

## 1 Things to discuss

### 1.1 Jin's code

- <https://github.com/ying531/MCMC-SymReg>

### 1.2 The hacky implementation of LinearCoefs means that the first k samples are not proper

### 1.3 Error with how I was tracking the variances

- Each sample has one residual variance
- But each tree has their own linear coefficients variances
- For now hacky fix

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bg,frame=single,framesep=5pt,rulecolor=code-comment,framerule=1pt,language=julia,label=,caption=  
,captionpos=b,numbers=none  $i > k$  ?  $previous_i = i - k$  :  $previous_i = iold_a = chain.samples[previous_i].[:$   
 $a]old_b = chain.samples[previous_i].[: b]$

### 1.4 Acceptance ratio calculation

#### 1.4.1 Error with transition probabilities

- I had MH reversed in my head
- Numerator transition proposal -> old
- Denominator transition old -> proposal

#### 1.4.2 Standard MH

- On Jin's paper they don't use the probability of the LinearCoef
  - I understand not using the probability of jumping between coefficients
    - \* Because it is symmetric (or in this case just from the prior)
- But why not include the probability of each coefficient?

$f(\Theta \mid S)$

- They don't use either the probability of the variances (residuals + LinearCoef)
  - I had already included it in the ratio calculation without RJMCMC because I hadn't noticed they omit it

$p(\Sigma)$

- Maybe I'm just misunderstanding the equations

#### 1.4.3 With RJMCMC

- I was confused with what operations were set notation or vector notation
- The papers/tutorials you sent me have been the best source
- I thought that some notation in Jin's paper were typos, but I think it makes sense now
  - Except 1 on shrinkage
- I need to refactor parts of the code to accommodate the procedure
- ... And I need a bit of scaffolding with the Jacobian D:
  - O Jin's code they use  $2^{\text{no. linear operators}}$ 
    - \* I think

#### 1. Expansion

- (a)  $\Theta$  is the set of old parameters
- (b)  $\Theta^*$  is the set of new parameters
- (c) We sample variances
- (d)  $\dim(u_\Theta) = \dim(\Theta)$
- (e)  $\dim(u_n) = \dim(\Theta^*) - \dim(\Theta)$
- (f) We sample  $u_\Theta$  and  $u_n$  from the prior  $p(\Theta)$
- (g)  $\Theta^* = (\text{mean}(\Theta, u_\Theta), u_n)$  (set addition)
- (h)  $h(U) = \prod^{\vee(u_\Theta \cup u_n)} p(u)$
- (i) We keep  $U^* = \frac{\Theta - u_\Theta}{2}$ 
  - For the jacobian ????

(a) Example

$$(\theta_1, \theta_2) \rightarrow (\theta_1^* \dots \theta_4^*) = j(\Theta, u_\Theta, u_n) = (\theta_1 + u_{\Theta 1}, \theta_2 + u_{\Theta 2}, u_{n1}, u_{n2})$$

$$J = \left| \frac{\partial \Theta^*}{\partial (\Theta, U)} \right| = \left| \frac{\partial j(\Theta, U)}{\partial (\Theta, U)} \right| =$$

$$\begin{vmatrix} \frac{\partial \theta_1 + u_{\Theta 1}}{\partial \theta_1} & \frac{\partial \theta_1 + u_{\Theta 1}}{\partial \theta_2} & \frac{\partial \theta_1 + u_{\Theta 1}}{\partial X} & \frac{\partial \theta_1 + u_{\Theta 1}}{\partial X} \\ \frac{\partial \theta_2 + u_{\Theta 2}}{\partial \theta_1} & \frac{\partial \theta_2 + u_{\Theta 2}}{\partial \theta_2} & \frac{\partial \theta_2 + u_{\Theta 2}}{\partial X} & \frac{\partial \theta_2 + u_{\Theta 2}}{\partial X} \\ \frac{\partial u_{n1}}{\partial \theta_1} & \frac{\partial u_{n1}}{\partial \theta_2} & \frac{\partial u_{n1}}{\partial X} & \frac{\partial u_{n1}}{\partial X} \\ \frac{\partial u_{n2}}{\partial \theta_1} & \frac{\partial u_{n2}}{\partial \theta_2} & \frac{\partial u_{n2}}{\partial X} & \frac{\partial u_{n2}}{\partial X} \end{vmatrix}$$

- What are  $X$ ?
  - Could be  $u_\Theta$
  - or  $u_n$
  - or this doesn't make sense?

## 2. Shrinkage

(a)  $\Theta$  is the set of old parameters

(b) We sample variances

(c)  $\Theta_0$  are the parameters we keep

(d)  $\Theta_d$  are the parameters we discard

(e) We sample  $U$  of size  $\dim(\Theta_0)$  from  $N(0, \sigma_{ab}^2)$

(f)  $\Theta^* = \Theta_0 + U$  (vector addition)

- $\theta_i^* = \theta_i + U_i$

(g)  $h(U) = \prod^{U_i} p(U_i)$

(h) We keep  $U^* = (\Theta - U, \Theta_0)$  (set addition)

- For the jacobian ????

(a) Example

$$(\theta_1 \dots \theta_4) \rightarrow (\theta_1^*, \theta_2^*) = j(\Theta, U) = (\theta_1 + U_1, \theta_2 + U_2)$$

$$J = \left| \frac{\partial \Theta^*}{\partial (\Theta, U)} \right| = \left| \frac{\partial j(\Theta, U)}{\partial (\Theta, U)} \right| =$$

$$\begin{vmatrix} \frac{\partial \theta_1 + U_1}{\partial \theta_1} & \frac{\partial \theta_1 + U_1}{\partial \theta_2} & \frac{\partial \theta_1 + U_1}{\partial \theta_3} & \frac{\partial \theta_1 + U_1}{\partial \theta_4} \\ \frac{\partial \theta_2 + U_2}{\partial \theta_1} & \frac{\partial \theta_2 + U_2}{\partial \theta_2} & \frac{\partial \theta_2 + U_2}{\partial \theta_3} & \frac{\partial \theta_2 + U_2}{\partial \theta_4} \\ \dots & & & \\ \dots & & & \end{vmatrix}$$

- What are the other two rows?
  - The  $U$ s sampled?
    - \* Shouldn't them be on the denominators as well?
  - Or what happens with the  $U$ \*s?
  - Or this doesn't make sense?

$$\begin{vmatrix} \frac{\partial \theta_1 + U_1}{\partial \theta_1} & \frac{\partial \theta_1 + U_1}{\partial \theta_2} & \frac{\partial \theta_1 + U_1}{\partial \theta_3} & \frac{\partial \theta_1 + U_1}{\partial \theta_4} \\ \frac{\partial \theta_2 + U_2}{\partial \theta_1} & \frac{\partial \theta_2 + U_2}{\partial \theta_2} & \frac{\partial \theta_2 + U_2}{\partial \theta_3} & \frac{\partial \theta_2 + U_2}{\partial \theta_4} \\ \frac{\partial U_1}{\partial \theta_1} & \frac{\partial U_1}{\partial \theta_2} & \frac{\partial U_1}{\partial \theta_3} & \frac{\partial U_1}{\partial \theta_4} \\ \frac{\partial U_2}{\partial \theta_1} & \frac{\partial U_2}{\partial \theta_2} & \frac{\partial U_2}{\partial \theta_3} & \frac{\partial U_2}{\partial \theta_4} \end{vmatrix}$$

## 1.5 Type stability

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- Why??
- If I force step(...)::Sample, the warning disappears (as expected)
- No performance differences
- FIXED: NaN return when optim ! failed.
- I believe all the program is type stable now.

## 1.6 ExprBugs

- There weren't any bugs :D
  - Couldn't reproduce them
  - I misunderstood how mutation, scope, and assigning(=) worked before when I thought there were bugs.
- (apart from the insert! one)
  - <https://github.com/sisl/ExprRules.jl/pull/31>

## 2 Notes