Rejoinder

Default Priors and Robust Estimation for Generalized Linear Models

LPEPs

- Is there a way to address potential misspecification?
  - Great question! We have not thought much about this.
  - Using power **likelihoods** (in addition to power **priors**) seems like a good option indeed.
  - Results cited seem to focus on parameter estimation. Would they extend to **model** selection? Maybe a collaboration?
- Poor performance as the number of non-zero coefficients in the true model increases?
  - Strong impact of prior on model spaces often goes unacknowledged.
  - Some of what you are seeing is because Beta-Binomial(1,1) prior on model space heavily favors sparsity!

LPEPs

- What is needed to generalize to the case when p grows with n? Is there any hope for p = n or p > n?
  - We have worked on consistency results when p grows with n
  - Theory is based on asymptotic behavior of BIC, it does include some strong constraints on the rate of growth and the models under consideration
  - For p=n or p>n we likely need to drop the standard practice of n*=n and X*=X
  - Another answer (channeling Perichi): **use the intrinsic prior**
  - In binary regression, we need to be careful about avoiding separation
- Catalytic prior distributions (Huang, Stein, Rubin, and Kou (2020))?
  - Thank you for the reference, we will include it in the revised paper!
  - Very close to PEPs, different way to choose X*
  - Paper seems to be focused on estimation rather than model selection.
  - We have tried using non-null models for m*, with terrible results

Spherical models

- Any guidance to choosing the geometry/manifold family? Are nested manifolds preferable?
  - Difficult question!
  - In our case, the choice of geometry was driven by the application (horseshoe theory)
  - In the context of network data, some guidance has been developed to select between constant-curvature manifolds (session at ISBA 2022)
  - Extensive CS/ML/Math literature on "geometric embeddings". Focused
- Can we benefit from the existing literature on priors on manifolds

Spherical models

- Can we benefit from the existing literature on priors on manifolds?
  - The short answer is yes!
  - One difference between our work and most of the paper referenced is that it is not the observed data that lives in the (interesting) manifold. Instead, the manifold corresponds to a latent space
  - Priors need to be flexible enough to capture the properties that we need!