

WEEK 1 SUMMARY

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1. Nonzero gamma. I finished implementing the model that handles nonzero γ in the likelihood. I ran some experiments using this algorithm on the voting records data set: $\beta = 0.9$ allowed for an acceptance probability of around 40%, and $\gamma = 1$ correctly classified around 87% of the unlabeled senators. See [Figure 1](#), [Figure 2](#). The full parameters of the run are as follows:

Iterations	10000
Burn in period	5000
Weight function parameters (p, q, l)	$(2, 2, 1)$
β	0.9
γ	1
τ	0
α	1
Labeled +1	280, 281, 282, 283
Labeled -1	25, 26, 27, 28
Percent of correct classification	0.868852

FIG. 1. *Average of sign sample vector post burn-in period*

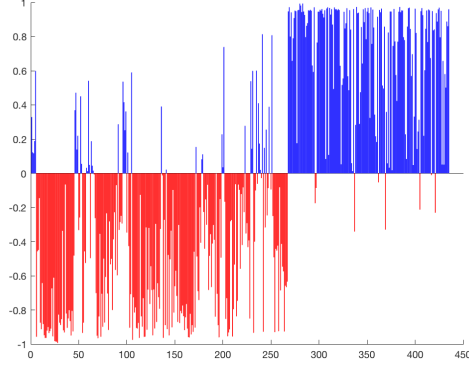
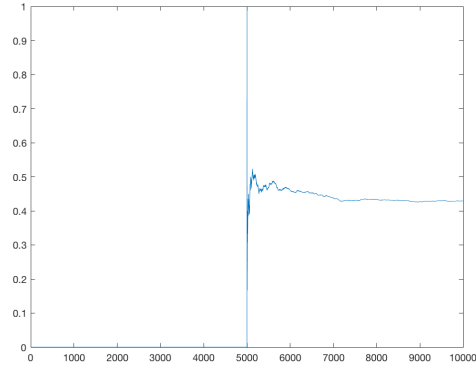


FIG. 2. *Running average of MCMC acceptance probability post burn-in period*



2. Learning τ, α . I implemented [Algorithm 1](#), a hierarchical algorithm on τ and α . I additionally restricted the proposals for $\tau \in [0, 1]$ and $\alpha \in [0, 10]$. The results do not indicate that the MCMC is converging on a value for τ, α at 100,000 iterations, so maybe there is a bug

Algorithm 1 Hierarchical on τ, α

Initialize $\mu^{(0)} = (0, 1, 0, 0, \dots)$, which is the Fiedler vector written in the orthonormal basis of the eigenvectors
Initialize $u^{(0)}$ as $\mu^{(0)}$ expressed in the standard basis.
Initialize $\tau^{(0)}, \alpha^{(0)}$. Select $\beta \in [0, 1]$
Initialize ϵ
for $i = 0$ to n **do**
 Sample ξ from the prior distribution and expressed in the eigenbasis $\triangleright u|y, \tau, \alpha$
 Set a proposal $\nu^{(i)} = (1 - \beta^2)^{1/2} \mu^{(i)} + \beta \xi$
 Compute $v^{(i)}$ as $\nu^{(i)}$ in the standard basis
 Set $u^{(i+1)} = v^{(i)}$ and $\mu^{(i+1)} = \nu^{(i)}$ with probability $\min(1, \exp(\Phi(u^{(i)}) - \Phi(v^{(i)})))$
 Set a proposal $t^{(i)} = \tau^{(i)} + \epsilon \zeta^{(i)}$ for $\zeta^{(i)} \sim N(0, 1)$ $\triangleright \tau|y, u, \alpha$
 Set $\tau^{(i+1)} = t^{(i)}$ with probability given by the ratio between the joint posterior functions on u, τ, α : $f(\mu^{(i+1)}, t^{(i)}, \alpha^{(i)})/f(\mu^{(i+1)}, \tau^{(i)}, \alpha^{(i)})$ (using the eigenbasis representation to simplify computation)
 Set a proposal $a^{(i)} = \alpha^{(i)} + \epsilon \zeta^{(i)}$ for $\zeta^{(i)} \sim N(0, 1)$ $\triangleright \alpha|y, u, \tau$
 Set $\alpha^{(i+1)} = a^{(i)}$ with probability given by $f(\mu^{(i+1)}, \tau^{(i+1)}, a^{(i)})/f(\mu^{(i+1)}, \tau^{(i+1)}, \alpha^{(i)})$
end for
return u, τ, α

in the algorithm or the code. Some of the gathered results follow. The parameters omitted in the following tables have the same values as in the nonzero gamma MCMC.

Iterations	100000
Burn in period	50000
ϵ	0.1
Initial τ	0
Initial α	1
Average τ	0.304877
Average α	7.014584
Percent of correct classification	0.871194
Time elapsed	918.02 s

Iterations	100000
Burn in period	50000
ϵ	0.1
Initial τ	0.5
Initial α	0.5
Average τ	0.154294
Average α	2.960191
Percent of correct classification	0.868852
Time elapsed	925.47 s

FIG. 3. $\tau^{(0)} = 0, \alpha^{(0)} = 1$, τ acceptance probability

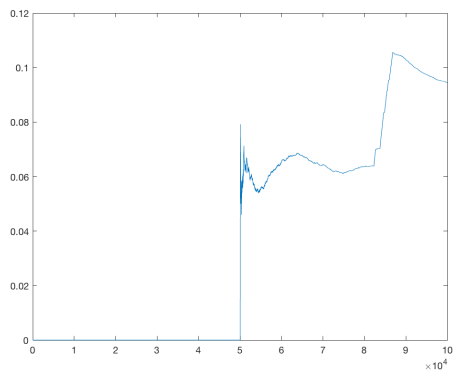


FIG. 4. $\tau^{(0)} = 0.5, \alpha^{(0)} = 0.5$, τ acceptance probability

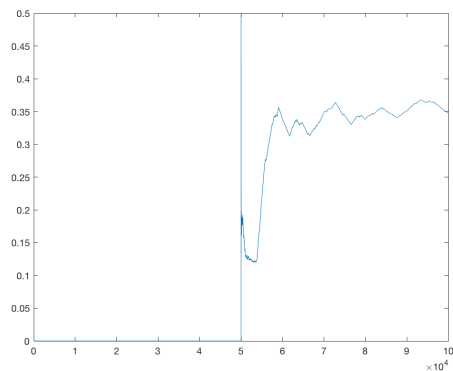


FIG. 5. $\tau^{(0)} = 0, \alpha^{(0)} = 1$, τ average

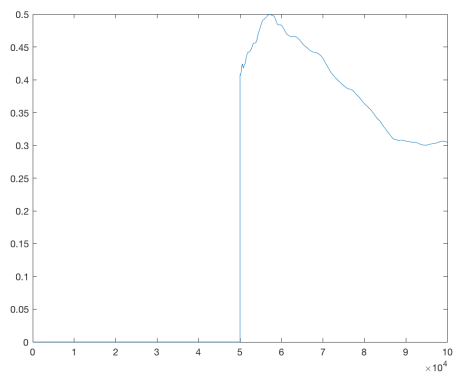


FIG. 6. $\tau^{(0)} = 0.5, \alpha^{(0)} = 0.5$, τ average

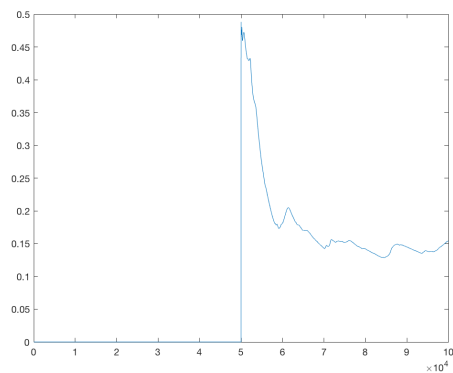


FIG. 7. $\tau^{(0)} = 0, \alpha^{(0)} = 1$, α acceptance probability.

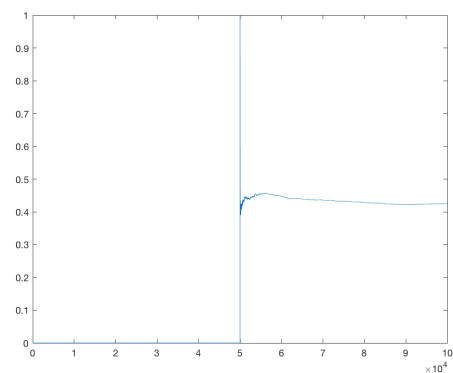


FIG. 8. $\tau^{(0)} = 0.5, \alpha^{(0)} = 0.5$, α acceptance probability.

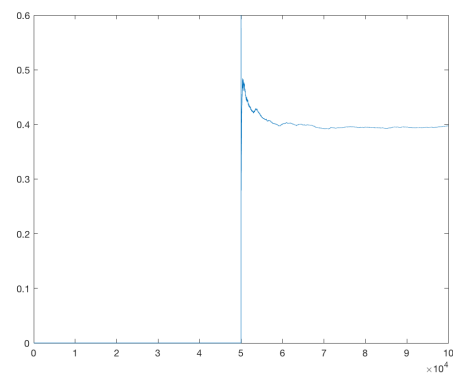


FIG. 9. $\tau^{(0)} = 0, \alpha^{(0)} = 1, \alpha$ *average*

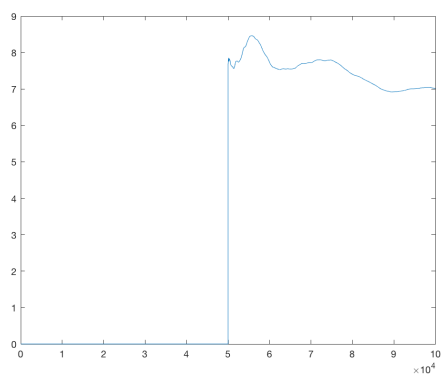


FIG. 10. $\tau^{(0)} = 0.5, \alpha^{(0)} = 0.5, \alpha$ *average*

