Journal of Data Science 23 (1), 48–51
January 2025
DOI: 10.6339/25-JDS1161A
Discussion

Discussion of "Power Priors for Leveraging Historical Data: Looking Back and Looking Forward"☆

Lei Nie[1]

[1]DB IV/OB/OTS/CDER/FDA, 10903 New Hampshire Ave, Silver Spring, MD 20993, USA

It is a privilege to serve as a discussant for the paper titled *"Power Priors for Leveraging Historical Data: Looking Back and Looking Forward"* by Dr. Chen and colleagues (Chen et al., 2025). The authors provide a comprehensive discussion of power priors, highlighting their development, extensions and variations, versatility, and tremendous applications. They also present a list of available software for implementing power priors and references that guide readers in understanding the theoretical justification of the power priors and their connections to other Bayesian methods, including the Bayesian Hierarchical Models (BHM). Additionally, they offer valuable practical considerations for real-world applications and propose directions for future research.

This commentary focuses on two key scientific aspects. First, it seeks to appreciate the contributions of the authors while reflecting on the broader implications of power priors, including their connections to related methodologies. These include BHMs, variations such as commensurate power priors, partial and by-part borrowing power priors, and their potential influence on other methods like elastic priors, robust meta-analytical mixture priors, and self-adapting mixture priors. Second, it reflects on considerations in the elicitation of the discounting parameter a_0, which determines the level of borrowing.

By introducing the discounting parameter a_0, power priors offer a systematic way to integrate historical data with current data while controlling the weight given to the historical data. As demonstrated in Ibrahim, Chen and Sinha (2003), the power prior g minimizes the weighted sum of Kullback–Leibler (KL) divergences of $(1-a_0)K(g|f_0 + a_0K(g|f_1)$, where $K(g|f_0)$ is the KL divergence between g and f_0, the density function of the parameter of interest when only the current data is used, and $K(g|f_1)$ is the KL divergence between g and f_1, the density function of the parameter of interest when the current and historical data are pooled. In addition, as discussed in Chen and Ibrahim (2006), power priors are strongly related to BHM in the sense that a particular selection of a_0 could match a BHM. Because of the relationship, elicitation of a_0 using the historical data can be made to match the equivalent BHM as an option. As for BHM, when the number of historical studies is small, results can be sensitive to the selection of hyperpriors Gelman et al. (1995). For further insights, refer to Chu and Yuan (2018); Freidlin and Korn (2013); Jiang et al. (2021). Compared to Bayesian hierarchical models, which rely on current and historical data to determine the borrowing strength, power priors offer additional flexibility for determining a_0 by incorporating auxiliary covariates or external information, such as covariates or data-generating mechanism, to better understand the similarity or differences between the current and historical data.

This flexibility is further explored in Robust Meta-Analytic Predictive Priors $(1-w)P_V(\theta)+wP_I(\theta)$ in Schmidli et al. (2014), where $P_V(\theta)$ represents a noninformative prior and $P_I(\theta)$ is an empirical distribution derived from meta-analysis of the historical data. Determining w, similar to determining a_0, remains a significant challenge. The ideal weight should accurately reflect the

☆Main article: https://doi.org/10.6339/24-JDS1161.

degree of relevance of the historical data to the current data and the congruence between the two datasets. Unfortunately, the information is typically unknown at the design stage of the study, making it difficult to pre-specify these values. Two potential approaches are worth considering addressing this issue. First, a_0 and the weight w could be determined through dynamic borrowing based on observed data, as illustrated in a self-adapting mixture (SAM) prior in the work of Yang et al. (2023). Second, a_0 and the weight could also be determined by additional information or external outcome that would predict the expected congruence between the two datasets, which will be further discussed below.

The flexibility of power priors is further enhanced by exploring variations like normalized power priors Neuenschwander, Branson and Spiegelhalter (2009), commensurate power priors Hobbs et al. (2011), partial borrowing power priors Shi et al. (2022), borrowing-by-part power priors Yuan, Chen and Zhong (2021), individualized subject-level power priors Wang et al. (2022), These approaches make personalized/subgroup-specific borrowing more feasible, a feature not easily achievable by some other methods.

The primary objective of the elastic prior shares a common goal with that of power priors. By using any $0 < a_0 < 1$, the information contained in the historical data would be "reduced" and the variance would be "inflated". The power priors are analogous to a likelihood derived from the same sufficient statistic but with a variance that is inflated by a factor of $1/a_0$. In equivalent terms, this corresponds to a discounted historical sample size of $n_0 = a_0 \times n$. The elastic prior is formulated by inflating the variance of the posterior distribution derived from external data, through an inverse elastic function $g(T)$, and the degree of inflation is determined by the degree of similarity of the current and historical data and by the control of a utility function, Jiang, Nie and Yuan (2023). The elastic prior approach focuses exclusively on the parameter of interest, which is similar to the idea of partial borrowing power priors.

The power priors are attractive as the discounting parameter is straightforward to interpret. As the authors noted, eliciting a is of utmost importance, yet it presents a notable challenge in determining the level of borrowing. However, the challenge is not unique to power priors as determination of an adequate level of borrowing is a shared goal across all Bayesian approaches. While the authors have already presented many excellent works and ideas, a few additional reflections are shared below for consideration.

1. Fixed a_0 or random: Whether a_0 is treated a fixed value or a random variable is a matter of choice. When it is considered a fixed value, specific value(s) for a_0 are selected; When treated as a random variable, specific prior distribution(s) for a_0 are chosen. The selections of the value(s) or prior distribution(s) is critical for its implementation.
2. Tipping point analysis: One may construct a range of a_0 values (or prior distributions), assess how sensitive the results are to the choices of a_0, and finally identify the threshold value that would tip the conclusion. See FDA (2019) for a demonstration of the idea.
3. Elicitation based on current and historical data of outcome of interest: To facilitate the choice of a_0, some criteria, e.g. Ibrahim et al. (2015) or utility functions e.g. Jiang et al. (2023) could be used to determine borrowing strength. The criteria and utility function, relying only on outcomes of interest from current and historical studies used to construct power priors, should generally help to reduce prior-data conflict to minimize erroneous conclusions.
4. Elicitation based on additional information or external outcome. There is merit to determine the borrowing strength based on external information such as facts about or scientific understanding of the expected similarities and difference between the current and historical data. To highlight the importance of this approach, let us consider a hypothetical scenario where two identically designed and conducted studies, in the same concurrent populations, give

very different results. If we rely solely on the outcomes of interest themselves, an adequate Bayesian method would generally discourage borrowing information across the two studies. However, since they are identically designed and conducted studies, one should strongly encourage borrowing information across studies to adequately estimate the parameters. Similar to eliciting subjective prior distributions from experts, we can establish priors based on the additional information or external data; unlike the former, we use information, scientific factors or assumptions, to inform the similarity between current and historical data.

In conclusion, Dr. Chen and colleagues have provided a comprehensive overview of power priors and their applications. This paper not only enhances our understanding of power priors but also invites further exploration of related methodologies. I commend the authors for their thoughtful work and encourage continued research into practical implementations and innovative extensions of these methods. Thank you for the opportunity to engage with this important contribution.

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