

Bayesian Modeling, Inference, Prediction and Decision-Making

4: Continuous Outcomes (Gaussian Modeling)

David Draper

*Department of Applied Mathematics and Statistics
University of California, Santa Cruz*

SHORT COURSE (DAYS 1 AND 2)
UNIVERSITY OF READING (UK)

© David Draper (all rights reserved)

2.8 Continuous Outcomes

For **continuous outcomes** there's an analogue of de Finetti's Theorem that's **equally central** to Bayesian model-building (e.g., Bernardo and Smith, 1994):

de Finetti's Theorem for Continuous Outcomes.

If Y_1, Y_2, \dots is an infinitely exchangeable sequence of **real-valued** random quantities with probability measure p , there exists a probability measure Q over \mathcal{D} , the space of all distribution functions on R , such that the joint distribution function of Y_1, \dots, Y_n has the form

$$p(y_1, \dots, y_n) = \int_{\mathcal{D}} \prod_{i=1}^n F(y_i) dQ(F), \quad (70)$$

where $Q(F) \stackrel{P}{=} \lim_{n \rightarrow \infty} p(F_n)$ and F_n is the **empirical cumulative distribution function** based on Y_1, \dots, Y_n .

In other words, exchangeability of real-valued observables is **equivalent** to the hierarchical model

$$\begin{array}{ccc} F & \sim & p(F) \quad (\text{prior}) \\ (Y_1, \dots, Y_n | F) & \stackrel{\text{IID}}{\sim} & F \quad (\text{likelihood}) \end{array} \quad (71)$$

for some **prior distribution** p on the **set \mathcal{D} of all possible distribution functions**.

This prior makes the continuous form of de Finetti's Theorem **considerably harder to apply**: to take the elicitation task seriously is to try to specify a measure on a **function space** (F is in effect an **infinite-dimensional** parameter).

(**NB** This task is not unique to Bayesians—it's equivalent to asking **"Where does the likelihood come from?"** in frequentist analyses of observational data.)

Continuous Outcomes (continued)

What people often do in practice is to appeal to considerations that narrow down the field, such as an *a priori* judgment that the Y_i ought to be **symmetrically** distributed about a measure of center μ , and then try to use a fairly **rich parametric family** satisfying (e.g.) the symmetry restriction as a substitute for all of \mathcal{D} .

Strictly speaking you're not supposed to look at the Y_i while specifying your prior on \mathcal{D} —this can lead to a failure to fully assess and propagate **model uncertainty**—but not doing so can permit the data to surprise you in ways that would make you want to go back and revise your prior (an example of **Cromwell's Rule** in action).

As mentioned earlier, in this short course I'll suggest two potential ways out of this dilemma, based on **out-of-sample predictive validation** (the model-checking in the LOS data above was an example of this; see part 4) and **Bayesian nonparametrics/semi-parametrics** (part 7).

Case Study: *Measurement of physical constants.* What used to be called the National Bureau of Standards (NBS) in Washington, DC, conducts extremely high precision measurement of physical constants, such as the actual weight of so-called **check-weights** that are supposed to serve as reference standards (like the official kg).

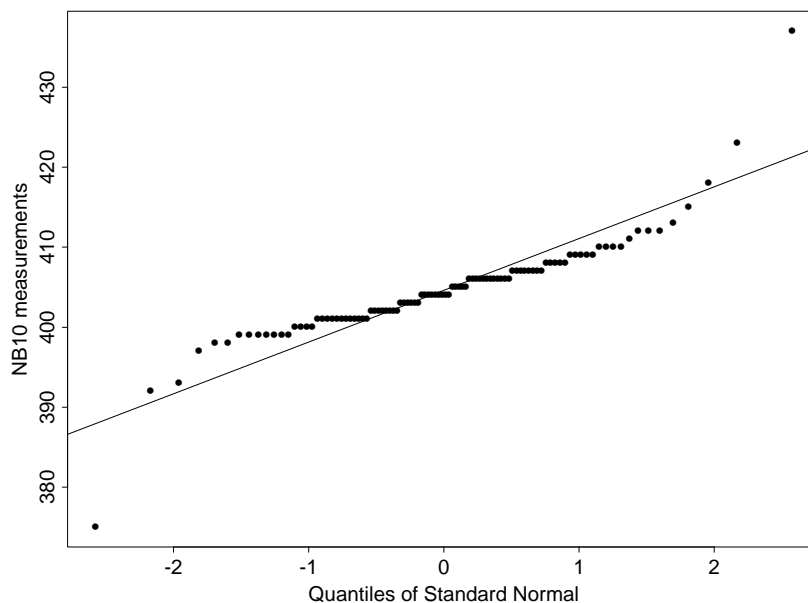
In 1962–63, for example, $n = 100$ weighings (listed below) of a block of metal called **NB10**, which was supposed to weigh exactly 10g, were made under conditions **as close to IID as possible** (Freedman et al., 1998).

Value	375	392	393	397	398	399	400	401
Frequency	1	1	1	1	2	7	4	12
Value	402	403	404	405	406	407	408	409
Frequency	8	6	9	5	12	8	5	5
Value	410	411	412	413	415	418	423	437
Frequency	4	1	3	1	1	1	1	1

NB10 Modeling

Q: (a) How much does NB10 **really weigh**? (b) How certain are you given the data that the true weight of NB10 is **less than** (say) 405.25? And (c) How accurately can you **predict** the 101st measurement?

The graph below is a **normal qqplot** of the 100 measurements $y = (y_1, \dots, y_n)$, which have a mean of $\bar{y} = 404.6$ (the units are **micrograms below 10g**) and an SD of $s = 6.5$.



Evidently it's plausible in answering these questions to assume **symmetry** of the “underlying distribution” F in de Finetti's Theorem.

One standard choice, for instance, is the **Gaussian:**

$$\begin{aligned} (\mu, \sigma^2) &\sim p(\mu, \sigma^2) \\ (Y_i | \mu, \sigma^2) &\stackrel{\text{IID}}{\sim} N(\mu, \sigma^2). \end{aligned} \quad (72)$$

Here $N(\mu, \sigma^2)$ is the familiar **normal density**

$$p(y_i | \mu, \sigma^2) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left[-\frac{1}{2} \left(\frac{y_i - \mu}{\sigma}\right)^2\right]. \quad (73)$$

Gaussian Modeling

Even though you can see from the previous graph that (73) is **not a good model** for the NB10 data, I'm going to fit it to the data for practice in working with the normal distribution from a Bayesian point of view (later we'll **improve** upon the Gaussian).

(73) is more **complicated** than the models in the AMI and LOS case studies because the parameter θ here is a **vector**:
 $\theta = (\mu, \sigma^2)$.

To warm up for this new complexity let's first consider a **cut-down version of the model** in which we pretend that σ is known to be $\sigma_0 = 6.5$ (the sample SD).

This **simpler model** is then

$$\left\{ \begin{array}{l} \mu \sim p(\mu) \\ (Y_i|\mu) \stackrel{\text{IID}}{\sim} N(\mu, \sigma_0^2) \end{array} \right\}. \quad (74)$$

The **likelihood function** in this model is

$$\begin{aligned} l(\mu|y) &= \prod_{i=1}^n \frac{1}{\sigma_0 \sqrt{2\pi}} \exp\left[-\frac{1}{2\sigma_0^2}(y_i - \mu)^2\right] \\ &= c \exp\left[-\frac{1}{2\sigma_0^2} \sum_{i=1}^n (y_i - \mu)^2\right] \\ &= c \exp\left[-\frac{1}{2\sigma_0^2} \left(\sum_{i=1}^n y_i^2 - 2\mu \sum_{i=1}^n y_i + n\mu^2\right)\right] \\ &= c \exp\left[-\frac{1}{2\left(\frac{\sigma_0^2}{n}\right)} (\mu - \bar{y})^2\right]. \end{aligned} \quad (75)$$

Thus the likelihood function, when thought of as a **density** for μ , is a **normal distribution** with mean \bar{y} and SD $\frac{\sigma_0}{\sqrt{n}}$.

Gaussian Modeling (continued)

Notice that this SD is the same as the frequentist **standard error** for \bar{Y} based on an IID sample of size n from the $N(\mu, \sigma_0^2)$ distribution.

(75) also shows that the sample mean \bar{y} is a **sufficient statistic** for μ in model (72).

In finding the conjugate prior for μ it would be nice if the **product of two normal distributions is another normal distribution**, because that would demonstrate that the conjugate prior is normal.

Suppose therefore, to see where it leads, that the **prior for μ** is (say) $p(\mu) = N(\mu_0, \sigma_\mu^2)$.

Then **Bayes' Theorem** would give

$$\begin{aligned}
 p(\mu|y) &= c p(\mu) l(\mu|y) & (76) \\
 &= c \exp\left[-\frac{1}{2\sigma_\mu^2}(\mu - \mu_0)^2\right] \exp\left[-\frac{n}{2\sigma_0^2}(\mu - \bar{y})^2\right] \\
 &= c \exp\left\{-\frac{1}{2}\left[\frac{(\mu - \mu_0)^2}{\sigma_\mu^2} + \frac{n(\mu - \bar{y})^2}{\sigma_0^2}\right]\right\},
 \end{aligned}$$

and we want this to **be of the form**

$$\begin{aligned}
 p(\mu|y) &= c \exp\left\{-\frac{1}{2}[A(\mu - B)^2 + C]\right\} \\
 &= c \exp\left\{-\frac{1}{2}[A\mu^2 - 2AB\mu + (AB^2 + C)]\right\} & (77)
 \end{aligned}$$

for some B, C , and $A > 0$.

Maple can help **see if this works**:

```
> collect( ( mu - mu0 )^2 / sigmamu^2 +
           n * ( mu - ybar )^2 / sigma0^2, mu );
```

$$\frac{1}{2\sigma_\mu^2} + \frac{n}{2\sigma_0^2} \left| \mu - \frac{\mu_0}{2} - \frac{n\bar{y}}{2} \right|^2 + \frac{\mu_0^2}{2\sigma_\mu^2} - \frac{n\bar{y}^2}{2\sigma_0^2} + \frac{\mu_0^2}{2\sigma_\mu^2} + \frac{n\bar{y}^2}{2\sigma_0^2}$$

Gaussian Modeling

Matching coefficients for A and B
(we don't really care about C) gives

$$A = \frac{1}{\sigma_\mu^2} + \frac{n}{\sigma_0^2} \quad \text{and} \quad B = \frac{\frac{\mu_0}{\sigma_\mu^2} + \frac{n\bar{y}}{\sigma_0^2}}{\frac{1}{\sigma_\mu^2} + \frac{n}{\sigma_0^2}}. \quad (78)$$

Since $A > 0$ this demonstrates two things: (1) the **conjugate prior** for μ in model (72) is **normal**, and (2) the **conjugate updating rule** (when σ_0 is assumed known) is

$$\left\{ \begin{array}{l} \mu \sim N(\mu_0, \sigma_\mu^2) \\ (Y_i|\mu) \stackrel{\text{IID}}{\sim} N(\mu, \sigma_0^2), \\ i = 1, \dots, n \end{array} \right\} \rightarrow (\mu|y) = (\mu|\bar{y}) = N(\mu_*, \sigma_*^2), \quad (79)$$

where the **posterior mean and variance** are given by

$$\mu_* = B = \frac{\left(\frac{1}{\sigma_\mu^2}\right) \mu_0 + \left(\frac{n}{\sigma_0^2}\right) \bar{y}}{\frac{1}{\sigma_\mu^2} + \frac{n}{\sigma_0^2}} \quad \text{and} \quad \sigma_*^2 = A^{-1} = \frac{1}{\frac{1}{\sigma_\mu^2} + \frac{n}{\sigma_0^2}}. \quad (80)$$

It becomes useful in understanding the meaning of these expressions to define the **precision** of a distribution, which is just the **reciprocal** of its variance—whereas the variance and SD scales measure **uncertainty**, the precision scale quantifies **information** about an unknown.

With this convention (80) has a series of **intuitive interpretations**, as follows:

- The **prior**, considered as an **information source**, is Gaussian with mean μ_0 , variance σ_μ^2 , and **precision** $\frac{1}{\sigma_\mu^2}$, and when viewed as a data set consists of n_0 (to be determined below) observations;
- The **likelihood**, considered as an **information source**, is Gaussian with mean \bar{y} , variance $\frac{\sigma_0^2}{n}$, and **precision** $\frac{n}{\sigma_0^2}$, and when viewed as a data set consists of n observations;

Gaussian Modeling (continued)

- The **posterior**, considered as an **information source**, is Gaussian, and the posterior mean is a **weighted average** of the prior mean and data mean, with weights given by the **prior and data precisions**;
- The **posterior precision** (the reciprocal of the posterior variance) is just the **sum** of the prior and data precisions (this is why Bayesians invented the idea of precision—on this scale **knowledge** about μ in model (74) is **additive**); and

- **Rewriting μ_* as**

$$\mu_* = \frac{\left(\frac{1}{\sigma_\mu^2}\right) \mu_0 + \left(\frac{n}{\sigma_0^2}\right) \bar{y}}{\frac{1}{\sigma_\mu^2} + \frac{n}{\sigma_0^2}} = \frac{\left(\frac{\sigma_0^2}{\sigma_\mu^2}\right) \mu_0 + n\bar{y}}{\frac{\sigma_0^2}{\sigma_\mu^2} + n}, \quad (81)$$

you can see that the **prior sample size** is

$$n_0 = \frac{\sigma_0^2}{\sigma_\mu^2} = \frac{1}{\left(\frac{\sigma_\mu}{\sigma_0}\right)^2}, \quad (82)$$

which makes sense: the **bigger** σ_μ is in relation to σ_0 , the **less prior information** is being incorporated in the conjugate updating (79).

Bayesian inference with multivariate θ . Returning now to (72) with σ^2 unknown, (as mentioned above) this model has a ($p = 2$)-dimensional **parameter vector** $\theta = (\mu, \sigma^2)$.

When $p > 1$ you can still use Bayes' Theorem directly to obtain the **joint posterior distribution**,

$$\begin{aligned} p(\theta|y) &= p(\mu, \sigma^2|y) = c p(\theta) l(\theta|y) \\ &= c p(\mu, \sigma^2) l(\mu, \sigma^2|y), \end{aligned} \quad (83)$$

Multivariate Unknown θ

where $y = (y_1, \dots, y_n)$, although making this calculation directly requires a p -dimensional **integration** to evaluate the normalizing constant c ; for example, in this case

$$\begin{aligned} c &= [p(y)]^{-1} = \left(\iint p(\mu, \sigma^2, y) d\mu d\sigma^2 \right)^{-1} \\ &= \left(\iint p(\mu, \sigma^2) l(\mu, \sigma^2 | y) d\mu d\sigma^2 \right)^{-1}. \end{aligned} \quad (84)$$

Usually, however, you'll be more interested in the **marginal posterior distributions**, in this case $p(\mu|y)$ and $p(\sigma^2|y)$.

Obtaining these requires p integrations, each of dimension $(p - 1)$, a process that people refer to as **marginalization** or **integrating out the nuisance parameters**—for example,

$$p(\mu|y) = \int_0^\infty p(\mu, \sigma^2|y) d\sigma^2. \quad (85)$$

Predictive distributions also involve a p -dimensional integration: for example, with $y = (y_1, \dots, y_n)$,

$$\begin{aligned} p(y_{n+1}|y) &= \iint p(y_{n+1}, \mu, \sigma^2|y) d\mu d\sigma^2 \\ &= \iint p(y_{n+1}|\mu, \sigma^2) p(\mu, \sigma^2|y) d\mu d\sigma^2. \end{aligned} \quad (86)$$

And, finally, if you're interested in a **function of the parameters**, you have some more hard integrations ahead of you.

For instance, suppose you wanted the posterior distribution for the **coefficient of variation** $\lambda = g_1(\mu, \sigma^2) = \frac{\sqrt{\sigma^2}}{\mu}$ in model (72).

Multivariate Unknown θ

Then one fairly direct way to get this posterior (e.g., Bernardo and Smith, 1994) is to (a) introduce a **second function** of the parameters, say $\eta = g_2(\mu, \sigma^2)$, such that the mapping $f = (g_1, g_2)$ from (μ, σ^2) to (λ, η) is **invertible**; (b) compute the joint posterior for (λ, η) through the usual **change-of-variables formula**

$$p(\lambda, \eta|y) = p_{\mu, \sigma^2}[f^{-1}(\lambda, \eta)|y] |J_{f^{-1}}(\lambda, \eta)|, \quad (87)$$

where $p_{\mu, \sigma^2}(\cdot, \cdot|y)$ is the joint posterior for μ and σ^2 and $|J_{f^{-1}}|$ is the **determinant** of the **Jacobian** of the inverse transformation; and (c) **marginalize** in λ by integrating out η in $p(\lambda, \eta|y)$, in a manner analogous to (85).

Here, for instance, $\eta = g_2(\mu, \sigma^2) = \mu$ would create an invertible f , with **inverse** defined by $(\mu = \eta, \sigma^2 = \lambda^2 \eta^2)$; the **Jacobian determinant** comes out $2\lambda\eta^2$ and (87) becomes

$$p(\lambda, \eta|y) = 2\lambda\eta^2 p_{\mu, \sigma^2}(\eta, \lambda^2\eta^2|y).$$

This process involves **two integrations**, one (of dimension p) to get the normalizing constant that defines (87) and one (of dimension $(p - 1)$) to get rid of η .

You can see that when p is a lot bigger than 2 all these integrals may create **severe computational problems**—this has been the **big stumbling block** for applied Bayesian work for a long time.

More than 200 years ago **Laplace** (1774)—perhaps the second Bayesian in history (after Bayes himself)—developed, as one avenue of solution to this problem, what people now call **Laplace approximations** to high-dimensional integrals of the type arising in Bayesian calculations (see, e.g., Tierney and Kadane, 1986).

Starting in the next case study after this one, we'll use another, computationally intensive, **simulation-based** approach: **Markov chain Monte Carlo** (MCMC).

Gaussian Modeling

Back to model (72). The conjugate prior for $\theta = (\mu, \sigma^2)$ in this model (e.g., Gelman et al., 2003) turns out to be most simply described **hierarchically**:

$$\begin{aligned} \sigma^2 &\sim \text{SI-}\chi^2(\nu_0, \sigma_0^2) \\ (\mu|\sigma^2) &\sim N\left(\mu_0, \frac{\sigma^2}{\kappa_0}\right). \end{aligned} \quad (88)$$

Here saying that $\sigma^2 \sim \text{SI-}\chi^2(\nu_0, \sigma_0^2)$, where SI stands for **scaled inverse**, amounts to saying that the precision $\tau = \frac{1}{\sigma^2}$ follows a **scaled** χ^2 distribution with parameters ν_0 and σ_0^2 .

The scaling is chosen so that σ_0^2 can be interpreted as a **prior estimate** of σ^2 , with ν_0 the **prior sample size** of this estimate (i.e., **think of a prior data set with ν_0 observations and sample SD σ_0**).

Since χ^2 is a special case of the Gamma distribution, **SI- χ^2** must be a special case of the **inverse Gamma** family—its **density** (see Gelman et al. (2003), Appendix A) is

$$\begin{aligned} \sigma^2 &\sim \text{SI-}\chi^2(\nu_0, \sigma_0^2) \leftrightarrow \quad (89) \\ p(\sigma^2) &= \frac{\left(\frac{1}{2}\nu_0\right)^{\frac{1}{2}\nu_0}}{\Gamma\left(\frac{1}{2}\nu_0\right)} (\sigma_0^2)^{\frac{1}{2}\nu_0} (\sigma^2)^{-(1+\frac{1}{2}\nu_0)} \exp\left(\frac{-\nu_0 \sigma_0^2}{2\sigma^2}\right). \end{aligned}$$

As may be verified with Maple, this distribution has **mean** (provided that $\nu_0 > 2$) and **variance** (provided that $\nu_0 > 4$) given by

$$E(\sigma^2) = \frac{\nu_0}{\nu_0 - 2} \sigma_0^2 \quad \text{and} \quad V(\sigma^2) = \frac{2\nu_0^2}{(\nu_0 - 2)^2(\nu_0 - 4)} \sigma_0^4. \quad (90)$$

Gaussian Modeling (continued)

The parameters μ_0 and κ_0 in the second level of the prior model (88), $(\mu|\sigma^2) \sim N\left(\mu_0, \frac{\sigma^2}{\kappa_0}\right)$, have **simple parallel interpretations** to those of σ_0^2 and ν_0 : μ_0 is the **prior estimate** of μ , and κ_0 is the **prior effective sample size** of this estimate.

The **likelihood function** in model (72), with **both** μ and σ^2 **unknown**, is

$$\begin{aligned}
 l(\mu, \sigma^2|y) &= c \prod_{i=1}^n \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left[-\frac{1}{2\sigma^2}(y_i - \mu)^2\right] \\
 &= c (\sigma^2)^{-\frac{1}{2}n} \exp\left[-\frac{1}{2\sigma^2} \sum_{i=1}^n (y_i - \mu)^2\right] \quad (91) \\
 &= c (\sigma^2)^{-\frac{1}{2}n} \exp\left[-\frac{1}{2\sigma^2} \left(\sum_{i=1}^n y_i^2 - 2\mu \sum_{i=1}^n y_i + n\mu^2\right)\right].
 \end{aligned}$$

The **expression in brackets** in the last line of (91) is

$$\begin{aligned}
 [\cdot] &= -\frac{1}{2\sigma^2} \left[\sum_{i=1}^n y_i^2 + n(\mu - \bar{y})^2 - n\bar{y}^2 \right] \quad (92) \\
 &= -\frac{1}{2\sigma^2} [n(\mu - \bar{y})^2 + (n-1)s^2],
 \end{aligned}$$

where $s^2 = \frac{1}{n-1} \sum_{i=1}^n (y_i - \bar{y})^2$ is the **sample variance**. Thus

$$l(\mu, \sigma^2|y) = c (\sigma^2)^{-\frac{1}{2}n} \exp\left\{-\frac{1}{2\sigma^2} [n(\mu - \bar{y})^2 + (n-1)s^2]\right\},$$

and it's clear that the **vector** (\bar{y}, s^2) is **sufficient** for $\theta = (\mu, \sigma^2)$ in this model, i.e., $l(\mu, \sigma^2|y) = l(\mu, \sigma^2|\bar{y}, s^2)$.

Gaussian Analysis

Maple can be used to make **3D** and **contour plots** of this likelihood function with the NB10 data:

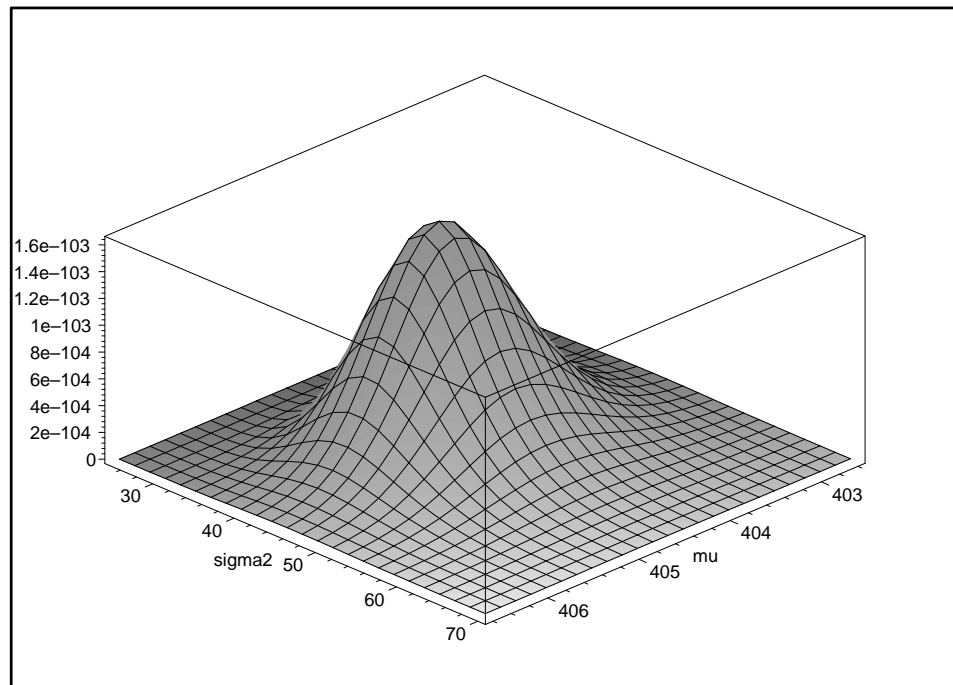
```
> l := ( mu, sigma2, ybar, s2, n ) -> sigma2^( - n / 2 ) *  
    exp( - ( n * ( mu - ybar )^2 + ( n - 1 ) * s2 ) / ( 2 * sigma2 ) );
```

```
l := (mu, sigma2, ybar, s2, n) ->
```

$$\text{sigma2}^{(-1/2 n)} \exp\left(-\frac{1}{2} \frac{n (\mu - \text{ybar})^2 + (n - 1) s2}{\text{sigma2}}\right)$$

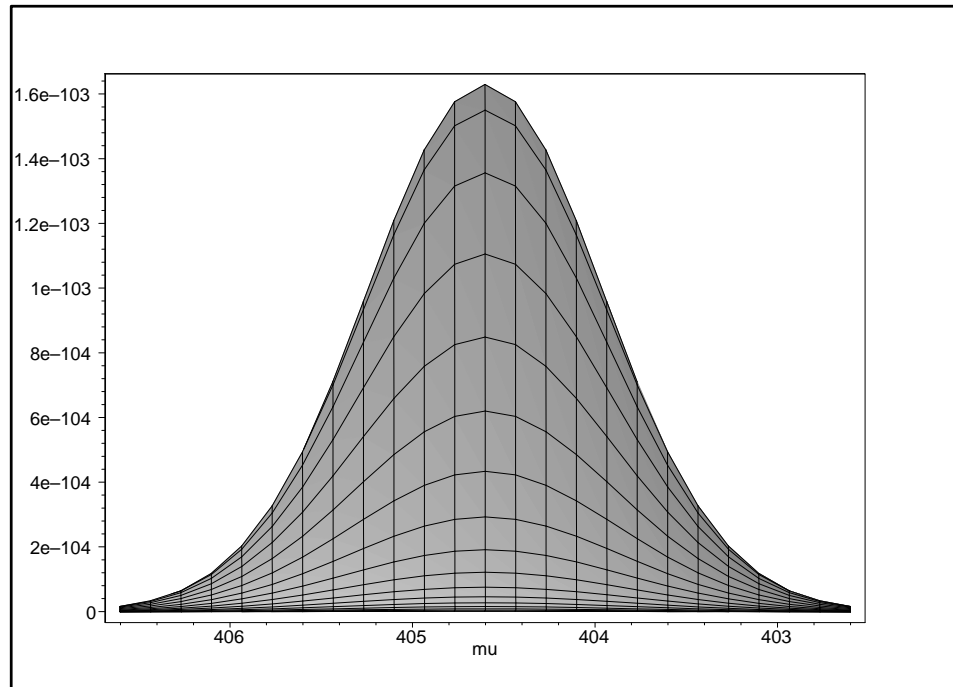
```
> plotsetup( x11 );
```

```
> plot3d( l( mu, sigma2, 404.6, 42.25, 100 ), mu = 402.6 .. 406.6,  
    sigma2 = 25 .. 70 );
```

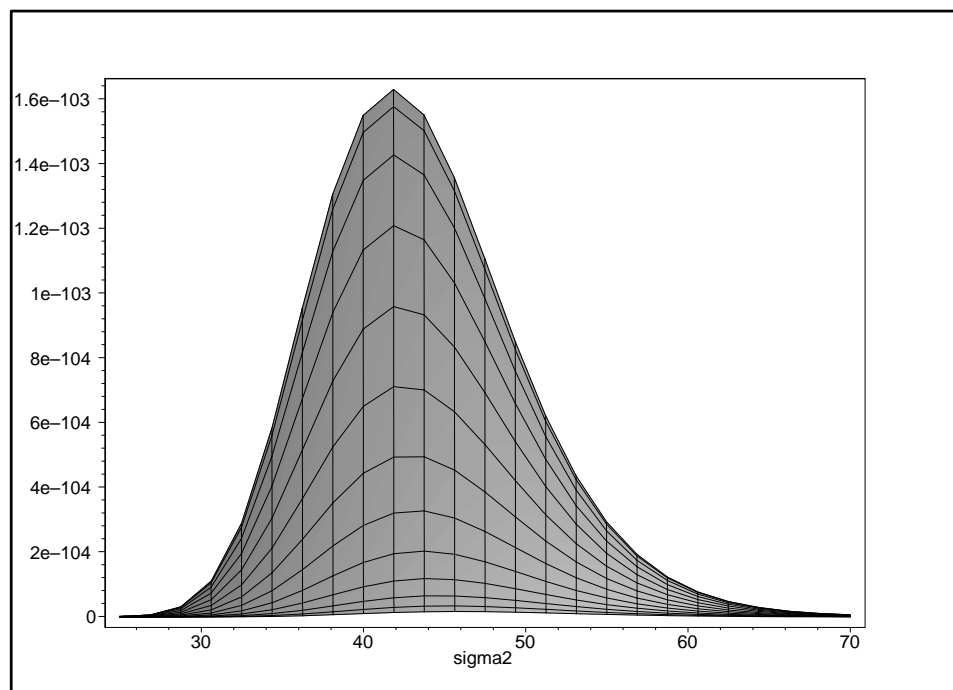


You can use the mouse to **rotate** 3D plots and get **other useful views** of them:

Gaussian Analysis



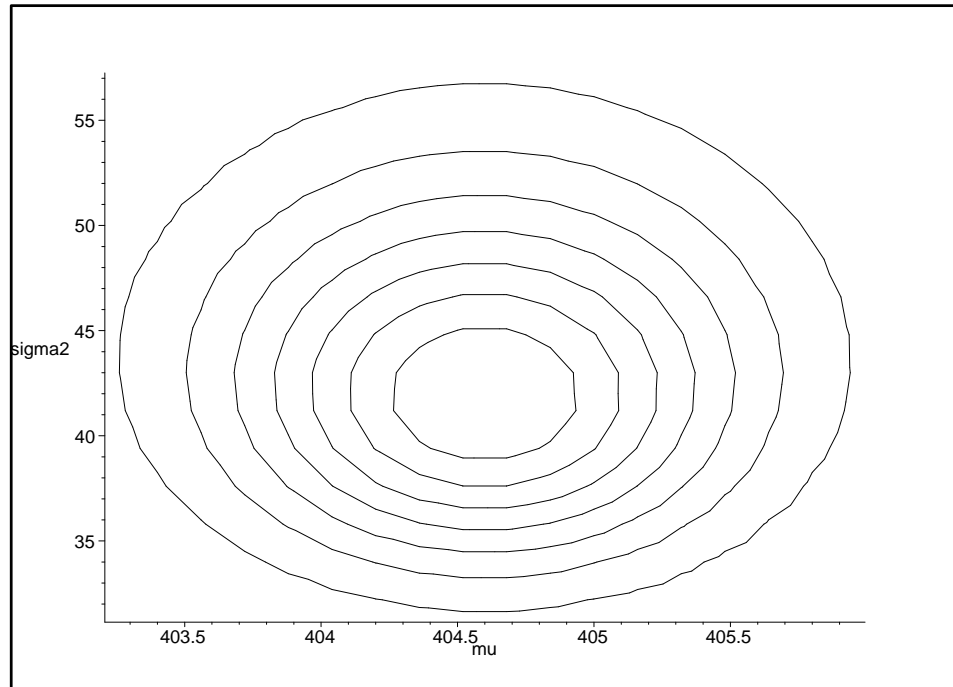
The **projection** or **shadow plot** of μ looks a lot like a **normal** (or maybe a *t*) distribution.



And the shadow plot of σ^2 looks a lot like a **Gamma** (or maybe an **inverse Gamma**) distribution.

Gaussian Analysis

```
> plots[ contourplot ]( 10^100 * l( mu, sigma2, 404.6, 42.25, 100 ),
  mu = 402.6 .. 406.6, sigma2 = 25 .. 70, color = black );
```



The **contour plot** shows that μ and σ^2 are **uncorrelated** in the likelihood distribution, and the **skewness** of the marginal distribution of σ^2 is also evident.

Posterior analysis. Having adopted the **conjugate prior** (88), what I'd like next is simple expressions for the **marginal posterior distributions** $p(\mu|y)$ and $p(\sigma^2|y)$ and for **predictive distributions** like $p(y_{n+1}|y)$.

Fortunately, in model (72) all of the **integrations** (such as (85) and (86)) may be done **analytically** (see, e.g., Bernardo and Smith 1994), yielding the following results:

$$\begin{aligned}
 (\sigma^2|y, \mathcal{G}) &\sim \text{SI-}\chi^2(\nu_n, \sigma_n^2), \\
 (\mu|y, \mathcal{G}) &\sim t_{\nu_n}\left(\mu_n, \frac{\sigma_n^2}{\kappa_n}\right), \quad \text{and} \\
 (y_{n+1}|y, \mathcal{G}) &\sim t_{\nu_n}\left(\mu_n, \frac{\kappa_n + 1}{\kappa_n} \sigma_n^2\right).
 \end{aligned} \tag{93}$$

NB10 Gaussian Analysis

In the above **expressions**

$$\begin{aligned}
 \nu_n &= \nu_0 + n, \\
 \sigma_n^2 &= \frac{1}{\nu_n} \left[\nu_0 \sigma_0^2 + (n-1)s^2 + \frac{\kappa_0 n}{\kappa_0 + n} (\bar{y} - \mu_0)^2 \right], \quad (94) \\
 \mu_n &= \frac{\kappa_0}{\kappa_0 + n} \mu_0 + \frac{n}{\kappa_0 + n} \bar{y}, \quad \text{and} \\
 \kappa_n &= \kappa_0 + n,
 \end{aligned}$$

\bar{y} and s^2 are the usual **sample mean** and **variance** of y , and \mathcal{G} denotes the assumption of the **Gaussian model**.

Here $t_\nu(\mu, \sigma^2)$ is a **scaled** version of the usual t_ν distribution, i.e., $W \sim t_\nu(\mu, \sigma^2) \iff \frac{W-\mu}{\sigma} \sim t_\nu$.

The scaled t distribution (see, e.g., Gelman et al. (2003) Appendix A) has **density**

$$\eta \sim t_\nu(\mu, \sigma^2) \leftrightarrow p(\eta) = \frac{\Gamma\left[\frac{1}{2}(\nu+1)\right]}{\Gamma\left(\frac{1}{2}\nu\right) \sqrt{\nu\pi\sigma^2}} \left[1 + \frac{1}{\nu\sigma^2}(\eta - \mu)^2\right]^{-\frac{1}{2}(\nu+1)}. \quad (95)$$

This distribution has **mean** μ (as long as $\nu > 1$) and **variance** $\frac{\nu}{\nu-2}\sigma^2$ (as long as $\nu > 2$).

Notice that, as with all previous conjugate examples, the posterior mean is again a **weighted average** of the prior mean and data mean, with weights determined by the **prior sample size** and the **data sample size**:

$$\mu_n = \frac{\kappa_0}{\kappa_0 + n} \mu_0 + \frac{n}{\kappa_0 + n} \bar{y}. \quad (96)$$

NB10 Gaussian Analysis (continued)

NB10 Gaussian Analysis. *Question (a):* I don't know anything about what NB10 is supposed to weigh (down to the nearest microgram) or about the accuracy of the NBS's measurement process, so I want to use a **diffuse prior** for μ and σ^2 .

Considering the meaning of the **hyperparameters**, to provide little prior information I want to choose both ν_0 and κ_0 **close to 0**.

Making them exactly 0 would produce an **improper** prior distribution (which doesn't integrate to 1), but choosing positive values as close to 0 as you like yields a **proper and highly diffuse prior**.

You can see from (93, 94) that the result is then

$$(\mu|y, \mathcal{G}) \sim t_n \left[\bar{y}, \frac{(n-1)s^2}{n^2} \right] \doteq N \left(\bar{y}, \frac{s^2}{n} \right), \quad (97)$$

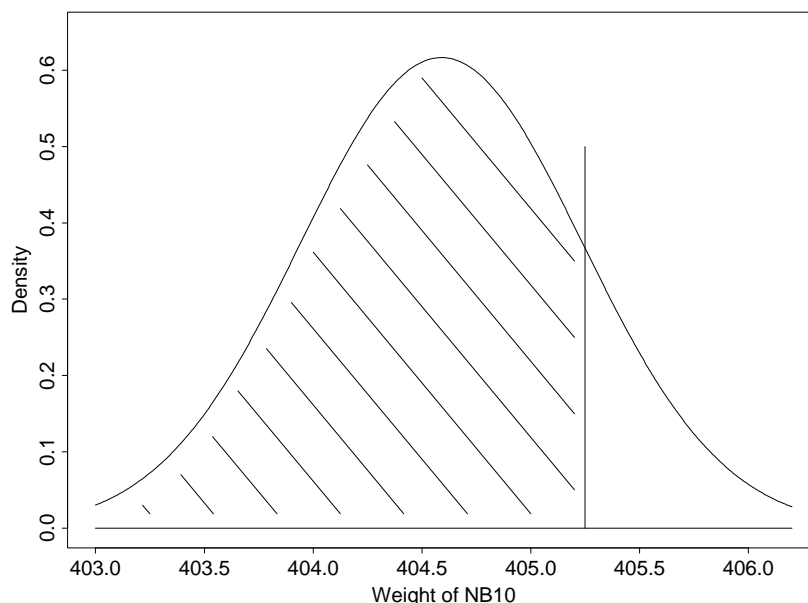
i.e., with diffuse prior information (as with the Bernoulli model in the AMI case study) the 95% central Bayesian interval **virtually coincides** with the usual frequentist 95% confidence interval

$$\bar{y} \pm t_{n-1}^{.975} \frac{s}{\sqrt{n}} = 404.6 \pm (1.98)(0.647) = (403.3, 405.9).$$

Thus both {frequentists who assume \mathcal{G} } and {Bayesians who assume \mathcal{G} with a diffuse prior} conclude that **NB10 weighs about 404.6 μ g below 10g, give or take about 0.65 μ g**.

Question (b). If interest focuses on whether NB10 weighs **less than some value** like 405.25, when reasoning in a Bayesian way you can answer this question directly: the posterior distribution for μ is shown below, and $P_B(\mu < 405.25|y, \mathcal{G}, \text{diffuse prior}) \doteq .85$, i.e., your **betting odds** in favor of the proposition that $\mu < 405.25$ are about 5.5 to 1.

NB10 Gaussian Analysis (continued)



When reasoning in a frequentist way $P_F(\mu < 405.25)$ is **undefined**; about the best you can do is to test $H_0: \mu < 405.25$, for which the p -value would (approximately) be $p = P_{F,\mu=405.25}(\bar{y} > 405.59) = 1 - .85 = .15$, i.e., **insufficient evidence to reject H_0** at the usual significance levels (note the **connection** between the p -value and the posterior probability, which arises in this example because the null hypothesis is **one-sided**).

NB The significance test tries to answer a **different question**: in Bayesian language it looks at $P(\bar{y}|\mu)$ instead of $P(\mu|\bar{y})$.

Many people find the latter quantity **more interpretable**.

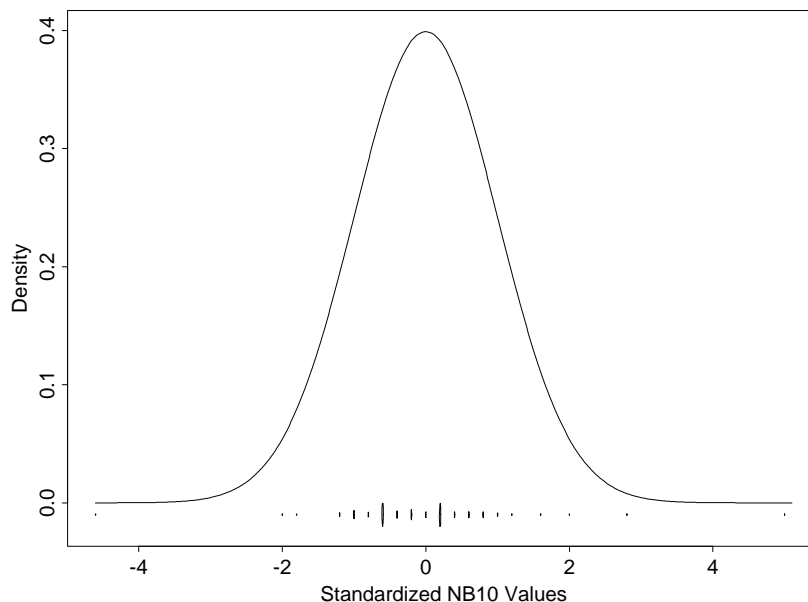
Question (c). We saw earlier that **in this model**

$$(y_{n+1}|y, \mathcal{G}) \sim t_{\nu_n} \left[\mu_n, \frac{\kappa_n + 1}{\kappa_n} \sigma_n^2 \right], \quad (98)$$

and for n large and ν_0 and κ_0 close to 0 this is $(y_{n+1}|y, \mathcal{G}) \sim N(\bar{y}, s^2)$, i.e., a **95% posterior predictive interval** for y_{n+1} is (392, 418).

Model Expansion

A **standardized version** of this predictive distribution is plotted below, with the standardized NB10 data values **superimposed**.



It's evident from this plot (and also from the normal qqplot given earlier) that the Gaussian model provides a **poor fit** for these data—the three most extreme points in the data set in standard units are -4.6 , 2.8 , and 5.0 .

With the **symmetric heavy tails** indicated in these plots, in fact, the empirical CDF looks quite a bit like that of a t distribution with a rather small number of **degrees of freedom**.

This suggests revising the previous model by **expanding** it: **embedding** the Gaussian in the t family and adding a parameter k for **tail-weight**.

Unfortunately there's no standard **closed-form conjugate** choice for the prior on k .

A more **flexible** approach to computing is evidently needed—this is where **Markov chain Monte Carlo** methods (our next main topic) come in.

2.9 The Exponential Family

It was noticed a long time ago that many of the standard sampling distributions that you're likely to want to use in constructing likelihood functions have the **same general form**, which is referred to as the **exponential family**:

Definition (e.g., Bernardo and Smith, 1994): Given data y_1 (a sample of size 1) and a parameter vector $\theta = (\theta_1, \dots, \theta_k)$, the (marginal) sampling distribution $p(y_1|\theta)$ belongs to the **k -dimensional exponential family** if it can be expressed in the form

$$p(y_1|\theta) = c f_1(y_1) g_1(\theta) \exp \left[\sum_{j=1}^k \phi_j(\theta) h_j(y_1) \right] \quad (99)$$

for $y_1 \in \mathcal{Y}$ and 0 otherwise; if \mathcal{Y} does not depend on θ the family is called **regular**.

$(\phi_1(\theta), \dots, \phi_k(\theta))$ in (99) is referred to as the **natural parameterization** of the exponential family.

In this case the **joint distribution** $p(y|\theta)$ of a **sample** $y = (y_1, \dots, y_n)$ of size n which is conditionally IID from (99) (which also defines, as usual, the **likelihood function** $l(\theta|y)$) will be

$$\begin{aligned} p(y|\theta) &= l(\theta|y) = \prod_{i=1}^n p(y_i|\theta) && (100) \\ &= c \left[\prod_{i=1}^n f_1(y_i) \right] [g_1(\theta)]^n \exp \left[\sum_{j=1}^k \phi_j(\theta) \sum_{i=1}^n h_j(y_i) \right]. \end{aligned}$$

The Exponential Family (continued)

This leads to **another way** to define the exponential family: in (99) take $f(y) = \prod_{i=1}^n f_1(y_i)$ and $g(\theta) = [g_1(\theta)]^n$ to yield

Definition: Given data $y = (y_1, \dots, y_n)$ (a conditionally IID sample of size n) and a parameter vector $\theta = (\theta_1, \dots, \theta_k)$, the (joint) sampling distribution $p(y|\theta)$ belongs to the **k -dimensional exponential family** if it can be expressed in the form

$$p(y|\theta) = c f(y) g(\theta) \exp \left[\sum_{j=1}^k \phi_j(\theta) \sum_{i=1}^n h_j(y_i) \right]. \quad (101)$$

Either way you can see that $\{\sum_{i=1}^n h_1(y_i), \dots, \sum_{i=1}^n h_k(y_i)\}$ is a set of **sufficient** statistics for θ under this sampling model, because the likelihood $l(\theta|y)$ depends on y only through the values of $\{h_1, \dots, h_k\}$.

I bring up the exponential family in part because, if the likelihood $l(\theta|y)$ is of the form (101), then in searching for a **conjugate** prior $p(\theta)$ —that is, a prior of the same functional form as the likelihood—you can see directly what will work:

$$p(\theta) = c g(\theta)^{\tau_0} \exp \left[\sum_{j=1}^k \phi_j(\theta) \tau_j \right], \quad (102)$$

for some $\tau = (\tau_0, \dots, \tau_k)$.

The Exponential Family (continued)

With this choice the **posterior** for θ will be

$$p(\theta|y) = c g(\theta)^{1+\tau_0} \exp \left\{ \sum_{j=1}^k \phi_j(\theta) \left[\tau_j + \sum_{i=1}^n h_j(y_i) \right] \right\}, \quad (103)$$

which is indeed of the **same form** (in θ) as (102).

As a first example, with $s = \sum_{i=1}^n y_i$, the **Bernoulli/binomial** likelihood in (41) can be written

$$\begin{aligned} l(\theta|y) &= \theta^s (1 - \theta)^{n-s} \\ &= (1 - \theta)^n \left(\frac{\theta}{1 - \theta} \right)^s \\ &= (1 - \theta)^n \exp \left[s \log \left(\frac{\theta}{1 - \theta} \right) \right], \end{aligned} \quad (104)$$

which shows (a) that this sampling distribution is a member of the **exponential family** with $k = 1$, $g(\theta) = (1 - \theta)^n$, the natural parameterization $\phi_1(\theta) = \log \left(\frac{\theta}{1 - \theta} \right)$ (**NB** the basis of **logistic regression**), and $h_1(y_i) = y_i$, and (b) that $\sum_{i=1}^n h_1(y_i) = s$ is sufficient for θ .

Then (102) says that the **conjugate prior** for the Bernoulli/binomial likelihood is

$$\begin{aligned} p(\theta) &= c (1 - \theta)^{n\tau_0} \exp \left[\tau_1 \log \left(\frac{\theta}{1 - \theta} \right) \right] \\ &= c \theta^{\alpha-1} (1 - \theta)^{\beta-1} = \text{Beta}(\alpha, \beta) \end{aligned} \quad (105)$$

for some α and β , as we've already seen is **true**.

The Exponential Family (continued)

As an example of a **non-regular** exponential family, suppose that a reasonable model for the data is to take the observed values $(y_i|\theta)$ to be conditionally IID from the **uniform** distribution

$U(0, \theta)$ on the interval $(0, \theta)$ for unknown θ :

$$p(y_1|\theta) = \left\{ \begin{array}{ll} \frac{1}{\theta} & \text{for } 0 < y_1 < \theta \\ 0 & \text{otherwise} \end{array} \right\} = \frac{1}{\theta} I(0, \theta), \quad (106)$$

where $I(A) = 1$ if A is true and 0 otherwise.

θ in this model is called a **range-restriction** parameter; such parameters are fundamentally different from **location** and **scale** parameters (like the mean μ and variance σ^2 in the $N(\mu, \sigma^2)$ model, respectively) or **shape** parameters (like the degrees of freedom ν in the t_ν model).

(106) is an **example of (99)** with $c = 1$, $f_1(y) = 1$, $g_1(\theta) = \frac{1}{\theta}$, $h_1(y) = 0$, and $\phi_1(\theta) =$ anything you want (e.g., 1), but only when the set $\mathcal{Y} = (0, \theta)$ is taken to depend on θ .

(**Truncated** distributions with **unknown truncation point** also lead to non-regular exponential families.)

It turns out that inference in non-regular exponential families is **similar** in some respects to the story when the exponential family is regular, but there are some **important differences** too (e.g., with a conditionally IID sample of size n from (106), $V(\theta|y) = O(n^{-2})$ (!) instead of the more familiar $O(n^{-1})$).

The Exponential Family (continued)

For an example with $p > 1$, take $\theta = (\mu, \sigma^2)$ with the **Gaussian likelihood**:

$$\begin{aligned} l(\theta|y) &= \prod_{i=1}^n \frac{1}{\sigma\sqrt{2\pi}} \exp\left[-\frac{1}{2\sigma^2}(y_i - \mu)^2\right] \quad (107) \\ &= \sigma^{-n} (2\pi)^{-\frac{n}{2}} \exp\left[-\frac{1}{2\sigma^2} \left(\sum_{i=1}^n y_i^2 - 2\mu \sum_{i=1}^n y_i + n\mu^2\right)\right]. \end{aligned}$$

This is of the form (101) with $k = 2$, $c = (2\pi)^{-\frac{n}{2}}$, $f(y) = 1$, $g(\theta) = \sigma^{-n} \exp\left(-\frac{n\mu^2}{2\sigma^2}\right)$, $\phi_1(\theta) = -\frac{1}{2\sigma^2}$, $\phi_2(\theta) = \frac{\mu}{\sigma^2}$, $h_1(y_i) = y_i^2$, and $h_2(y_i) = y_i$, which shows that

$[h_1(y) = \sum_{i=1}^n y_i^2, h_2(y) = \sum_{i=1}^n y_i]$ or equivalently (\bar{y}, s^2) is **sufficient** for θ .

Some **unpleasant algebra** then demonstrates that an application of (102) leads to (88) as the **conjugate prior** for the Gaussian likelihood when both μ and σ^2 are unknown.

2.10 References

- Bernardo JM, Smith AFM (1994). *Bayesian Theory*. New York: Wiley.
- Craig PS, Goldstein M, Seheult AH, Smith JA (1997). Constructing partial prior specifications for models of complex physical systems. *The Statistician*, **46**, forthcoming.
- Draper D (1995). Inference and hierarchical modeling in the social sciences (with discussion). *Journal of Educational and Behavioral Statistics*, **20**, 115–147, 233–239.
- Draper D, Hodges JS, Mallows CL, Pregibon D (1993). Exchangeability and data analysis (with discussion). *Journal of the Royal Statistical Society, Series A*, **156**, 9–37.
- de Finetti B (1930). Funzione caratteristica di un fenomeno aleatorio. *Mem. Acad. Naz. Lincei*, **4**, 86–133.
- de Finetti B (1964). Foresight: its logical laws, its subjective sources. In *Studies in Subjective Probability*, HE Kyburg, Jr., and HE Smokler, eds., New York: Wiley (1980), 93–158.
- de Finetti B (1974/5). *Theory of Probability*, **1–2**. New York: Wiley.
- Fisher RA (1922). On the mathematical foundations of theoretical statistics. *Philosophical Transactions of the Royal Society of London A*, **222**, 309–368.
- Fisher RA (1956). *Statistical Methods and Scientific Inference*. London: Oliver and Boyd.
- Freedman D, Pisani R, Purves R, Adhikari A (1998). *Statistics*, third edition. New York: Norton.
- Gelman A, Carlin JB, Stern HS, Rubin DB (2003). *Bayesian Data Analysis*, second edition. London: Chapman & Hall.
- Hacking I (1975). *The Emergence of Probability*. Cambridge: Cambridge University Press.
- Johnson NL, Kotz S (1970). *Distributions in statistics: Continuous univariate distributions*, **1**. New York: Wiley.
- Kadane JB, Dickey JM, Winkler RL, Smith WS, Peters SC (1980). Interactive elicitation of opinion for a normal linear model. *Journal of the American Statistical Association*, **75**, 845–854.

References (continued)

- Kadane JB, Wolfson LJ (1997). Experiences in elicitation. *The Statistician*, **46**, forthcoming.
- Kahn K, Rubenstein L, Draper D, Kosecoff J, Rogers W, Keeler E, Brook R (1990). The effects of the DRG-based Prospective Payment System on quality of care for hospitalized Medicare patients: An introduction to the series. *Journal of the American Medical Association*, **264**, 1953–1955 (with editorial comment, 1995–1997).
- Laplace PS (1774). Mémoire sur la probabilité des causes par les événements. *Mémoires de l'Académie des Sciences de Paris*, **6**, 621–656. English translation in 1986 as “Memoir on the probability of the causes of events,” with an introduction by SM Stigler, *Statistical Science*, **1**, 359–378.
- O'Hagan A (1997). Eliciting expert beliefs in substantial practical applications. *The Statistician*, **46**, forthcoming.
- Samaniego FJ, Reneau DM (1994). Toward a reconciliation of the Bayesian and frequentist approaches to point estimation. *Journal of the American Statistical Association*, **89**, 947–957.
- Tierney L, Kadane JB (1986). Accurate approximations for posterior moments and marginal densities. *Journal of the American Statistical Association*, **81**, 82–86.

