Bayesian Causal Inference in Stan

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A Practical Introduction to Bayesian Estimation of Causal Effects: Parametric and Nonparametric Approaches

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REVIEW / TUTORIAL PAPER

A Practical Introduction to ... **Effects:**
Parametric and

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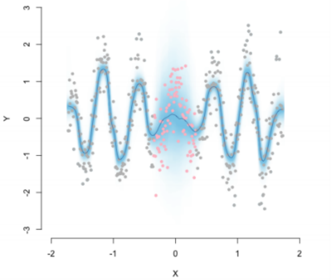

Review/Tutorial paper

A Practical Introduction to B... Effects:
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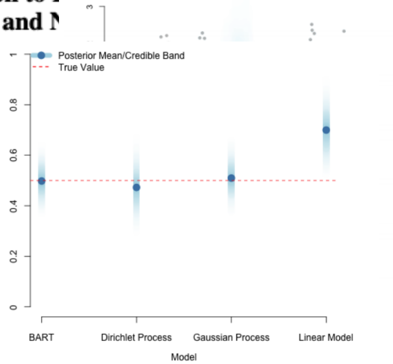

A Practical Introduction to B... Effects:

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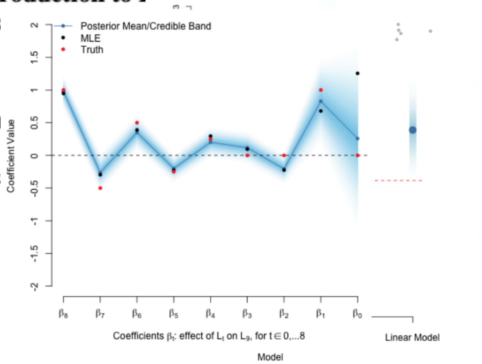

What is Causal Inference?

What would have happened had everyone in the target population if ...

- ... everyone took treatment 1 versus treatment 0?
- ... were vaccinated ?
- ... were enrolled in a job training program?

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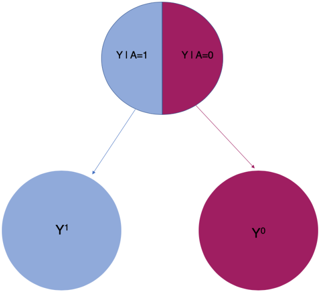

IDENTIFICATION VIA THE g-FORMULA

$D = \{Y_i, A_i, L_i, V_i\}_{1:n}$.
Define potential outcomes Y^a for $a \in \{0, 1\}$

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Under some identification assumptions

$$E[Y^a \mid V = v] = \int_{\mathcal{L}} \underbrace{E[Y \mid A = a, V = v, L]}_{\text{Regression, } \mu(a,v,l)} \underbrace{dP(L)}_{\text{Confounder}}$$

Regression Modeling

- Parametric Approaches:

$$\mu(A, V, L) = g^{-1}(\beta_0 + \beta_1 A + \beta_2 V + \beta_3' L)$$

Need priors on βs.

- Nonparametric Approaches:

$$\mu(A, V, L) = g^{-1}(f(A, V, L))$$

Need prior for f.

Why Bayes?

- Priors can help us compute causal effects under sparsity.
- Avoid *ad hoc* approaches.
- Powerful suite of nonparametric models (BART, DP, GP, etc).
- Probabilistic sensitivity analyses.

Logistic Model For CATEs

Suppose Y is binary and $V \in \{1, 2, 3, 4, 5\}$ (e.g., race/ethnicity)

$$Y \mid A, V, L \sim Ber\big(\mu(A, V)\big)$$

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$$Y \mid A, V, L \sim Ber\big(\mu(A, V)\big)$$

Specify logistic regression

$$\mu(A, V, L) = g^{-1}(\beta_v + \beta_L' L + \theta_v A)$$

with parameters $\omega = (\beta_1 \ldots, \beta_5, \beta_L, \theta_1, \ldots, \theta_5)$

Prior for race effects

$$\mu(A, V, L) = g^{-1}(\beta_v + \beta_L' L + \theta_v A)$$

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- Belief: the race effects shouldn't be *that* different.
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- Belief: the race effects shouldn't be *that* different.
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- Note: implies

$$\theta_4 - \theta_5 \sim N(0, 2\phi)$$

As opposed to setting $\phi \approx 0$

$$\theta_4 - \theta_5 \sim \delta_0$$

We have a data model...now what?

Suppose we want to compute Causal Odds Ratio:

$$\Psi(v) = \frac{E(Y^1 \mid v)/[1 - E(Y^1 \mid v)]}{E(Y^0 \mid v)/[1 - E(Y^0 \mid v)]}$$

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Using g-computation,

$$E(Y^a \mid v) = \int_{\mathcal{L}} \mu(a, v, L) dP(L)$$

But what about model for $P(L)$?

The Bayesian Bootstrap

- Frequentist estimate: $\hat{P}(L = l) = \sum_{i=1}^{n} \frac{1}{n} \cdot \delta_{L_i}(l)$

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  - prior:
    $$p_{1:n} \sim Dirichlet(0_n)$$
  - posterior:
    $$p_{1:n} \mid L \sim Dirichlet(1_n)$$
    $$E[p_i \mid L] = 1/n$$

Full MCMC Inference

1. Obtain m^{th} set of posterior draws $\omega^{(m)}$ and for each $A = a$

$$\mu^{(m)}(a, v, L_i) = \beta_v^{(m)} + \beta_L^{(m)} L_i + \theta_v^{(m)} a$$

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3. Integrate of confounder distribution

$$E^{(m)}(Y^a \mid v) = \int_{\mathcal{L}} \mu(a, v, L) dP(L) \approx \sum_{i=1}^{n} \mu^{(m)}(a, v, L_i) p_i$$

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4. Compute draw of causal odds ratio:

$$\Psi^{(m)}(v) = \frac{E^{(m)}(Y^1 \mid v)/[1 - E^{(m)}(Y^1 \mid v)]}{E^{(m)}(Y^0 \mid v)/[1 - E^{(m)}(Y^1 \mid v)]}$$

Implementation in Stan

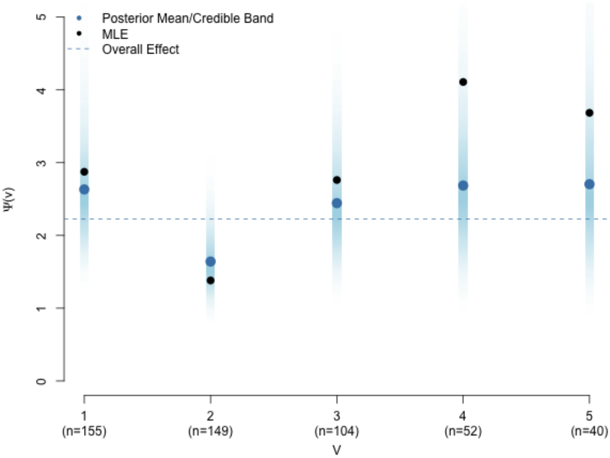
```
generated quantities {
vector[N] bb_weights = dirichlet_rng( rep_vector( 1, N) ) ;

...

for( v in 1:Pv ){
  for(i in 1:N){
    cond_mean_y1[i] = inv_logit( L[i]*beta_L + beta_v[v] + theta[v]);
    cond_mean_y0[i] = inv_logit( L[i]*beta_L + beta_v[v] );
  }
  marg_mean_y1 = bb_weights' * cond_mean_y1 ;
  marg_mean_y0 = bb_weights' * cond_mean_y0 ;

  odds_1 = marg_mean_y1/(1 - marg_mean_y1);
  odds_0 = marg_mean_y0/(1 - marg_mean_y0);
  odds_ratio[v] = odds_1 / odds_0;
}
...
}
```

Synthetic Example



Sensitivity Analysis

Identification requires conditional ignorability

$$Y^a \perp A \mid L, V = v$$

But, what if ignorability is violated?

$$E[Y^a \mid A = 1, L, v] \neq E[Y^a \mid A = 0, L, v]$$

Consequence of Violation

Define,

$$\Delta^a(L) = E[Y^a \mid A = 1, L, v] - E[Y^a \mid A = 0, L, v]$$

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$$\Delta^a(L) = E[Y^a \mid A = 1, L, v] - E[Y^a \mid A = 0, L, v]$$

$$\int \mu(1, v, L) - \mu(0, v, L)\, dP(L) = E[Y^1 - Y^0 \mid v] + \xi$$

Estimate of risk difference is biased by ξ.

Form of Violation

Trade-offs involved in sensitivity analyses

$$\xi = \int \Delta^1(L)(1 - \pi(L)) + \Delta^0(L)\pi(L) \, dP(L)$$

Simplify $\Delta := \Delta^1 = \Delta^0$ and $\Delta \perp L$. Then,

$$\xi = \Delta$$

Now we can specify priors over Δ.

Priors over bias

Note that $-1 < E[Y^1 - Y^0 \mid v] < 1$ and recall:

$$\Delta = E[Y^a \mid A = 1, L, v] - E[Y^a \mid A = 0, L, v]$$

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- Treated patients systematically worse:

$$\Delta \sim U(0, 1)$$

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- Treated patients systematically worse:

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- Treated patients systematically better:

$$\Delta \sim U(-1, 0)$$

- Biased with uncertain direction:

$$\Delta \sim U(-1, 1)$$

Modified MCMC Inference

In Step 3 at m^{th} iteration:
Draw $\Delta^{(m)}$ from the prior and compute,

$$E^{(m)}(Y^a \mid v) = \left\{ \sum_{i=1}^{n} \mu^{(m)}(a, v, L_i) p_i \right\} - \Delta^{(m)}$$

Implementation in Stan

- Could specify prior for Δ in "model" block. Manipulate in "generated quantities".
- Could draw Δ from specified distribution in "generated quantities" block.

Some Resources

- A Practical Introduction to Bayesian Estimation of Causal Effects: Parametric and Nonparametric Approaches `https://arxiv.org/pdf/2004.07375.pdf`
- Companion GitHub repo for paper: `https://github.com/stablemarkets/intro_bayesian_causal`
- GitHub Repo for this talk: `https://github.com/stablemarkets/StanCon2020_BayesCausal`

Thank you!