Dr. Carl F. Falk
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The following are intended to give you an idea of what the scope may be for a final project idea. It is possible that some of you may pursue ideas along these lines. Of course, you should provide some more detail than I provide here. I may provide some advice on how the complexity of the model and/or examined conditions can be scaled up or down as there may be some kind of interaction between how complicated the model is, how much manual coding is done, your prior level of statistical computing experience, and if you want to ideally aim for something in the long-term that actually is publishable. Proposals should be challenging, but achievable by you.

Example Final Project Ideas:

1. Implement ML estimation and standard error estimation for some model that we have not already done so during labs/assignments. Check that it is implemented correctly in a small set of simulations and/or by checking against extant software.
2. Conduct a small simulation study to compare Wald, Likelihood ratio, and/or Score tests for some novel data/model that we have not examined in simulations in class. That is, compare Type I error and Power rates under a small number of conditions designed to tease apart when we might expect similarities/differences among the methods.
3. Simulate data under some known model, but estimate a misspecified model. Examine whether some search procedure can recover the true model. The search procedure could be in line with what MacCallum has tried, or some alternative approach. Do this more times – either multiple replications of the same procedure, or 2+ situations where the models may differ in terms of degree of misspecification. It does not have to be a large set of simulations, but you should have some theoretical expectations regarding what will happen for the examined models or conditions.
4. Manually estimate a model with Metropolis w/in Gibbs sampling; it should be some model we have not already done this for in lab/assignments. Check that it is implemented correctly in a small set of simulations (note: you will only get back the model parameters if priors are weak and/or sample size is very large).
5. While Metropolis w/in Gibbs is implemented for a logistic regression, the sensitivity of the estimates to different prior distribution specifications or at different sample sizes has not yet been investigated. This could be explored in a very small set of simulations for this or some other model.
6. Replicate some results from Vrieze (2012) in terms of which models AIC and BIC tend to pick. You do not necessarily have to replicate all simulation studies or all conditions, just a subset.
7. Conduct a small simulation to assess the assertion that sandwich covariance matrices (vs other ways to estimate standard errors) accurately estimate standard errors when there is some kind of misspecification. Typically this will involve simulating data under either correctly or incorrectly specified models, then examining whether the average obtained standard error matches that of the actual standard deviation of estimates

across simulated datasets. Type I error, coverage rates of confidence intervals could also be outcomes, depending on how misspecification is set up (i.e., these are easiest if the misspecification is distributional, which is also easiest if the model assumes normal data and some technique for nonnormal data generation is used).

8. Create a function to compute the criterion used in the Alignment method, and test it on an example dataset using some built-in optimizer (e.g., such as nlm). Report point estimates of item parameters afterwards. Side-note: if you are trying to replicate Mplus, note that this is more difficult than you may think; get in touch if you are trying this option.
9. Implement the delta method or likelihood-based confidence intervals for some novel quantity of interest and/or model that is not already discussed in the relevant notes. The interest in the new quantity/model should be theoretically motivated to some extent and quite different than what is already illustrated in notes. Check that it is implemented correctly with a small simulation study or by checking it against extant software.

Most of the above ideas are within the realm of things we have discussed or have covered in the class to some extent, and are vaguely described in terms of the particular models or research questions. I could of course say more about specific things that are of curiosity (e.g., below), though I cannot say for sure whether any of these are publishable:

1. Comparison of sandwich standard errors vs. likelihood-based intervals for inference and interval estimation of variance components in multilevel models or in latent growth curve models. Which is better when distributional assumptions are violated?
2. Compare stochastic information complexity (SIC) to AIC and BIC for selecting among candidate models. This may require you to manually implement SIC, depending on the model. I may prefer if you do not do this for SEM as I have extant research in this area and wish to avoid overlap with student final projects. Other types of models are possible candidates.
3. This approach to estimating sandwich covariance matrices in SEM is severely understudied: https://doi.org/10.1080/10705511.2018.1505522. Even just replicating some of the simulation study results could be attempted. Note: the coding involved may be challenging.
4. Simulate data under conditions in which Heywood cases are very common (i.e., negative variance estimates) or under which a similar phenomenon occurs in multilevel modeling. Explore whether Bayes modal estimation is a viable remedy to this problem, along the lines of the following paper, but not requiring MCMC: https://psycnet.apa.org/doi/10.1037/met0000435
5. Simulated annealing can be implemented for different model specification searches; the search space is discrete, which may require some modification of the code I have provided. A simple example would be the inclusion/exclusion of predictors in a multiple linear regression model, but other novel applications could be examined.

6. An alternative to simulated annealing is a simultaneous perturbation stochastic approximation method. This could be implemented; would likely be quite challenging.
7. We have not yet had time to discuss approaches to estimating models when there is missing data. Direct maximum likelihood could be manually implemented for some models.