Thesis Bayesian Notes

* **Bayes factor** performance (TYP1 and TYPE 2 error probs) compared to classical null hypothesis test for correlation coefficients (for relative small samples *Fosdick Raftery 2012 Estimating the correlation in bivariate normal data with known variances and small sample sizes*). What about unknown variance? What about both unknown? Also, testing intraclass correlation is interesting.
* **BSEM** – Improving the measurement invariance model testing by placing priors on otherwise constrained/fixed parameters (loadings and intercepts) (Muthen, Asparouhov 2010)
* **Specifying non-informative priors for variance parameter** in hierarchical modeling (Gelman 2006). Figure 1. Extend to random slopes and intercepts. Find a dataset 50 obs or more and just take a look at small number of groups Matrix generalize dversio of inv. Invers wishart look into it. Write gibbs for random intercept and extedn to random intercept and random slope. Winbugs, openbugs. Matrix F prior estimating tsting covariance matrix. Book 114. Inverse Wishart is equivalent of to inv gamma and find the . Bayesian multilevel few groups . Maybe do ML esitimate and wha if you do Bayesian use in-wishart similar to inv-gama .0001. Logitudinal Mixeddata Anlaysis. For refresher f

General Idea: Specifying a non-informative prior for variance component in hierarchical models can be tricky. Gelsman 2006 has already showed how one of the standard priors used by programs such a Stan and Winbugs is actually problematic (the inv-gamma(.0001, .0001). What Gelsman did relates to random intercepts models, what we would like to do is extend his analysis to a random intercept random slope model where we need to specify a prior for the sigma matrix (variances of the random slopes and intercepts and covariance). The usual approach (common in Stan and Winbugs) is to use an inv-Wishart distribution as a prior for the sigma matrix. There is an approach to making this distribution non-informative that is equivalent to the inv-gamma used for the random intercept case. We would like to show the problems of this approach in a similar fashion to what Gelsman 2006 does in figure 1.

Steps:

* Generate data (function to generate data that can be analyzed w/ random intercept random slopes approach.
* Fit RI-RS model w/ Wishart prior. Here you can first try to use Stan (and or Stan packages for R, some links: [1](http://www.maths.bath.ac.uk/~jjf23/stan/), [2](https://rpubs.com/kaz_yos/stan-multi-1)) and then try to replicate the results with a Gibbs sampler (to fit RI-RS model with invers Wishart prior) programmed by you. This should be shown on both real datasets (e.g. see data used in link 1 of this bullet point) and simulated ones.
* A third step will be to fit the Wishart model a Matrix F prior distribution as suggested in Mulder Pericchi 2018 (to read) and compare results. The comparison should be between a regular ML fit, a Bayesian Framework fit with inv-Wishart and a Bayesian Framework with Matrix F distribution as prior.

Notes and Refreshers:

* Longitudinal Mixed data analysis book for overview of mixed model framework of interest (repeated measures) (page 114 in particular for the type of data that you want to work with). Maybe alternative book Linear Mixed Models for Longitudinal Data
* Review prior use in regression, in estimate of the variance components (start with Hoff 2009, then move to more in-depth material such as Browne and Draper 2005 (“A comparison of Bayesian and likelihood-based methods for ﬁtting multilevel models.” Bayesian Analysis, This issue.) or other material suggested by Gelman 2006