MAS3902: Bayesian Inference

Dr. Lee Fawcett

School of Mathematics, Statistics & Physics

Semester 2, 2022/23

Contact details

My name: Lee Fawcett

Office: Room 2.07 Herschel Building

Phone: 0191 208 7228

Email: lee.fawcett@ncl.ac.uk

www: www.mas.ncl.ac.uk/∼nlf8

Timetable and Administrative arrangements

- **Classes** take place on Tuesdays (3pm, Herschel LT2) and Thursdays (9am, online – fortnightly only; 12pm, Herschel LT1)
- Two of these classes will be **lectures**, and the other session will be a **problems class/drop-in**
  - Lectures will *ordinarily* take place in the in-person slots in the lecture theatres
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  - Friday 3rd February (11am, Herschel LT2)
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Assessment

Assessment is by:

- 2-hour end-of-semester exam in May/June (**80%**)
- In course assessment (**20%**), comprising four short written assignments:

Date set	Deadline	Marks/weighting
Friday 10th February	4pm, Friday 24th February	20/5%
Friday 24th February	4pm, Friday 10th March	20/5%
Friday 10th March	4pm, Friday 24th March	20/5%
Friday 24th March	4pm, Friday 5th May	20/5%

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Recommended textbooks

- "*Bayes' Rule: A Tutorial Introduction to Bayesian Analysis*" - James Stone
- "*Doing Bayesian Data Analysis: A Tutorial with R, JAGS, and Stan*" - John Krushke
- "*Bayesian Statistics: An Introduction*" - Peter Lee

"Bayes' rule" is a good introduction to the main concepts in Bayesian statistics but doesn't cover everything in this course. The other books are broader references which go well beyond the contents of this course.

Other stuff

- Notes (with gaps) will be available for use in lectures – you can fill in the gaps during lectures
- A (very!) summarised version of the notes will be used in lectures as slides
- These notes and slides will be posted on the course Canvas page after each topic is finished, along with any other course material – such as problems sheets, model solutions to assignment questions, supplementary handouts etc.

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Chapter 1

Single parameter problems

1.1 Prior and posterior distributions

Data: $\boldsymbol{x} = (x_1, x_2, \ldots, x_n)^T$

Model: pdf/pf $f(\boldsymbol{x}|\theta)$ depends on a single parameter θ

$\rightarrow$ Likelihood function $f(\boldsymbol{x}|\theta)$

considered as a function of θ for known $\boldsymbol{x}$

Prior beliefs: pdf/pf $\pi(\theta)$

Combine using Bayes Theorem

Posterior beliefs: pdf/pf $\pi(\theta|\boldsymbol{x})$

Posterior distribution summarises all our current knowledge about the parameter θ

Bayes Theorem

The posterior probability (density) function for θ is

$$\pi(\theta|\boldsymbol{x}) = \frac{\pi(\theta)\, f(\boldsymbol{x}|\theta)}{f(\boldsymbol{x})}$$

where

$$f(\boldsymbol{x}) = \begin{cases} \int_{\Theta} \pi(\theta)\, f(\boldsymbol{x}|\theta)\, d\theta & \text{if } \theta \text{ is continuous,} \\ \\ \sum_{\Theta} \pi(\theta)\, f(\boldsymbol{x}|\theta) & \text{if } \theta \text{ is discrete.} \end{cases}$$

As $f(\boldsymbol{x})$ is not a function of θ, Bayes Theorem can be rewritten as

$$\pi(\theta|\boldsymbol{x}) \propto \pi(\theta) \times f(\boldsymbol{x}|\theta)$$

i.e. **posterior** $\propto$ **prior** $\times$ **likelihood**

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Example 1.1

- Data

Year	1998	1999	2000	2001	2002	2003	2004	2005
Cases	2	0	0	0	1	0	2	1

Table: Number of cases of foodbourne botulism in England and Wales, 1998–2005

- Assume that cases occur at random at a constant rate θ in time
- This means the data are from a Poisson process and so are a random sample from a Poisson distribution with rate θ
- An expert was consulted to construct a suitable prior distribution for the rate θ

Example 1.1

(a) What might be an appropriate probability model for the rate θ? Why is this termed the *prior distribution*?

(b) Suppose the epidemiologist tells you that she expects around two cases of foodbourne botulism per year in England and Wales. After further discussions with the epidemiologist, you are also able to elicit that $SD(\theta) \approx \sqrt{2}$. Using your answer to part (a) find your full prior distribution for θ, and write down its density.

(c) Determine the posterior distribution for θ.

Solution

. . . Solution...

Summary

- Model: $X_i|\theta \sim Po(\theta)$, $i = 1, 2, \ldots, 8$ (independent)
- Prior: $\theta \sim Ga(2, 1)$
- Data: in Table above
- Posterior: $\theta|\boldsymbol{x} \sim Ga(8, 9)$

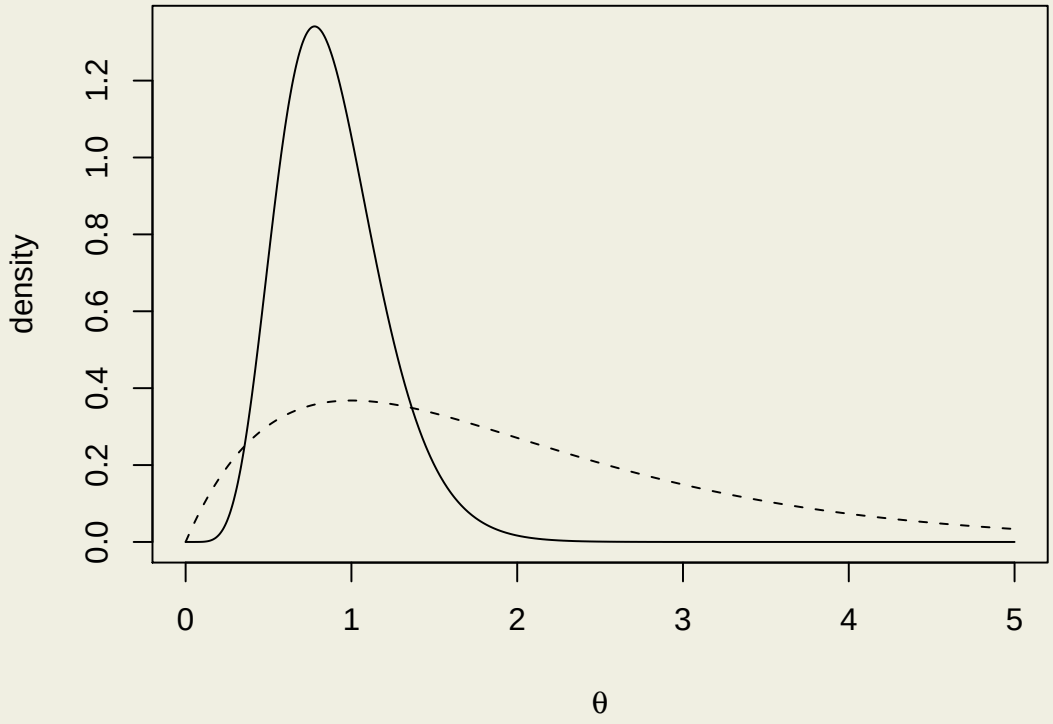


Figure: Prior (dashed) and posterior (solid) densities for θ

	Prior	Likelihood	Posterior
$Mode(\theta)$	1.00	0.75	0.78
$E(\theta)$	2.00	–	0.89
$SD(\theta)$	1.41	–	0.31

Table: Changes in beliefs about θ

- Likelihood mode $<$ prior mode $\rightarrow$ posterior mode moves in direction of likelihood mode $\rightarrow$ posterior mode $<$ prior mode
- Reduction in variability from the prior to the posterior

Example 1.2

We now consider the general case (of Example 1.1). Suppose $X_i|\theta \sim Po(\theta)$, $i = 1, 2, \ldots, n$ (independent) and our prior beliefs about θ are summarised by a $Ga(g, h)$ distribution (with g and h known), with density

$$\pi(\theta) = \frac{h^g \, \theta^{g-1} e^{-h\theta}}{\Gamma(g)}, \quad \theta > 0. \tag{1.1}$$

Determine the posterior distribution for θ.

Solution

...

(1.2)

(1.3)

Summary

- Model: $X_i|\theta \sim Po(\theta)$, $i = 1, 2, \ldots, n$ (independent)
- Prior: $\theta \sim Ga(g, h)$
- Data: observe $\boldsymbol{x}$
- Posterior: $\theta|\boldsymbol{x} \sim Ga(g + n\bar{x}, h + n)$
- Taking $g \geq 1$

	Prior (1.1)	Likelihood (1.2)	Posterior (1.3)
$Mode(\theta)$	$(g-1)/h$	$\bar{x}$	$(g + n\bar{x} - 1)/(h + n)$
$E(\theta)$	g/h	–	$(g + n\bar{x})/(h + n)$
$SD(\theta)$	$\sqrt{g}/h$	–	$\sqrt{g + n\bar{x}}/(h + n)$

Table: Changes in beliefs about θ

Comments

- Posterior mean is greater than the prior mean if and only if the likelihood mode is greater than the prior mean, that is,

$$E(\theta|\boldsymbol{x}) > E(\theta) \quad \Longleftrightarrow \quad Mode_\theta\{f(\boldsymbol{x}|\theta)\} > E(\theta)$$

- Standard deviation of the posterior distribution is smaller than that of the prior distribution if and only if the sample mean is not too large, that is

$$SD(\theta|\boldsymbol{x}) < SD(\theta) \quad \Longleftrightarrow \quad Mode_\theta\{f(\boldsymbol{x}|\theta)\} < \left(2 + \frac{n}{h}\right) E(\theta),$$

and that this will be true in large samples.

Example 1.3

Suppose we have a random sample from a normal distribution with unknown mean μ but known precision τ: $X_i|\mu \sim N(\mu, 1/\tau)$, $i = 1, 2, \ldots, n$ (independent).

Suppose our prior beliefs about μ can be summarised by a $N(b, 1/d)$ distribution, with probability density function

$$\pi(\mu) = \left(\frac{d}{2\pi}\right)^{1/2} \exp\left\{-\frac{d}{2}(\mu - b)^2\right\}. \tag{1.4}$$

Determine the posterior distribution for μ.

Hint:

$$d(\mu - b)^2 + n\tau(\bar{x} - \mu)^2 = (d + n\tau)\left\{\mu - \left(\frac{db + n\tau\bar{x}}{d + n\tau}\right)\right\}^2 + c$$

where c does not depend on μ.

Solution

. . .

(1.5)

(1.6)

(1.7)

Summary

- Model: $X_i|\mu \sim N(\mu, 1/\tau)$, $i = 1, 2, \ldots, n$ (independent), with τ known
- Prior: $\mu \sim N(b, 1/d)$
- Data: observe $\boldsymbol{x}$
- Posterior: $\mu|\boldsymbol{x} \sim N(B, 1/D)$, where

$$B = \frac{db + n\tau\bar{x}}{d + n\tau} \qquad \text{and} \qquad D = d + n\tau$$

	Prior (1.4)	Likelihood (1.5)	Posterior (1.7)
$Mode(\mu)$	b	$\bar{x}$	$(db + n\tau\bar{x})/(d + n\tau)$
$E(\mu)$	b	–	$(db + n\tau\bar{x})/(d + n\tau)$
$Precision(\mu)$	d	–	$d + n\tau$

Table: Changes in beliefs about μ

- Posterior mean is greater than the prior mean if and only if the likelihood mode (sample mean) is greater than the prior mean, that is

$$E(\mu|\boldsymbol{x}) > E(\mu) \quad \Longleftrightarrow \quad Mode_{\mu}\{f(\boldsymbol{x}|\mu)\} > E(\mu)$$

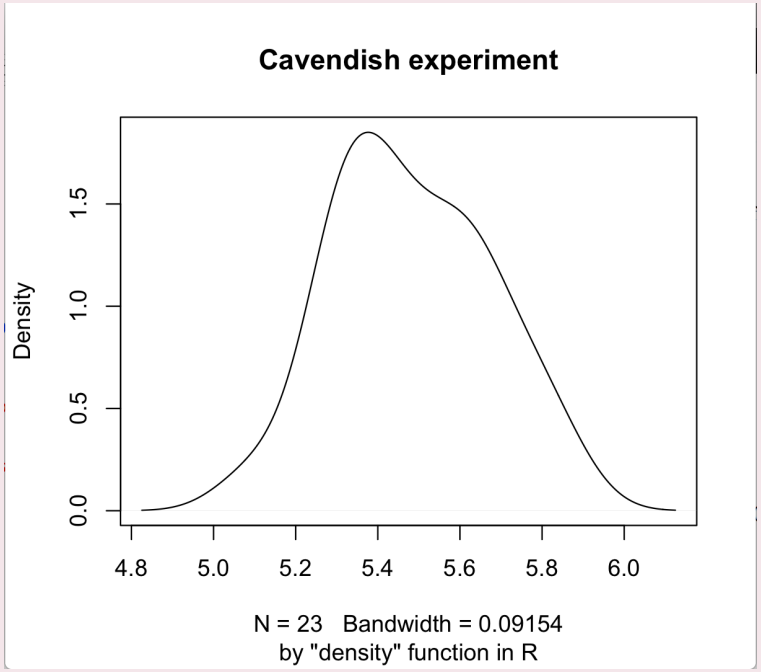
- Standard deviation of the posterior distribution is smaller than that of the prior distribution, that is

$$SD(\mu|\boldsymbol{x}) < SD(\mu)$$

Example 1.4

The 18th century physicist Henry Cavendish made 23 experimental determinations of the earth's density, and these data (in g/cm^3) are shown below.

5.36	5.29	5.58	5.65	5.57	5.53	5.62	5.29
5.44	5.34	5.79	5.10	5.27	5.39	5.42	5.47
5.63	5.34	5.46	5.30	5.78	5.68	5.85	



Example 1.4

- Cavendish asserts that the error standard deviation of these measurements is $0.2\,g/cm^3$
- Assume that they are normally distributed with mean equal to the true earth density μ, that is, $X_i|\mu \sim N(\mu, 0.2^2)$, $i = 1, 2, \ldots, 23$
- Use a normal prior distribution for μ with mean $5.41\,g/cm^3$ and standard deviation $0.4\,g/cm^3$
- Derive the posterior distribution for μ

Solution

...

Summary

- Small increase in mean from prior to posterior
- Large decrease in uncertainty from prior to posterior

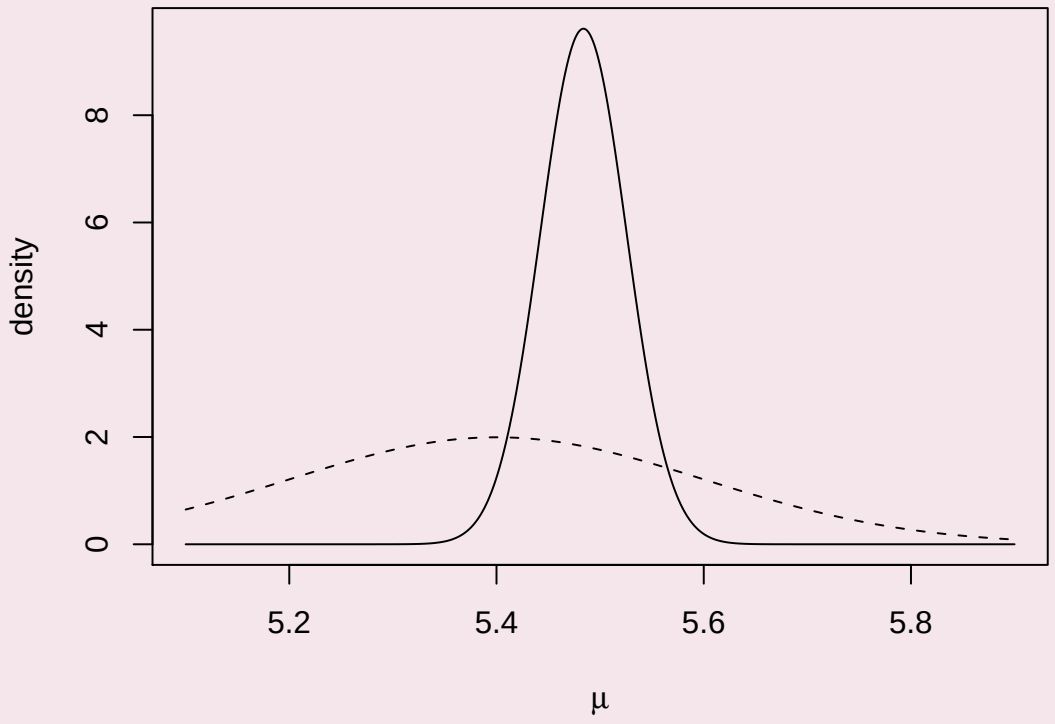


Figure: Prior (dashed) and posterior (solid) densities for the earth's density

Summary

- The actual mean density of the earth is $5.515\,g/cm^3$ (Wikipedia)
- We can determine the (posterior) probability that the mean density is within 0.1 of this value as follows...
- The posterior distribution is $\mu|\boldsymbol{x} \sim N(5.484, 0.0415^2)$ and so

$$Pr(5.415 < \mu < 5.615|\boldsymbol{x}) = 0.9510,$$

calculated using the R command

```
pnorm(5.615,5.484,0.0415)-pnorm(5.415,5.484,0.0415)
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Summary

- Without the data, the only basis for determining the earth's density is via the prior distribution
- Here the prior distribution is $\mu \sim N(5.4, 0.4^2)$ and so the (prior) probability that the mean density is within 0.1 of the (now known) true value is

$$Pr(5.415 < \mu < 5.615) = 0.1896,$$

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1.2 Different levels of prior knowledge

1.2.1 Substantial Prior Knowledge

- We have *substantial prior information* for θ when the prior distribution *dominates* the likelihood function, that is $\pi(\theta|\boldsymbol{x}) \sim \pi(\theta)$

- Difficulties:
  1. Intractability of mathematics in deriving the posterior
  2. Practical formulation of the prior distribution – coherently specifying prior beliefs in the form of a probability distribution is far from straightforward, let alone reconciling differences between experts!

1.2.2 Limited prior information

Pragmatic approach:

- Choose a distribution which makes the Bayes updating from prior to posterior mathematically straightforward
- Use what prior information is available to determine the parameters of this distribution

Previous examples:

1. Poisson random sample, Gamma prior distribution $\longrightarrow$ Gamma posterior distribution
2. Normal random sample (known variance), Normal prior distribution $\longrightarrow$ Normal posterior distribution

In these examples, the prior distribution and the posterior distribution come from the same family

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Definition 1.1 (Conjugate priors)

Suppose that data $\boldsymbol{x}$ are to be observed with distribution $f(\boldsymbol{x}|\theta)$. A family $\mathfrak{F}$ of prior distributions for θ is said to be *conjugate* to $f(\boldsymbol{x}|\theta)$ if for every prior distribution $\pi(\theta) \in \mathfrak{F}$, the posterior distribution $\pi(\theta|\boldsymbol{x})$ is also in $\mathfrak{F}$.

Comment

The conjugate family depends crucially on the model chosen for the data $\boldsymbol{x}$.

For example, the only family conjugate to the model "random sample from a Poisson distribution" is the Gamma family. Here, the likelihood is $f(\boldsymbol{x}|\theta) \propto \theta^{n\bar{x}} e^{-n\theta}$, $\theta > 0$. Therefore we need a family with density $f(\theta|\boldsymbol{a})$ and parameters $\boldsymbol{a}$ such that

$$f(\theta|\boldsymbol{A}) \propto f(\theta|\boldsymbol{a}) \times \theta^{n\bar{x}} e^{-n\theta}, \quad \theta > 0$$

$$\implies \quad f(\theta|\boldsymbol{a}) \propto \theta^{a_1} e^{-a_2\theta}, \quad \theta > 0$$

that is, the Gamma family of distributions

1.2.3 Vague prior knowledge/prior ignorance

- Have very little or no prior information about θ
- Still must choose a prior distribution
- Sensible to choose a prior distribution which is not concentrated about any particular value, that is, one with a very large variance
- Most of the information about θ will be passed through to the posterior distribution via the data, and so we have $\pi(\theta|\boldsymbol{x}) \sim f(\boldsymbol{x}|\theta)$
- Vague prior: Represent vague prior knowledge by using a prior distribution which is conjugate to the model for $\boldsymbol{x}$ and which has as large a variance as possible
- Prior ignorance: Uniform prior? Jeffreys prior?

$$I(\theta) = E_{\boldsymbol{X}|\theta}\left[-\frac{\partial^2}{\partial\theta^2}\log f(\boldsymbol{X}|\theta)\right], \tag{1.8}$$

and then:

$$\pi(\theta) \propto \sqrt{I(\theta)}. \tag{1.9}$$

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Example 1.5

In constructing the prior in Example 1.1, did we assume (i) substantial prior knowledge; (ii) limited prior knowledge; or (iii) prior ignorance?

Solution

...

Example 1.6

Suppose the parameter θ represents a probability. What might be the simplest prior to use here, if we are prior ignorant?

Solution

...

Example 1.7

Suppose we have a random sample from a $N(\mu, 1/\tau)$ distribution (with τ known). Determine the posterior distribution assuming a vague prior for μ.

Solution

...

Example 1.8

Suppose we have a random sample from an Poisson distribution, that is, $X_i|\theta \sim Po(\theta)$, $i = 1, 2, \ldots, n$ (independent). Determine the posterior distribution assuming a vague prior for θ.

Solution

- The conjugate prior distribution is a Gamma distribution
- The $Ga(g, h)$ distribution has mean $m = g/h$ and variance $v = g/h^2$
- Rearranging gives $g = m^2/v$ and $h = m/v$
- Clearly $g \to 0$ and $h \to 0$ as $v \to \infty$ (for fixed m)
- We have seen that, for this model, using a $Ga(g, h)$ prior distribution results in a $Ga(g + n\bar{x}, h + n)$ posterior distribution
- Therefore, taking a vague prior distribution will give a $Ga(n\bar{x}, n)$ posterior distribution

Note that the posterior mean is $\bar{x}$ (the likelihood mode) and that the posterior variance $\bar{x}/n \to 0$ and $n \to \infty$.

Example 1.9

Suppose we have a random sample from an exponential distribution, that is, $X_i|\theta \sim Exp(\theta)$, $i = 1, 2, \ldots, n$ (independent). Determine the Jeffreys prior for this model.

Solution

$\cdots$

What have we done so far?

1. **Posterior $\propto$ Prior $\times$ Likelihood**

   - **Example: Poisson distribution** with gamma prior (food poisoning, and generic/algebraic example)
   - **Example: Normal distribution** (known precision) with Normal prior for the mean (generic/algebraic example, and Cavendish experiment). (Memorise the results from the algebraic example!)
   - **Example: Binomial distribution** with beta prior (homework)
   - **Example: Exponential distribution** with Normal prior (homework)
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What have we done so far?

2. Different levels of prior information

- **Substantial** prior information: $\pi(\theta|\boldsymbol{x}) \sim \pi(\theta)$, but often difficult to construct
- **Limited** prior information: Use conjugate prior with parameters determined by the information provided by the expert
- **Vague** prior: Use conjugate prior with maximised variance
- **Ignorance** prior: Use a Jeffreys prior, or perhaps a $U(0,1)$?
- For vague/ignorance priors, $\pi(\theta|\boldsymbol{x}) \sim f(\boldsymbol{x}|\theta)$
- Lots of **Examples**: Examples 1.5–1.9 in notes

3. Posterior distribution when the sample is very large

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1.3 Asymptotic Posterior Distribution

Background

- There are many asymptotic results in Statistics
- The **Central Limit Theorem** is a statement about the asymptotic distribution of $\bar{X}_n$ as the sample size $n \to \infty$, where the X_i are i.i.d. with known mean μ and known (finite) variance σ^2
- Under different distributions of X_i, $\bar{X}_n$ has the same moments, $E(\bar{X}_n) = \mu$ and $Var(\bar{X}_n) = \sigma^2/n$, but its distribution varies
- The CLT says that as $n \to \infty$, regardless of the distribution of X_i,

$$\frac{\sqrt{n}(\bar{X}_n - \mu)}{\sigma} \xrightarrow{\mathcal{D}} N(0,1)$$

Theorem

Suppose we have a statistical model $f(\boldsymbol{x}|\theta)$ for data $\boldsymbol{x} = (x_1, x_2, \ldots, x_n)^T$, together with a prior distribution $\pi(\theta)$ for θ. Then

$$\sqrt{J(\hat{\theta})}\,(\theta - \hat{\theta})|\boldsymbol{x} \xrightarrow{\mathcal{D}} N(0,1) \qquad \text{as } n \to \infty,$$

where $\hat{\theta}$ is the likelihood mode and $J(\theta)$ is the observed information

$$J(\theta) = -\frac{\partial^2}{\partial\theta^2} \log f(\boldsymbol{x}|\theta)$$

Usage

In large samples,

$$\theta|\boldsymbol{x} \sim N\left(\hat{\theta}, J(\hat{\theta})^{-1}\right), \qquad \text{approximately.}$$

- In large samples (n large), how the prior distribution is specified does not matter.

Example 1.10

Suppose we have a random sample from a $N(\mu, 1/\tau)$ distribution (with τ known). Determine the asymptotic posterior distribution for μ.
Recall that

$$f(\boldsymbol{x}|\mu) = \left(\frac{\tau}{2\pi}\right)^{n/2} \exp\left\{-\frac{\tau}{2}\sum_{i=1}^{n}(x_i-\mu)^2\right\},$$

and therefore

$$\log f(\boldsymbol{x}|\mu) = \frac{n}{2}\log\tau - \frac{n}{2}\log(2\pi) - \frac{\tau}{2}\sum_{i=1}^{n}(x_i-\mu)^2$$

$$\Rightarrow \quad \frac{\partial}{\partial\mu}\log f(\boldsymbol{x}|\mu) = -\frac{\tau}{2}\times\sum_{i=1}^{n}-2(x_i-\mu) = \tau\sum_{i=1}^{n}(x_i-\mu) = n\tau(\bar{x}-\mu)$$

$$\Rightarrow \quad \frac{\partial^2}{\partial\mu^2}\log f(\boldsymbol{x}|\mu) = -n\tau \qquad \Rightarrow \quad J(\mu) = -\frac{\partial^2}{\partial\mu^2}\log f(\boldsymbol{x}|\mu) = n\tau.$$

Solution

...

1.4 Bayesian inference

- The posterior distribution $\pi(\theta|\boldsymbol{x})$ summarises all our information about θ to date
- It can answer the questions: How to estimate the value of θ, and what is the uncertainty of the estimator?

1.4.1 Estimation

Point estimates

Many useful summaries, such as

- the mean: $E(\theta|\boldsymbol{x})$
- the mode: $Mode(\theta|\boldsymbol{x})$
- the median: $Median(\theta|\boldsymbol{x})$

Interval Estimates

- A more useful summary of the posterior distribution is one which also reflects its variation
- A $100(1-\alpha)\%$ *Bayesian confidence interval* for θ is any region C_α that satisfies $Pr(\theta \in C_\alpha | \boldsymbol{x}) = 1 - \alpha$
- If θ is continuous with posterior density $\pi(\theta|\boldsymbol{x})$ then

$$\int_{C_\alpha} \pi(\theta|\boldsymbol{x})\, d\theta = 1 - \alpha$$

- The usual correction is made for discrete θ, that is, we take the largest region C_α such that $Pr(\theta \in C_\alpha | \boldsymbol{x}) \leq 1 - \alpha$
- Bayesian confidence intervals are sometimes called *credible regions* or *plausible regions*
- Clearly these intervals are not unique, since there will be many intervals with the correct probability coverage for a given posterior distribution

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Highest density intervals

- A $100(1-\alpha)\%$ *highest density interval* (HDI) for θ is the region

$$C_\alpha = \{\theta : \ \pi(\theta|\boldsymbol{x}) \geq \gamma\}$$

  where γ is chosen so that $Pr(\theta \in C_\alpha|\boldsymbol{x}) = 1-\alpha$
- It is a $100(1-\alpha)\%$ Bayesian confidence interval but only includes the most likely values of θ
- This region is sometimes called a *most plausible Bayesian confidence interval*
- If the posterior distribution has many modes then it is possible that the HDI will be the union of several disjoint regions

Highest density intervals

- If the posterior distribution is unimodal (has one mode) and symmetric about its mean then the HDI is an equi-tailed interval, that is, takes the form $C_\alpha = (a, b)$, where

$$Pr(\theta < a|\boldsymbol{x}) = Pr(\theta > b|\boldsymbol{x}) = \alpha/2$$

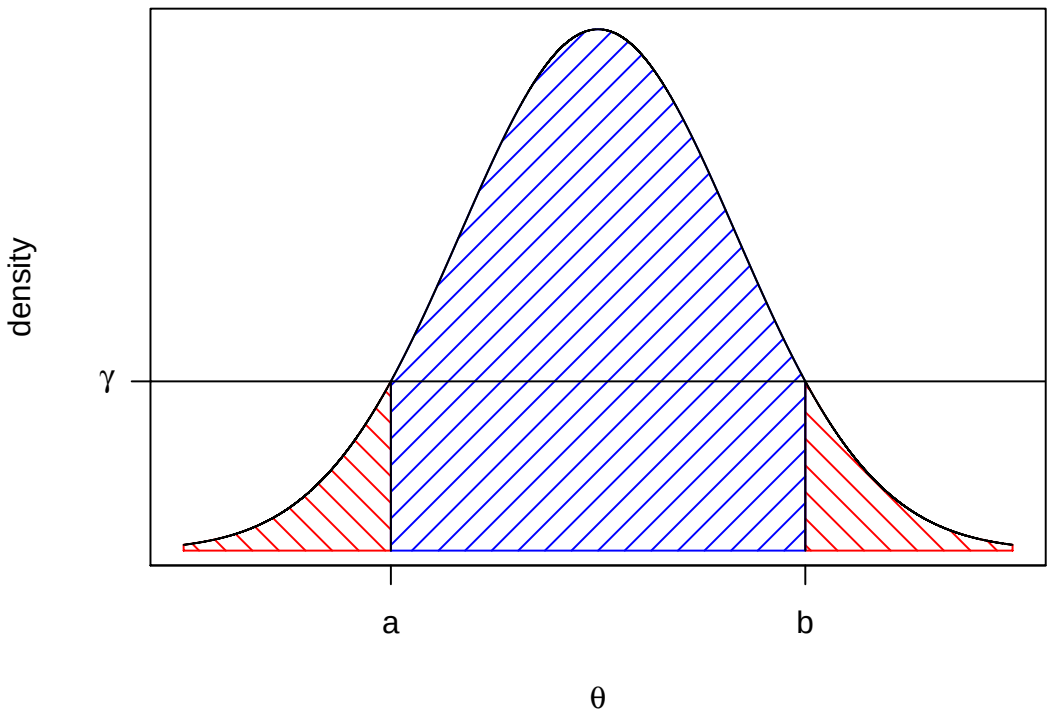

Figure: HDI for θ

Example 1.11

Suppose we have a random sample $\boldsymbol{x} = (x_1, x_2, \ldots, x_n)^T$ from a $N(\mu, 1/\tau)$ distribution (where τ is known). We have seen that, assuming vague prior knowledge, the posterior distribution is $\mu|\boldsymbol{x} \sim N\{\bar{x}, 1/(n\tau)\}$. Determine the $100(1-\alpha)\%$ HDI for μ.

Solution

...

Comment

Note that this interval is numerically identical to the 95% frequentist confidence interval for the (population) mean of a normal random sample with known variance. However, the interpretation is very different.

Interpretation of confidence intervals

C_B is a 95% Bayesian confidence interval for θ

C_F is a 95% frequentist confidence interval for θ

These intervals do not have the same interpretation:

- the probability that C_B contains θ is 0.95
- the probability that C_F contains θ is either 0 or 1
- the interval C_F covers the true value θ on 95% of occasions — in repeated applications of the formula

Example 1.12

Recall Example 1.1 on the number of cases of foodbourne botulism in England and Wales. The data were modelled as a random sample from a Poisson distribution with mean θ. Using a $Ga(2, 1)$ prior distribution, we found the posterior distribution to be $\theta|\boldsymbol{x} \sim Ga(8, 9)$, with density

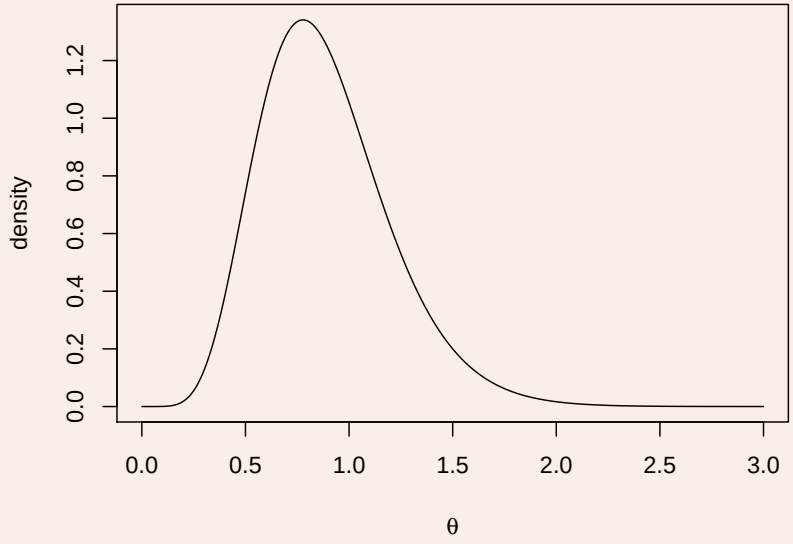

Figure: Posterior density for θ

Determine the 95% HDI for θ.

Solution

. . .

Simple way to calculate the HDI

- Use the `R` function `hdiGamma` in the package `nclbayes`
- It calculates the HDI for any Gamma distribution
- Here we use

```
library(nclbayes)
hdiGamma(p=0.95,a=8,b=9)
```

- The package also has functions
  - `hdiBeta` for the Beta distribution
  - `hdiInvchi` for the Inv-Chi distribution (introduced in Chapter 3)

1.4.2 Prediction

- Much of statistical inference (both Frequentist and Bayesian) is aimed towards making statements about a parameter θ
- Often the inferences are used as a yardstick for similar future experiments
- For example, we may want to predict the outcome when the experiment is performed again

Predicting the future

- There will be uncertainty about the future outcome of an experiment
- Suppose this future outcome Y is described by a probability (density) function $f(y|\theta)$
- If θ were known, say θ_0, then any prediction can do no better than one based on $f(y|\theta = \theta_0)$
- What if θ is unknown?

Frequentist solution

- Get estimate $\hat{\theta}$ and use $f(y|\theta = \hat{\theta})$ but this ignores uncertainty on $\hat{\theta}$
- Better: use $E_{\hat{\theta}}\{f(y|\theta = \hat{\theta})\}$ to average over uncertainty on $\hat{\theta}$

Bayesian solution

- Use the *predictive distribution*, with density

$$f(y|\boldsymbol{x}) = \int_{\Theta} f(y|\theta)\,\pi(\theta|\boldsymbol{x})\,d\theta$$

  when θ is a continuous quantity
- Notice this could be rewritten as

$$f(y|\boldsymbol{x}) = E_{\theta|\boldsymbol{x}}\{f(y|\theta)\}$$

- Uses $f(y|\theta)$ but weights each θ by our posterior beliefs

Prediction interval

- Useful range of plausible values for the outcome of a future experiment
- Similar to a HDI interval
- A $100(1-\alpha)\%$ *prediction interval* for Y is the region

$$C_\alpha = \{y : \ f(y|\boldsymbol{x}) \geq \gamma\}$$

where γ is chosen so that $Pr(Y \in C_\alpha|\boldsymbol{x}) = 1-\alpha$

Example 1.13

Recall Example 1.1 on the number of cases of foodbourne botulism in England and Wales.

The data for 1998–2005 were modelled as a random sample from a Poisson distribution with mean θ.

Using a $Ga(2, 1)$ prior distribution, we found the posterior distribution to be $\theta|\boldsymbol{x} \sim Ga(8, 9)$.

Determine the predictive distribution for the number of cases for the following year (2006).

Solution

...

Comments

- This predictive probability function is related to that of a negative binomial distribution
- If $Z \sim NegBin(r, p)$ then

$$Pr(Z = z) = \binom{z-1}{r-1} p^r (1-p)^{z-r}, \quad z = r, r+1, \ldots$$

and so $W = Z - r$ has probability function

$$Pr(W = w) = Pr(Z = w+r) = \binom{w+r-1}{r-1} p^r (1-p)^w, \quad w = 0, 1, \ldots$$

- This is the same probability function as our predictive probability function, with $r = 8$ and $p = 0.9$
- Therefore $Y|\mathbf{x} \sim NegBin(8, 0.9) - 8$
- Note that, unfortunately, `R` also calls the distribution of W a negative binomial distribution with parameters r and p: `dnbinom(y,r,p)`

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Comparison between predictive and naive predictive distributions

- Can compare the predictive distribution $Y|\boldsymbol{x}$ with a naive predictive $Y|\theta = \hat{\theta} \sim Po(0.75)$ where

$$f(y|\theta = \hat{\theta}) = \frac{0.75^y \, e^{-0.75}}{y!}, \quad y = 0, 1, \ldots \ .$$

- Probability functions:

y `y = 0:5`	correct $f(y\|\boldsymbol{x})$ `dnbinom(y,8,0.9)`	naive $f(y\|\theta = \hat{\theta})$ `dpois(y,0.75)`
0	0.430	0.472
1	0.344	0.354
2	0.155	0.133
3	0.052	0.033
4	0.014	0.006
5	0.003	0.001
≥ 6	0.005	0.002

- The naive predictive distribution is a predictive distribution which uses a degenerate posterior distribution $\pi^*(\theta|\boldsymbol{x})$
- Here $Pr_{\pi^*}(\theta = 0.75|\boldsymbol{x}) = 1$ and standard deviation $SD_{\pi^*}(\theta|\boldsymbol{x}) = 0$
- The correct posterior standard deviation of θ is $SD_{\pi}(\theta|\boldsymbol{x}) = \sqrt{8}/9 = 0.314$
- Using a degenerate posterior distribution results in the naive predictive distribution having too small a standard deviation:

$$SD(Y|x = 1) = \begin{cases} 0.994 & \text{using the correct } \pi(\theta|\boldsymbol{x}) \\ 0.866 & \text{using the naive } \pi^*(\theta|\boldsymbol{x}), \end{cases}$$

  these values being calculated from $NegBin_{\mathrm{R}}(8, 0.9)$ and $Po(0.75)$ distributions
- $\{0, 1, 2\}$ is a 92.9% prediction set/interval
- $\{0, 1, 2\}$ is a 95.9% prediction set/interval using the the more "optimistic" naive predictive distribution

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Predictive distribution (general case)

- Generally requires calculation of a non-trivial integral (or sum)

$$f(y|\boldsymbol{x}) = \int_{\Theta} f(y|\theta)\,\pi(\theta|\boldsymbol{x})\,d\theta$$

- Easier method available when using a conjugate prior distribution
- Suppose θ is a continuous quantity and $\boldsymbol{X}$ and Y are independent given θ
- Using Bayes Theorem, the posterior distribution for θ given $\boldsymbol{x}$ and y is

$$\begin{aligned}
\pi(\theta|\boldsymbol{x}, y) &= \frac{\pi(\theta) f(\boldsymbol{x}, y|\theta)}{f(\boldsymbol{x}, y)} \\
&= \frac{\pi(\theta) f(\boldsymbol{x}|\theta) f(y|\theta)}{f(\boldsymbol{x}) f(y|\boldsymbol{x})} \qquad \text{since } \boldsymbol{X} \text{ and } Y \text{ are indep given } \theta \\
&= \frac{\pi(\theta|\boldsymbol{x})\, f(y|\theta)}{f(y|\boldsymbol{x})}.
\end{aligned}$$

Rearranging, we obtain ...

Predictive distribution (general case)

- Generally requires calculation of a non-trivial integral (or sum)

$$f(y|\boldsymbol{x}) = \int_{\Theta} f(y|\theta)\,\pi(\theta|\boldsymbol{x})\,d\theta$$

- Easier method available when using a conjugate prior distribution
- Suppose θ is a continuous quantity and $\boldsymbol{X}$ and Y are independent given θ
- Using Bayes Theorem, the posterior distribution for θ given $\boldsymbol{x}$ and y is

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&= \frac{\pi(\theta|\boldsymbol{x})\, f(y|\theta)}{f(y|\boldsymbol{x})}.
\end{aligned}$$

Rearranging, we obtain ...

Candidate's formula

- The predictive p(d)f is

$$f(y|\boldsymbol{x}) = \frac{f(y|\theta)\pi(\theta|\boldsymbol{x})}{\pi(\theta|\boldsymbol{x}, y)}$$

- The RHS looks as if it depends on θ but it doesn't: all terms in θ cancel
- For this formula to be useful, we have to be able to work out $\theta|\boldsymbol{x}$ and $\theta|\boldsymbol{x}, y$ fairly easily
- This is the case when using conjugate priors

Example 1.14

Rework Example 1.13 using Candidate's formula to determine the number of cases in 2006.

Solution

...

1.5 Sequential Bayesian Updating

- Last year, and so far this year: Bayes Theorem to update beliefs about θ after observing a single sample $\boldsymbol{x}$
- Real-world: New samples of data coming online continuously!
- First sample $\boldsymbol{x}^{(1)} + \pi(\theta) \longrightarrow \pi(\theta|\boldsymbol{x}^{(1)})$
- New sample $\boldsymbol{x}^{(2)}$?
  - Use $\pi(\theta|\boldsymbol{x}^{(1)})$ as the "new prior"
  - Update once again to obtain the "new posterior" $\pi(\theta|\boldsymbol{x}^{(1)}, \boldsymbol{x}^{(2)})$

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1.5 Sequential Bayesian Updating

In other words, we might replace the usual mantra

$$\text{Posterior} \propto \text{Prior} \times \text{Likelihood}$$

with

$$\text{Revised} \propto \text{Current} \times \text{New likelihood},$$

with the ability to update our likelihood function with each new sample of data. Why does this work?

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Suppose we have data assumed drawn from a probability distribution with parameter θ

1. Before we make any observations at all, our prior beliefs about θ are represented by $\pi(\theta)$. We might refer to this as our "original prior"
2. Now we observe a sample $\boldsymbol{x} = (x_1, x_2, \ldots, x_n)^T$; our posterior is then

$$\pi(\theta|\boldsymbol{x}) \propto \pi(\theta) \times f(\boldsymbol{x}|\theta) = \pi(\theta) \times \prod_{i=1}^{n} f(x_i|\theta),$$

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1.5 Sequential Bayesian Updating

3. Now suppose we make a new observation x_{n+1} assumed from the same probability distribution as $\boldsymbol{x}$
   - Beforehand our *current* beliefs about θ are represented by $\pi(\theta|\boldsymbol{x})$; re-label this $\pi_n(\theta)$, our "new prior"
   - Assume the *new likelihood* has the same form as the likelihood for $\boldsymbol{x}$
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Example 1.15

Table 1.6 provides an update to table 1.1, giving the number of cases of foodbourne botulism in England and Wales between 2006 and 2010.
Use your solution to Example 1.1, and sequential Bayesian updating, to obtain your new posterior distribution for θ.

Year	2006	2007	2008	2009	2010
Cases	1	0	0	1	1

Table: Number of cases of foodbourne botulism in England and Wales, 2006–2010

Solution

. . .

Example 1.16

Devise a generic sequential Bayesian updating plan for successive random samples from a Poisson distribution, assuming a conjugate prior specification.

Solution

...

1.6 Learning objectives

By the end of this chapter, you should be able to:

1. Determine the likelihood function using a random sample from **any** distribution
2. Combine this likelihood function with **any** prior distribution to obtain the posterior distribution
3. Name the posterior distribution if it is a "standard" distribution listed in these notes or on the exam paper – this list may well include distributions that are standard within the subject but which you have not met before. If the posterior is not a "standard" distribution then it is okay just to give its density (or probability function) up to a constant.
4. Do all the above for a particular data set or for a general case with random sample $x_1, \ldots, x_n$

5. Describe the different levels of prior information; determine and use conjugate priors and vague priors
6. Determine the asymptotic posterior distribution
7. Determine the predictive distribution, particularly when having a random sample from any distribution and a conjugate prior via Candidate's formula
8. Describe and calculate the confidence intervals, HDIs and prediction intervals
9. Operate sequential Bayesian updating schemes

Chapter 2

Inference for a Normal population

2.1 Bayes Theorem for many parameters

Data: $\boldsymbol{x} = (x_1, x_2, \ldots, x_n)^T$

Model: depends on many parameters $\boldsymbol{\theta} = (\theta_1, \theta_2, \ldots, \theta_p)^T$
pdf/pf $f(\boldsymbol{x}|\boldsymbol{\theta}) \rightarrow$ Likelihood function $f(\boldsymbol{x}|\boldsymbol{\theta})$

Prior beliefs: pdf/pf $\pi(\boldsymbol{\theta})$

Combine using Bayes Theorem

Posterior beliefs: pdf/pf $\pi(\boldsymbol{\theta}|\boldsymbol{x})$

Posterior distribution summarises all our current knowledge about the parameter $\boldsymbol{\theta}$

Bayes Theorem

The posterior probability (density) function for $\boldsymbol{\theta}$ is

$$\pi(\boldsymbol{\theta}|\boldsymbol{x}) = \frac{\pi(\boldsymbol{\theta})\, f(\boldsymbol{x}|\boldsymbol{\theta})}{f(\boldsymbol{x})}$$

where

$$f(\boldsymbol{x}) = \begin{cases} \int_{\Theta} \pi(\boldsymbol{\theta})\, f(\boldsymbol{x}|\boldsymbol{\theta})\, d\boldsymbol{\theta} & \text{if } \boldsymbol{\theta} \text{ is continuous,} \\ \\ \sum_{\Theta} \pi(\boldsymbol{\theta})\, f(\boldsymbol{x}|\boldsymbol{\theta}) & \text{if } \boldsymbol{\theta} \text{ is discrete.} \end{cases}$$

As before, this can be rewritten as

$$\pi(\boldsymbol{\theta}|\boldsymbol{x}) \propto \pi(\boldsymbol{\theta}) \times f(\boldsymbol{x}|\boldsymbol{\theta})$$

$$i.e. \quad \text{posterior} \propto \text{prior} \times \text{likelihood}$$

Generalised t distribution: $X \sim t_a(b, c)$

- Density for $x \in \mathbb{R}$

$$f(x|a, b, c) = \frac{\Gamma\left(\frac{a+1}{2}\right)}{\sqrt{ac\pi}\,\Gamma\left(\frac{a}{2}\right)} \left\{1 + \frac{(x-b)^2}{ac}\right\}^{-\frac{a+1}{2}}$$

- Parameters: $a > 0$, $b \in \mathbb{R}$, $c > 0$
- $E(X) = Mode(X) = b$ and $Var(X) = \dfrac{ac}{a-2}$, if $a \geq 2$
- Generalisation of the standard t-distribution since $(X - b)/\sqrt{c} \sim t_a$
- $t_a(0, 1) \equiv t_a$
- $\lim_{a\to\infty} t_a(b, c) = N(b, c)$

Example 2.1

- If $X \sim t_a(b, c)$ then show that $Y = (X - b)/\sqrt{c} \sim t_a$, with density

$$f(y) = \frac{\Gamma\left(\frac{a+1}{2}\right)}{\sqrt{a\pi}\,\Gamma\left(\frac{a}{2}\right)} \left\{1 + \frac{y^2}{a}\right\}^{-\frac{a+1}{2}}, \qquad -\infty < y < \infty,$$

Recall the general result: if X is a random variable with probability density function $f_X(x)$ and g is a bijective (1–1) function then the random variable $Y = g(X)$ has probability density function

$$f_Y(y) = f_X\left\{g^{-1}(y)\right\} \left| \frac{d}{dy} g^{-1}(y) \right|. \tag{2.1}$$

Solution

...

Comments

- `R` functions `pgt` and `dgt` in the package `nclbayes` give values for $F_X(x)$ and $f_X(x)$ when $X \sim t_a(b, c)$
- Relationship between the generalised t distribution and the standard t distribution is similar to that of the normal distribution and the standard normal distribution:

$$X \sim N(b, c) \quad \Longrightarrow \quad \frac{X - b}{\sqrt{c}} \sim N(0, 1)$$

$$X \sim t_a(b, c) \quad \Longrightarrow \quad \frac{X - b}{\sqrt{c}} \sim t_a$$

Inverse Chi distribution: $Y \sim Inv\text{-}Chi(a, b)$

- Density

$$f(y|a, b) = \frac{2b^a y^{-2a-1} e^{-b/y^2}}{\Gamma(a)}, \quad y > 0$$

- Parameters: $a > 0$, $b > 0$
- $E(Y) = \dfrac{\sqrt{b}\,\Gamma(a - 1/2)}{\Gamma(a)}$
- $Var(Y) = \dfrac{b}{a-1} - E(Y)^2$, if $a \geq 1$
- The name of the distribution comes from the fact that $1/Y^2 \sim Ga(a, b) \equiv \chi^2_{2a}/(2b)$

2.2 Prior to posterior analysis

- Data: $X_i|\mu,\tau \sim N(\mu, 1/\tau)$, $i = 1, 2, \ldots, n$ (indep)
- Prior: $\mu|\tau \sim N\left(b, \frac{1}{c\tau}\right)$, $\tau \sim Ga(g, h)$, with joint density, for $\mu \in \mathbb{R}$, $\tau > 0$

$$\begin{aligned}
\pi(\mu,\tau) &= \pi(\mu|\tau)\pi(\tau) \\
&= \left(\frac{c\tau}{2\pi}\right)^{1/2} \exp\left\{-\frac{c\tau}{2}(\mu-b)^2\right\} \times \frac{h^g \tau^{g-1} e^{-h\tau}}{\Gamma(g)} \\
&\propto \tau^{g-\frac{1}{2}} \exp\left\{-\frac{\tau}{2}\left[c(\mu-b)^2 + 2h\right]\right\} \qquad (2.2)
\end{aligned}$$

- We write $\begin{pmatrix}\mu \\ \tau\end{pmatrix} \sim NGa(b, c, g, h)$
- Determine the posterior distribution for $\begin{pmatrix}\mu \\ \tau\end{pmatrix}$

  Hint:

$$c(\mu-b)^2 + n(\bar{x}-\mu)^2 = (c+n)\left\{\mu - \left(\frac{cb+n\bar{x}}{c+n}\right)\right\}^2 + \frac{nc(\bar{x}-b)^2}{c+n}$$

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Solution

$$\cdots \tag{2.3}$$

2.2.1 Marginal distributions

- If $\begin{pmatrix} \mu \\ \tau \end{pmatrix} \sim NGa(b, c, g, h)$ then $\tau \sim Ga(g, h)$
- The (marginal) density for μ is, for $\mu \in \mathbb{R}$

$$
\begin{aligned}
\pi(\mu) &= \int_0^\infty \pi(\mu, \tau)\, d\tau \\
&\propto \int_0^\infty \tau^{g-\frac{1}{2}} \exp\left\{-\frac{\tau}{2}\left[c(\mu-b)^2 + 2h\right]\right\} d\tau \\
&\propto \int_0^\infty \tau^{g+\frac{1}{2}-1} \exp\left\{-\frac{\tau}{2}\left[c(\mu-b)^2 + 2h\right]\right\} d\tau \\
&\propto \frac{\Gamma\left(g+\frac{1}{2}\right)}{[\{c(\mu-b)^2+2h\}/2\}]^{g+\frac{1}{2}} \quad \text{using } \int_0^\infty \theta^{a-1} e^{-b\theta}\, d\theta = \frac{\Gamma(a)}{b^a} \\
&\propto h^{-g-1/2}\left\{1 + \frac{c(\mu-b)^2}{2h}\right\}^{-g-1/2} \\
&\propto \left\{1 + \frac{c(\mu-b)^2}{2h}\right\}^{-\frac{2g+1}{2}} \\
&\text{i.e.} \quad \mu \sim t_{2g}\left(b, \frac{h}{gc}\right)
\end{aligned}
\tag{2.4}
$$

Summary of marginal distributions

- The data: $X_i|\mu,\tau \sim N(\mu, 1/\tau)$
- Priors: $\mu|\tau \sim N(b, 1/c\tau)$, $\tau \sim Ga(g,h)$
- The joint prior $\begin{pmatrix}\mu\\ \tau\end{pmatrix} \sim NGa(b,c,g,h)$ has marginal distributions
  - $\mu \sim t_{2g}\left(b, \frac{h}{gc}\right)$ (Exactly the same proof as for $\mu|\boldsymbol{x}$)
  - $\tau \sim Ga(g,h)$

  Also $\sigma = 1/\sqrt{\tau} \sim Inv\text{-}Chi(g,h)$ (One for you in assignment 3!)
- The posterior $\left.\begin{pmatrix}\mu\\ \tau\end{pmatrix}\right| \boldsymbol{x} \sim NGa(B,C,G,H)$ has marginal distributions
  - $\mu|\boldsymbol{x} \sim t_{2G}\left(B, \frac{H}{GC}\right)$ (Proven in yesterday's lecture)
  - $\tau|\boldsymbol{x} \sim Ga(G,H)$

  Also $\sigma|\boldsymbol{x} \sim Inv\text{-}Chi(G,H)$ (One for you in assignment 3!)

Example 2.2

- The 18th century physicist Henry Cavendish made 23 experimental determinations of the earth's density, and these data (in g/cm^3) are

5.36	5.29	5.58	5.65	5.57	5.53	5.62	5.29
5.44	5.34	5.79	5.10	5.27	5.39	5.42	5.47
5.63	5.34	5.46	5.30	5.78	5.68	5.85	

  with sufficient statistics $n = 23$, $\bar{x} = 5.4848$, $s = 0.1882$
- We consider $X|\mu, \tau \sim N(\mu, 1/\tau)$, with τ unknown
- In Example 1.4 we assumed $X_i|\mu \sim N(\mu, 0.2^2)$ with $\mu \sim N(5.41, 0.4^2)$ and τ known with $\tau = 1/0.2^2 = 25$.
- Must specify the parameters in the $NGa(b, c, g, h)$ prior distribution for $(\mu, \tau)^T$. Suppose we choose $Var(\tau) = 250$.
- Choice of b and c: the NGa prior distribution has $\mu|\tau \sim N\{b, 1/(c\tau)\}$. Matching the prior for $\mu|\tau = 25$ gives $b = 5.41$ and $c = 0.25$

  Choice of g and h: the NGa prior distribution has $\tau \sim Ga(g, h)$. Choose $E(\tau) = 25$, giving $g = 2.5$ and $h = 0.1$

- Summary: take prior

$$\begin{pmatrix} \mu \\ \tau \end{pmatrix} \sim NGa(b = 5.41, c = 0.25, g = 2.5, h = 0.1)$$

- Is the marginal prior distribution for μ close to what we used in Example 1.4? Yes, see plot below

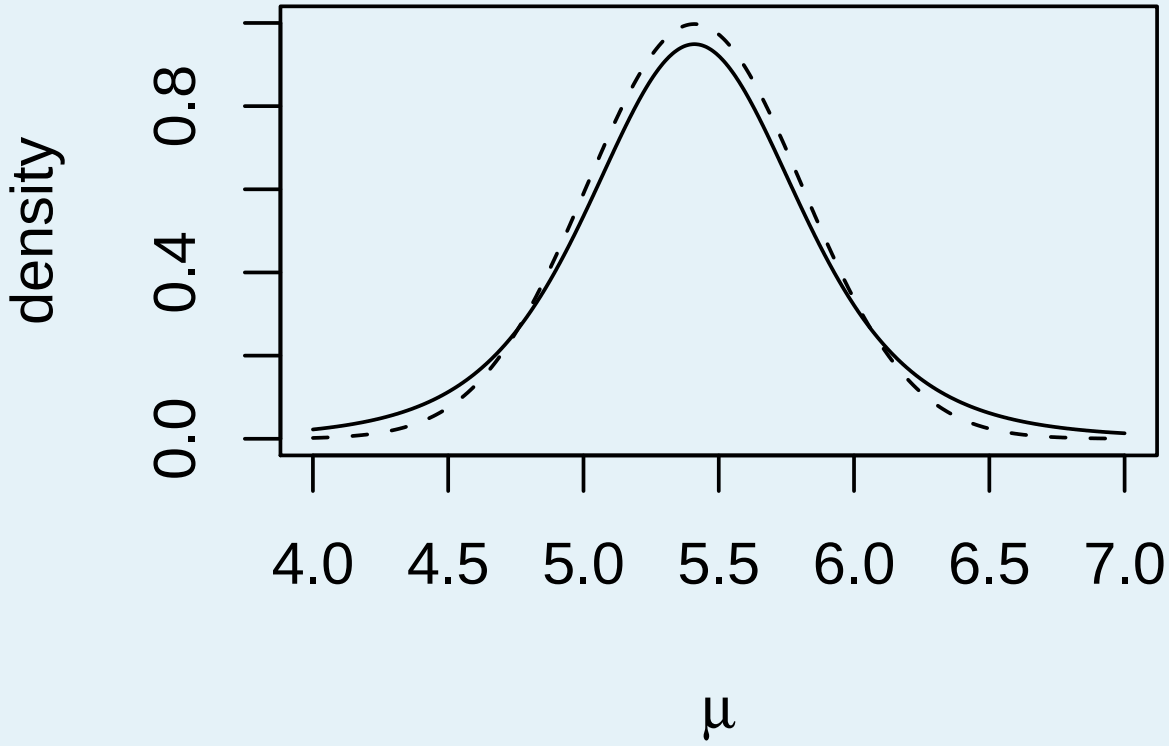


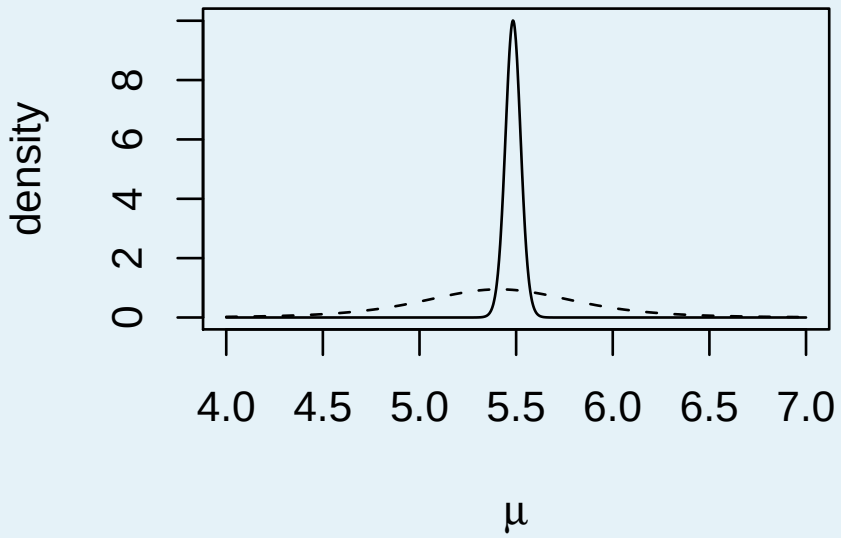
Figure: Marginal prior density for μ: new version (solid) and previous version (dashed)

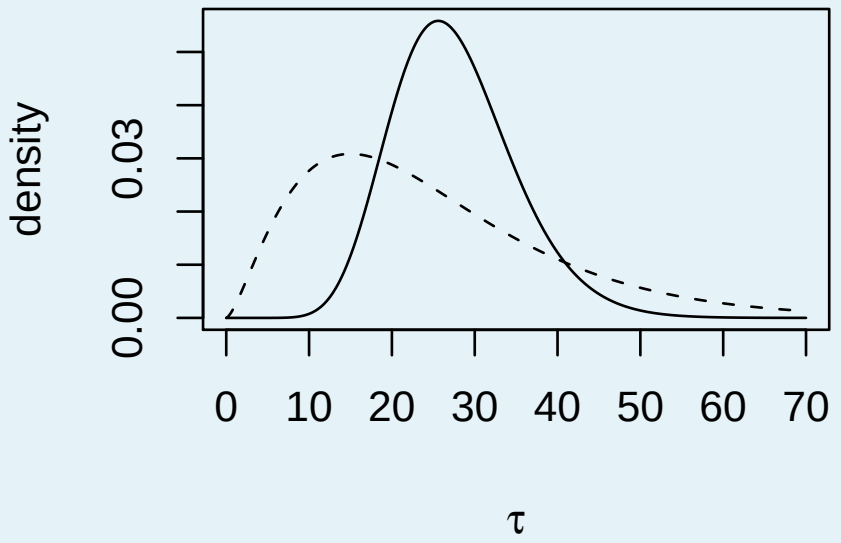
- Determine the posterior distribution for $(\mu, \tau)^T$. Also determine the marginal prior distribution for τ and for σ, and the marginal posterior distribution for each of μ, τ and σ.

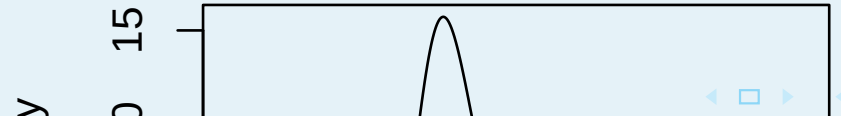
Solution

...

Comparison of prior and posterior marginal distributions







Review of contour plots for bivariate distribution

- Bivariate normal: $\begin{pmatrix} X \\ Y \end{pmatrix} \sim N\left\{\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_x^2 & \rho\sigma_x\sigma_y \\ \rho\sigma_x\sigma_y & \sigma_y^2 \end{pmatrix}\right\}$, with density $\frac{1}{2\pi\sigma_x\sigma_y\sqrt{1-\rho^2}} \exp\left\{-\frac{1}{2(1-\rho^2)}\left(\frac{x^2}{\sigma_x^2} + \frac{y^2}{\sigma_y^2} - 2\rho\frac{xy}{\sigma_x\sigma_y}\right)\right\}$.

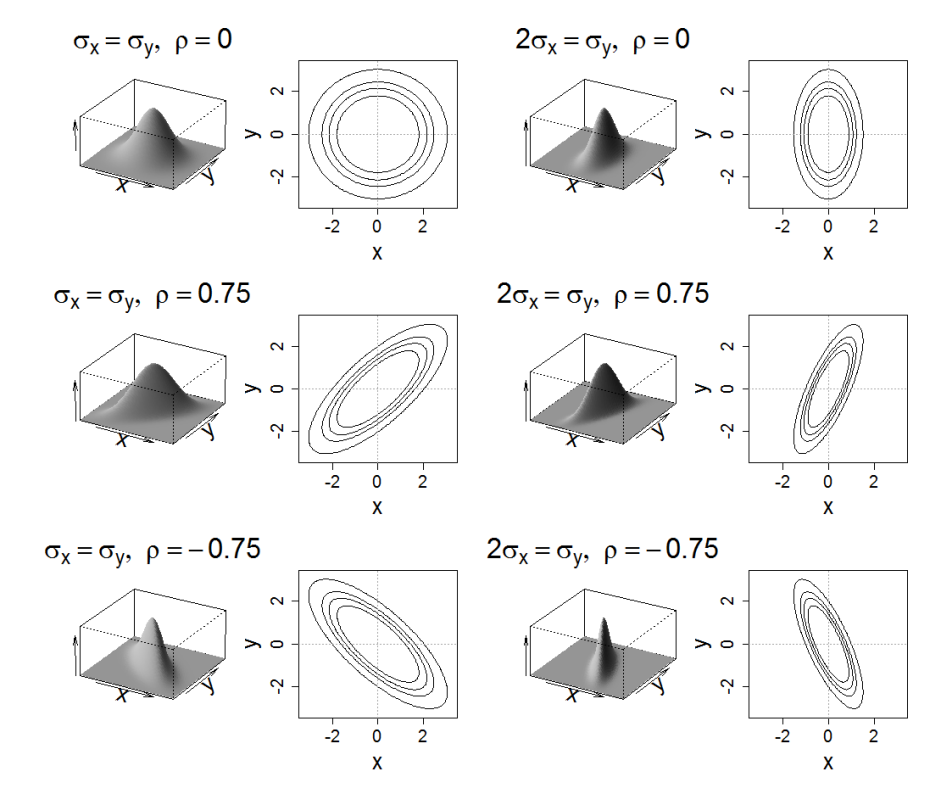


Figure: Contour plots for different bivariate normal densities

Comparison of prior and posterior distributions

- Can plot their contours using R command NGacontour:

```
mu=seq(4.5,6.5,len=1000); tau=seq(0,71,len=1000)
NGacontour(mu,tau,b,c,g,h,lty=3); NGacontour(mu,tau,B,C,G,H,add=TRUE)
```

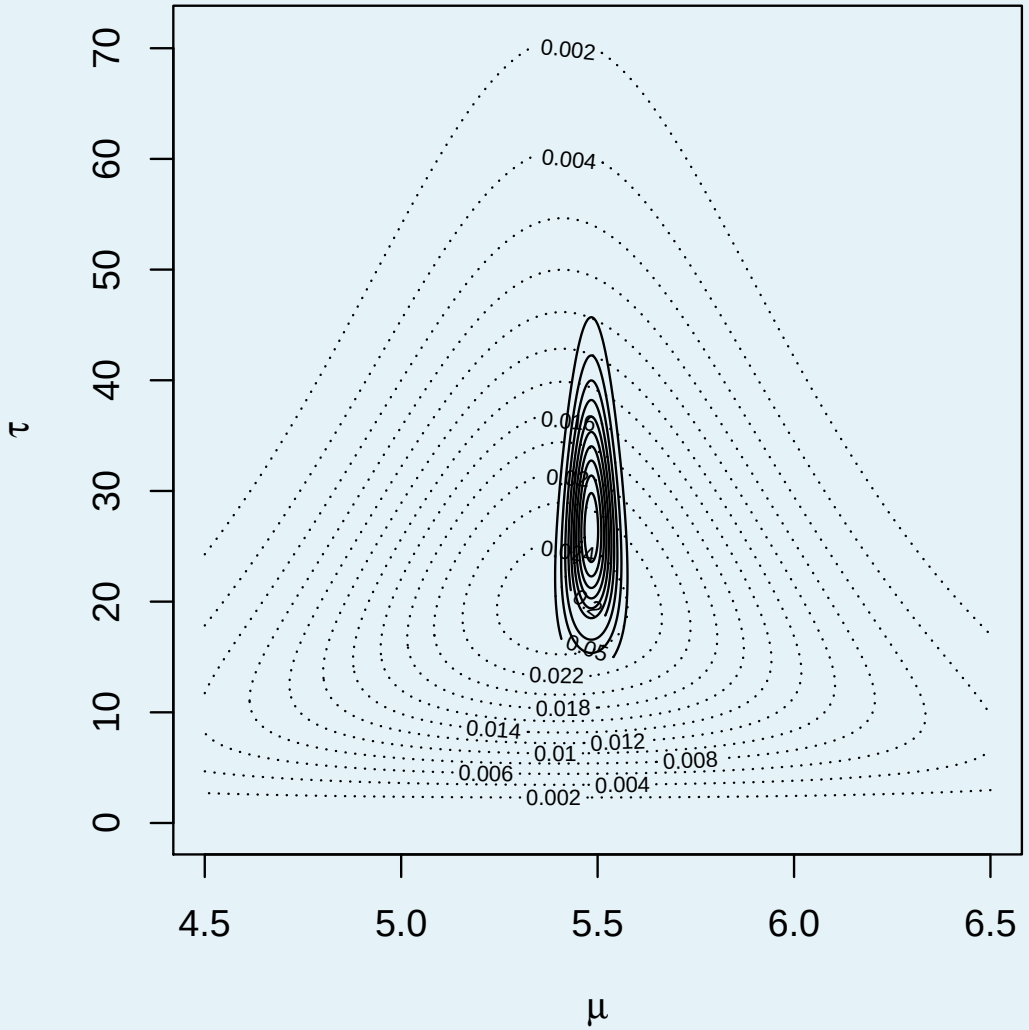


Figure: Contour plot of the prior (dashed) and posterior (solid) densities for $(\mu, \tau)^T$.

Comments

- Wikipedia tells us that the actual mean density of the earth is $5.515\, g/cm^3$
- What is the (posterior) probability that the mean density is within 0.1 of this value?

$$\mu|\boldsymbol{x} \sim t_{28}(5.484, 0.001561) \quad \Rightarrow \quad Pr(5.415 < \mu < 5.615|\boldsymbol{x}) = 0.9529$$

using
`pgt(5.615,28,5.484,0.001561)-pgt(5.415,28,5.484,0.001561)`

- Without the data, the only basis for determining the earth's density is via the prior distribution

$$\mu \sim t_5(5.41, 0.16) \quad \Rightarrow \quad Pr(5.415 < \mu < 5.615) = 0.1802$$

using `pgt(5.615,5,5.41,0.16)-pgt(5.415,5,5.41,0.16)`

- These probability calculations demonstrate that the data have been very informative and changed our beliefs about the earth's density

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- These probability calculations demonstrate that the data have been very informative and changed our beliefs about the earth's density

Example 2.3

Determine the $100(1-\alpha)\%$ highest density interval (HDI) for the population mean μ in terms of quantiles of the standard t-distribution

Solution

...

Calculating 95% posterior confidence intervals using R

- $\mu|\boldsymbol{x} \sim t_{2G}\{B, H/(GC)\}$
  Symmetric distribution $\rightarrow$ HDI and equi-tailed intervals are the same
  `c(qgt(0.025,2*G,B,H/(G*C)),qgt(0.975,2*G,B,H/(G*C)))`

- $\tau|\boldsymbol{x} \sim Ga(G, H)$
  Skewed distribution $\rightarrow$ HDI and equi-tailed intervals are different
  `hdiGamma(0.95,G,H)`
  `c(qgamma(0.025,G,H),qgamma(0.975,G,H))`

- $\sigma|\boldsymbol{x} \sim \textit{Inv-Chi}(G, H)$
  Skewed distribution $\rightarrow$ HDI and equi-tailed intervals are different
  `hdiInvchi(0.95,G,H)`
  `c(qinvchi(0.025,G,H),qinvchi(0.975,G,H))`

Results from this data analysis . . .

	Prior	Posterior	
μ:	$(4.3818, 6.4382)$	$(5.4031, 5.5649)$	
τ:	$(1.4812, 55.9573)$	$(14.0193, 42.2530)$	$\leftarrow$ HDI
	$(4.1561, 64.1625)$	$(15.0674, 43.7625)$	
σ:	$(0.1062, 0.4246)$	$(0.1466, 0.2505)$	$\leftarrow$ HDI
	$(0.1248, 0.4905)$	$(0.1512, 0.2576)$	

- Posterior HDI and equi-tailed intervals for τ are fairly similar but prior intervals are not
- Ditto for σ
- Why?

  The prior distributions are quite skewed but the posterior distributions are fairly symmetric

Results from this data analysis . . .

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- Ditto for σ
- Why?

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Confidence regions

- We have looked at (marginal) HDIs
- Can be useful to also look at (joint) confidence regions

Example 2.4

Determine a joint α confidence region for $(\mu, \tau)^T$ by calculating k satisfying $P(\pi(\mu, \tau) > k) = \alpha$ or $P(\pi(\mu, \tau) > k \mid \boldsymbol{x}) = \alpha$.

Solution

...

- Can plot these regions using `NGacontour` by using the appropriate value for the contour level

```
mu=seq(3.5,7.5,len=1000)
tau=seq(0,80,len=1000)
NGacontour(mu,tau,b,c,g,h,p=c(0.95,0.9,0.8),lty=3)
NGacontour(mu,tau,B,C,G,H,p=c(0.95,0.9,0.8),add=TRUE)
```

Confidence regions for $(\mu, \tau)^T$

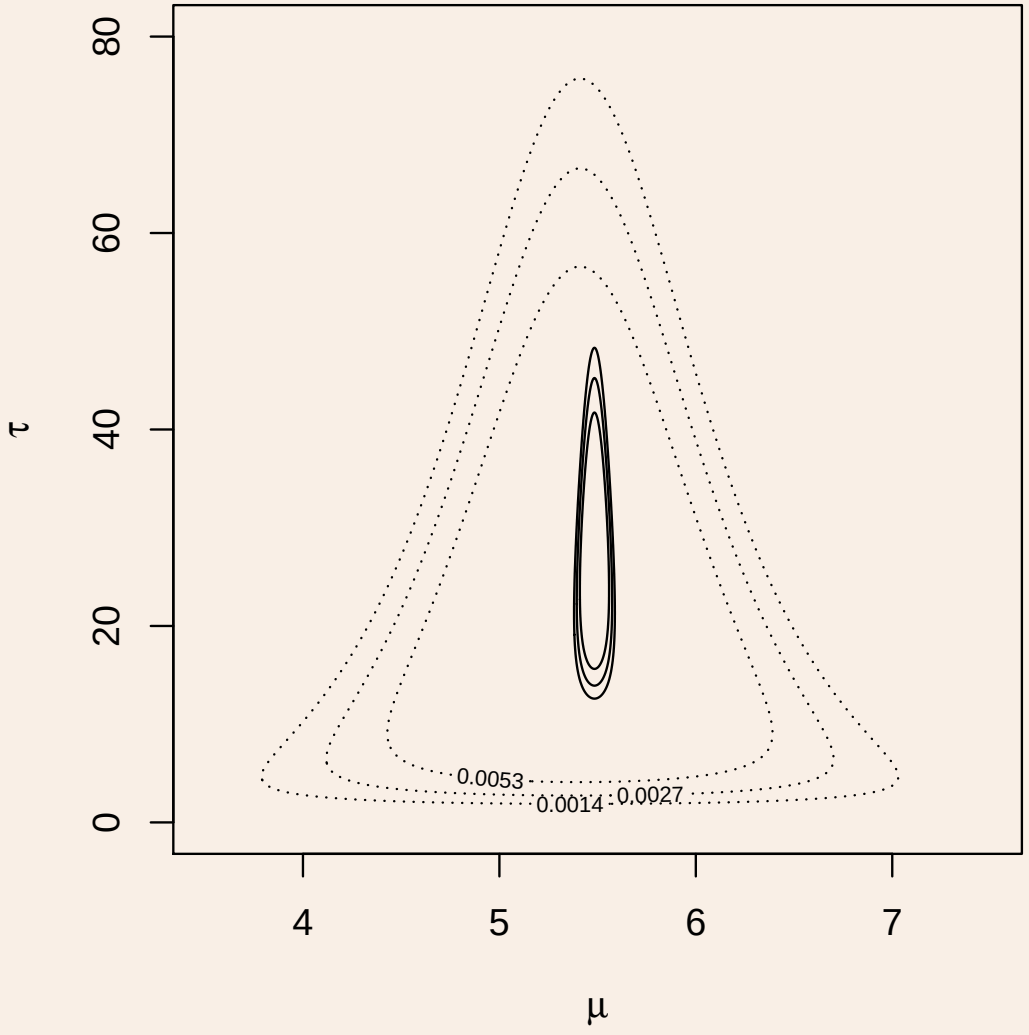
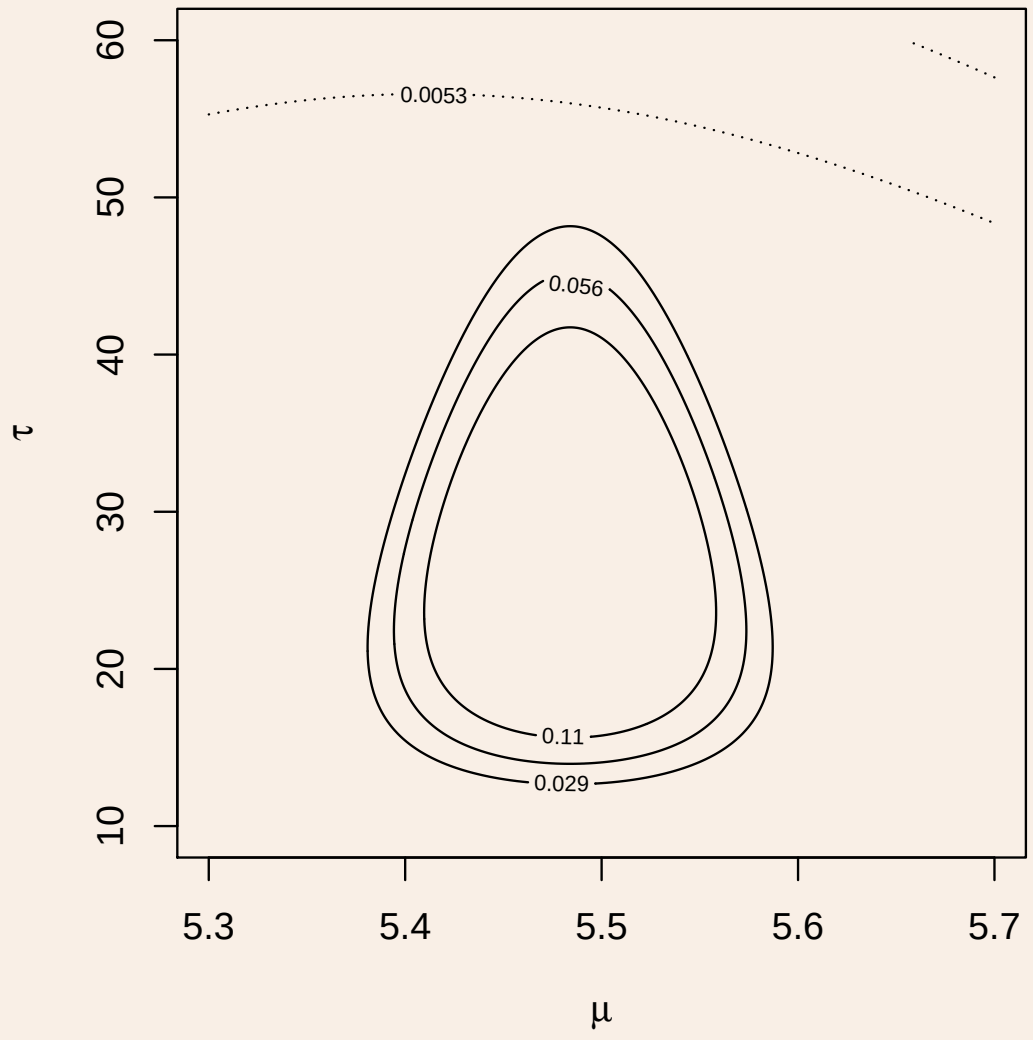


Figure: 95%, 90% and 80% prior (dashed) and posterior (solid) confidence regions for $(\mu, \tau)^T$; 95% (outer), 80% (inner).

Focusing on central part of plot . . .



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2.4 Predictive distributions

- In this model we can determine the predictive distribution via

$$f(y|\boldsymbol{x}) = \int f(y|\mu,\tau)\,\pi(\mu,\tau|\boldsymbol{x})\,d\mu\,d\tau$$

  or by using Candidate's formula (as this is a conjugate analysis)
- But, for this model, there is a more straightforward way

. . .

- These predictive intervals can be calculated easily using the R function qgt
- In Example 2.2, the prior and posterior predictive HDIs for a new value Y from the population are $(4.2604, 6.5596)$ and $(5.0855, 5.8825)$ respectively, calculated using

```
c(qgt(0.025,2*g,b,h*(c+1)/(g*c)),qgt(0.975,2*g,b,h*(c+1)/(g*c)))
c(qgt(0.025,2*G,B,H*(C+1)/(G*C)),qgt(0.975,2*G,B,H*(C+1)/(G*C)))
```

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c(qgt(0.025,2*G,B,H*(C+1)/(G*C)),qgt(0.975,2*G,B,H*(C+1)/(G*C)))
```

2.5 Summary

Suppose we have a normal random sample with $X_i|\mu,\tau \sim N(\mu, 1/\tau)$, $i = 1, 2, \ldots, n$ (independent)

(i) $(\mu,\tau)^T \sim NGa(b, c, g, h)$ is a conjugate prior distribution

(ii) The posterior distribution is $(\mu,\tau)^T|\boldsymbol{x} \sim NGa(B, C, G, H)$ where the posterior parameters are given in the proof in Section 2.2.

(iii) The marginal prior distributions are $\mu \sim t_{2g}\{b, h/(gc)\}$, $\tau \sim Ga(g, h)$, $\sigma = 1/\sqrt{\tau} \sim \textit{Inv-Chi}(g, h)$

(iv) The marginal posterior distributions are $\mu|\boldsymbol{x} \sim t_{2G}\{B, H/(GC)\}$, $\tau|\boldsymbol{x} \sim Ga(G, H)$, $\sigma|\boldsymbol{x} \sim \textit{Inv-Chi}(G, H)$

(v) Prior and posterior means and standard deviations for μ, τ and σ can be calculated from the properties of the t, *Gamma* and *Inv-Chi* distributions

(vi) Prior and posterior probabilities and densities for μ, τ and σ can be calculated using the `R` functions `pgt, dgt, pgamma, dgamma, pinvchi, dinvchi`

Suppose we have a normal random sample with $X_i|\mu,\tau \sim N(\mu, 1/\tau)$, $i = 1, 2, \ldots, n$ (independent)

(vii) HDIs or equi-tailed CIs for μ, τ and σ can be calculated using `qgt`, `hdiGamma`, `hdiInvchi`, `qgamma`, `qinvchi`

(viii) Contour plots of the prior and posterior densities for $(\mu, \tau)^T$ can be plotted using the `NGacontour` function

(ix) Prior and posterior confidence regions for $(\mu, \tau)^T$ can be plotted using the `NGacontour` function

(x) The predictive distribution for a new observation Y from the population is $Y|\boldsymbol{x} \sim t_{2G}\{B, H(C+1)/(GC)\}$ and its HDI can be calculated using the `qgt` function

2.6 Why do we have so many different distributions?

- So far we have used many distributions, some you will have met before and some will be new
- After a while the variety and sheer number of different distributions can become overwhelming
- Why do we need so many distributions and why do we name so many of them?

Justification

- Statistics studies the random variation in experiments, samples and processes
- The variety of applications leads to their randomness being described by many different distributions
- In many applications, bespoke distributions need to be formulated
- However, some distributions come up time and time again for modelling random variation in data and for describing prior beliefs

Justification (continued)

- It is helpful for us to be able to refer to these distributions – and so we give each one a name – and be able to quote known results for these distributions such as their mean and variance
- For example, in this chapter you have been introduced to
  - a generalisation of the t-distribution
  - the inverse chi distribution
  - The Normal-Gamma distribution
- We have been able to use results for their mean and variance to study prior and posterior distributions and have been able to plot these distributions using functions in the `R` package
- You will meet several other new distributions in the remainder of the module

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Justification (continued)

- Obviously it's useful to have a working knowledge of each of these distributions but not vital to remember all their properties
- The exam paper will contain a list of all the distributions used in the exam, together with their density (or probability function) and any useful proprieties such as their mean and variance (as needed for the exam)

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- The exam paper will contain a list of all the distributions used in the exam, together with their density (or probability function) and any useful proprieties such as their mean and variance (as needed for the exam)

2.7 Learning objectives

By the end of this chapter, you should be able to:

1. Determine the posterior distribution for $(\mu, \tau)^T$
2. Determine and use the univariate prior and posterior distributions
3. Determine confidence intervals, HDIs and confidence regions
4. Determine the predictive distribution of another value from the population, and its predictive interval
5. Determine the predictive distribution of the mean of another random sample from the population

both in general and for a particular prior and data set.

Also you should be able to:

6. Appreciate the benefit of naming distributions and for having lists of properties for these distributions