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Rejoinder

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We appreciate the many insightful comments and critiques in the discussions. Several discussions pointed out important BNP models and classes of problems that we missed in the paper. **Gelman** proposes consideration of models for classification trees (CART, BART). We actually considered including the Bayesian CART (Chipman et al. 1998; Denison et al. 1998) in the review paper, and strongly agree that models like the BART model (Chipman et al. 2010) turn out to be amazingly versatile in many applications. **Kolossiatis** draws attention to recent literature on correlated NRMI's as an alternative to DDP priors for multiple related random probability measures. We appreciate the discussed models as alternatives to the DDP, and also for their elegance. See Sections 2.3. and 4.3. of the main paper for the definition of NRMI's and the DDP model. **Kottas, DeYoreo** and **Poynor** highlight curve fitting regression approaches as another important alternative implementation of fully nonparametric regression. We strongly agree and appreciate that their discussion added this important class of approaches to the review. **Perron** mentions models for copulas. **Tokdar** reviews quantile curves as another great example for problems where principled BNP inference can address limitations in currently used approaches.

Several discussions highlight some features and limitations of BNP inference, beyond what is already discussed in the paper. **Robert** and **Rousseau** point out that while asymptotic properties of the estimation of the random curve or probability measure are understood for many BNP priors, asymptotics for other important inference summaries are not. We agree that this is an important current limitation of BNP and thank the discussants for highlighting this issue. **Carlin** and **Murray** give a spirited discussion as die hard Bayesian parametricians. By re-analyzing some of the data used in the paper they argue for alternative parametric models. We comment on details for the specific examples below. But we agree with the overall assertion that well chosen parametric models can often achieve similarly flexible inference. **Parmigiani** and **Trippa** make a related comment, by pointing out the sometimes blurred nature of the boundary between parametric and BNP methods in Bayesian inference. **Hoff** argues that BNP priors in practice rarely represent actual prior beliefs. In many cases, and with respect to many details of the BNP prior, this is probably true. However, several steps can be taken, and are used by many authors, to mitigate this concern. Many BNP priors allow convenient prior centering. In the manuscript we discussed this for the DP and the PT prior. Also, investigators can use prior simulation to verify that typical prior realizations do in fact match actual prior beliefs. We did this, for example, when setting up the prior in Example 4 (Berger et al. 2012). However, in many cases BNP priors include features that are not directly related to actual prior information. For example, the hierarchical prior on the partition boundaries in mixture of PT models is used only to reduce the posterior sensitivity with respect to partition boundaries. Hoff's discussion

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