Lecture 3: Multiparameter Models

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1/22/24

Announcements

- Today: Chapter 3
- Next: Chapter 4 (can skim) and Chapter 5

Bayesian inference in the normal model

- Assume $y_1, \ldots y_n \sim N(\mu, \sigma^2)$ with σ^2 a known constant
- Let's start with a Jeffreys' (improper prior): $p(\mu) \propto \text{const}$
- What is the posterior distribution $p(\mu \mid y_1, \ldots y_n, \sigma^2)$?

Bayesian inference in the normal model

- Assume $y_1, \ldots y_n \sim N(\mu, \sigma^2)$ with σ^2 a known constant
- The normal prior distribution is conjugate for μ in the normal sampling model
- Sampling distribution, prior distribution and posterior distribution are all normal.
- Assume the prior is $p(\mu) \sim N(\mu_0, \sigma^2/\kappa_0)$
- What are the parameters of the posterior $p(\mu \mid y_1, \ldots y_n, \sigma^2)$?

A conjugate prior for the normal likelihood

- The normal distribution is conjugate for the normal likelihood
  - Often called the “normal-normal model”
- $Y_i \sim N(\mu, \sigma^2)$ and $\mu \sim N(\mu_0, \sigma^2/\kappa_0)$ implies that the posterior distribution $p(\mu \mid y)$ is also normally distributed:

$$\mu \mid Y \sim N(\mu_n, \tau_n^2)$$

where $\mu_n = \frac{\frac{\kappa_0}{\sigma^2}\mu_0 + \frac{n}{\sigma^2}\bar{y}}{\frac{\kappa_0}{\sigma^2} + \frac{n}{\sigma^2}}$ and $\tau_n^2 = \frac{1}{\frac{\kappa_0}{\sigma^2} + \frac{n}{\sigma^2}}$

The posterior mean and pseudo-counts

$$\begin{aligned}\mu_n &= \frac{\frac{1}{\tau^2}}{\frac{1}{\tau^2}+\frac{n}{\sigma^2}}\mu_0 + \frac{\frac{n}{\sigma^2}}{\frac{1}{\tau^2}+\frac{n}{\sigma^2}}\overline{y} \\ &= (1-w)\mu_0 + w\bar{y}\end{aligned}$$

where $w = \frac{\frac{n}{\sigma^2}}{\frac{1}{\tau^2}+\frac{n}{\sigma^2}}$

Known mean, unknown variance

- Assume we have n mean-zero normal observations with variance σ^2
- Define $d_i = (y_i - \mu)$ for notational convenience
- What is $p(\sigma^2 \mid \mu, d_1, \ldots d_n)$?

$$L\left(\sigma^2\right) \propto \left(\sigma^2\right)^{-n/2} \exp\left\{-\sum_{i=1}^{n} d_i^2 / \left(2\sigma^2\right)\right\},\ \sigma^2 > 0$$

Known mean, unknown variance

- Assume we have n mean-zero normal observations with variance σ^2
- Jeffreys prior $p(\sigma^2) \propto \frac{1}{\sigma^2}$ (careful!)
- The posterior:
  $p(\sigma^2 \mid y) \propto \left(\sigma^2\right)^{-n/2-2} \exp\left\{-\sum_{i=1}^{n} d_i^2 / \left(2\sigma^2\right)\right\}$
- This distribution called an *inverse-Gamma* distribution.
  - If $X \sim \text{Gamma}(a, b)$ then $\frac{1}{X} \sim \text{Inv-Gamma}(a, b)$.

A conjugate prior distribution

- In general, the conjugate prior distribution has the form:

$$p(\sigma^2) \propto (\sigma^2)^{-k_1} e^{\frac{k_2}{\sigma^2}}$$

- Inverse-gamma: $p(y \mid a, b) = \frac{b^a}{\Gamma(a)} y^{-a-1} \exp\left(-\frac{b}{y}\right)$
  - The mean of an inverse-Gamma is b/(a-1)

Joint inference for the mean and variance

In the normal model we typically factorize the prior distribution $p(\mu, \sigma) = p(\mu \mid \sigma)p(\sigma)$.

Specifically:

$$\begin{aligned} \sigma^2 &\sim Inv - Gamma(\nu_0/2, \nu_0/2\sigma_0^2) \\ \mu|\sigma^2 &\sim \text{ normal } \left(\mu_0, \sigma^2/\kappa_0\right) \\ Y_1, \ldots, Y_n|\mu, \sigma &\sim \text{ i.i.d. normal } \left(\mu, \sigma^2\right) \end{aligned}$$

- ν_0 is interpreted as the prior sample size
- σ_0^2 is a prior sample variance

Joint inference for the mean and variance

- We write down $p(\mu, \sigma \mid y_1, \ldots y_n) \propto L(\mu, \sigma) p(\mu, \sigma)$. Now what?
- Estimands of potential interest:
  - $E[\mu \mid y_1, \ldots y_n]$
  - $E[\sigma \mid y_1, \ldots y_n]$
  - $E[\sigma/\mu| \mid y_1, \ldots y_n]$ (coefficient of variation)

Posterior inference for arbitrary functions

Method of transformations

1. Find the inverse, $\theta = g^{-1}(\gamma) = \frac{e^{\gamma}}{1+e^{\gamma}}$
2. Compute $\frac{dg^{-1}(\gamma)}{d\gamma}$
3. Find

$$p_{\gamma}(\gamma \mid y_1, \ldots y_n) = \left| \frac{dg^{-1}(\gamma)}{d\gamma} \right| \times p_{\theta}(g^{-1}(\gamma) \mid y_1, \ldots y_n)$$

Posterior inference for arbitrary functions

For any $\gamma = g(\theta)$ we have

$$E(g(\theta)|y) = \int g(\theta)p(\theta|y)d\theta$$

Examples:

- $E[\gamma \mid y] = \int \log(\frac{\theta}{1-\theta})p(\theta \mid y)d\theta$
- $Pr(\theta \in R \mid y) = E(I\left[\theta \in R\right]|y)$

$$\int g(\theta)p_\theta(\theta \mid y_1, \ldots y_n)d\theta = \int \gamma p_\gamma(\gamma \mid y_1, \ldots y_n)d\gamma$$

Law of the Unconscious Statstician


LE CASINO
CASINO
MONTE-CARLO
CASINO NIGHT
À CIEL OUVERT
ROCK
GRAFF
GRAFF

Monte Carlo Method

- $\overline{\theta} = \sum_{s=1}^{S} \theta^{(s)} / S \to \mathrm{E}[\theta | y_1, \ldots, y_n]$
- $\sum_{s=1}^{S} \left(\theta^{(s)} - \overline{\theta} \right)^2 / (S-1) \to \mathrm{Var}[\theta | y_1, \ldots, y_n]$
- $\# \left(\theta^{(s)} \leq c \right) / S \to \Pr(\theta \leq c | y_1, \ldots, y_n)$
- the α-percentile of $\left\{ \theta^{(1)}, \ldots, \theta^{(S)} \right\} \to \theta_\alpha$

Almost sure convergence due to the SLLN

Monte Carlo Error

- If posterior samples are independent then:

$$p(\overline{g(\theta)}) \rightarrow N\left(g(\theta), \frac{\mathbf{Var}(g(\theta) \mid y_1, \ldots y_n)}{S}\right)$$

-

- Just because we can write down the (proportional) posterior, doesn't mean we can sample from the distribution!
  - With exponential families and conjugate priors, sampling algorithms are available
  - For more "complicated" distributions we need new tools (e.g. MCMC)

Back to the normal model

Example: midge wing length

- Modeling wing length of different specifies of midge (small, two-winged flies)
- From prior studies: mean wing length close to 1.9mm.
- Prior mean for μ is $\mu_0 = 1.9$ and Jeffreys prior for σ^2.
- Prior sample sizes: choose $\kappa_0 = 1$
- $(\bar{y}, s^2) = (1.804, 0.0169)$ are the sufficient statistics

Working with the log posterior

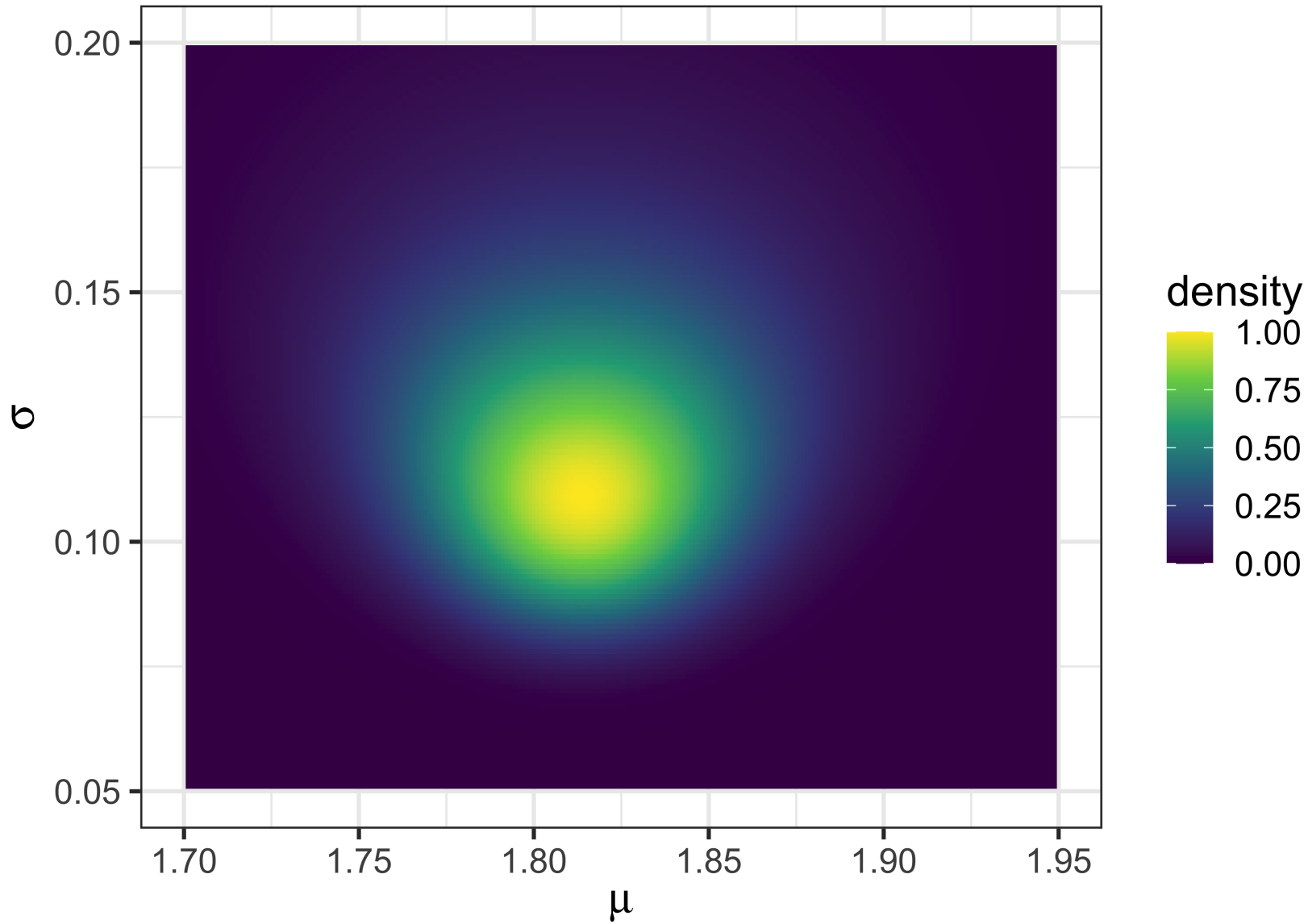
- As always, we will write down $p(\theta \mid y) \propto p(y \mid \theta)p(\theta)$
- In code, we always work with the **log-posterior** for numerical reasons
  - Mathematically it makes no difference, but computationally it is important
  - $L(\theta) \propto \prod p(y_i \mid \theta)$ is very small for moderate sample size (underflow)
  - $\ell(\theta) = \sum log(p(y_i \mid \theta))$ is numerically stable
- Monte Carlo methods only require that we can evaluate the log posterior

Grid approximation

```r
log_normal_posterior <- Vectorize(function(mu, sigma) {

  ### log likelihood
  sum(dnorm(y, mu, sigma, log=TRUE)) +
  ## plus log prior
  dnorm(mu, mu0, sigma/sqrt(k0), log=TRUE) +
  -2*log(sigma)

})


post_grid <- as_tibble(
  expand.grid(seq(1.6, 2.0, by=0.001),
              seq(0.01, 0.25, by=0.001)))
colnames(post_grid) <- c("mu", "s")
```

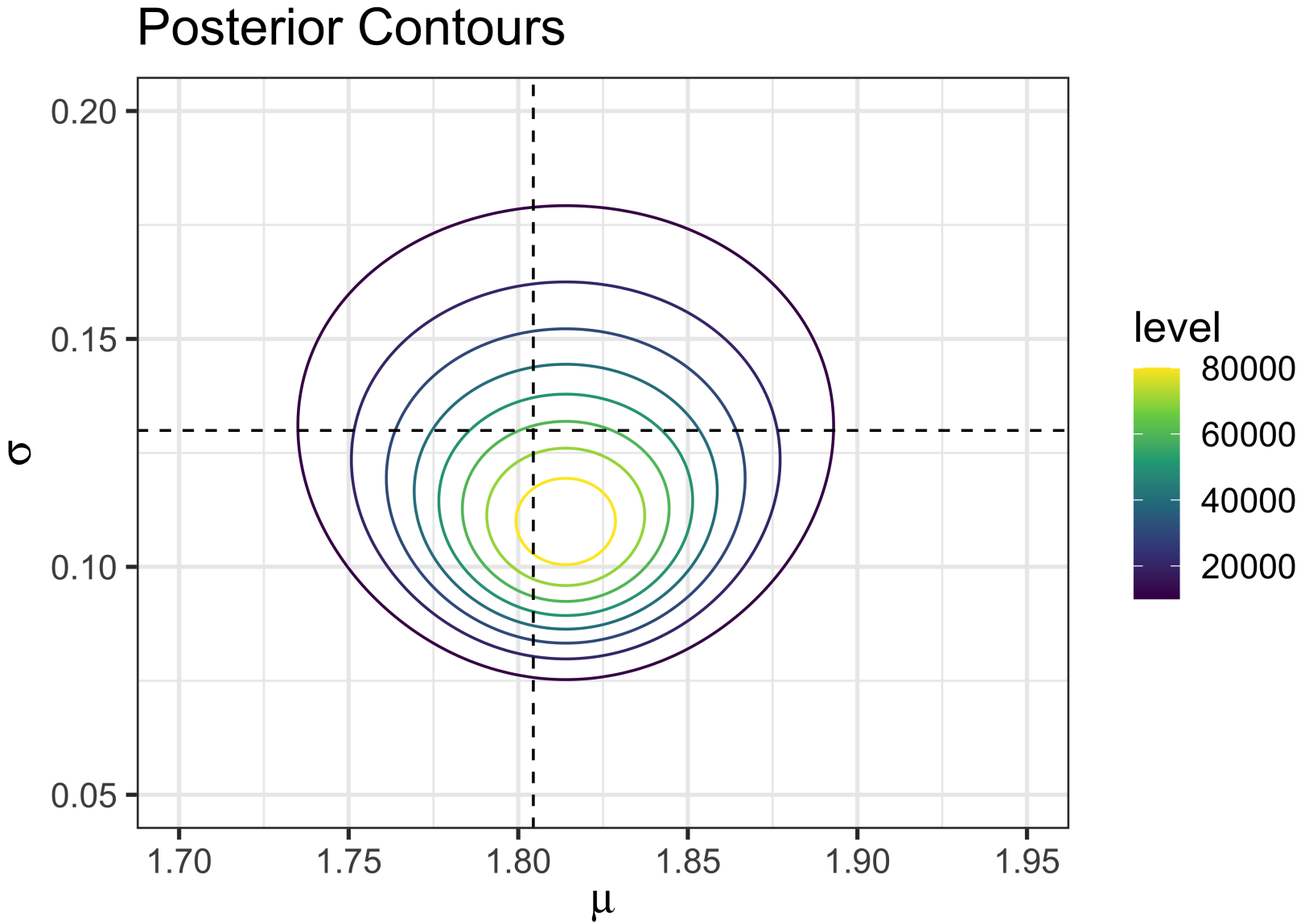
Grid approximation

```
post_grid %>%
  mutate(log_density = log_normal_posterior(mu, s)) %>%
  mutate(density = exp(log_density - max(log_density))) %>%
  ggplot() +
  geom_raster(aes(mu, s, fill=density)) +
  xlim(c(1.7, 1.95)) + ylim(c(0.05, 0.2)) +
  xlab(expression(mu)) +
  ylab(expression(sigma)) +
  theme_bw(base_size=16
           ) +
  scale_fill_continuous(type="viridis")
```


0.20
0.15
0.10
0.05
σ
1.70
1.75
1.80
1.85
1.90
1.95
μ
density
1.00
0.75
0.50
0.25
0.00

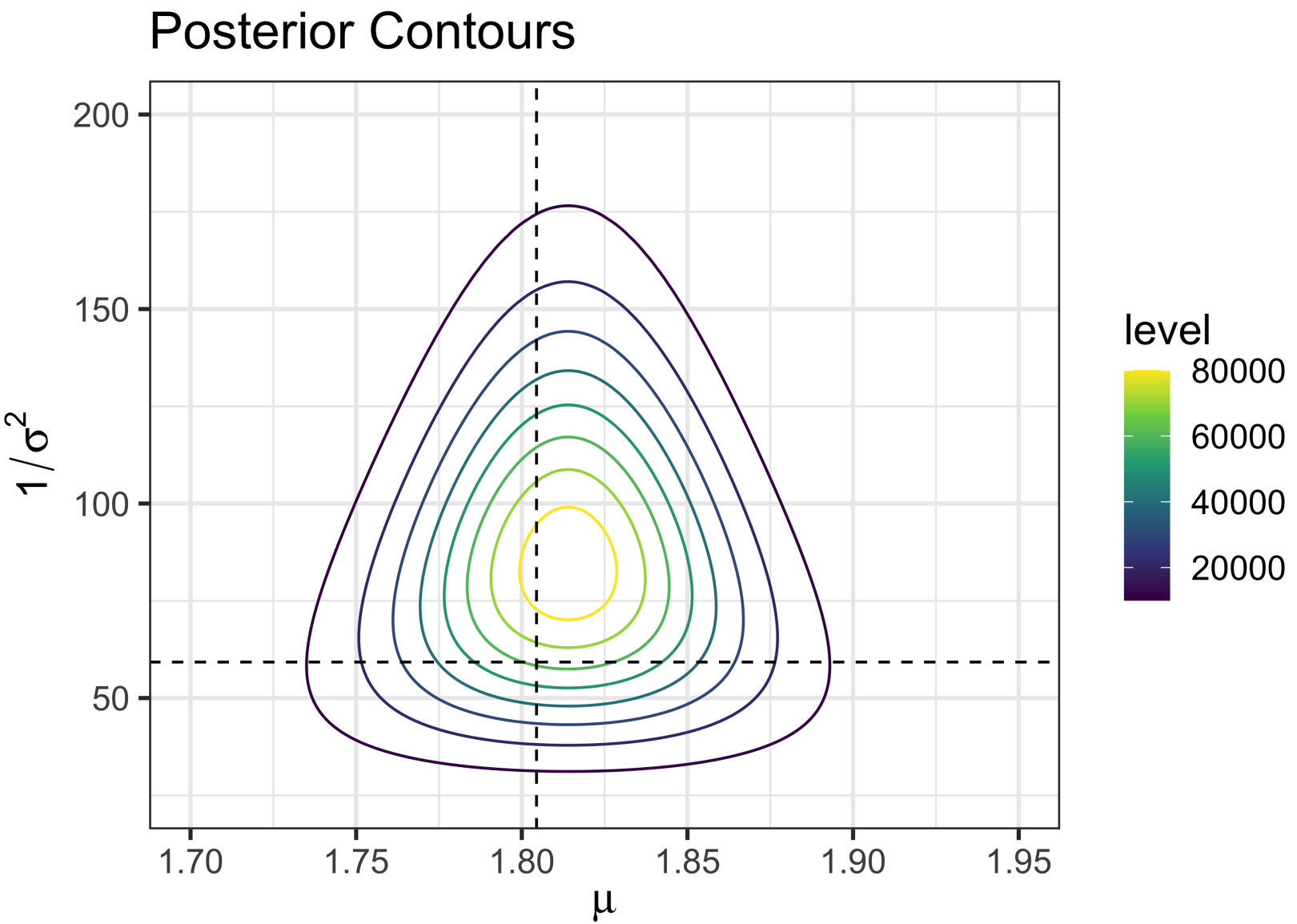
Contour Plot (Standard Deviation)

```r
post_grid %>%
  mutate(density = exp(log_normal_posterior(mu, s))) %>%
  ggplot() +
  geom_contour(aes(mu, s, z=density, colour=stat(level))) +
  xlim(c(1.7, 1.95)) + ylim(c(0.05, 0.2)) +
  xlab(expression(mu)) + ylab(expression(sigma)) +
  ggtitle("Posterior Contours") +
  theme_bw(base_size=16) +
  scale_color_continuous(type="viridis") +
  geom_hline(yintercept=s, linetype="dashed") +
  geom_vline(xintercept=ybar, linetype="dashed")
```


Posterior Contours
0.20
0.15
0.10
0.05
σ
1.70
1.75
1.80
1.85
1.90
1.95
μ
level
80000
60000
40000
20000

Contour Plot (Precision)

```r
post_grid$prec <- 1/post_grid$s^2

post_grid %>%
  mutate(density = exp(log_normal_posterior(mu, sqrt(1/prec)))) %>%
  ggplot() +
  geom_contour(aes(mu, prec, z=density, colour=stat(level))) +
  xlim(c(1.7, 1.95)) + ylim(c(25, 200)) +
  xlab(expression(mu)) + ylab(expression(1/sigma^2)) +
  ggtitle("Posterior Contours") +
  theme_bw(base_size=16) +
  scale_color_continuous(type="viridis") +
  geom_hline(yintercept=1/s^2, linetype="dashed") +
  geom_vline(xintercept=ybar, linetype="dashed")
```

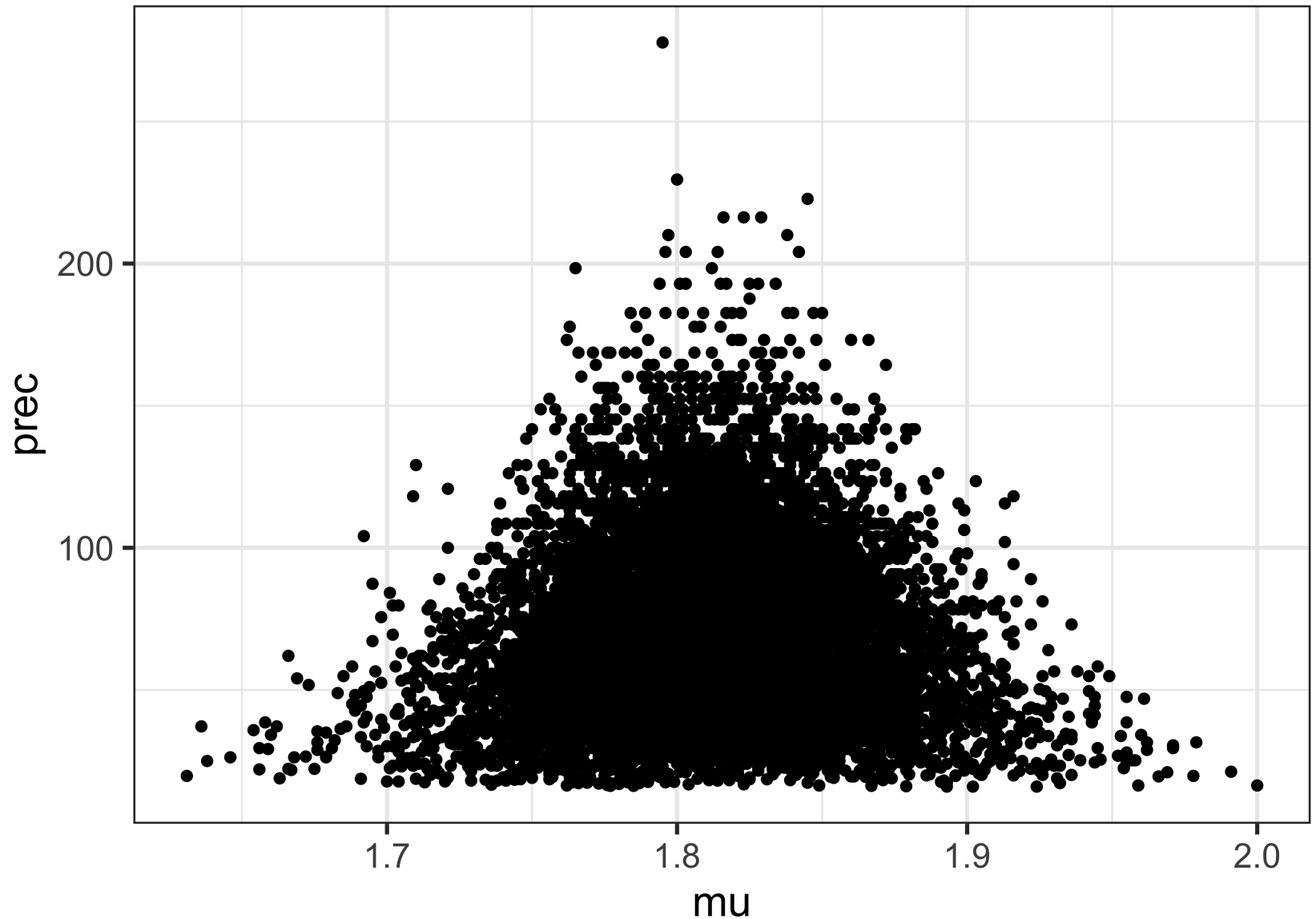

Posterior Contours
200
150
100
50
1/σ²
1.70
1.75
1.80
1.85
1.90
1.95
μ
level
80000
60000
40000
20000

Sampling from the joint posterior

- Contour and raster plots allow us to visualize the posterior (in two dimensions)
  - Grid sampling approximates posterior samples
  - Need to know approximately where the high posterior density is (not easy)
- When we have more than 2 parameters visualization isn't feasible
- How do we summarize the posterior?
  - e.g. posterior means, posterior probabilities, intervals, etc..

Visualizing Posterior Samples

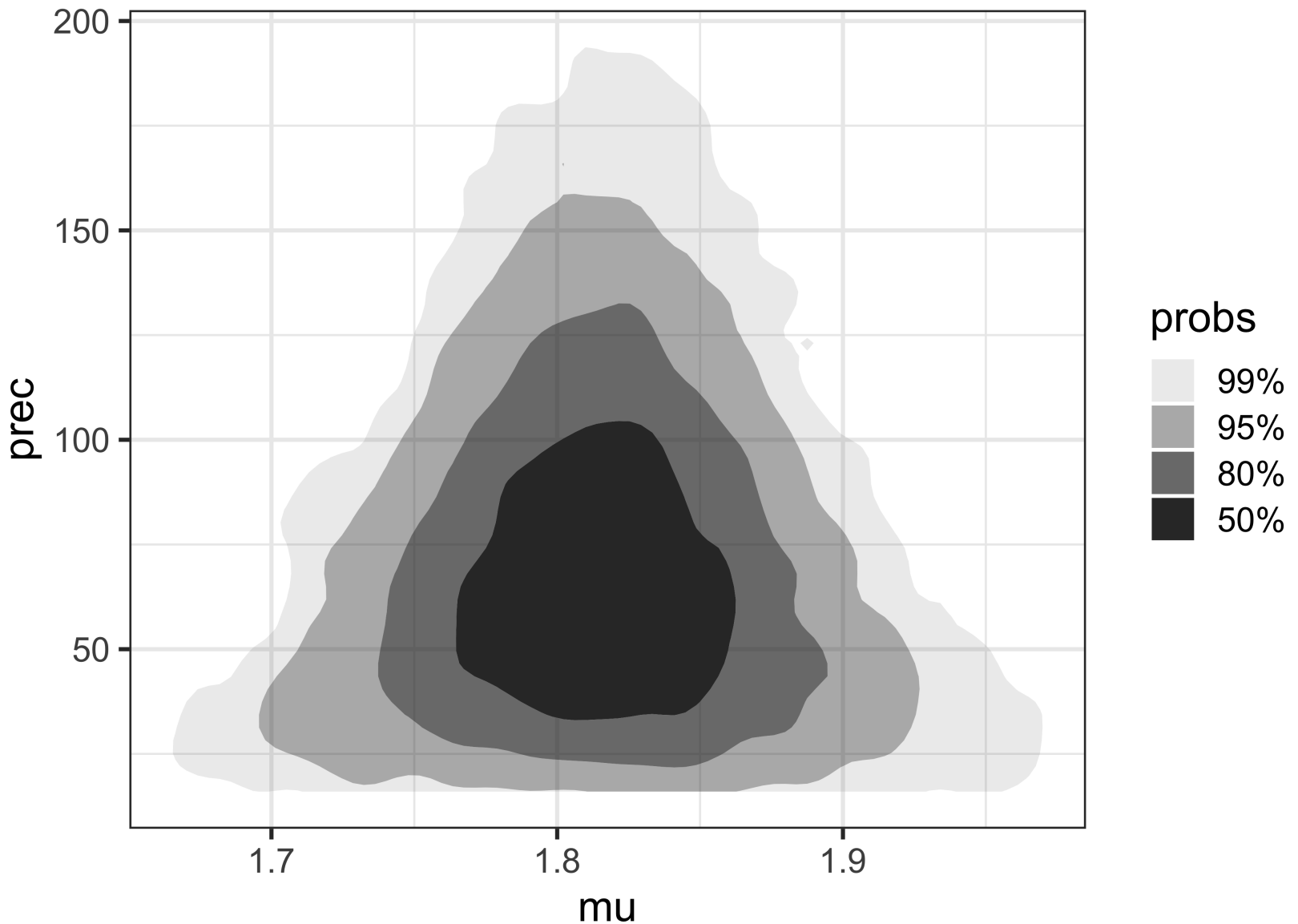
```r
post_grid %>%
  mutate(density = exp(log_normal_posterior(mu, sqrt(1/prec)))) %>%
  mutate(density = density / sum(density)) -> post_grid

sample_indices <- sample(1:nrow(post_grid), size=10000, replace=TRUE, prob=

post_grid[sample_indices, ] %>%
  mutate(prec = 1/s^2) %>%
  ggplot() +
  geom_point(aes(x=mu, y=prec)) +
  theme_bw(base_size=16)
```


200
100
prec
1.7
1.8
1.9
2.0
mu

Visualizing Posterior Samples

```
post_grid %>%
  mutate(density = exp(log_normal_posterior(mu, sqrt(1/prec)))) %>%
  mutate(density = density / sum(density)) -> post_grid

sample_indices <- sample(1:nrow(post_grid), size=10000, replace=TRUE, prob=

post_grid[sample_indices, ] %>%
  mutate(prec = 1/s^2) %>%
  ggplot() +
  ggdensity::geom_hdr(aes(x=mu, y=prec)) +
  theme_bw(base_size=16)
```

Visualizing Posterior Samples



Direct Sampling

- $p(\mu, \sigma^2 \mid y) = p(\mu \mid \sigma^2, y) p(\sigma^2 \mid y)$
- Need to know how to sample from $p(\sigma^2 \mid y) = \int p(\mu, \sigma^2 \mid y) d\mu$ and $p(\mu \mid \sigma^2, y)$
- With the proposed conjugate priors, this integral is tractable

Direct Sampling

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- With the proposed conjugate priors, this integral is tractable

$$\left\{1/\sigma^2 \mid y_1, \ldots, y_n\right\} \sim \text{gamma}\left(\nu_n/2, \nu_n \sigma_n^2/2\right), \text{ where}$$

$$\nu_n = \nu_0 + n$$

$$\sigma_n^2 = \frac{1}{\nu_n}\left[\nu_0 \sigma_0^2 + (n-1)s^2 + \frac{\kappa_0 n}{\kappa_n}(\bar{y} - \mu_0\right.$$

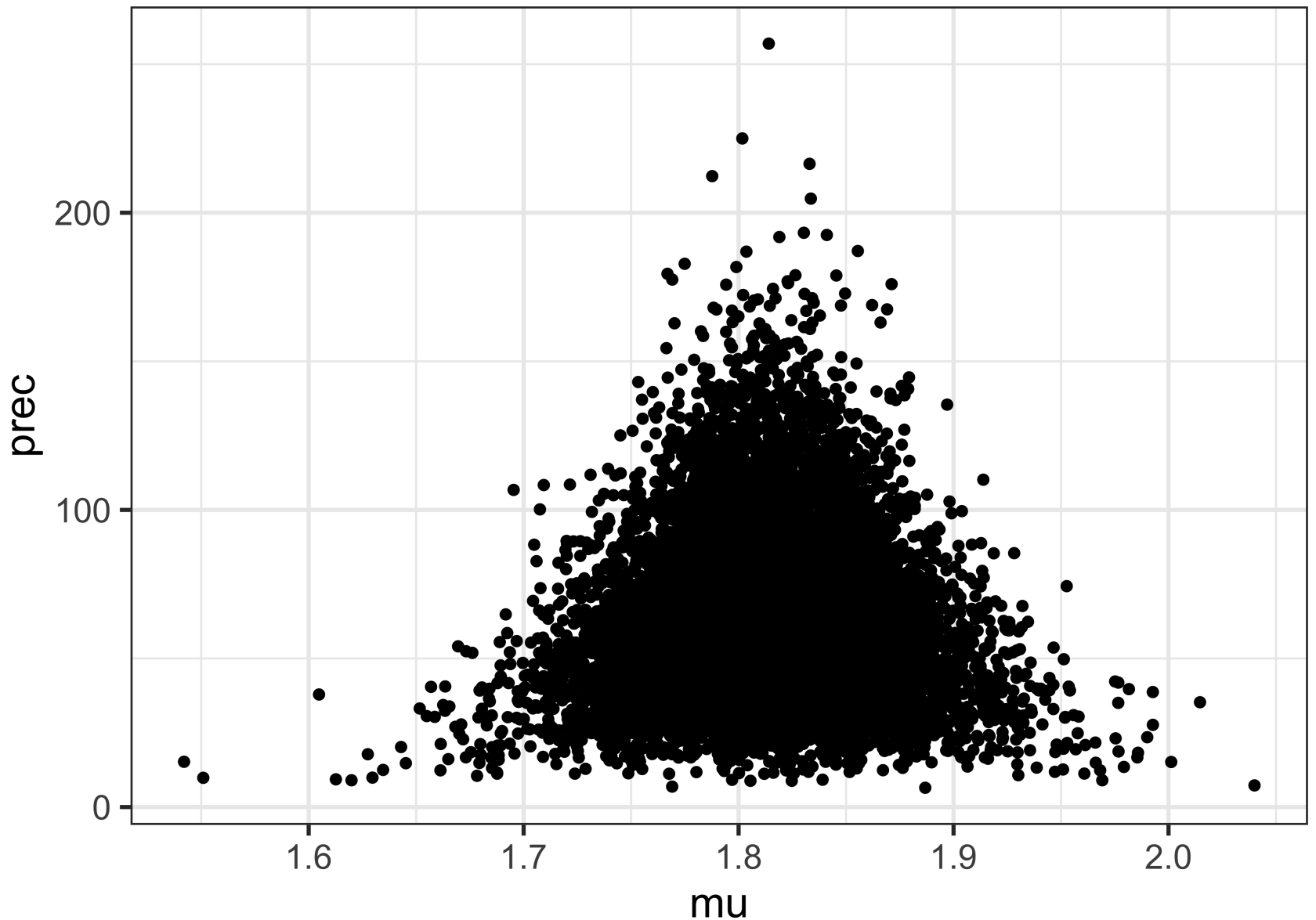
Direct Sampling

```r
## posterior parameters
kn <- k0 + n
nun <- nu0 + n
mun <- (k0 * mu0 + n * ybar) / kn
s2n <- (nu0*s20 + (n-1)*s2  + k0*n / kn * (ybar - mu0)^2) / nun

nsamps <- 10000
prec_samps <- rgamma(nsamps, nun/2, nun*s2n/2)
mu_samps <- rnorm(nsamps, mun, sqrt((1/prec_samps) / kn))

tibble(mu=mu_samps, prec=prec_samps) %>%
  ggplot() +
  geom_point(aes(x=mu, y=prec)) +
  #ggdensity::geom_hdr(aes(x=mu, y=prec)) +
  theme_bw(base_size=16)
```

Direct Sampling



Bayes Estimators

Why the posterior mean?

- Often times we need to make a “decision” by providing a single estimate
- The posterior provides a full distribution over θ, which can be summarized in infinitely many ways
- Specify a *loss function* which describes the cost of estimating $\hat{\theta}$ when the truth is θ

Bayes Estimators

- The *loss function*: $L(\hat{\theta}, \theta)$
  - Squared error: $L(\hat{\theta}, \theta) = (\hat{\theta} - \theta)^2$
  - Absolute error: $L(\hat{\theta}, \theta) = |\hat{\theta} - \theta|$
- The *Bayes risk* is the posterior expected loss: $E_{\theta|y}[L(\hat{\theta}, \theta)]$
- Summarize the posterior by minimizing the Bayes risk.
- An estimator $\hat{\theta}$ is said to be a Bayes estimator if it minimizes the Bayes risk among all estimators.

Examples Squared error loss

$$\min_{\hat{\theta}} E_{\theta|y}(\hat{\theta} - \theta)^2 = \min_{\hat{\theta}} \int (\hat{\theta} - \theta)^2 p(\theta \mid y) d\theta$$

The Bias-Variance Tradeoff

- The prior distribution (usually) makes your estimator biased…
- But the prior distribution also (usually) reduces the variance!
- Bayes estimators are (usually) consistent
- Example: compute the frequentist mean and variance of the posterior mean.

Example: IQ scores

- Scoring on IQ tests is designed to yield a N(100, 15) distribution for the general population
- We observe IQ scores for a sample of n individuals from a particular town and estimate μ, the town-specific IQ score
- If we lacked knowledge about the town, a natural choice would be $\mu_0 = 100$
- Suppose the true parameters for this town are $\mu = 112$ and $\sigma = 13$
  - The town is smarter on average than the general population

Example: IQ scores

- What is the mean squared error of the MLE? MSE of the posterior mean?

Example: IQ scores

- What is the mean squared error of the MLE? MSE of the posterior mean?

- $\text{MSE}\left[\hat{\mu}_{MLE}\right] = \text{Var}\left[\hat{\mu}_{MLE}\right] = \frac{\sigma^2}{n} = \frac{169}{n}$

Example: IQ scores

- What is the mean squared error of the MLE? MSE of the posterior mean?

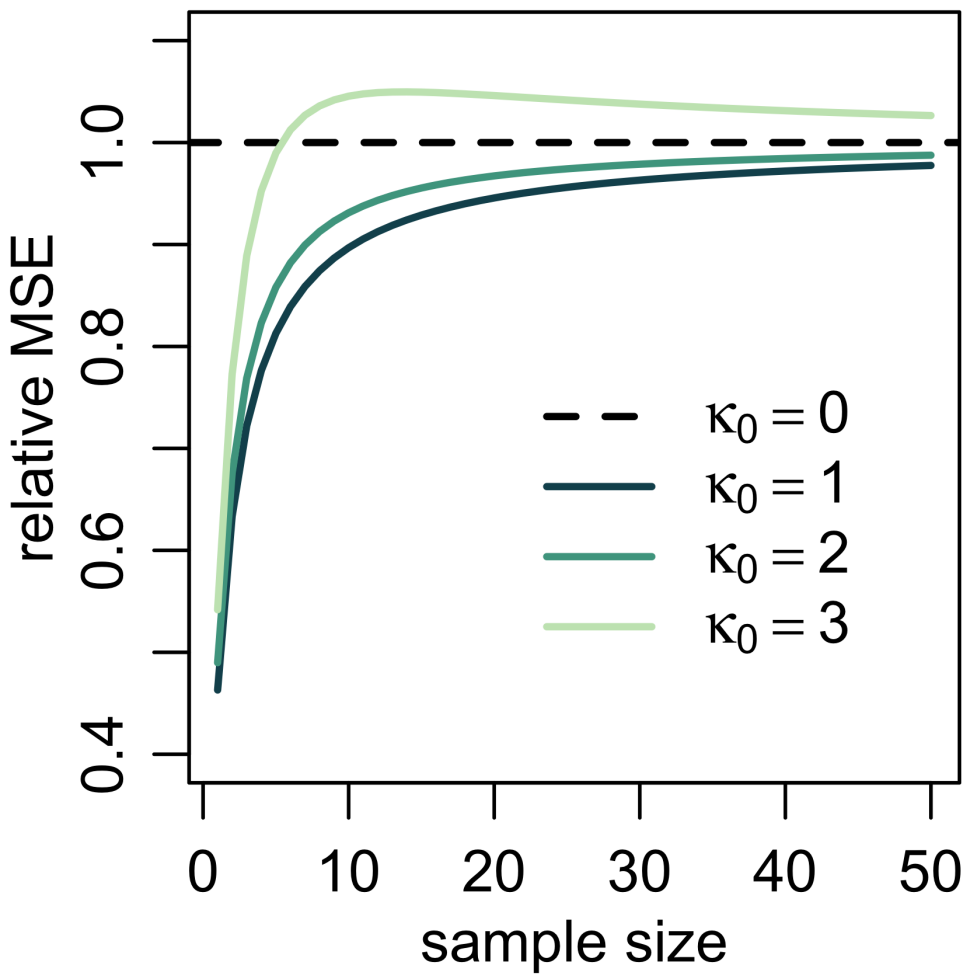
- $\mathrm{MSE}\left[\hat{\mu}_{MLE}\right] = \mathrm{Var}\left[\hat{\mu}_{MLE}\right] = \frac{\sigma^2}{n} = \frac{169}{n}$

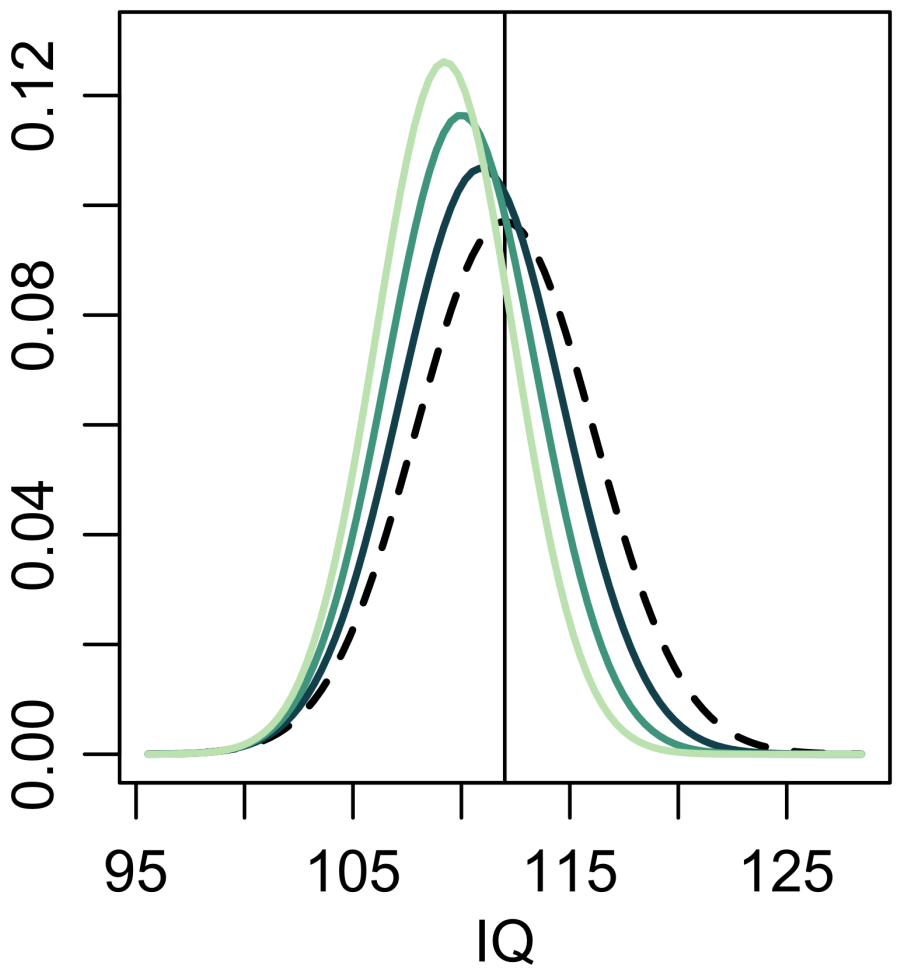
- $\mathrm{MSE}\left[\hat{\mu}_{PM}|\theta_0\right] = w^2 \frac{169}{n} + (1-w)^2 144$

Example: IQ scores

- What is the mean squared error of the MLE? MSE of the posterior mean?
- $\mathrm{MSE}\left[\hat{\mu}_{MLE}\right] = \mathrm{Var}\left[\hat{\mu}_{MLE}\right] = \frac{\sigma^2}{n} = \frac{169}{n}$
- $\mathrm{MSE}\left[\hat{\mu}_{PM}|\theta_0\right] = w^2\frac{169}{n} + (1-w)^2 144$
- Reminder: $w = \frac{n}{\kappa_0+n}$. For what values of n and κ_0 is the MSE smaller for the posterior mean estimator than the maximum likelihood?

Example: IQ scores





The Multivariate Normal Distribution

Dirichlet-Multinomial

Metagenomics example

- Metagenomics is the study of genetic material recovered directly from environmental samples
- Map counts of genetic material to counts of microbial species
- Assume species are sampled with replacement
  - Observed sample is a multinomial distribution
- Total counts isn’t meaningful (hard to control how much total sample)
- Relative counts are meaningful

Multinomial Density

- Let $\theta = (\theta_1, \theta_2, \ldots, \theta_k)$ with $\sum_i = 1^k \theta_i = 1$
- If $Y = (Y_1, \ldots, Y_K) \sim Mult(n, \theta)$, then:
  - $Y_i \sim Bin(n, \theta_i)$
  - $Y_i + Y_j \sim Bin(n, \theta_i + \theta_j)$
- What is $\hat{\theta}_{MLE}$?

Dirichlet Distribution