The role of Bias in Statistics

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Statistics
U Toronto

April 12 2012
U Western Ontario

Joint work; references at end
The journal Science recognizes that
The journal recognizes that

Data are everywhere!
Science, Nature - major science journals
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Issue - 38 pages on Data
- 15 articles
Science, Nature - major science journals

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See: Word Cloud
Word histogram
- frequency of each word in articles
Science, Nature - major science journals

Issue - 38 pages on Data - 15 articles

See: Word Cloud
Word histogram - frequency of each word in articles
But: "Statistics" is not there!
Science, Nature - major science journals

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See: Word Cloud
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- frequency of each word in articles

But: "Statistics" is not there!

"Statistics" is not part of Data!
Outline

- Data and Statistics:
  (a) Journals: Data, Groves, Vioxx, Replication

- Statistics:
  (b) Two logics
  (c) What are they?

- Can Right prior do it all:
  (d) Linear: Yes
  (e) Curved: No

- How to get the "Right" prior
  (f) from Continuity!
  (g) from information!

- Measure bias in prior... (if not "Right")
  (h) Available to 2nd order
Rethinking Clinical Trials

The biomedical industry spends over $50 billion per year on research and development and produces some 20 new drugs. One reason for this disappointing output is the byzantine U.S. clinical trial system that requires large numbers of patients. Half of all trials are delayed, 80 to 90% of them because of a shortage of trial participants. Patient limitations also cause large and unpredicted expenses to pharmaceutical and biotech companies as they are forced to tread water. As the industry moves toward biologics and personalized medicine, this limitation will become even greater. A breakthrough in regulation is needed to create a system that does more with fewer patients.

The current clinical trial system in the United States is more than 50 years old. Its architecture was conceived when electronic manipulation of data was limited, slow, and expensive. Since then, network and connectivity costs have declined ten thousand-fold, data storage costs over a million-fold, and computation costs by an even larger factor. Today, complex and powerful applications like electronic commerce are deployed on a large scale. Amazon.com is a good example. A large database of customers and products form the kernel of its operation. A customer's characteristics (like buying history and preferences) are observed and stored. Customers can be grouped and the buying behavior of any individual or group can be compared with corresponding behavior of others. Amazon can also track how a group or an individual responds to an outside action (such as advertising).

We might conceptualize an “e-trial” system along similar lines. Drug safety would continue to be ensured by the U.S. Food and Drug Administration. While safety-focused Phase I trials would continue under their jurisdiction, establishing efficacy would no longer be under their purview. Once safety is proven, patients could access the medicine in question through qualified physicians. Patients' responses to a drug would be stored in a database, along with their medical histories. Patient identity would be protected by biometric identifiers, and the database would be open to qualified medical researchers as a “commons.” The response of any patient or group of patients to a drug or treatment would be tracked and compared to those of others in the database who were treated in a different manner or not at all. These comparisons would provide insights into the factors that determine real-life efficacy: how individuals or subgroups respond to the drug. This would liberate drugs from the tyranny of the averages that characterize trial information today. The technology would facilitate such comparisons at incredible speeds and could quickly highlight negative results. As the patient population in the database grows and time passes, analysis of the data would also provide the information needed to conduct postmarketing studies and comparative effectiveness research.

Today's e-commerce systems started small and took nearly 20 years to develop. Adopting this kind of capability to medical information would be a monumental undertaking. Initiating and overseeing it would be an appropriate task for the professional societies. There are encouraging signs, including a call in 2004 by the American Medical Association for public registries of drugs, as well as a proposal for trials that incorporate feed-forward mechanisms. Another proposal would allow patients to choose between medicines whose efficacy has been determined in different manners. There is also a suggestion to use control of pricing to encourage drug developers to move forward in a “progressive” trial design. Ideas, however, are not enough. We need the professions to mobilize and take advantage of this enormous opportunity.

—Andrew Grove


www.sciencemag.org SCIENCE VOL 333 23 SEPTEMBER 2011 1679
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2003  Earned: $2.46b    Big bucks!
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Again, and Again, and Again...

Replication—the confirmation of results and conclusions from one study obtained independently in another—is considered the scientific gold standard. New tools and technologies, massive amounts of data, long-term studies, interdisciplinary approaches, and the complexity of the questions being asked are compounding replication efforts, as are increased pressures on scientists to advance their research. The five Perspectives in this section (and associated News and Career stories, Readers' Poll, and Editorial) explore some of the issues associated with replicating results across various fields.

Ryan (p. 1229) highlights the excitement and challenges that come with field-based research. In particular, observing processes as they occur in nature allows for discovery but makes replication difficult, because the precise conditions surrounding the observations are unique. Further, although laboratory research allows for the specification of experimental conditions, the conclusions may not apply to the real world. Debate about the merits of lab-based and field-based studies has been a persistent theme over time. Tommasello and Call (p. 1227) further contribute to this debate in their discussion of some obvious barriers to replication in primate cognition and behavior research (small numbers of subjects, expense, and ethics issues) as well as more subtle ones, such as the nontrivial challenge of designing tasks that elicit complex cognitive behaviors.

New technologies continue to produce a deluge of data from different varieties, raising expectations for new knowledge that will translate into meaningful therapeutics and insights into health. Londraville and Khovay (p. 1230) outline multiple steps for validating such large-scale data on the path to clinical utility and make suggestions for incentives (and penalties) that could enhance the availability of reliable data and analyses.

Peng (p. 1226) discusses the need for a minimum standard of reproducibility in computer science, arguing that enough information about methods and code should be available for independent researchers to reach consistent conclusions using original raw data. Specifically, he describes a model that one journal has used to make this a reality.

The need to convince the public that data are replicable has grown as science and public policy-making intersect, an issue that has been of climate change studies. As Santer et al. (p. 1233) describe, having multiple groups examining the same data and generating new data has led to robust conclusions.

The importance of replication and reproducibility for scientists is unquestioned. Sometimes attempts to replicate reveal scientific uncertainties. This is one of the main ways that science progresses (see associated News stories of faster-than-light neutrinos and alginates, pp. 1200 and 1194). Unfortunately, in rare instances (compared to the body of scientific work), it can also indicate fraud (see the Editorial by Crocker and Cooper, p. 1182). How do we promote the publication of replicable data? The authors in this section come up with possibilities that are targeted at funders, journals, and the research culture itself. In the Readers' Poll, you can make your views known as well.

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Data Replication & Reproducibility

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M. Tomasello and J. Loeb

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1230 Improving Validation Practices in "Omics" Research
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1232 The Reproducibility of Observational Estimates of Surface and Atmospheric Temperature Change
S. D. Santer et al.

See also Editorial pp. 1182; News stories, pp. 1194 and 1200; Readers' Poll, p. 1182; Science Careers content p. 1179; and www.sciencemag.org/journal/databases
It was a core of statistics…

6 articles again, again, again
INTRODUCTION
Again, and Again, and Again ...

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Unfortunately, if statistics can also indicate fraud — once upon a time!

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Science again

Replication again, again, again

6 articles
9 pages

Unfortunately, of statistics once upon a time!

Maybe!

"Fortunately it can also indicate fraud"
Replication—The Confirmation of Results and Conclusions from One Study Obtained Independently in Another—is Considered the Scientific Gold Standard. New Tools and Technologies, Masses of Data, Long-Term Studies, Interdisciplinary Approaches, and the Complexity of the Questions Being Asked Are Complicating Replication Efforts, as Are Increasing Pressures on Scientists to Advance Their Research. The Five Perspectives in This Section (and Associated News and Career Stories, Readers' Poll, and Editorial) Explore Some of the Issues Associated With Replicating Results Across Various Fields.

Ryan (p. 1229) Highlights the Excitement and Challenges That Come With Field-Based Research. In Particular, Observing Processes as They Occur in Nature Allows for Discovery But Makes Replication Difficult, Because the Precise Conditions Surrounding the Observations Are Unique. Further, Although Laboratory Research Allows for the Specification of Experimental Conditions, the Conclusions May Not Apply to the Real World. Debate About the Merits of Lab-Based and Field-Based Studies Has Been a Persistent Theme Over Time. Tomasello and Call (p. 1227) Further Contribute to This Debate in Their Discussion of Some Obvious Barriers to Replication in Primate Cognition and Behavior Research (Small Numbers of Subjects, Expense, Ethical Invasions) as Well as More Subtle Ones, Such as the Nonsensical Challenge of Designing Tasks That Elicit Complex Cognitive Behaviors.

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The Need to Convince the Public That Data Are Replicable Has Grown as Science and Public Policy-Making Intersect, an Issue That Has Harmed Climate Change Studies. As Sander et al. (p. 1233) Describe, Having Multiple Groups Examining the Same Data and Generating New Data Has Led to Robust Conclusions.

The Importance of Replication and Reproducibility for Scientists Is Unquestioned. Sometimes Attempts to Replicate Result in Scientific Uncertainty. This Is One of the Main Ways That Science Progresses (see Associated News Stories of Faster-Than-Light Neutrinos and Airplanes, Pp. 1206 and 1194). Unfortunately, in Rare Instances (Compared to the Body of Scientific Work), It Can Also Indicate Fraud (see the Editorial by Crocker and Cooper, P. 1182). How Do We Promote the Publication of Replicable Data? The Authors in This Section Come Up With Possibilities That Are Targeted at Funders, Journals, and the Research Culture Itself. In the Readers' Poll, You Can Make Your Views Known as Well.

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www.sciencemag.org SCIENCE VOL. 334 2 DECEMBER 2011
Messages

Data: No role for statistics
Messages?

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Overt statistics
Hidden statistics
Business as usual
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Is the issue: public relations?
or the discipline itself?
(b) Statistics: Two logics

How can that happen? How to answer?
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How can that happen? How to answer?

A Invert dist'n fn:

B Invert density fn:
(b) Statistics: Two logics

How can that happen? How to answer?

A  Invert dist'n fn: need to get pivot

B  Invert density fn:
(b) Statistics: Two logics

How can that happen? How to answer?

A) Invert dist'n fn: need to get \( \text{pivot} \)

B) Invert density fn: need to get \( \pi(\theta) \)
(b) Statistics: Two logics

How can that happen? How to answer?

A Invert dist’n fn: need to get pivot documentation (it’s there)

B Invert density fn: need to get prior π(θ)
(b) Statistics: Two logics

How can that happen? How to answer?

A. Invert dist'n fn: need to get pivot documentation (it's there)

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various versions
(b) Statistics: Two logics

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B) Invert density fn: need to get prior \( \pi(\theta) \) various versions

Two logics? Various versions?
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Various versions

Two logics? Various versions?

As a discipline:

Can we afford it? "PR" or "substance"

Who else has two logics?
(c) What are the versions?

(i) \( \pi(\Theta) \) describes source of \( \Theta \)
(C) What are the versions?

(i) \( \tau(\Theta) \) describes source of \( \Theta \)

Been around as long as prob. theory
(C) What are the versions?

(i) $\pi(\Theta)$ describes source of $\Theta$

Been around as long as prob. theory

Options:
- Combine the prob's
- Record separately
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Where Bayes started in 1763!
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Again Can we afford it? "PR" in "Substance"
Who else has two logics? Versions?
Versions:
(ii) for convenience: the real Bayes ...

Bayes (1763)
Laplace (1820)
Jeffreys (1946)
Jeffreys (1961)
Bernardo (1979)

... more recent ...

original
onto something good
mechanize: use \( \Pi = \sqrt{i(\theta)} \) \( \frac{1}{2} \) (root information)
modify
reference priors (measure spaces)
later

Can the right \( \Pi(\theta) \) do it all?
(d) Can the "right" $\pi(\theta)$ do it all?

Need a vector parameter $\theta = (\theta_1, \theta_2)$
(d) Can the "right" $\pi(\Theta)$ do it all?

Need a vector parameter $\Theta = (\Theta_1, \Theta_2)$

Try: Normal on the plane

$y_1 = \Theta_1 + z_1$
$y_2 = \Theta_2 + z_n$

$z_i \sim N(0,1)$
(d) Can the "right" $\pi(\theta)$ do it all?

Need a vector parameter $\theta = (\theta_1, \theta_2)$

Try: Normal on the plane

$y_1 = \theta_1 + z_i,$  \hspace{1cm} z_i \sim N(0, 1)$

$y_2 = \theta_2 + z_n$
(d) Can the "right" $\mathbf{r}(\Theta)$ do it all?

Need a vector parameter $\Theta = \begin{pmatrix} \theta_1 \\ \theta_2 \end{pmatrix}$

Try:

Normal on the plane

\[ y_1 = \theta_1 + z_i \]
\[ y_2 = \theta_2 + z_n \] for $z_i \sim N(0,1)$
(d) Can the "right" $\pi(\theta)$ do it all?

Need a vector parameter $\theta = (\theta_1, \theta_2)$

Try:

Normal on the plane

\[ y_1 = \theta_1 + z_i \]
\[ y_2 = \theta_2 + z_i \]

$z_i \sim N(0, 1)$

![Diagram with 1σ and 2σ contours]
(i) Linear interest parameter: $\Theta_1 = 7$
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Observed data $(y_1, y_2) = (6, 0)$
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Observed data $(y_1, y_2) = (6, 0)$

How to measure $\Theta_1$? Use $y_1$. 
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Observed p-value $p(7) = 15.9\%$
(i) Linear interest parameter: $\theta_1 = 7$

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How to measure $\theta_1$? Use $y_1$

Observed $p$-value $p(7) = 15.9\%$

Bayes view
(i) Linear interest parameter: $\Theta_1 = 7$

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Bayes view
(i) Linear interest parameter: $\theta_1 = 7$

Observed data $(y_1, y_2) = (6, 0)$

How to measure $\theta_1$? Use $y_1$.

Observed p-value $p(7) = 15.9\%$

Bayes view

Normal at data $(6, 0)$
Prob larger than $\theta_1 = 7$
$s(7) = 15.9^\circ$

$p(7) = s(7) = 15.9\%$
All OK!
(e) Curved interest parameter: \( y(\theta) = 7 \)

\( H_0: \) circle \( r = 7 \)
(e) Curved interest parameter: $y(\theta) = 7$

$H_0$: circle $r = 7$
(e) Curved interest parameter: \( y(\theta) = 7 \)

\[ H_0: \text{circle } r = 7 \]

Observed data \((x_1, x_2) = (6, 0)\)
(e) Curved interest parameter: \( y(\theta) = 7 \)

Observed data \((y_1, y_2) = (6, 0)\)

\( H_0: \) circle \( r = 7 \)

How to measure \( y \)? Use \( r \)

\( r^0 = 6 \)
(e) Curved interest parameter: $\psi(\theta) = 7$

Observed data $(y_1, y_2) = (6, 0)$

$H_0$: circle $r = 7$

14.1%

How to measure $\psi$? Use $r$

$r^0 = 6$

Observed p-value $p(\theta) = 14.1\%$
(e) Curved interest parameter: \( \psi(\theta) = 7 \)

Observed data \((y_1, y_2) = (6, 0)\)

How to measure \(\psi\)? Use \(r\)

\[ r^2 = 6 \]

Observed p-value \(p(7) = 14.1\%\)

Bayes View
(e) Curved interest parameter: \( y(\Theta) = 7 \)

Observed data \((y_1, y_2) = (6, 0)\)

\[ \text{NCX}(6; 7) \]

 OBSERVED p-value \( p(7) = 14.1\% \)

Bayes view

How to measure \( y \)? Use \( r \)

\[ r^2 = 6 \]

Normal at data \((6, 0)\)
(e) Curved interest parameter: \( \psi(\theta) = 7 \)

Observed data \((y_1, y_2) = (6, 0)\)

\[ \text{NCX}(6; 7) \]

Observed p-value \( p(7) = 14.1\% \)

How to measure \( \psi \)? Use \( r \)

\[ r^2 = 6 \]

Bayes view:

Prob larger than \( \psi = 7 \)

\( \delta(7) = 17.8\% \)
(e) Curved interest parameter: $y(\theta) = 7$

- $H_0$: circle $r = 7$
- Observed data $(y_1, y_2) = (6, 0)$

How to measure $y$? Use $r$

- $r^2 = 6$
- Observed $p$-value $p(7) = 14.1\%$

Bayes view

- Prob larger than $y = 7$
  - $\delta(7) = 17.8\%$

Introduce curvature:

$p$-value, $s$-value go opposite directions
What did that say?

1) Linear parameter of interest
   frequency p-value 
   Bayes s-value are equal
What did that say?

1) **Linear parameter of interest**
   
   frequency $p$-value and Bayes $s$-value are equal

2) Introduce parameter curvature (say +)
   
   frequency $p$-value decreases!
   Bayes $s$-value increases!
What did that say?

1) **Linear** parameter of interest
   
   frequency \( p \)-value \( \) are equal
   
   Bayes \( s \)-value

2) Introduce parameter **curvature** (say +)
   
   frequency \( p \)-value decreases!
   
   Bayes \( s \)-value increases!

Which, if either, is **right**?

\( p \)-value has repetition **validity**!

Confidence distribution

Bayes \( " \) \( \) Can't handle curvature
What did that say?

1) Linear parameter of interest
   
   frequency p-value 
   Bayes s-value 
   are equal

2) Introduce parameter curvature (say +)
   
   frequency p-value decreases!
   Bayes s-value increases!

Which, if either, is right?

p-value has repetition validity!

Confidence distribution Bayes " Can't handle curvature

Dawid Stone Zidek 1973 F Reid 2002
(f) Priors: from Continuity

Regular models: "2nd order" theory says prior widely available
(f) Priors: from Continuity

Regular models: "2nd order" theory says prior widely available
Case: Have a quantile representation

(ii) Regression: \[ y = X\beta + \sigma z \quad z \sim \Theta(0, I) \]

(ii) General: \[ y = y(\Theta, z) \quad z \sim \Theta \]
(f) Priors: from **Continuity**

Regular models: "2nd order" theory says prior widely available

**Case:** Have a quantile representation

(i) Regression: \[ y = X \beta + \sigma z \quad z \sim \mathcal{N}(0, I) \]

(ii) **General:** \[ y = y(\theta, z) \quad z \sim \mathcal{N} \]

**Continuity** \( \frac{dy}{d\theta} \bigg|_{\theta^0} = V(\theta) = \text{How parameter affects dist'n at } y^0 \)
Priors: from Continuity

Regular models: "2nd order" theory says prior widely available

Case: Have a quantile representation

(i) Regression: \( y = X\beta + \sigma z \quad z \sim \Theta(0, I) \)

(ii) General: \( y = y(\theta, z) \quad z \sim \Theta \)

Continuity \( \Rightarrow \frac{dy}{d\theta} |_{y^0} = V(\theta) = \text{How parameter affects dist'n at } y^0 \)

Prior: \( \pi(\theta) d\theta = |V(\theta)| d\theta \)
(f) Priors: from Continuity

Regular models: "2nd order" theory says prior widely available

Case: Have a quantile representation

(i) Regression: \( y = X \beta + \sigma z \quad z \sim \Theta(0, I) \)

(ii) General: \( y = y(\Theta, z) \) \quad z \sim \Theta

Continuity \( \Rightarrow \frac{dv}{d\theta} |_{y^0} = V(\theta) = \) How parameter affects dist'n at \( y^0 \)

Prior: \( \pi(\theta) d\theta = |V(\theta)| d\theta \)

Ex: \( y = X \beta + \sigma z \quad V(\theta) = (X, z(\theta)) \quad z(\theta) = (y^0 - X \beta)/\sigma \)
(f) Priors: from Continuity

Regular models: "2nd order" theory says prior widely available
Case: Have a quantile representation

(i) Regression: \( y = X\beta + \sigma z \quad z \sim \Theta(0, I) \)

(ii) General: \( y = y(\theta, z) \quad z \sim \Theta \)

Continuity \( \Rightarrow \frac{du}{d\theta} \bigg|_{y_0} = V(\theta) = \text{How parameter affects dist'n at } y_0 \)

Prior: \( \pi(\theta) d\theta = |V(\theta)| d\theta \)

Ex: \( y = X\beta + \sigma z \)
\( V(\theta) = (X, \hat{z}(\theta)) \)
\( \hat{z}(\theta) = (y^0 - X\beta)/\sigma \)

Prior: \( \pi(\theta) d\theta = d\beta d\sigma/\sigma \)

(Jeffreys original) \( d\beta d\sigma/\sigma^p \)
(f) Priors: from Continuity

Regular models: "2nd order" theory says prior widely available
Case: Have a quantile representation

(i) Regression: \( y = X\beta + \sigma z \quad z \sim \mathcal{N}(0, I) \)

(ii) General: \( y = y(\theta, z) \quad z \sim \mathcal{N} \)

Continuity \( \Rightarrow \frac{du}{d\theta} \bigg|_{y^o} = V(\theta) = \text{How parameter affects dist'n at } y^o \quad \eta \in \mathbb{R}^p \)

Prior: \( \pi(\theta) d\theta = |V(\theta)| d\theta \)

Ex.: \( y = X\beta + \sigma z \quad V(\theta) = (X, z(\theta)) \quad \hat{z}(\theta) = (y^o - X\beta)/\sigma \)

Prior: \( \pi(\theta) d\theta = d\beta d\sigma / \sigma \quad (\text{Jeffreys original}) \quad \frac{d\beta d\sigma / \sigma}{p} \)

(4) Often can write \( \hat{\theta} = \hat{\theta}(\theta, \hat{z}) \)

Continuity \( \Rightarrow \frac{d\hat{\theta}}{d\theta} \bigg|_{\theta^o} = \frac{V(\theta)}{p_p} \quad \text{Prior: } \pi(\theta) d\theta = |V(\theta)| d\theta \)
(g) Priors from information

Case: Exponential models; e.g. GLM canonical link

\[ f(s; \varphi) = \exp\{ \varphi^t s - k(\varphi) \} \]
(g) Priors from information

Case: Exponential models; e.g. GLM canonical link

\[ f(s; \varphi) = \exp\{ \varphi' s - k(\varphi) \} h(s) \]

Curious properties:
1) Exptd Info = Obs Info.
2) \( k(\varphi) \) free of \( s \).
(g) Priors from information

Case: Exponential models; e.g. GLM canonical link

\[ f(s; \varphi) = \exp\{ \varphi s - k(\varphi) \} \ln(s) \]

Curious properties: 1) \( \text{Exp'd Info} = \text{Obs Info} \).

2) \( j_{\varphi \varphi}(\varphi) \) free of \( s \).

3) Jeffreys prior = \( \left| j_{\varphi \varphi}(\varphi) \right|^{1/2} = \left| j_{\varphi \varphi}(\varphi) \right|^{1/2} \) can be "Badly biased" if \( p > 1 \). 

Jeffreys 1961
(g) **Priors from information**

Case: Exponential models; e.g. GLM canonical link

\[ f(s; \varphi) = \exp\{ \varphi's - k(\varphi) \} h(s) \]

Curious properties:  
1) Exp'd Info = Obs Info.  
2) \( j_{\varphi \varphi}(\varphi) \) free of \( s \).  
3) Jeffreys prior = \( | j_{\varphi \varphi}(\varphi) |^{\frac{1}{2}} \) can be "Badly biased" if \( p > 1 \) (Jeffreys 1961)

Another property (recent)

4) Prior with repetition validity exists (2nd order, moderate deviations)

Write: \( \varphi = \varphi^0 + Pu \)  \( u \) is unit vector
(9) **Priors from information**

Case: Exponential models; e.g. GLM canonical link

\[ f(s; \varphi) = \exp\{ \varphi s - k(\varphi) \} h(s) \]

Curious properties:

1) Exp\(\alpha\) Info = Obs Info  
2) \(j_{\varphi \varphi}(\varphi)\) free of \(s\)  
3) Jeffreys prior = \(|j_{\varphi \psi}(\varphi)|^{1/2} = |j_{\psi \psi}(\varphi)|^{1/2}\) can be "Badly biased" if \(p > 1\)

Another property (recent)

4) Prior with "repetition validity" exists (2nd order, moderate deviations)

Write: \(\varphi = \hat{\varphi}^0 + p \vec{u}\) \(\vec{u}\) is unit vector

2nd order prior = \(|j_{\varphi \varphi}(\varphi)|^{1/2}\) one dimensional ... radially
(g) Priors from information

Case: Exponential models; e.g. GLM canonical link
\[ f(s; \varphi) = \exp\{ \varphi' s - k(\varphi) \} \cdot h(s) \]

Curious properties:  
1) Expd Info = Obs Info.  
2) \( j_{\varphi\varphi}(\varphi) \) free of \( s \).  
3) Jeffreys prior = \( | j_{\varphi\varphi}(\varphi) |^{1/2} = | j_{\varphi\varphi}(\varphi) |^{1/2} \) can be "Badly biased" if \( p > 1 \) (Jeffreys 1961)

Another property (recent)
4) Prior with "repetition validity" exists (2nd order, moderate deviations)
Write: \( \varphi = \hat{\varphi}^0 + \rho \hat{\mu} \) \( \hat{\mu} \) is unit vector

2nd order prior = \( | j_{\rho\rho}(\varphi) |^{1/2} \) one dimensional ... radially

Uniqueness ... 2nd order

Scalar \( \varphi \): Welch Peers 1963.  Vector \( \varphi \): F 2012 JRSSB in review
(h) Measure the "bias" from a prior

1. The simple Normal $y \sim N(\theta; 1)$
   Try prior $\pi(\theta) = \exp\{a\theta\}$
(h) Measure the bias from a prior

1) The simple Normal \( y \sim N(\theta; 1) \)

Try prior \( \pi(\theta) = \exp\{a\theta\} \)

Get: \( \pi(\theta; y) \) \( \theta \sim N(y^* + a; 1) \)

Bias from prior/Shift of Stated Lik. is \( B = a \)
(h) Measure the bias from a prior

1) The simple \underline{Normal} \quad y \sim N(\theta;1)

Try prior \quad \pi(\theta) = \exp\{a\theta\}

Get: \quad \pi(\theta; y) \quad \theta \sim N(y^* + a; 1)

Bias from prior/Shift of Stąded Lik. is \quad B = a

2) \underline{First order analysis}

Stąded \quad \log L(\theta) = -\frac{1}{2} (\theta - \hat{\theta})^T \sigma_0^2(\theta - \hat{\theta}) \quad \ldots \quad O(n^{1/2})

Stąded prior \quad \pi(\theta) = \exp\{a\theta / n^{1/2}\}
(b) Measure the bias from a prior

1) The simple Normal \( y \sim N(\theta; 1) \)

Try prior \( \pi(\theta) = \exp\{a\theta\} \)

Get: \( \pi(\theta; y) \quad \theta \sim N(y^* + a; 1) \)

Bias from prior/Shift of Stdized Lik. is \( B = a \)

2) First order analysis

Stdized \( \log L(\theta) = -\frac{1}{2} (\theta - \hat{\theta})^T \Sigma^{-1}(\theta - \hat{\theta}) \quad \ldots \quad o(n^{-1/2}) \)

Stdized prior \( \pi(\theta) = \exp\{a\theta/n^{1/2}\} \)

Get: \( \pi(\theta; y) \quad \ldots \quad \text{just "log Likelihood"} \)

\( \ldots \quad \text{no effect from prior} \)
3) Measure the **bias** from a prior: **2nd order analysis**

Case: Scalar parameter  (vector analogous)
3) Measure the bias from a prior: 2nd order analysis

Case: Scalar parameter (vector analogous)

a) Welch-Pears location parameter

\[ \beta = \int_{\phi} \int_{\phi} \frac{1}{2} (\mu) \cdot d\phi \]

"d\beta = \int \frac{1}{2} d\phi"
3) Measure the bias from a prior: 2nd order analysis

Case: Scalar parameter (vector analogous)

a) Welch–Peers location parameter

$$\beta = \int_{\phi_0}^{\phi} \int_{\phi_0}^{\phi} \phi^2 \, d\phi$$

"$$d\beta = \phi^2 d\phi"$$  \hspace{1cm} \beta \text{ has constant info } = 1
3) Measure the bias from a prior: 2nd order analysis

Case: Scalar parameter (vector analogous)

a) Welch–Peers location parameter

\[ \beta = \int_{\phi_0}^{\phi_0} \int_{\phi} \frac{1}{2} (\phi - \mu) \, d\phi \quad \text{"d} \beta = j^{1/2} d\phi " \quad \beta \text{ has constant info } = 1 \]

"flat" re \( \beta \Rightarrow \text{"Bayes = frequency"} " \]
3) Measure the bias from a prior: 2nd order analysis

Case: Scalar parameter (vector analogous)

a) Welch-Peers location parameter

$$\beta = \int_{\phi_0}^{\phi} \int \phi \, d\phi \, d\phi$$

"flat" re $\beta$ => "Bayes = frequency"

b) Proposed prior $\pi(\phi)$ re parameter $\phi$

equivalent to prior $\pi(\phi) \int \phi \, d\phi \, d\phi$ re parameter $\beta$

$\beta$ has constant info = 1
3) Measure the bias from a prior: 2nd order analysis

Case: Scalar parameter (vector analogous)

a) Welch–Peers location parameter

\[ \beta = \int_{\phi_0}^{\phi} \phi^2 \cdot d\phi \]

"flat" re \( \beta \) => "Bayes = frequency"

b) Proposed prior \( \Pi(\phi) \) re parameter \( \phi \)

equivalent to prior \( \Pi(\phi) \phi^{-1/2} \) re parameter \( \beta \)

c) Bayes = frequency requires \( \Pi(\phi) \phi^{-1/2} \) be flat re \( \beta \)
3) Measure the bias from a prior: 2nd order analysis

Case: Scalar parameter (vector analogous)

- Welch–Peers location parameter

  \[ \beta = \int_{\hat{\phi}_0}^{\phi} \int \varphi \, d\varphi \]  \\
  \[ d\beta = \frac{1}{2} d\varphi \]  \\
  "flat" re \( \beta \Rightarrow "Bayes = frequency" " \]

b) Proposed prior \( \Pi_0(\varphi) \) re parameter \( \varphi \)

  Equiv to prior \( \Pi_0(\varphi) \int \varphi \, d\varphi \) re parameter \( \beta \)

c) Bayes = freq'ly requires \( \Pi_0(\varphi) \int \varphi \, d\varphi \) be flat re \( \beta \)

d) \% Bias \( B = \frac{\partial}{\partial \beta} \log \Pi_0(\varphi) \int \varphi \, d\varphi \) \[ r \to r + B \]

  \[ = \left\{ \frac{\partial}{\partial \varphi} \log \Pi_0(\varphi) - \frac{\partial}{\partial \varphi} \log \int \varphi \, d\varphi \right\}_{\hat{\phi}_0}^{\varphi_0} \cdot \int \varphi \, d\varphi \]  \\
  \[ \text{given} \Rightarrow \text{Jeffreys' } \]

  \[ = \text{Amount by which std'd likelihood is displaced} \]

F 2012 PJ SOR To appear
References:

Jeffreys 1946 Proc R.S.A. An invariant form for the prior probability.

Welch 1963 JRSSB On formula for confidence points.


Bernardo 1979 JRSSB Reference posterior distributions.

F Reid 2002 JSPI Strong matching for frequentist and Bayesian.

F Reid Marras Yi 2010 JRSSB Default priors for Bayesian and freq.


F 2012 PJSOR 2012 Bias in Bayes and how to measure it.

F 2012 JRSSB (in review) An adjusted Jeffreys prior.

Can find the good prior - via continuity: $LW(\theta)$

via info: $L_{\theta}(\theta)$

If not good, can calculate bias: $B$