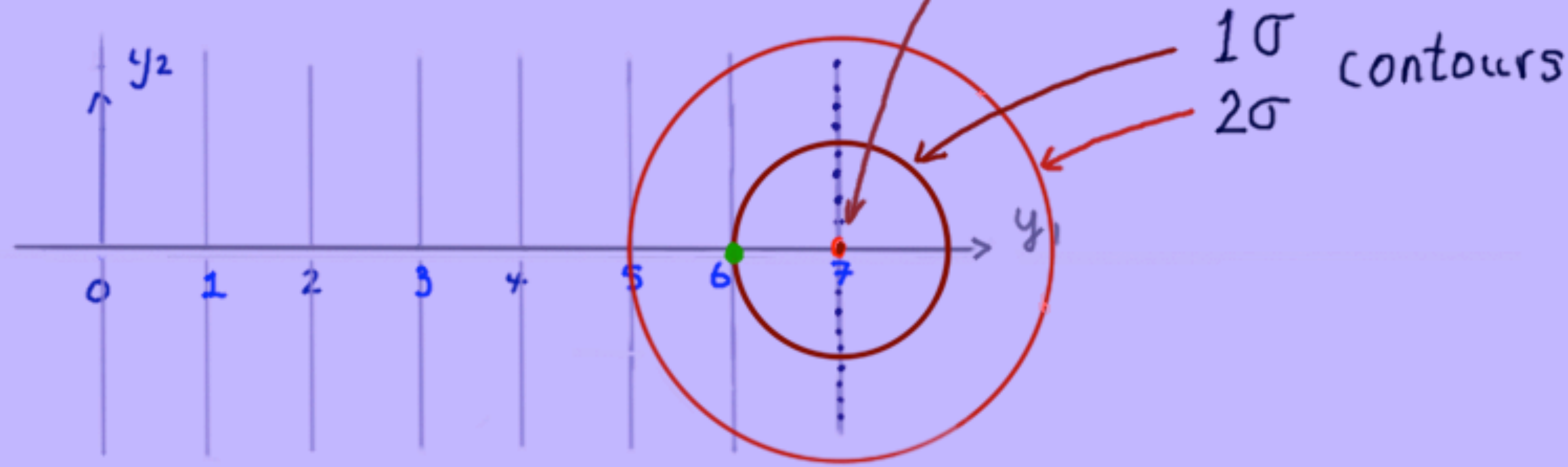
Linear

(i) What probability says:



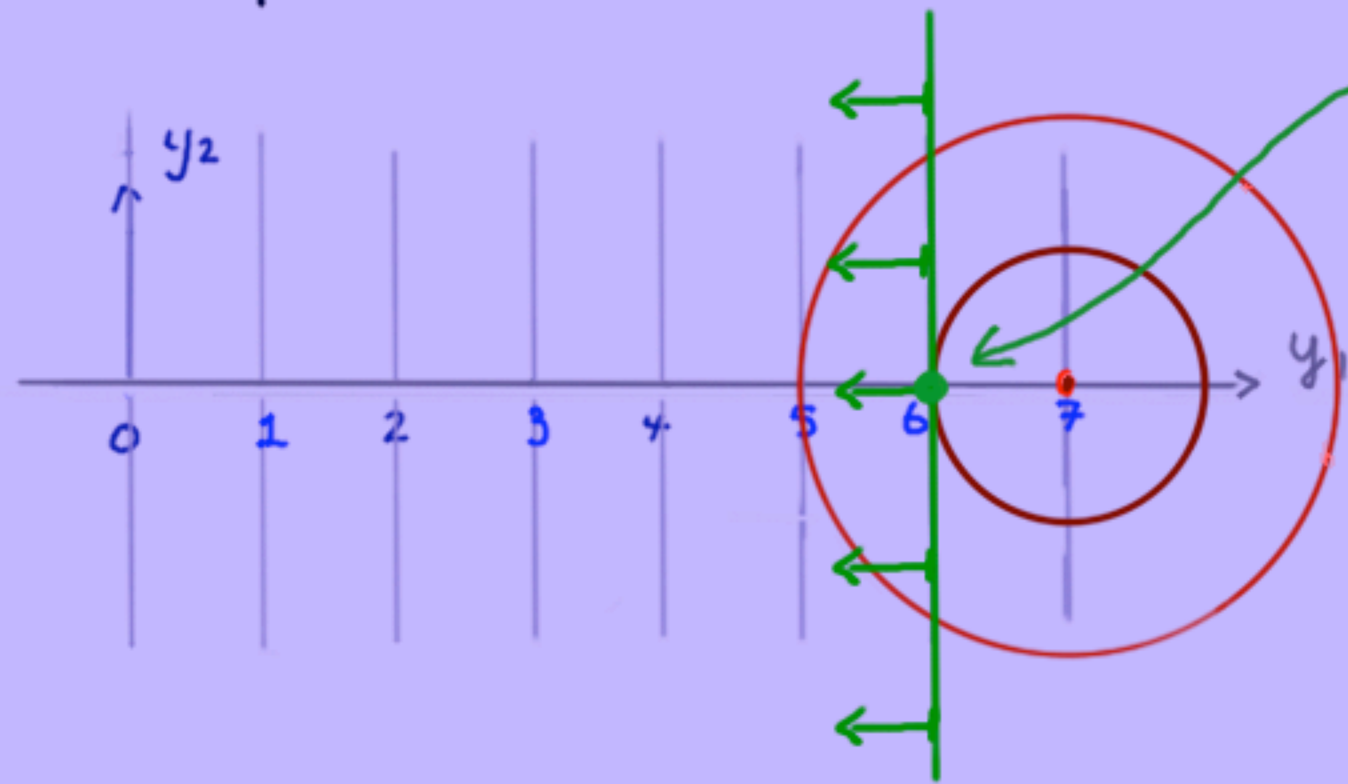
(ii) What Bayes says:

(i) What <u>probability</u> says: If $\theta_1 = 7$ then $y \sim N\{\binom{7}{\theta_2}; I\}$ $y_1 \sim N\ 7\ 1$



(ii) What <u>Bayes</u> says:

(i) What probability says: If $\theta_1 = 7$ then $y \sim N\left\{\binom{7}{\theta_2}; I\right\}$ $y_1 \sim N\ 7\ 1$



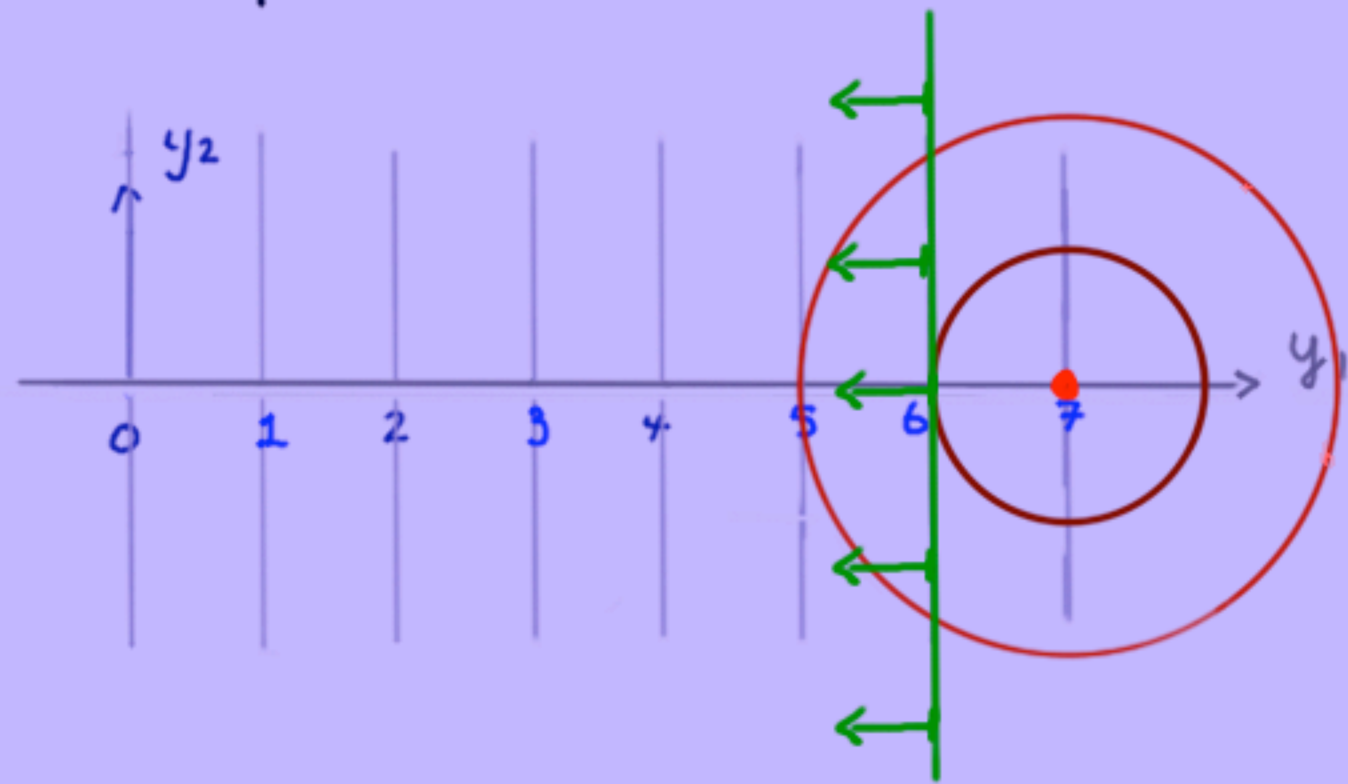
For data $y_1^o = 6$ ....

Prob left of data $= \Phi(-1) = \Phi\left(\frac{6-7}{1}\right) =$

$= p\text{-value} = 16\%$

(ii) What Bayes says:

(i) What probability says: If $\theta_1 = 7$ then $y \sim N\{\binom{7}{\theta_2}; I\}$ $y_1 \sim N\ 7\ 1$

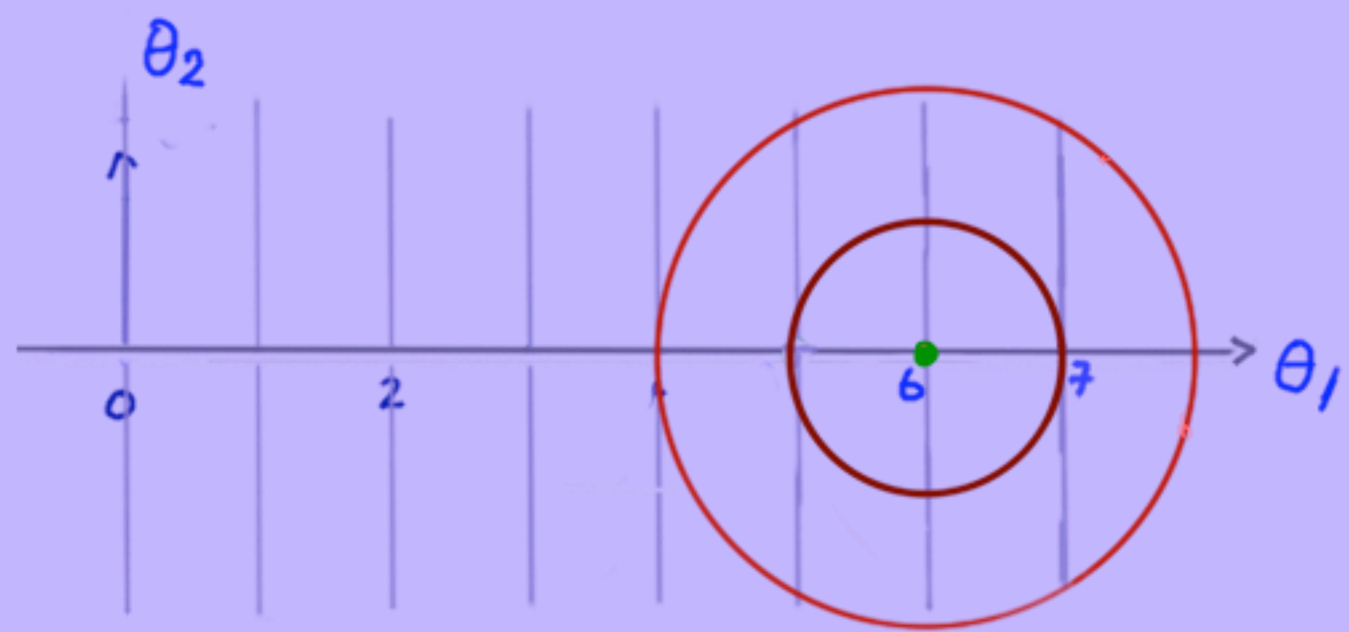


For data $y_1^0 = 6$ ....

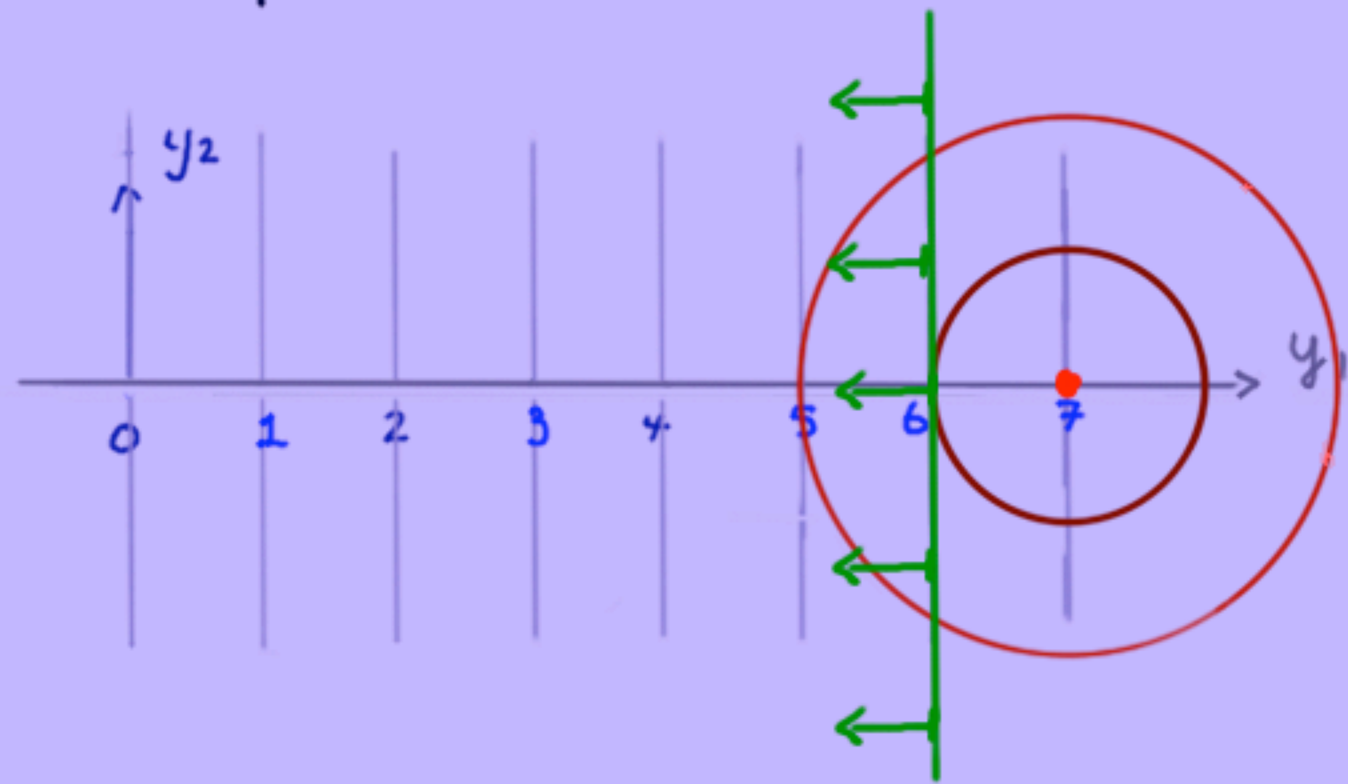
Prob left of data $= \Phi(-1) = \Phi\left(\frac{6-7}{1}\right) =$

$= p\text{-value} = 16\%$

(ii) What Bayes says: If $y^0 = 6$ then $\theta \sim N\{\binom{6}{0}; I\}$ $\theta_1 \sim N\ 6\ 1$



(i) What probability says: If $\theta_1 = 7$ then $y \sim N\{\binom{7}{\theta_2}; I\}$ $\quad y_1 \sim N\ 7\ 1$

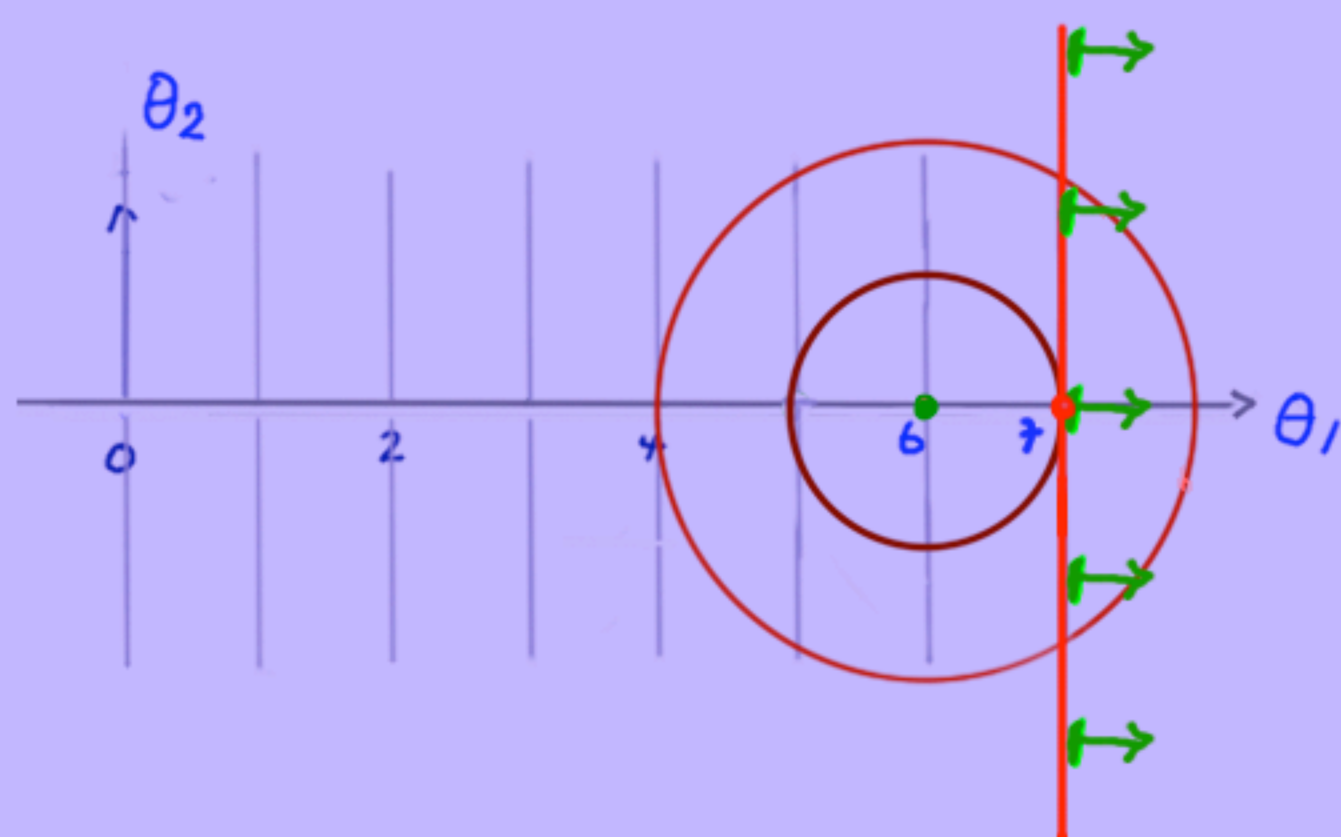


For data $y_1^o = 6$ ....

Prob left of data $= \Phi(-1) = \Phi\left(\frac{6-7}{1}\right) =$

$=$ p-value $= 16\%$

(ii) What Bayes says: If $y^o = 6$ then $\theta \sim N\{\binom{6}{0}; I\}$ $\quad \theta \sim N(6;1)$



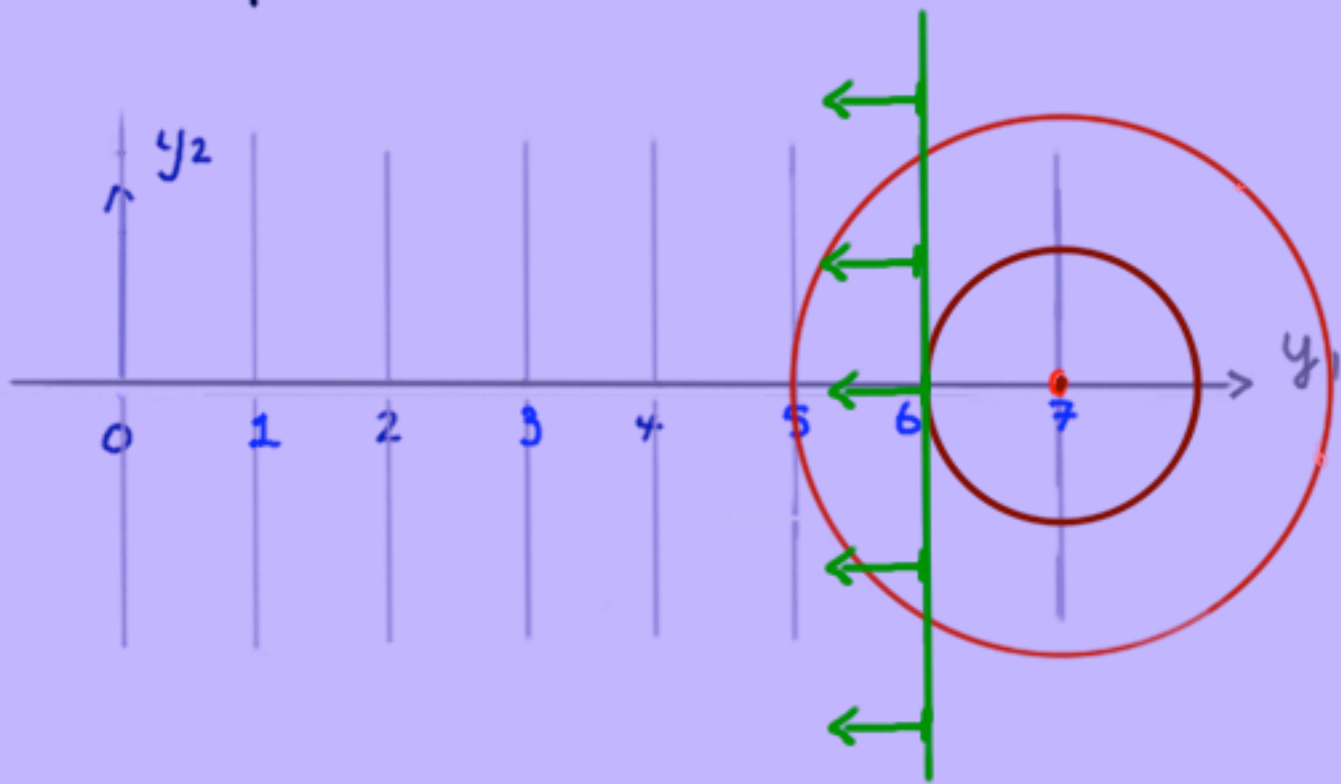
For para. value $\theta_1 = 7$ ...

'Prob' larger than $\theta_1 = 7$

$=$ s-value $= 16\%$

"posterior survivor value"

(i) What <u>probability</u> says: If $\theta_1 = 7$ then $y \sim N\{\binom{7}{\theta_2}; I\}$ $y_1 \sim N\ 7\ 1$

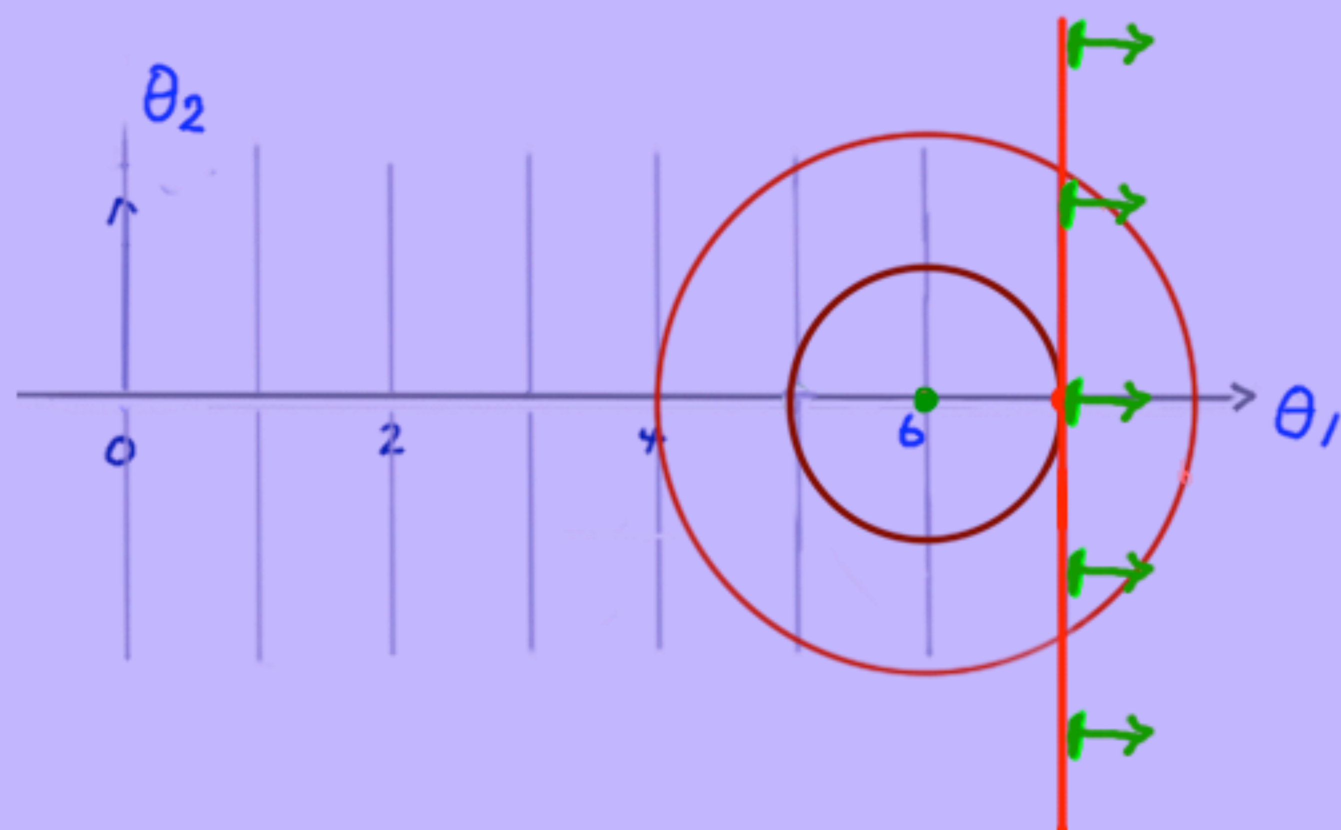


For data $y_1^\circ = 6$ ....

Prob left of data $= \Phi(-1) = \Phi(\frac{6-7}{1}) =$

$= p\text{-value} = 16\%$

(ii) What <u>Bayes</u> says: If $y^\circ = 6$ then $\theta \sim N\{\binom{6}{0}; I\}$ $\theta \sim N(6;1)$



For para. value $\theta_1 = 7$ ...

'Prob' larger than $\theta_1 = 7$

$= s\text{-value} = 16\%$

"posterior survivor value"

They are equal! ... <u>for any linear parameter</u>

$16\% = 16\%$

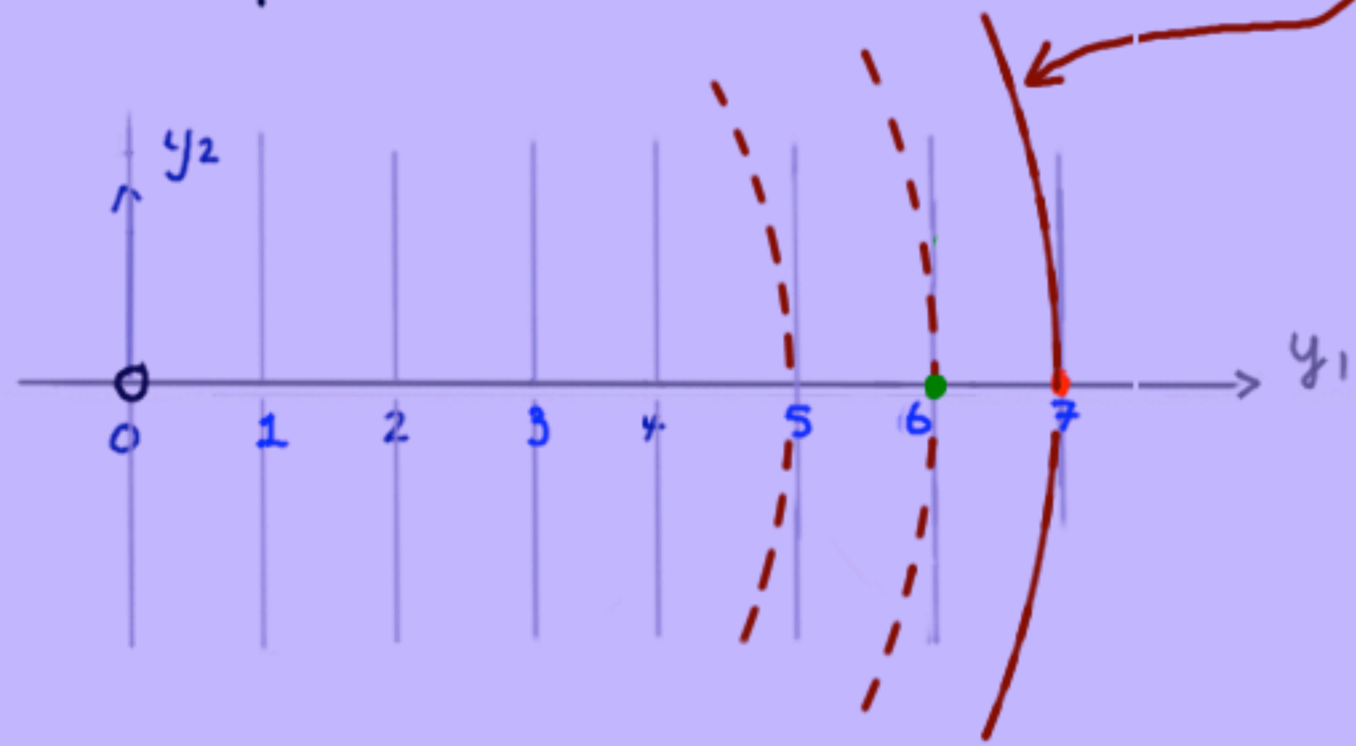
Bayes is "right on"!
Bayes "works"!
Bayes is easy, exact!

BUT...

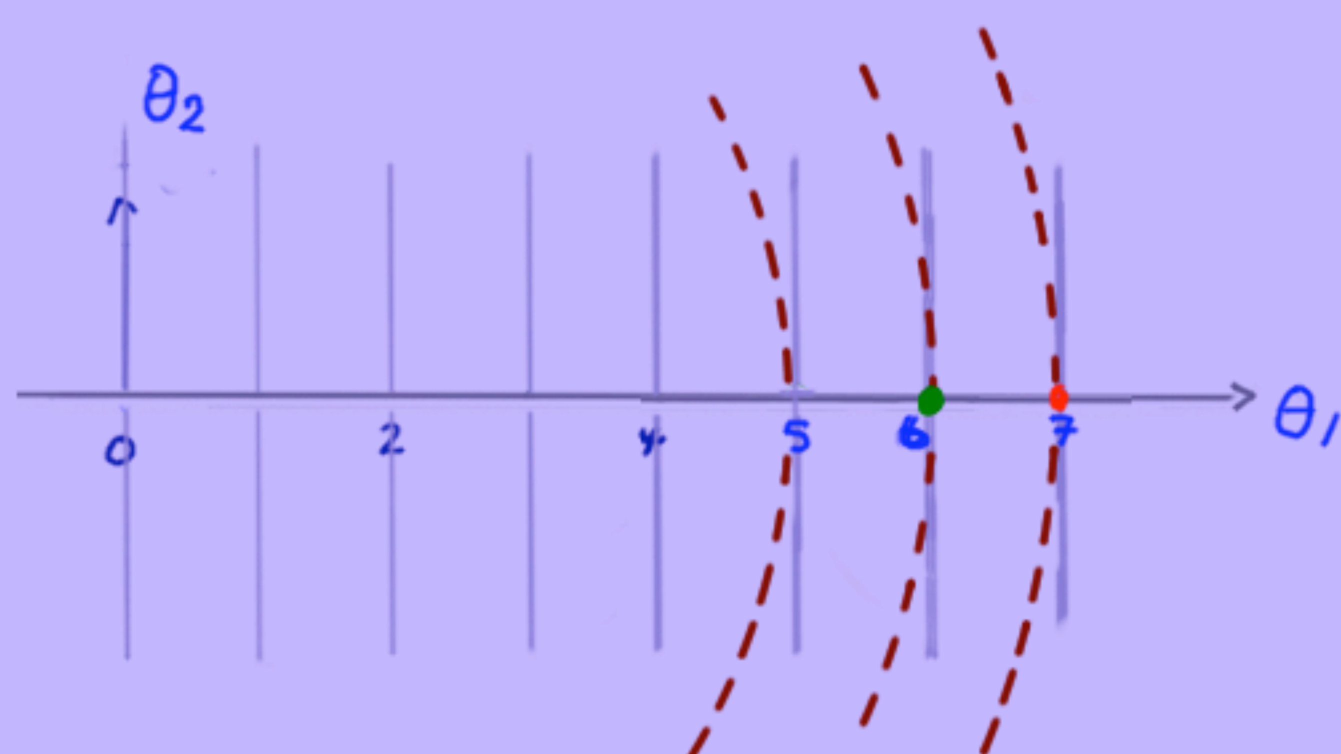
7 .... What about Curved parameters? Ex $\psi(\theta) = \{\theta_1^2 + \theta_2^2\}^{1/2}$

(Segments of circles)

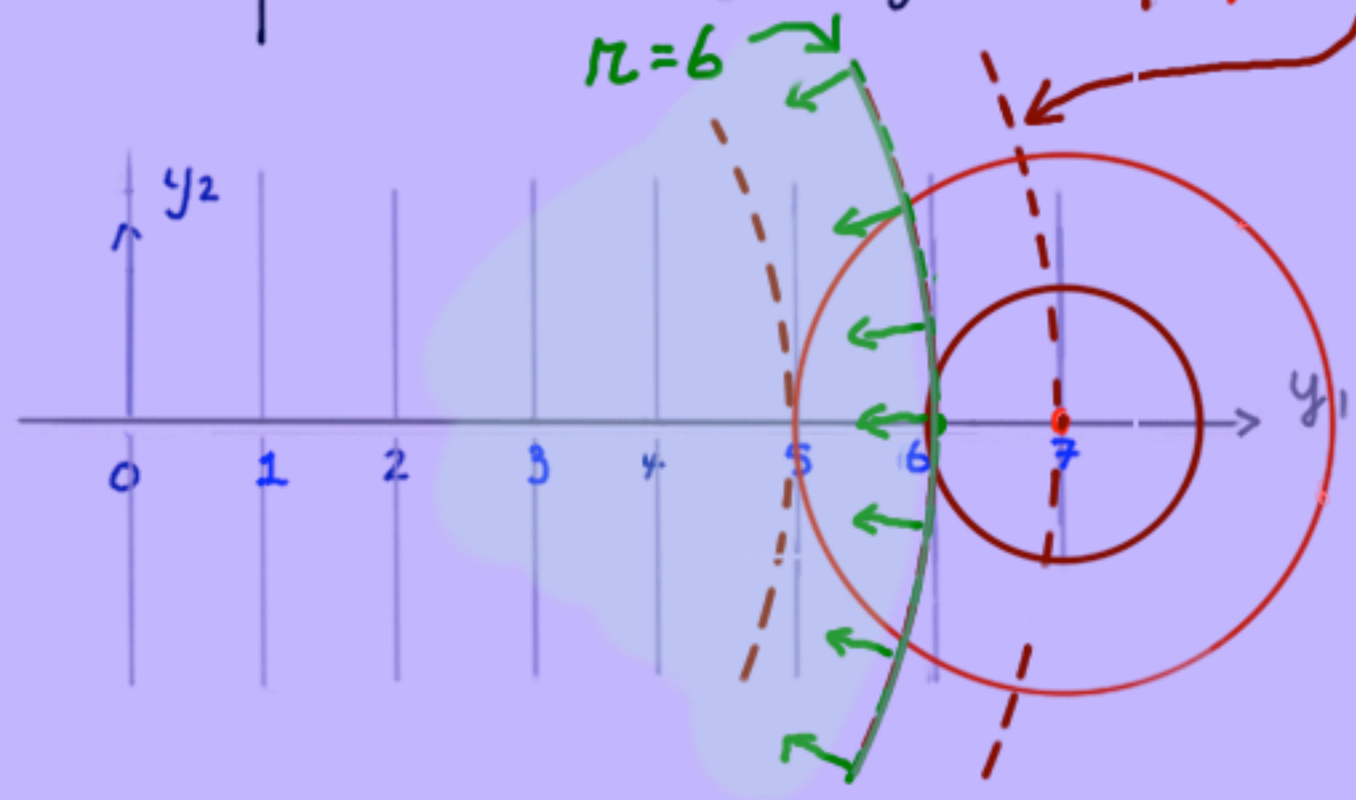
(i) What probability says: If $\psi = 7$



(ii) What Bayes says: If $y^0 = 6$



(i) What probability says: If $\psi = 7$ then $r^2 \sim NC\chi^2$ with 2 df and $NC = 7^2$

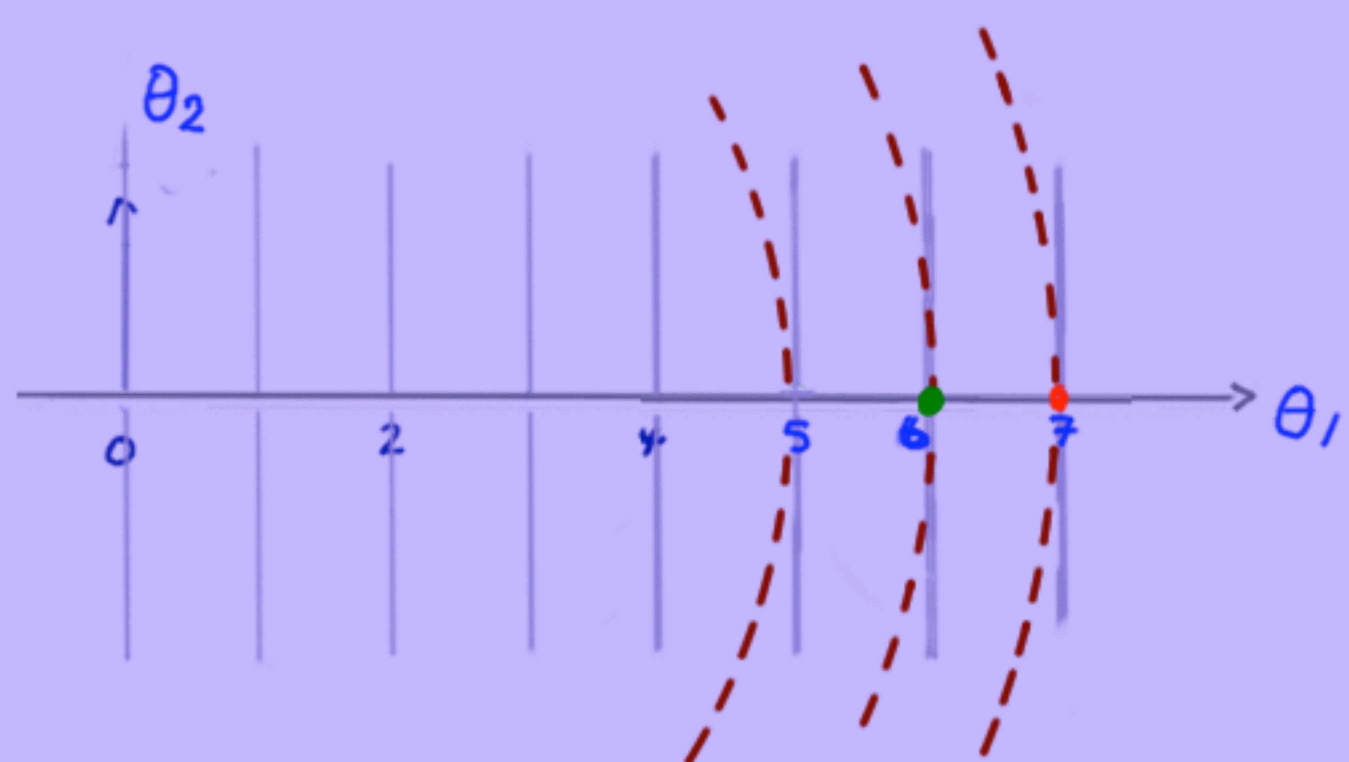


For data $y_1^o = 6$ ....

Prob left of data $= H_2(6^2; 7^2)$

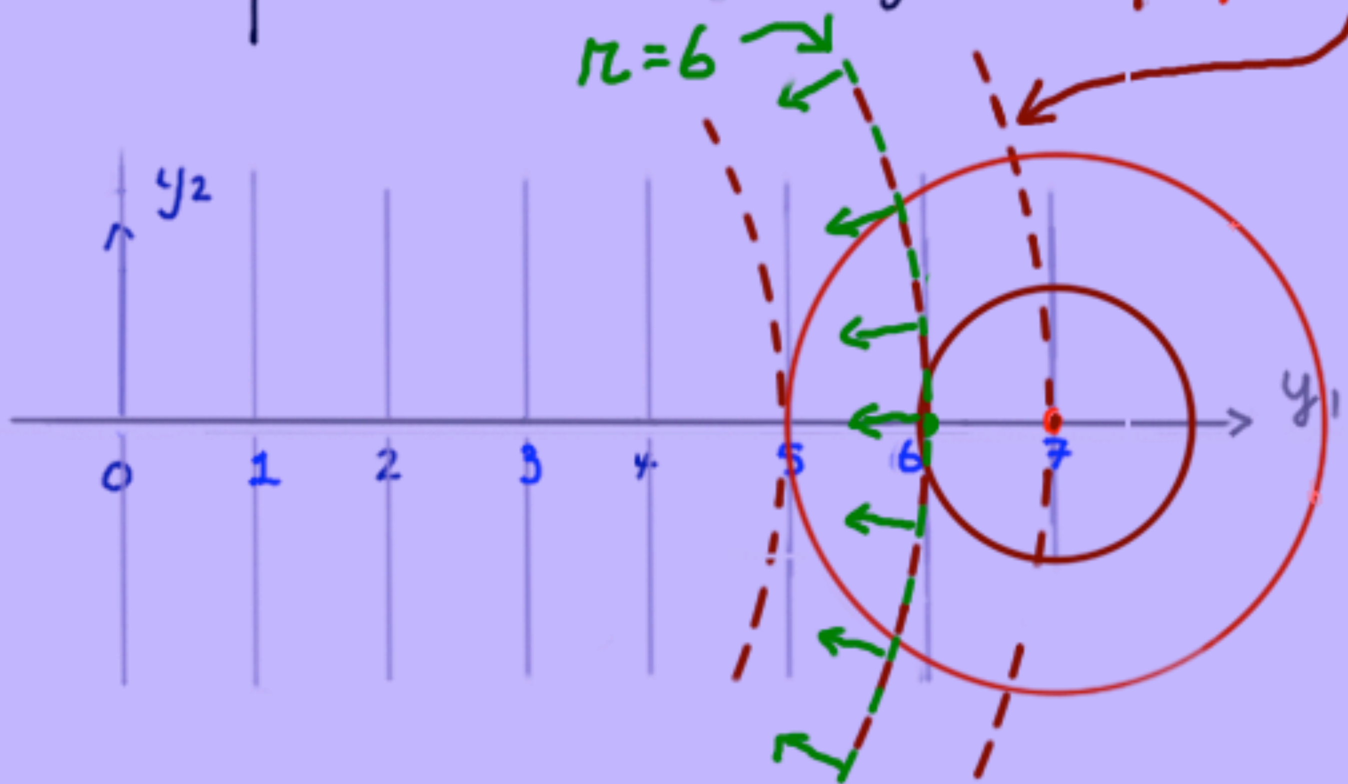
$=$ p-value $= 14.1\%$

(ii) What Bayes does: If $y^o = 6$



Curved parameters Ex $\psi(\theta) = \{\theta_1^2 + \theta_2^2\}^{1/2}$

(i) What probability says: If $\psi = 7$ then $r^2 \sim NC\chi^2$ with 2 df and $NC = 7^2$

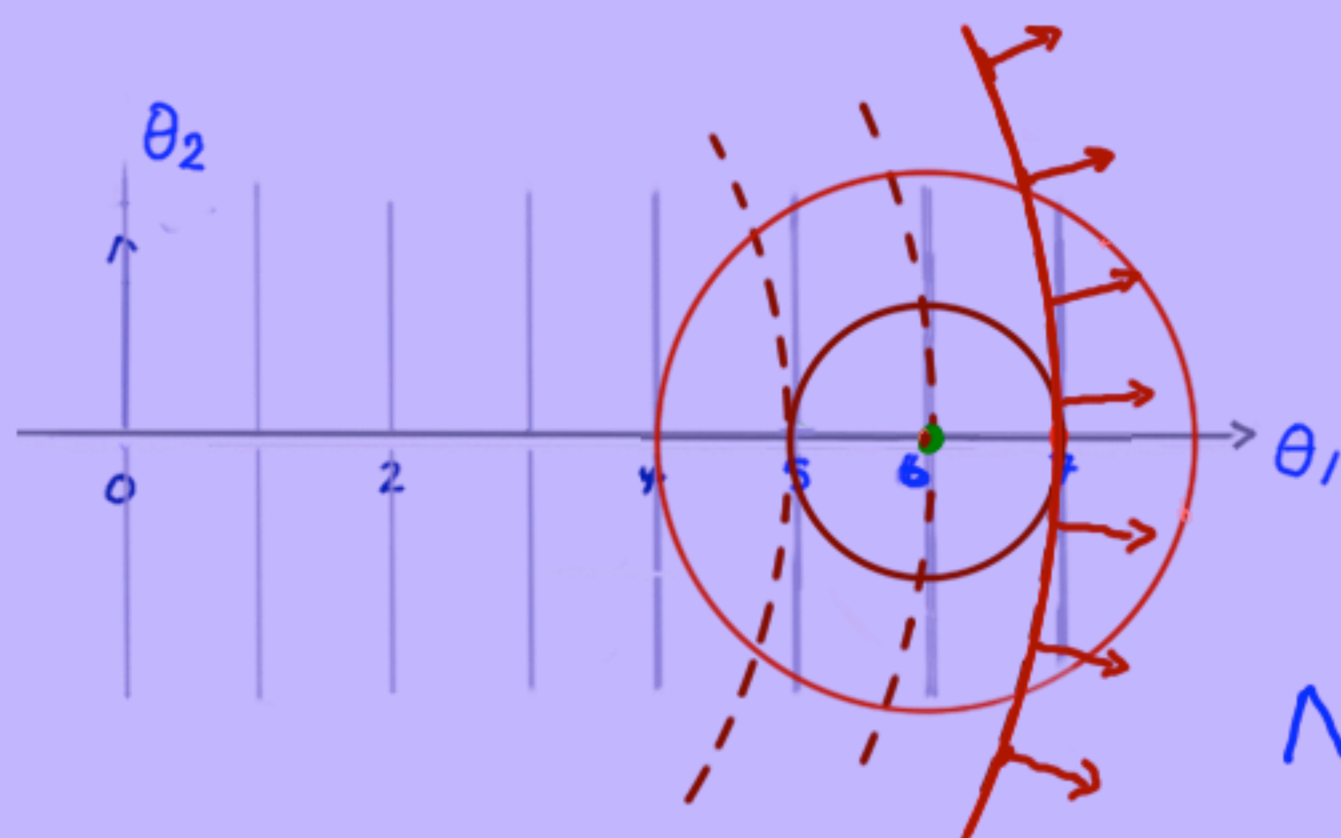


For data $y_1^0 = 6$ ....

Prob left of data $= H_2(6^2; 7^2)$

$= p\text{-value} = 14.1\%$

(ii) What Bayes says: If $y^0 = 6$ then $\theta^2 \sim NC\chi^2$ with 2 df and $NC = 6^2$



'Prob' larger than $|\theta| = 7$

$= 1 - H_2(7^2; 6^2)$

$= s\text{-value} = 17.8\%$

"posterior survivor value"

Not hard to see why they are different: Curvature!

- In nature of Bayes!

And... Assess $|\theta| \geq 7$ with <u>other</u> data points

Data y_1^o	4	5	6	7
p-value	.10%	1.9%	<u>14.1%</u>	47.1%
s-value	.18%	2.8%	<u>17.8%</u>	52.9%

And... Assess $|\theta| \geq 7$ with <u>other</u> data points

Data y_1^o	4	5	6	7
p-value	.10%	1.9%	<u>14.1%</u>	47.1%
s-value	.18%	2.8%	<u>17.8%</u>	52.9%

With positive curvature $\underset{\text{Bayes}}{s(4)} \underset{\text{uniformly}}{>} \underset{\text{freq}}{p(4)}$ ... <u>always</u>

And... Assess $|\theta| \geq 7$ with other data points

Data y_1°	4	5	6	7
p-value	.10%	1.9%	14.1%	47.1%
s-value	.18%	2.8%	17.8%	52.9%

With positive curvature $\overset{\text{Bayes}}{s(4)} \underset{\text{uniformly}}{>} \overset{\text{freq}}{p(4)}$ ... always

$\Rightarrow$ Uniformly wrong with curvature ! ... Bayes is uncalibrated

And… Assess $|\theta| \geq 7$ with other data points

Data y_i^o	4	5	6	7
p-value	.10%	1.9%	14.1%	47.1%
s-value	.18%	2.8%	17.8%	52.9%

With positive curvature $\overset{\text{Bayes}}{s(4)} \underset{\text{uniformly}}{>} \overset{\text{freq}}{p(4)}$ … always

$\Rightarrow$ Uniformly wrong with curvature ! … Bayes is uncalibrated

"Two ways of thinking of same problem?"

"Hidden" in DSZ 1973

"Paradigm" is broken !

8 Curved models!

Ex: $y \sim N(\theta, \sigma^2(\theta))$ $\qquad \sigma^2(\theta) = 1 + \gamma\theta^2/2n$

8 Curved models !

$\Phi(z_\beta) = \beta$

Ex: $y \sim N(\theta, \sigma^2(\theta))$ $\quad \sigma^2(\theta) = 1 + \gamma\theta^2/2n$

	Linear $\gamma = 0$	Curved $\gamma > 0$	
β-confidence (lower bound)	$\hat{\theta}_\beta = y - z_\beta$	$\hat{\theta}_\beta = y - z_\beta\left\{1 + \gamma\frac{(y-z_\beta)^2}{4n}\right\}$	$O(n^{-3/2})$

8 Curved models !

$$\Phi(z_\beta) = \beta$$

Ex: $y \sim N(\theta, \sigma^2(\theta))$ $\quad \sigma^2(\theta) = 1 + \gamma\theta^2/2n$

	Linear $\gamma = 0$	Curved $\gamma > 0$
β-confidence (lower bound)	$\hat\theta_\beta = y - z_\beta$	$\hat\theta_\beta = y - z_\beta\left\{1 + \gamma\frac{(y-z_\beta)^2}{4n}\right\}$

A "prior" cannot give this β-confidence quantile !

.... cannot convert likelihood to confidence !

F 2010
Stat. Sc.
247.pdf

8 Curved models!

$\Phi(z_\beta) = \beta$

Ex: $y \sim N(\theta, \sigma^2(\theta))$ $\qquad \sigma^2(\theta) = 1 + \gamma\theta^2/2n$

	Linear $\gamma = 0$	Curved $\gamma > 0$
β-confidence (lower bound)	$\hat{\theta}_\beta = y - z_\beta$	$\hat{\theta}_\beta = y - z_\beta\left\{1 + \gamma\dfrac{(y - z_\beta)^2}{4n}\right\}$

A "prior" cannot give this β-confidence quantile!

...... cannot convert likelihood to confidence!

F 2010
Stat. Sc.
247.pdf

Bayes can't handle curvature!

DSZ didn't "broadcast" the real message

and

Case 2 priors

No need to use opinion priors to analyze unless statistics seems too hard!

<u>Does it matter</u>: Bayes can't handle curvature ?

- a "number" is called a "probability"
- and it doesn't have the performance property
- Is it ... "Wall St" deception ?

Does it matter: Bayes can't handle curvature ?

- a "number" is called a "probability"
- and it doesn't have the performance property
- Is it ... "Wall St" deception ?

Stainforth, Allen, Tredger, Smith (2007) Phil Trans Roy Soc A 365

Two weather models: Different measurement processes

Flat priors for parameter

Simulations

Contradictory results

Does it matter: Bayes can't handle curvature ?

- a "number" is called a "probability"
- and it doesn't have the performance property
- Is it ... "Wall St" deception ?

Stainforth, Allen, Tredger, Smith (2007) Phil Trans Roy Soc A 365

Two weather models: Different measurement processes

Flat priors for parameter

Simulations

Contradictory results

The Economist "Gambling on tomorrow" Aug 18, 2007:

"... the way you pick the individual values to plug into the model can cause trouble."

Does it matter: Bayes can't handle curvature ?

- a "number" is called a "probability"
- and it doesn't have the performance property
- Is it ... "Wall St" deception ?

Stainforth, Allen, Tredger, Smith (2007) Phil Trans Roy Soc A365

Two weather models. Different measurement processes

Flat priors for parameter

Simulations

Contradictory results

The Economist "Gambling on tomorrow" Aug 18, 2007:

"... the way you pick the individual values to plug into the model can cause trouble."

"... the Bayesian bolt-on does not come easily to scientists"

Does it matter: Bayes can't handle curvature ?

- a "number" is called a "probability"
- and it doesn't have the performance property
- Is it ... "Wall St" deception ?

Stainforth, Allen, Tredger, Smith (2007) Phil Trans Roy Soc A365

Two weather models   Different measurement processes
Flat priors for parameter
Simulations
Contradictory results

The Economist "Gambling on tomorrow" Aug 18, 2007 :

"... the way you pick the individual values to plug into the model can cause trouble."
"... the Bayesian bolt-on does not come easily to scientists"
"... garbage in, garbage out."

Does it matter: Bayes can't handle curvature ?

- a "number" is called a "probability"
- and it doesn't have the performance property
- Is it ... "Wall St" deception ?

Stainforth, Allen, Tredger, Smith (2007) Phil Trans Roy Soc A365

Two weather models

Different measurement processes

Flat priors for parameter

Simulations

Contradictory results

The Economist "Gambling on tomorrow" Aug 18, 2007 :

"... the way you pick the individual values to plug into the model can cause trouble."

"... the Bayesian bolt-on does not come easily to scientists"

"... garbage in, garbage out."

"The difficulty comes when you do not know what garbage looks like"

Should Statisticians ignore this?

...in Phil Trans. Roy. Soc ?

...in The Economist ?

Should Statisticians ignore this?

...in Phil Trans. Roy. Soc ?

...in The Economist ?

Elsewhere would be called Fraud

Should Statisticians ignore this?

...in Phil Trans. Roy. Soc ?

...in The Economist ?

Elsewhere would be called Fraud

Bayes posterior: Great for exploring with likelihood !

- frequentists should have used their own likelihood !

Should Statisticians ignore this?

...in Phil Trans. Roy. Soc ?

...in The Economist ?

Elsewhere would be called Fraud

Bayes posterior: <u>Great</u> for exploring with likelihood !

- frequentists <u>should</u> have used their <u>own</u> likelihood !

and it <u>may</u> give <u>approximate</u> confidence

Should Statisticians ignore this?

...in Phil Trans. Roy. Soc ?

...in The Economist ?

Elsewhere would be called Fraud

Bayes posterior: Great for exploring with likelihood !

- frequentists should have used their own likelihood !

and it may give approximate confidence

- it does not give more than confidence

Should Statisticians ignore this?

...in Phil Trans. Roy. Soc ?

...in The Economist ?

Elsewhere would be called Fraud

Bayes posterior: Great for exploring with likelihood !

- frequentists should have used their own likelihood !

  and it may give approximate confidence

- it does not give more than confidence

- To claim otherwise is fraud

Should Statisticians ignore this?

...in Phil Trans. Roy. Soc ?

...in The Economist ?

Elsewhere would be called Fraud

Bayes posterior: Great for exploring with likelihood !

- frequentists should have used their own likelihood !

  and it may give approximate confidence

- it does not give more than confidence

- To claim otherwise is fraud

The Tool Box needs a lot of calibration!

Some references

Jeffreys (1939) Theory of Probability Oxford

Neyman (1937) Phil Trans Roy Soc

Jeffreys (1946) An invariant form ... Proc Roy Soc A

Dawid Stone Zidek (1973) JRSSB

Reid, F. (2010) Biometrika

Stainforth, Allen, Tredger, Smith (2007) Phil Trans Roy Soc A 365

F., Reid, Marras, Yi (2010) JRSSB (Default priors)

F., (2010) "Is Bayes posterior..." Stat Sc in review

Fraser, F., Staicu (2010) Bernoulli to appear (Conditioning)

Some references

Jeffreys (1939) Theory of Probability Oxford

Neyman (1937) Phil Trans Roy Soc

Jeffreys (1946) An invariant form ... Proc Roy Soc A

Dawid Stone Zidek (1973) JRSSB

Reid, F. (2010) Biometrika 251.pdf

Stainforth, Allen, Tredger, Smith (2007) Phil Trans Roy Soc A365

F., Reid, Marras, Yi (2010) JRSSB (Default priors) 239.pdf

F., (2010) "Is Bayes posterior..." Stat Sc in review 247.pdf

Fraser, F., Staicu (2010) Bernoulli to appear (Conditioning) 240.pdf

www.utstat.utoronto.ca/dfraser/documents/ xxx.pdf