Nonparametric Bayesian approach for Cost-Effectiveness Analyses

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Monetary Value

$$MV^a(\kappa) = T^a\kappa - Y^a$$

Consider some existing cancer therapy (e.g. radiation vs. chemo, proton vs. photon, etc).

- Upon diagnosis, patients assigned some treatment $A = a$.
- Patients followed up for some period of time.
- Record effectiveness measure: survival time, T.
- Record cost measure: accrued costs ($), Y.

Formalizing our Questions

- Is treatment 1 any more or less cost-effective than treatment 0, on average?

$$E[NMB(\kappa)] = E[MV^1(\kappa) - MV^0(\kappa)]$$

- Are there subgroups with different cost-effectiveness profiles?
  $\exists\, L \subset \mathcal{L}$ such that

$$E[NMB(\kappa)] \neq E[NMB(\kappa) \mid L] \;?$$

Joint Cost-Effectiveness Model

Suppose we observe $D = \left\{ Y_i, T_i, \delta_i, X_i \right\}_{1:n}$

$$p(Y_i, T_i \mid X, \delta_i, \omega_i, \theta_i, \lambda_0) = p(Y_i \mid T_i, X, \delta_i, \omega_i) p(T_i \mid X, \delta_i, \theta_i, \lambda_0)$$

This distribution can be very complicated.

Conditional Cost Model

Let $\omega_i = (\beta_i, \phi_i)$

$$Y_i \mid T_i, X_i, \delta_i, \omega_i \sim \log N((X_i, T_i, \delta_i)'\beta_i, \phi_i)$$

Survival Time Model

$$T_i \mid X_i, \delta_i \sim \lambda_0(t)\exp\left(X_i'\theta_i\right)$$

Gamma Process Prior for Baseline Hazard

$$\lambda_0 \sim \mathcal{GP}\Big(b\lambda_0^*, b\Big)$$

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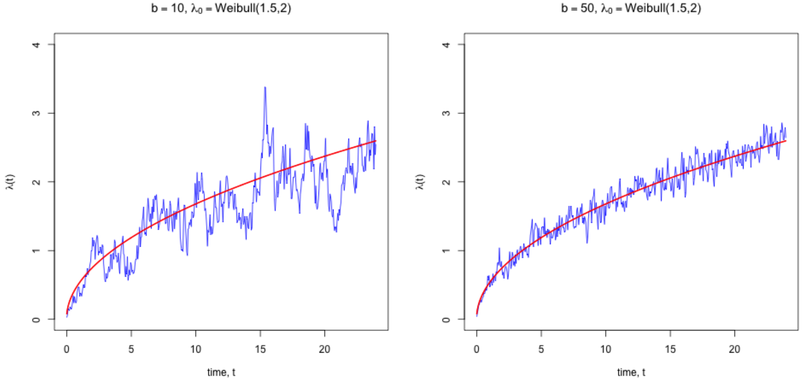

EDP Prior for Covariate Effects

$$\omega_i, \theta_i \sim G$$
$$G \sim EDP\left(\alpha_\omega, \alpha_\theta, G_0\right)$$

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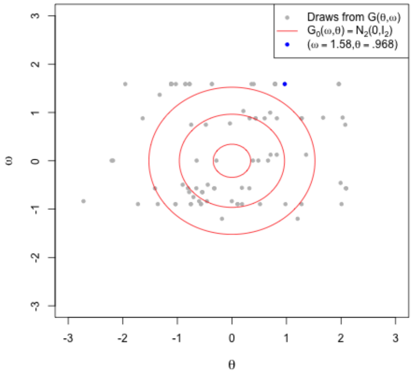


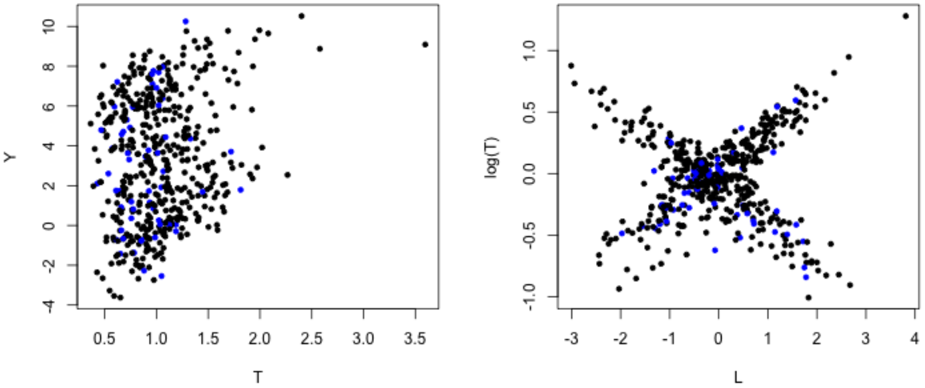
Markov Chain Monte Carlo (MCMC) used to obtain J draws from the posterior $\left\{\theta_{1:n}^{(j)}, \omega_{1:n}^{(j)}, \lambda_0^{(j)}\right\}_{j=1:J}$.

Non-parametric standardization

$$E[MV^a(\lambda) \mid \omega_{1:n}, \theta_{1:n}, \lambda_0] = \int_{\mathcal{L}} \int_{\mathcal{Y} \times \mathcal{T}} (\kappa T - Y) dP(Y, T \mid L, A = a, \omega_{1:n}, \theta_{1:n}, \lambda_0) dP(L)$$

- Bayesian bootstrap estimate of $P(L)$.

Synthetic Example



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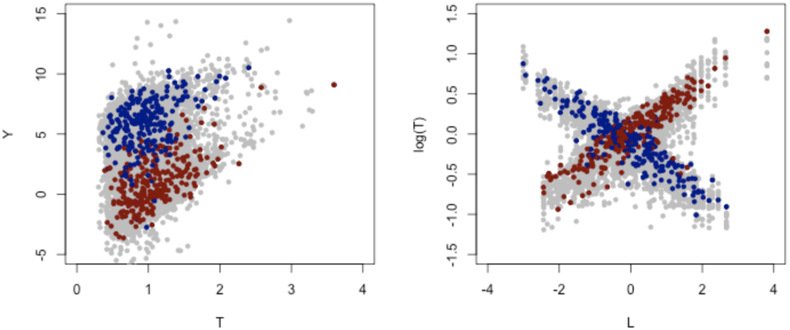

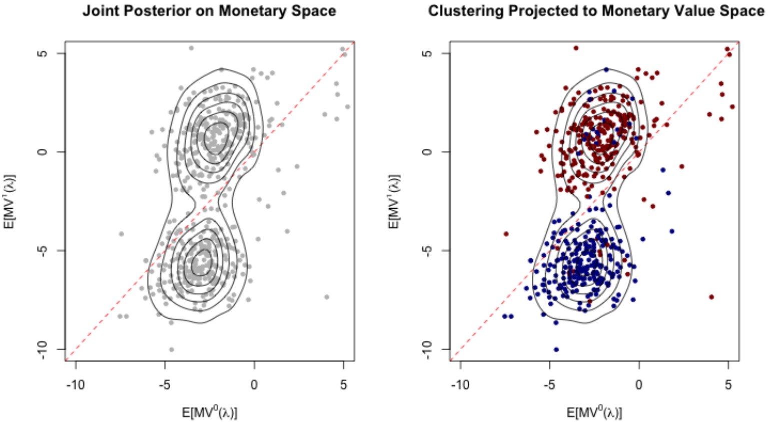
Joint Posterior on Monetary Space
Clustering Projected to Monetary Value Space
E[MV¹(λ)]
E[MV⁰(λ)]
-10
-5
0
5

In the paper...

- More formal treatment of censoring.
- MCMC details (including Bayesian bootstrap).
- Differential Subgroup Index.
- Data application using SEER Medicare claims data.

Thank You!

- (slightly outdated) Working draft: https://arxiv.org/abs/2002.04706
- Paper on zero-inflated costs: `https://onlinelibrary.wiley.com/doi/abs/10.1111/biom.13244`
- Interactive DP Tutorial with R Shiny: `https://stablemarkets.shinyapps.io/dpmixapp/`
- ChiRP R package: `https://stablemarkets.github.io/ChiRPsite/index.html`