I-priors in Bayesian Variable Selection: From Reproducing Kernel Hilbert Spaces to Hamiltonian Monte Carlo

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follow along at: **https://haziqjamil.github.io/**

Outline

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2. I-priors
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   - Estimation
   - The R/iprior package
3. Bayesian I-prior linear models
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   - Shrinkage properties of I-priors
   - Full Bayes estimation
4. Hamiltonian Monte Carlo
   - Hamiltonian dynamics
   - The HMC algorithm
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The I-prior Bayesian Variable Selection model

- For centred responses y_i and standardised covariates $x_{i1}, \dots, x_{ip}$,

$$y_i = \gamma_1 \beta_1 x_{i1} + \cdots + \gamma_p \beta_p x_{ip} + \epsilon_i$$
$$\epsilon_i \sim \mathrm{N}(0, \psi^{-1})$$
$$i = 1, \dots, n$$

$$\underline{\text{Priors}} \tag{1}$$

$$\boldsymbol{\beta} \sim \mathrm{N}(\mathbf{0}, \psi \boldsymbol{\Lambda} \mathbf{X}^\top \mathbf{X} \boldsymbol{\Lambda}), \text{ where } \boldsymbol{\Lambda} = \mathrm{diag}[\lambda_1, \dots, \lambda_p]$$
$$\gamma_j \sim \mathrm{Bern}(p_j), \; j = 1, \dots, p$$
$$\psi, \lambda_1^{-2}, \dots, \lambda_p^{-2} \sim \Gamma(c, d)$$

- Use MCMC methods to sample from posterior using software such as JAGS. Interested in two things:
  - Posterior model probabilities $\mathrm{P}[\boldsymbol{\gamma} = \boldsymbol{\gamma}' | \mathbf{y}]$ for model $\boldsymbol{\gamma}'$.
  - Posterior inclusion probabilities $\mathrm{P}[\gamma_j = 1 | \mathbf{y}]$ for variable X_j.

Why Bayesian Variable Selection?

Some criticisms

- The end-game of model selection is often prediction. If so, better methods exist e.g. Lasso
- Why not just put a reasonable prior?
- Unreliable Gibbs sampler - likely to get stuck in multiple modes.

But actually,

- Sometimes there is a need to know what is the most plausible, interpretable, and parsimonious model.
- Valid applications in social sciences, but perhaps not the $p > n$ cases.
- Gibbs sampler not too terrible.
- For as many critics to this "combinatorial approach", there are equally as many proponents.
- Prediction through Bayesian model averaging.

Simulation results are good...

...in comparison to: SSVS (George & McCulloch, 1993)

...in comparison to: KM (Kuo & Mallick, 1998)

...in comparison to: GVS (Dellaportas et. al., 2011)

...in comparison to: Lasso (Tibshirani, 1994)

...and so are some real world applications

1. **Modelling aerobic fitness through some exercise data** ($n = 30$, $p = 6$) [SAS/STAT User Guide, 2008]
   - Agreed with forward selection and backward elimination procedure except in the `Age` variable.
   - `Age` negatively correlated with `MaxPulse`.
2. **Effects of air pollution on mortality rate** ($n = 60$, $p = 15$) [McDonald & Schwing, 1978]
   - Which of `HC`, `NOx`, and/or `SO2` affects mortality rate in U.S. metropolitan areas?
   - Agreed with "ridge trace analysis" in identifying `SO2`.
3. **Factors affecting ozone depletion** ($n = 178$, $p = 12, 90$) [Casella & Moreno, 2006]
   - Model obtained had smaller out-of-sample RMSE.
   - Selection of squared and two-way interaction terms to improve RMSE without overcomplicating the model.

1 Bayesian Variable Selection

2 I-priors

3 Bayesian I-prior linear models

4 Hamiltonian Monte Carlo

5 Summary

Introduction

- For $i = 1, \ldots, n$, consider the regression model

$$y_i = \alpha + f(\mathbf{x}_i) + \epsilon_i$$
$$(\epsilon_1, \ldots, \epsilon_n) \sim \mathrm{N}(\mathbf{0}, \boldsymbol{\Psi}^{-1})$$

  where $f \in \mathcal{F}$, $y_i \in \mathbb{R}$, and $\mathbf{x}_i = (x_{i1}, \ldots, x_{ip}) \in \mathcal{X}$.

- Definition **(I-priors)**
  For the regression model above, let $\mathcal{F}$ be a reproducing kernel Hilbert space (RKHS) with kernel $h_{\boldsymbol{\lambda}} : \mathcal{X} \times \mathcal{X} \to \mathbb{R}$. Then, assuming it exists, the Fisher information for $I[f]$ for the function f is given by

$$I[f(\mathbf{x}_i), f(\mathbf{x}_i')] = \sum_{k=1}^{n} \sum_{l=1}^{n} \psi_{kl} h_{\boldsymbol{\lambda}}(\mathbf{x}_i, \mathbf{x}_k) h_{\boldsymbol{\lambda}}(\mathbf{x}_i', \mathbf{x}_l).$$

  Let π be a Gaussian distribution on the random vector f with mean f_0 and covariance kernel $I[f]$. Then π is called an I-prior for f.

Function spaces and kernels

- There is a bijection between the set of all positive-definite functions (reproducing kernels) $h : \mathcal{X} \times \mathcal{X} \to \mathbb{R}$ and the set of all RKHS.

$\mathcal{X} = \{x_i\}$	**Effect**	**Vector space** $\mathcal{F}$	**Kernel** $h(x_i, x_k)$
Real	"Straight line" functions	Canonical	$x_i x_k$
Real	"Curvy" functions (smoothing)	Fractional Brownian Motion (FBM)	$\lvert x_i\rvert^{2\gamma} + \lvert x_k\rvert^{2\gamma} - \lvert x_i - x_k\rvert^{2\gamma}$ with $\gamma \in (0, 1)$
Nominal	Grouping	Pearson	$\frac{\mathbb{1}[x_i = x_k]}{p_i} - 1$ where $p_i = \mathrm{P}[X = x_i]$

The w I-prior model

- The I-prior for f has the random-effect representation

$$f(\mathbf{x}_i) = \alpha + f_0(\mathbf{x}_i) + \sum_{k=1}^{n} h_{\boldsymbol{\lambda}}(\mathbf{x}_i, \mathbf{x}_k) w_k$$
$$(w_1, \ldots, w_n) \sim \mathrm{N}(\mathbf{0}, \boldsymbol{\Psi}).$$

- Putting this back into our regression model, we obtain the *w I-prior* model

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$$\mathbf{y} = \boldsymbol{\alpha} + \mathbf{f}_0 + \mathbf{H}_{\boldsymbol{\lambda}}\mathbf{w} + \boldsymbol{\epsilon}$$
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$$\boldsymbol{\epsilon} \sim \mathrm{N}(\mathbf{0}, \boldsymbol{\Psi}^{-1})$$

- Typically, $(\mathbf{H}_{\boldsymbol{\lambda}})_{ij} = \sum_{k=1}^{p} \lambda_k h_k(x_{ik}, x_{jk})$

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- Typically, $\mathbf{H}_{\boldsymbol{\lambda}} = \lambda_1 \mathbf{H}_1 + \cdots + \lambda_p \mathbf{H}_p$

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- The I-prior for f has the random-effect representation

$$f(\mathbf{x}_i) = \alpha + f_0(\mathbf{x}_i) + \sum_{k=1}^{n} h_{\boldsymbol{\lambda}}(\mathbf{x}_i, \mathbf{x}_k) w_k$$
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- Typically, $\mathbf{H}_{\boldsymbol{\lambda}} = \lambda_1 \mathbf{H}_1 + \cdots + \lambda_p \mathbf{H}_p$, $\boldsymbol{\Psi} = \psi \mathbf{I}_n$, and $\mathbf{f}_0 = \mathbf{0}$.

The w I-prior model

- The I-prior for f has the random-effect representation

$$f(\mathbf{x}_i) = \alpha + f_0(\mathbf{x}_i) + \sum_{k=1}^{n} h_{\boldsymbol{\lambda}}(\mathbf{x}_i, \mathbf{x}_k) w_k$$
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- Putting this back into our regression model, we obtain the *w I-prior* model

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- Typically, $\mathbf{H}_{\boldsymbol{\lambda}} = \lambda_1 \mathbf{H}_1 + \cdots + \lambda_p \mathbf{H}_p$, $\boldsymbol{\Psi} = \psi \mathbf{I}_n$, and $\mathbf{f}_0 = \mathbf{0}$.
- Parameters of interest are $\boldsymbol{\theta} = (\alpha, \lambda_1, \ldots, \lambda_p, \psi)$.

Maximum likelihood

- The marginal distribution of $\mathbf{y}$ is normal with mean and variance

$$\mathrm{E}[\mathbf{y}] = \boldsymbol{\alpha}$$
$$\mathrm{Var}[\mathbf{y}] = \psi \mathbf{H}_{\boldsymbol{\lambda}}^2 + \psi^{-1}\mathbf{I}_n =: \mathbf{V}_y$$

and thus, the marginal log-likelihood is given by

$$l(\boldsymbol{\theta}) = -\frac{n}{2}\log(2\pi) - \frac{1}{2}\log|\mathbf{V}_y| - \frac{1}{2}(\mathbf{y}-\boldsymbol{\alpha})^\top \mathbf{V}_y^{-1}(\mathbf{y}-\boldsymbol{\alpha}).$$

- MLE for intercept is $\hat{\alpha} = \bar{y} = \frac{1}{n}\sum_{i=1}^n y_i$.
- Usually no closed form estimates for $\boldsymbol{\lambda}$ and ψ, so use numerical optimisation to find MLE.
- Problem: Convergence is difficult when there are a lot of scale parameters.

EM algorithm

- A more stable method is using the EM algorithm. Treat the random effects $\mathbf{w}$ as "missing".
- The relevant distributions are easy enough to obtain:
  - $\mathbf{y} \sim \mathrm{N}(\boldsymbol{\alpha}, \mathbf{V}_y)$
  - $\mathbf{w} \sim \mathrm{N}(\mathbf{0}, \psi \mathbf{I}_n)$
  - $\begin{pmatrix} \mathbf{y} \\ \mathbf{w} \end{pmatrix} \sim \mathrm{N}\left(\begin{pmatrix} \boldsymbol{\alpha} \\ \mathbf{0} \end{pmatrix}, \begin{pmatrix} \mathbf{V}_y & \psi \mathbf{H}_{\boldsymbol{\lambda}} \\ \psi \mathbf{H}_{\boldsymbol{\lambda}} & \psi \mathbf{I}_n \end{pmatrix} \right)$
  - $\mathbf{w}|\mathbf{y} \sim \mathrm{N}\left(\psi \mathbf{H}_{\boldsymbol{\lambda}} \mathbf{V}_y^{-1}(\mathbf{y} - \boldsymbol{\alpha}), \mathbf{V}_y^{-1}\right)$
- For $t = 0, 1, \ldots,$ do:
  - E-step: Calculate $Q(\boldsymbol{\lambda}, \psi) = \mathrm{E}_{\mathbf{w}}\left[\log f(\mathbf{y}, \mathbf{w}; \boldsymbol{\theta}) | \mathbf{y}; \boldsymbol{\lambda}^{(t)}, \psi^{(t)}, \hat{\alpha}\right]$.
  - M-step: $(\boldsymbol{\lambda}^{(t+1)}, \psi^{(t+1)}) \leftarrow \arg\max_{(\boldsymbol{\lambda}, \psi)} Q(\boldsymbol{\lambda}, \psi)$.
- Problem: May be very slow to converge.

The R/iprior package

- An R package for regression modelling using I-priors.
  - Similar syntax to R's `lm()`.
  - Parameters estimated using maximum likelihood.
  - Available on CRAN and GitHub.
- Example: Look at how students' mathematics achievement varies across different high schools (High School & Beyond dataset).

```
str(hsbsmall)

## 'data.frame': 661 obs. of  3 variables:
##  $ mathach : num  16.663 -2.155 0.085 18.804 2.409 ...
##  $ ses     : num  0.322 0.212 0.682 -0.148 -0.468 0.842 0.072 0.3
##  $ schoolid: Factor w/ 16 levels "1374","1433",..: 1 1 1 1 1 1 1
```

The R/iprior package

- Fit a straight line regressing `mathach` against `ses`.

```
system.time(
  mod <- iprior(mathach ~ ses, data = hsbsmall)
)

## Iteration 0:    Log-likelihood = -19755.905 .......
## Iteration 100:  Log-likelihood = -2169.8515 ........
## Iteration 200:  Log-likelihood = -2169.8481 ....
## Iteration 258:  Log-likelihood = -2169.8481
## EM complete.
##    user  system elapsed
##  90.677   1.946  92.752
```

The R/iprior package

- Obtain the parameter estimates. Can also do `summary(mod)`.

```
print(mod)

##
## Call:
## iprior(formula = mathach ~ ses, data = hsbsmall)
##
## RKHS used: Canonical, with a single scale parameter.
##
##
## Parameter estimates:
## (Intercept)      lambda         psi
## 13.68325416  1.06084515  0.02421674
```

The R/iprior package

```
plot(mod, plots = "fitted")
```

The R/iprior package

```
plot(
  iprior(mathach ~ ses, hsbsmall, model = list(kernel = "FBM")
)
```

The R/iprior package

```
plot(
  iprior(mathach ~ ses + schoolid + ses:schoolid, hsbsmall)
)
```

The R/iprior package

```
plot(
  iprior(mathach ~ . ^ 2, hsbsmall, model = list(kernel = "FBM"))
)
```

The R/iprior package

- Compare mean squared errors and log-likelihood values of models.

```
##          Canonical      FBM Can. w/ intr FBM w/ intr
## MSE         41.232    40.86       34.809       34.31
## logLik -2169.850 -2171.18    -2137.800    -2138.64
```

- Other things available:
  - `fitted()` for fitted values.
  - `predict()` for fitted values of a new set of covariates.
  - `resid()` for model residuals.
  - `logLik()` and `deviance()` for model log-likelihood and deviance values respectively.
  - `ipriorOptim()` is a routine which combines EM algorithm and direct optimisation.

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The beta I-prior (linear) model

- For "straight line" functions in the Canonical RKHS, its kernel $h_{\boldsymbol{\lambda}} : \mathcal{X} \times \mathcal{X} \to \mathbb{R}$ is defined as

$$h_{\boldsymbol{\lambda}}(\mathbf{x}_i, \mathbf{x}_j) = \sum_{k=1}^{p} \lambda_k x_{ik} x_{jk}$$

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$$\begin{aligned}\mathbf{H}_{\boldsymbol{\lambda}} &= \lambda_1 \mathbf{X}_1 \mathbf{X}_1^\top + \cdots + \lambda_p \mathbf{X}_p \mathbf{X}_p^\top \\ &= \mathbf{X} \boldsymbol{\Lambda} \mathbf{X}^\top,\end{aligned}$$

where $\boldsymbol{\Lambda} = \text{diag}[\lambda_1, \ldots, \lambda_p]$.

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  where $\boldsymbol{\Lambda} = \text{diag}[\lambda_1, \ldots, \lambda_p]$.
- Putting this into the w I-prior model we have

$$\begin{aligned}\mathbf{y} &= \boldsymbol{\alpha} + \mathbf{H}_{\boldsymbol{\lambda}}\mathbf{w} + \boldsymbol{\epsilon} \\ &= \boldsymbol{\alpha} + \mathbf{X}\underbrace{\boldsymbol{\Lambda}\mathbf{X}^\top\mathbf{w}}_{\boldsymbol{\beta}} + \boldsymbol{\epsilon}\end{aligned}$$

  which implies $\text{E}[\boldsymbol{\beta}] = \mathbf{0}$ and $\text{Var}[\boldsymbol{\beta}] = \psi\boldsymbol{\Lambda}\mathbf{X}^\top\mathbf{X}\boldsymbol{\Lambda}$.

The beta I-prior (linear) model cont.

- The standard multiple regression model with an I-prior on $\boldsymbol{\beta}$

$$
\begin{aligned}
y_i &= \alpha + \beta_1 x_{i1} + \cdots + \beta_p x_{ip} + \epsilon_i \\
\boldsymbol{\beta} &\sim \mathrm{N}(\mathbf{0}, \psi \boldsymbol{\Lambda} \mathbf{X}^\top \mathbf{X} \boldsymbol{\Lambda}), \text{ where } \boldsymbol{\Lambda} = \mathrm{diag}[\lambda_1, \ldots, \lambda_p] \\
\epsilon_i &\sim \mathrm{N}(0, \psi^{-1}) \\
i &= 1, \ldots, n
\end{aligned}
\tag{2}
$$

  is an equivalent representation of the w I-prior model under the Canonical kernel.

- Estimate this model via ML methods as before, or fully Bayes, as we will see soon.

Shrinkage properties of I-priors

- Comparison to ridge regression and Lasso

$$Ridge : \hat{\boldsymbol{\beta}}^R = \arg\min_{\boldsymbol{\beta}} \|\mathbf{y} - \mathbf{X}\boldsymbol{\beta}\|^2 + \lambda \sum_{j=1}^{p} \beta_j^2$$

$$Lasso : \hat{\boldsymbol{\beta}}^L = \arg\min_{\boldsymbol{\beta}} \|\mathbf{y} - \mathbf{X}\boldsymbol{\beta}\|^2 + \lambda \sum_{j=1}^{p} |\beta_j|$$

Shrinkage properties of I-priors

- Comparison to ridge regression and Lasso

$$\textit{Ridge} : \beta_1, \ldots, \beta_p \sim \mathrm{N}(0, 1/\lambda)$$
$$\textit{Lasso} : \beta_1, \ldots, \beta_p \sim \mathrm{Laplace}(0, 1/\lambda)$$

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These only (typically) use one common shrinkage parameter λ.

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These only (typically) use one common shrinkage parameter λ.

- Other Bayesian Variable Selection priors
  - After standardising data $\mathbf{X}$, use weakly informative priors

$$\boldsymbol{\beta} \sim \mathrm{N}(\mathbf{0}, 10\mathbf{I}_p).$$

  - The objective g-prior are also popular

$$\boldsymbol{\beta} \sim \mathrm{N}(\mathbf{0}, g(\mathbf{X}^\top\mathbf{X})^{-1}).$$

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- I-priors have individual shrinkage coefficients on the $\boldsymbol{\beta}$, and also makes them correlated a priori.

Shrinkage properties of I-priors cont.

Demo

https://haziqjamil.shinyapps.io/iprior/

Full Bayes estimation

- The fully Bayes beta I-prior model is the following hierarchical model

$$
\begin{aligned}
y_i &= \alpha + \beta_1 x_{i1} + \cdots + \beta_p x_{ip} + \epsilon_i \\
\epsilon_i &\sim \mathrm{N}(0, \psi^{-1}) \\
i &= 1, \ldots, n
\end{aligned}
$$

$$
\begin{aligned}
&\underline{\text{Priors}} \\
&\alpha \sim \mathrm{N}(0, a^2) \\
&\boldsymbol{\beta} \sim \mathrm{N}(\mathbf{0}, \psi \boldsymbol{\Lambda} \mathbf{X}^\top \mathbf{X} \boldsymbol{\Lambda}), \text{ where } \boldsymbol{\Lambda} = \mathrm{diag}[\lambda_1, \ldots, \lambda_p] \\
&\psi, \lambda_1^{-2}, \ldots, \lambda_p^{-2} \sim \Gamma(c, d)
\end{aligned}
\tag{3}
$$

- The posterior distribution is

$$
\begin{aligned}
f(\alpha, \boldsymbol{\beta}, \psi, \boldsymbol{\lambda} | \mathbf{y}) &\propto f(\mathbf{y} | \alpha, \boldsymbol{\beta}, \psi, \boldsymbol{\lambda}) f(\alpha, \boldsymbol{\beta}, \psi, \boldsymbol{\lambda}) \\
&\propto f(\mathbf{y} | \alpha, \boldsymbol{\beta}, \psi) f(\alpha) f(\boldsymbol{\beta} | \psi, \boldsymbol{\lambda}) f(\psi) f(\lambda_1) \cdots f(\lambda_p)
\end{aligned}
$$

Estimation using JAGS

- Fit Bayesian models using JAGS (or WinBUGS or OpenBUGS).
- In R, many packages to run JAGS models: `rjags`, `R2Jags`, `runjags`.
- We will use `runjags` as it allows easy parallelisation of chains.
- Simulate a dataset:

```
n <- 100
p <- 2
beta.true <- matrix(c(10, 0), ncol = 1)
X <- matrix(rnorm(n * p, ncol = p)
Y <- X %*% beta.true + rnorm(n, mean = 0, sd = 2)
```

Estimation using JAGS

```
mod <- "
  model {
    for (i in 1:n) {
      Y[i] ~ dnorm(mu[i], psi)
      mu[i] <- alpha + inprod(X[i,1:p], beta[1:p])
    }

    alpha ~ dnorm(0, 0.0001)
    psi ~ dgamma(0.1, 0.0001)
    for (j in 1:p) {
      lambdasq[j] ~ dgamma(0.0001, 0.0001)
      for (k in 1:p) { LambdaInv[j, k] <- equals(j,k) * pow(lambdasq[k], -0.5) }
    }
    BetaPrec <- LambdaInv[1:p, 1:p] %*% XTX.inv %*% LambdaInv[1:p, 1:p] / psi
    beta[1:p] ~ dmnorm(rep(0, p), BetaPrec)

    sigma <- pow(psi, -0.5)
    lambda[1:p] <- pow(lambdasq[1:p], 0.5)
  }
  #data# Y, X, XTX.inv, n, p
  #inits# alpha, beta, psi, lambdasq
  #monitor# alpha, beta, sigma, lambda
"
```

Estimation using JAGS

```
(mod.fit <- run.jags(mod, n.chains = 4, sample = 2500, method = "parallel",
                     n.sims = 4))
```

```
##
## JAGS model summary statistics from 10000 samples (chains = 4; adapt+burnin = 500
##
##              Lower95     Median  Upper95      Mean        SD       Mode
## alpha       -0.42612  -0.049868  0.32838 -0.048748  0.19132  -0.064045
## beta[1]       9.3558     9.7517   10.125    9.7521  0.19742     9.7371
## beta[2]    -0.025936 1.6432e-10 0.068396  0.005928 0.035886 2.0344e-09
## sigma          1.652     1.9006   2.1908    1.9076  0.13874     1.8875
## lambda[1]    0.51966     2.5863   14.589    4.1712   4.4197     1.7098
## lambda[2] 2.0912e-18 1.1621e-08 0.013459 0.0022318 0.008198 7.8042e-10
##
##               MCerr MC%ofSD SSeff      AC.10    psrf
## alpha       0.001931       1  9816   0.010308  1.0001
## beta[1]    0.0019953       1  9789 -0.0051477 0.99987
## beta[2]   0.00066587     1.9  2904    0.16547  1.1782
## sigma      0.0018436     1.3  5664  -0.013357  1.0003
## lambda[1]    0.42891     9.7   106    0.77935  1.0368
## lambda[2] 0.00045661     5.6   322      0.481  1.4582
##
## Total time taken: 2.9 seconds
```

Estimation using JAGS

Estimation using JAGS

Problems

- Trace plot of λ_k can be very erratic, and samples found to be severely autocorrelated.
- Since the scale parameters are very important for Bayesian Variable Selection, it is imperative that these are estimated correctly.
- Suggestions:
  - Improve samples - Hamiltonian Monte Carlo?
  - Treat $\boldsymbol{\lambda}$ as fixed, replacing them with estimates obtained using ML methods.

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3 Bayesian I-prior linear models

4 Hamiltonian Monte Carlo

5 Summary

Introduction

- Introduced as Hybrid Monte Carlo by Duane et. al. 1987 for use in lattice models of quantum theory.
- Statistical applications started appearing in the 1990s: Neal (1993, 1996), Isharawan (1999), Liu (2001).
- Development of HMC software (Stan) began in 2011, motivated by the difficulties faced when doing full Bayesian inference on multilevel generalised linear models (Gelman and Hill, 2007).
- The basic idea behind HMC is to use Hamiltonian dynamics to propose new states, instead of "random walks".

$$\mathbf{x} \xrightarrow[\text{Transition}]{\text{Markov}} \mathbf{x}^*$$

- High probability of acceptance
- Distant move

Hamiltonian dynamics

- A reformulation of classical mechanics which describes motion through Hamilton's equations:

$$\frac{\mathrm{d}\mathbf{x}}{\mathrm{d}t} = \frac{\partial H}{\partial \mathbf{p}} \quad \text{and} \quad \frac{\mathrm{d}\mathbf{p}}{\mathrm{d}t} = -\frac{\partial H}{\partial \mathbf{x}},$$

where $H = H(\mathbf{x}, \mathbf{p})$ is the Hamiltonian of the system (total energy), and $(\mathbf{x}, \mathbf{p})$ are the position and momentum coordinates of the body in motion.

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$$H(\mathbf{x}, \mathbf{p}) = \underbrace{K(\mathbf{p})}_{\text{Kinetic energy}} + \underbrace{U(\mathbf{x})}_{\text{Potential energy}}$$

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Hamiltonian dynamics cont.

- To describe the evolution of $\big(\mathbf{x}(t), \mathbf{p}(t)\big)$ from time t to $t + T$, it is necessary to discretise time and split $T = L \cdot \epsilon$.

Hamiltonian dynamics cont.

- To describe the evolution of $\big(\mathbf{x}(t), \mathbf{p}(t)\big)$ from time t to $t+T$, it is necessary to discretise time and split $T = L \cdot \epsilon$.

- Solve the system of differential equations using Euler's method, or the more commonly used leapfrog integration:

$$\text{Step 1:}\quad \mathbf{p}(t+\epsilon/2) = \mathbf{p}(t) - \frac{\epsilon}{2} \cdot \frac{\partial}{\partial \mathbf{x}} U\big(\mathbf{x}(t)\big)$$

$$\text{Step 2:}\quad \mathbf{x}(t+\epsilon) = \mathbf{x}(t) + \epsilon \cdot \frac{\partial}{\partial \mathbf{p}} K\big(\mathbf{p}(t+\epsilon/2)\big)$$

$$\text{Step 3:}\quad \mathbf{p}(t+\epsilon) = \mathbf{p}(t+\epsilon/2) - \frac{\epsilon}{2} \cdot \frac{\partial}{\partial \mathbf{x}} U\big(\mathbf{x}(t+\epsilon)\big)$$

Steps 1-3 are repeated L times.

Hamiltonian dynamics cont.

Demo

https://haziqjamil.shinyapps.io/hmc1/

Probability and the Hamiltonian

- Given some energy function $E(\boldsymbol{\theta})$ over states $\boldsymbol{\theta}$, the *canonical distribution* of the states $\boldsymbol{\theta}$ is given by the pdf

$$f(\boldsymbol{\theta}) = \frac{1}{Z} \exp\left[-\frac{E(\boldsymbol{\theta})}{kT}\right].$$

where k is Boltzmann's constant, T is the absolute temperature of the system, and Z is a normalising constant.

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- The Hamiltonian $H(\mathbf{x}, \mathbf{p}) = K(\mathbf{p}) + U(\mathbf{x})$ is one such energy function over states $(\mathbf{x}, \mathbf{p})$.
- Notice that the distribution for $\mathbf{x}$ and $\mathbf{p}$ are independent:

$$f(\mathbf{x}, \mathbf{p}) \propto \exp\left[-\frac{K(\mathbf{p})}{kT}\right] \exp\left[-\frac{U(\mathbf{x})}{kT}\right] = f(\mathbf{x}) f(\mathbf{p}).$$

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- Typically, choose T such that $kT = 1$.

Choosing the energy functions

- Using a *quadratic kinetic energy function* $K(\mathbf{p}) = \mathbf{p}^\top \mathbf{M}^{-1}\mathbf{p}/2$ yields a normal density function

$$f(\mathbf{p}) \propto \exp\left[-\frac{1}{2}\mathbf{p}^\top \mathbf{M}^{-1}\mathbf{p}\right],$$

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- As for the potential energy, choose a function such that

$$U(\mathbf{x}) = -\log f(\mathbf{x}),$$

since $f(\mathbf{x}) \propto \exp[-U(\mathbf{x})]$, where $f(\mathbf{x})$ is the target density from which we wish to sample.

Hamiltonian Monte Carlo

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Hamiltonian Monte Carlo cont.

Demo

https://haziqjamil.shinyapps.io/hmc2/

Stan

http://mc-stan.org

- Stan interfaces: R, Python, shell, MATLAB, Julia, Stata, and Mathematica. Runs on Linux, Mac and Windows.
- R package `rstan` uses Stan modelling language. For expression-based Bayesian regression modelling, package `rstanarm` is available.
- Nice things about Stan
  - Tuning is done automatically.
  - Vast library of differentiable probability functions, or code your own.
  - Conjugacy has no computational advantage.
  - Optimising for efficiency possible, e.g. vectorisation.

Stan example

```
stan.iprior.mod <- "
  function {
    ...
  }
  data {
    int n; // number of data
    int p; // number of parameters
    vector[n] Y; // responses
    matrix[n, p] X; // (centred) data
  }
  transformed data {
    matrix[p, p] XTX;
    XTX = X' * X;
  }
  parameters {
    real alpha;  // intercept
    real<lower=0> sigma;  // s.d. of errors
    vector[p] beta;  // regression coefficients
    vector<lower=0>[p] lambda;  // I-prior scale parameters
  }
```

Stan example

```
transformed parameters {
  vector[p] lambdasq;
  cov_matrix[p] Sigma;
  vector[n] mu;
  lambdasq = lambda .* lambda;
  Sigma = diag_matrix(lambda) * XTX * diag_matrix(lambda) ./ (sigma ^ 2);
  mu = alpha + X * beta;
}
model {
  target += inv_gamma_lpdf(lambdasq | 0.0001, 0.0001);
  target += multi_normal_lpdf(beta | rep_vector(0, p), Sigma);
  target += normal_lpdf(Y | mu, sigma);
}
generated quantities {
  ...
}
"
```

Stan example

- Compile the Stan model.

```
m <- stan_model(model_code = stan.mod)
m@model_name <- "iprior"
```

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- Set the data for Stan to use.

```
stan.dat <- list(Y = as.vector(Y), X = Xs, n = n, p = p)
```

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- Set the data for Stan to use.

```
stan.dat <- list(Y = as.vector(Y), X = Xs, n = n, p = p)
```

- Begin sampling

```
fit.stan <- stan(model_code = stan.mod, data = stan.dat,
                 pars = c("alpha", "beta", "lambda", "sigma"),
                 iter = 50000, chains = 4, thin = 10)
```

Stan example

```
print(fit.stan)

## Inference for Stan model: iprior.
## 4 chains, each with iter=50000; warmup=25000; thin=10;
## post-warmup draws per chain=2500, total post-warmup draws=10000.
##
##              mean se_mean   sd    2.5%     25%     50%     75%   97.5%
## alpha       -1.04    0.00 0.19   -1.40   -1.16   -1.04   -0.92   -0.68
## beta[1]      9.71    0.00 0.20    9.32    9.58    9.71    9.84   10.10
## beta[2]      0.07    0.00 0.10   -0.10    0.01    0.06    0.12    0.31
## lambda[1]    2.26    0.03 2.55    0.70    1.14    1.61    2.47    7.78
## lambda[2]    0.03    0.00 0.06    0.01    0.01    0.02    0.03    0.09
## sigma        1.91    0.00 0.13    1.68    1.82    1.91    2.00    2.20
## lp__      -224.20    0.02 1.85 -228.60 -225.24 -223.88 -222.82 -221.62
##           n_eff Rhat
## alpha     10000    1
## beta[1]   10000    1
## beta[2]    9410    1
## lambda[1] 10000    1
## lambda[2]  9972    1
```

Stan example

Stan example

HMC unable to sample from discrete distributions

- HMC requires that the domain of $f(\mathbf{x})$ is continuous and $\partial \log f(\mathbf{x})/\partial \mathbf{x}$ is inexpensive to compute.
- This is a problem for our Bayesian Variable Selection model because we need posterior samples of $\gamma \in \{0, 1\}^p$.
- Three ideas:
  - Marginalise the discrete variables.
  - Use an underlying latent continuous variable.
  - Augment with Gibbs sampling.

Approach 1: Marginalise

- Let $\boldsymbol{\theta}$ be some continuous parameters and γ be some discrete parameters in the model with data $\mathbf{y}$.
- Since unable to sample from $f(\gamma|\mathbf{y})$, integrate out γ from the model, and just sample from the posterior of $\boldsymbol{\theta}$

$$f(\boldsymbol{\theta}|\mathbf{y}) = \sum_{\gamma} f(\boldsymbol{\theta}, \gamma|\mathbf{y}) = f(\boldsymbol{\theta}) \sum_{\gamma} f(\mathbf{y}|\boldsymbol{\theta}, \gamma) f(\gamma)$$

- The unnormalised posterior probability mass function for γ is

$$q(\gamma) = \frac{1}{M} \sum_{m=1}^{M} f(\boldsymbol{\theta}^{(m)}, \gamma|\mathbf{y})$$

  where $m = 1, \ldots, M$ is the index for the posterior draws.
- Problem: For Bayesian Variable Selection models, this is intractable because need to sum over all 2^p models.

Approach 2: Latent continuous variables

- For the Bayesian Variable Selection model, assume there is underlying standard normal random variable Z_j for each $j = 1, \ldots, p$ such that

$$\gamma_j = \begin{cases} 1 & Z_j \geq 0 \\ 0 & Z_j < 0 \end{cases}$$

- Probabilities are preserved: $\mathrm{P}[\gamma_j = 1] = \mathrm{P}[Z_j \geq 0] = 0.5$.
- Problems:
  - Does this make sense?
  - The discrete variables still "exist", so possibly derivatives will break.

Approach 3: Use Gibbs sampler

- Sample the continuous parameters $\boldsymbol{\theta}$ using HMC.
- At each iteration m, use $\boldsymbol{\theta}^{(m)}$ in the Gibbs conditional densities to sample $\boldsymbol{\gamma}$.
- Problem: Have to write code for the HMC sampler, which won't include all the automatic tuning that Stan has.

1 Bayesian Variable Selection

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Summary

- For our I-prior Bayesian Variable Selection model
  - Promising results in both simulated and real-world data.
  - The individual scale parameters $\lambda_1, \ldots, \lambda_p$ are important.
  - We have used ML estimate for $\boldsymbol{\lambda}$ in our Bayesian model.
- Things I want to do
  - Any model consistency results for Bayesian variable selection models?
  - Any mathematical justification as to why we should use individual scale parameters?
  - How does the off-diagonal elements in the I-prior covariance matrix help things?
- Wishlist: Make HMC work for Bayesian variable selection models.

What we've seen today

1. I-prior models estimated using ML methods (EM algorithm) and use of the `iprior` package in R.
2. Shrinkage properties of I-priors for use in Bayesian variable selection.
3. Bayesian estimation in JAGS.
4. Shiny apps for reactive programming.
5. Hamiltonian dynamics and Hamiltonian Monte Carlo.
6. Bayesian inference using HMC via Stan.
7. `knitr` for combining (evaluated) R code and plots into documents.
8. Git and GitHub for version control.

knitr example

- You type:

```
<<chunk.name, echo = TRUE>>=
x <- rnorm(100)
max(x)
hist(x)
@
```

- The output:

```
x <- rnorm(100)
max(x)

## [1] 2.375356
```

```
hist(x)
```

References I

Casella, G. and Moreno, E. (2006).
Objective Bayesian Variable Selection.
Journal of the American Statistical Association, 101(473):157–167.

Dellaportas, P., Forster, J. J., and Ntzoufras, I. (2002).
On Bayesian model and variable selection using MCMC.
Statistics and Computing, 12(1):27–36.

George, E. I. and McCulloch, R. E. (1993).
Variable Selection Via Gibbs Sampling.
Journal of the American Statistical Association, 88(423):881–889.

Kuo, L. and Mallick, B. (1998).
Variable selection for regression models.
Sankhya: The Indian Journal of Statistics, Series B, 60(1):65–81.

References II

McDonald, G. C. and Schwing, R. C. (1973).
Instabilities of regression estimates relating air pollution to mortality.
Technometrics, 15(3):463–481.

Ntzoufras, I. (2011).
Bayesian Modeling Using WinBUGS.
Wiley.

Zellner, A. (1986).
On assessing prior distributions and Bayesian regresison analysis with g-prior distributions.
Bayesian Inference and Decision Techniques: Essays in Honor of Bruno de Finetti, pages 233–243.

HMC References I

Betancourt, M. (2014).
Efficient Bayesian inference with Hamiltonian Monte Carlo.
Machine Learning Summer School (Iceland 2014).
https://www.youtube.com/watch?v=pHsuIaPbNbY.

Betancourt, M. (2016).
Scalable Bayesian Inference with Hamiltonian Monte Carlo.
Tokyo Stan. https://www.youtube.com/watch?v=VnNdhsm0rJQ.

Neal, R. M. et al. (2011).
MCMC using Hamiltonian dynamics.
Handbook of Markov Chain Monte Carlo, 2:113–162.

Stuff I

Chang, W., Cheng, J., Allaire, J., Xie, Y., and McPherson, J. (2016).
shiny: Web Application Framework for R.
R package version 0.13.2.

Plummer, M. (2016).
rjags: Bayesian Graphical Models using MCMC.
R package version 4-6. https://CRAN.R-project.org/package=rjags.

Stan Development Team (2015).
Stan: A C++ Library for Probability and Sampling.
Version 2.10.0. http://mc-stan.org/.

Wickham, H. (2015).
R Packages: Organize, Test, Document, and Share Your Code.
O'Reilly Media, Inc. http://r-pkgs.had.co.nz.

Stuff II

Xie, Y. (2016).
knitr: A General-Purpose Package for Dynamic Report Generation in R.
R package version 1.14. http://yihui.name/knitr/.

End

Thank you!

Minimising profiled deviance (à la `lme4`)

- Very fast algorithm to obtain MLEs of mixed-effects models by using sparse Cholesky decomposition.
- Consider the mixed-effects model

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \mathbf{Z}\mathbf{b} + \boldsymbol{\epsilon}$$
$$\boldsymbol{\epsilon} \sim \mathrm{N}(\mathbf{0}, \sigma^2 \mathbf{I}_n)$$
$$\mathbf{b} \sim \mathrm{N}(\mathbf{0}, \boldsymbol{\Sigma})$$

- Suppose that $\boldsymbol{\Sigma} = \sigma^2 \boldsymbol{\Lambda}_{\boldsymbol{\theta}} \boldsymbol{\Lambda}_{\boldsymbol{\theta}}^\top$. Then the following model is equivalent, where we have used the subsitution $\mathbf{b} = \boldsymbol{\Lambda}_{\boldsymbol{\theta}} \mathbf{u}$:

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \mathbf{Z}\boldsymbol{\Lambda}_{\boldsymbol{\theta}}\mathbf{u} + \boldsymbol{\epsilon}$$
$$\boldsymbol{\epsilon} \sim \mathrm{N}(\mathbf{0}, \sigma^2 \mathbf{I}_n)$$
$$\mathbf{u} \sim \mathrm{N}(\mathbf{0}, \sigma^2 \mathbf{I}_n)$$

Minimising profiled deviance (à la `lme4`) cont.

- The density of interest is $f(\mathbf{y}) = \int h(\mathbf{u})\,\mathrm{d}\mathbf{u}$, where

$$
\begin{aligned}
h(\mathbf{u}) &= f(\mathbf{y}|\mathbf{u})f(\mathbf{u}) \\
&= (2\pi\sigma^2)^{-(n+q)/2} \exp\left[-\frac{\|\mathbf{y} - \mathbf{X}\boldsymbol{\beta} - \mathbf{Z}\boldsymbol{\Lambda}_{\boldsymbol{\theta}}\mathbf{u}\|^2 + \|\mathbf{u}\|^2}{2\sigma^2}\right]
\end{aligned}
$$

Minimising profiled deviance (à la lme4) cont.

- The density of interest is $f(\mathbf{y}) = \int h(\mathbf{u})\,\mathrm{d}\mathbf{u}$, where

$$h(\mathbf{u}) = f(\mathbf{y}|\mathbf{u})f(\mathbf{u})$$
$$= (2\pi\sigma^2)^{-(n+q)/2} \exp\left[-\frac{\|\mathbf{y} - \mathbf{X}\boldsymbol{\beta} - \mathbf{Z}\boldsymbol{\Lambda}_{\boldsymbol{\theta}}\mathbf{u}\|^2 + \|\mathbf{u}\|^2}{2\sigma^2}\right]$$

- Each calculation of $f(\mathbf{y})$ involves obtaining the conditional modes

$$\tilde{\mathbf{u}}(\boldsymbol{\theta}, \boldsymbol{\beta}) = \arg\min_{\mathbf{u}} d(\mathbf{u}, \boldsymbol{\theta}, \boldsymbol{\beta})$$

by computing the sparse Cholesky factorisation

$$\mathbf{L}_{\boldsymbol{\theta}}\mathbf{L}_{\boldsymbol{\theta}}^\top = \boldsymbol{\Lambda}_{\boldsymbol{\theta}}^\top \mathbf{Z}^\top \mathbf{Z}\boldsymbol{\Lambda}_{\boldsymbol{\theta}} + \mathbf{I}_q,$$

and solving $\mathbf{L}_{\boldsymbol{\theta}}^\top \tilde{\mathbf{u}} = c(\boldsymbol{\theta}, \boldsymbol{\beta})$ by back substitution.

Minimising profiled deviance (à la lme4) cont.

- For linear mixed models, $f(\mathbf{y}) = \int h(\mathbf{u})\,\mathrm{d}\mathbf{u}$ has a closed-form expression in terms of $\mathbf{L}_{\boldsymbol{\theta}}$ and $\tilde{\mathbf{u}}(\boldsymbol{\theta}, \boldsymbol{\beta})$:

$$f(\mathbf{y}) = (2\pi\sigma^2)^{-n/2}|\mathbf{L}_{\boldsymbol{\theta}}|^{-1} \exp\left[-\frac{d(\tilde{\mathbf{u}}, \boldsymbol{\theta}, \boldsymbol{\beta})}{2\sigma^2}\right]. \tag{4}$$

- On the deviance scale, we have $D(\boldsymbol{\theta}, \boldsymbol{\beta}, \sigma) = -2\log f(\mathbf{y})$. The value of σ which minimises the deviance is

$$\sigma^2(\boldsymbol{\theta}, \boldsymbol{\beta}) = \frac{d(\tilde{\mathbf{u}}, \boldsymbol{\theta}, \boldsymbol{\beta})}{n}.$$

- Plugging this back into (4), we obtain the profiled deviance

$$D(\boldsymbol{\theta}, \boldsymbol{\beta}) = 2\log|\mathbf{L}_{\boldsymbol{\theta}}| + n\left(1 + \log\left(2\pi\frac{d(\tilde{\mathbf{u}}, \boldsymbol{\theta}, \boldsymbol{\beta})}{n}\right)\right)$$

which is then minimised to obtain MLEs $\hat{\boldsymbol{\theta}}$, $\hat{\boldsymbol{\beta}}$ and $\sigma^2(\hat{\boldsymbol{\theta}}, \hat{\boldsymbol{\beta}})$.

Minimising profiled deviance (à la `lme4`) cont.

- "Eliminate" fixed effects $\boldsymbol{\beta}$.
  - Find conditional modes $\tilde{\boldsymbol{\beta}}(\boldsymbol{\theta})$

$$\begin{pmatrix} \tilde{\mathbf{u}}(\boldsymbol{\theta}) \\ \tilde{\boldsymbol{\beta}}(\boldsymbol{\theta}) \end{pmatrix} = \arg\min_{(\mathbf{u},\boldsymbol{\beta})} d(\mathbf{u}, \boldsymbol{\beta}, \boldsymbol{\theta})$$

via a sparse Cholesky decomposition. Following a similar method as before, obtain a profiled deviance which depends only on $\boldsymbol{\theta}$

$$D(\boldsymbol{\theta}) = 2\log|\mathbf{L}_{\boldsymbol{\theta}}| + n\left(1 + \log\left(2\pi\frac{d(\tilde{\mathbf{u}}, \boldsymbol{\theta}, \tilde{\boldsymbol{\beta}})}{n}\right)\right).$$

Minimising profiled deviance (à la `lme4`) cont.

- "Eliminate" fixed effects $\boldsymbol{\beta}$.
  - Find conditional modes $\tilde{\boldsymbol{\beta}}(\boldsymbol{\theta})$

$$\begin{pmatrix} \tilde{\mathbf{u}}(\boldsymbol{\theta}) \\ \tilde{\boldsymbol{\beta}}(\boldsymbol{\theta}) \end{pmatrix} = \arg\min_{(\mathbf{u},\boldsymbol{\beta})} d(\mathbf{u}, \boldsymbol{\beta}, \boldsymbol{\theta})$$

    via a sparse Cholesky decomposition. Following a similar method as before, obtain a profiled deviance which depends only on $\boldsymbol{\theta}$

$$D(\boldsymbol{\theta}) = 2\log|\mathbf{L}_{\boldsymbol{\theta}}| + n\left(1 + \log\left(2\pi\frac{d(\tilde{\mathbf{u}}, \boldsymbol{\theta}, \tilde{\boldsymbol{\beta}})}{n}\right)\right).$$

  - In addition, use the restricted maximum likelihood (REML) criterion

$$D_R(\boldsymbol{\theta}, \sigma) = -2\log\int f(\mathbf{y})\,\mathrm{d}\boldsymbol{\beta}.$$

    Again, follow similar steps to obtain the profiled REML criterion

$$D_R(\boldsymbol{\theta}) = 2\log(|\mathbf{L}_{\boldsymbol{\theta}}|\mathbf{L}_{\mathbf{X}}|) + (n-p)\left(1 + \log\left(2\pi\frac{d(\tilde{\mathbf{u}}, \boldsymbol{\theta}, \tilde{\boldsymbol{\beta}})}{n-p}\right)\right).$$

Coerce the w I-prior model into a mixed-model

$$
\begin{aligned}
\mathbf{y} &= \boldsymbol{\alpha} + (\lambda_1 \mathbf{H}_1 + \cdots + \lambda_p \mathbf{H}_p)\mathbf{w} + \boldsymbol{\epsilon} \\
&= \underbrace{\begin{bmatrix} 1 \\ \vdots \\ 1 \end{bmatrix}}_{\mathbf{X}} \underbrace{[\alpha]}_{\boldsymbol{\beta}} + \underbrace{\begin{bmatrix} \mathbf{H}_1 & \cdots & \mathbf{H}_p \end{bmatrix}}_{\mathbf{Z}} \underbrace{\begin{bmatrix} \lambda_1 \mathbf{I}_n \\ \vdots \\ \lambda_p \mathbf{I}_n \end{bmatrix}}_{\boldsymbol{\Lambda}_{\boldsymbol{\lambda}}} \mathbf{w} + \boldsymbol{\epsilon} \\
&= \mathbf{X}\boldsymbol{\beta} + \mathbf{Z}\boldsymbol{\Lambda}_{\boldsymbol{\lambda}}\mathbf{w} + \boldsymbol{\epsilon} \\
&= \mathbf{X}\boldsymbol{\beta} + \mathbf{Z}\underbrace{\left(\frac{1}{\sigma^2}\boldsymbol{\Lambda}_{\boldsymbol{\lambda}}\right)}_{\boldsymbol{\Lambda}_{\boldsymbol{\theta}}} \underbrace{(\sigma^2 \mathbf{w})}_{\mathbf{u}} + \boldsymbol{\epsilon} \\
&= \mathbf{X}\boldsymbol{\beta} + \mathbf{Z}\boldsymbol{\Lambda}_{\boldsymbol{\theta}}\mathbf{u} + \boldsymbol{\epsilon}
\end{aligned}
$$

- Our scale parameters are contained in $\boldsymbol{\theta} = (\lambda_1/\sigma^2, \ldots, \lambda_p/\sigma^2)$.
- Problem: Our $\mathbf{Z}$ matrix is dense, so not able to use sparse Cholesky methods.

MLE vs Bayes for scale parameters

- For each $k = 1, \ldots, p$, the maximum a posteriori (MAP) estimate is

$$\begin{aligned}\hat{\lambda}_k^{MAP} &= \arg\max_{\lambda_k} f(\alpha, \boldsymbol{\beta}, \psi, \boldsymbol{\lambda}|\mathbf{y}) \\ &= \arg\max_{\lambda_k} f(\mathbf{y}, \boldsymbol{\beta}|\alpha, \psi, \boldsymbol{\lambda}) f(\psi) f(\lambda_1) \cdots f(\lambda_p) \\ &= \arg\max_{\lambda_k} f(\mathbf{y}, \boldsymbol{\beta}|\alpha, \psi, \boldsymbol{\lambda}) f(\lambda_k)\end{aligned}$$

  whereas the ML estimate is

$$\begin{aligned}\hat{\lambda}_k^{ML} &= \arg\max_{\lambda_k} f(\mathbf{y}; \boldsymbol{\lambda}, \psi) \\ &= \arg\max_{\lambda_k} \int f(\mathbf{y}, \boldsymbol{\beta}; \boldsymbol{\lambda}, \psi)\, \mathrm{d}\boldsymbol{\beta}\end{aligned}$$

- $\hat{\lambda}_k^{MAP} = \hat{\lambda}_k^{ML}$ if the beta I-prior model is marginalised over $\boldsymbol{\beta}$, and a uniform prior is used for each λ_k.