

Case Study 1-Group 1

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Introduction

- ▶ Data: Subset of National Collaborative Perinatal Project (CPP), comprised of 2380 observations of pregnant women [Longnecker et al., 2001].
- ▶ Goal: Assess how DDE and PCBs associate with risk of premature delivery, adjusting for confounding variables.

EDA and Preprocessing

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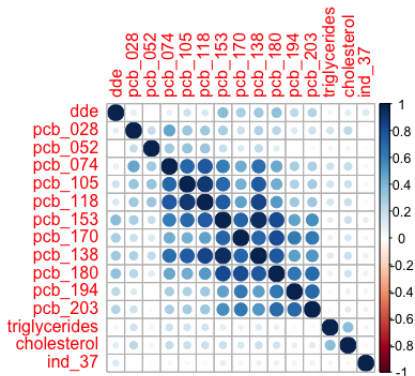
- ▶ Premature delivery: Gestational Age ≤ 36 .
- ▶ Standardize continuous variables.
- ▶ Missing data: Multivariate Imputations by Chained Equations (MICE package in R) for covariates. Deleted albumin because 93 percent missing. Only one observation missing in dde and pcb, deleted.
- ▶ Limit of Detection (LOD): Exists in some PCBs. All LODs are negligible compared to data scale (e.g. 0.01 compared to 0.3)

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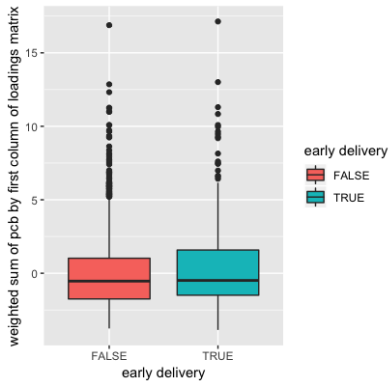
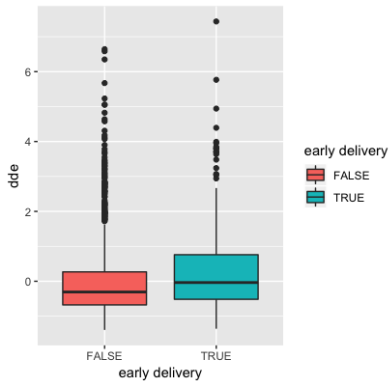
Loadings:

	Comp.1	Comp.2	Comp.3	Comp.4	Comp.5
pcb_028	0.161	0.243	0.833	0.342	0.154
pcb_052	0.116	0.376	0.223	-0.886	
pcb_074	0.306	0.314		0.189	-0.217
pcb_105	0.320	0.333	-0.208		-0.282
pcb_118	0.342	0.306	-0.248		-0.199
pcb_153	0.376		-0.160		0.332
pcb_170	0.325	-0.274		-0.123	0.323
pcb_138	0.383		-0.225		0.165
pcb_180	0.344	-0.277			0.375
pcb_194	0.253	-0.419	0.158	-0.100	-0.585
pcb_203	0.268	-0.409	0.203	-0.106	-0.290

	Comp.1	Comp.2	Comp.3	Comp.4	Comp.5
Standard deviation	2.4458646	1.3261098	0.94105657	0.89065865	0.70742028
Proportion of Variance	0.5440699	0.1599370	0.08054181	0.07214604	0.04551399
Cumulative Proportion	0.5440699	0.7040069	0.78454872	0.85669476	0.90220875



EDA and Preprocessing



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- ▶ Nonlinear Model

Model

- ▶ Generalized Additive Model (GAM)

$$g(Y_i) = \beta_0 + \sum_{j=1}^m f_j(x_{ij}) + \sum_{k=1}^l \beta_k z_{ik}$$

- ▶ Choice of g : probit or logit.
- ▶ $x_{.j}$ s include DDE, PCBs, maternal age, etc.
- ▶ $z_{.k}$ s include categorical variables and some confounding variables.

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- ▶ Bayesian Generalized Additive Model

$$g(Y_i) = \beta_0 + \sum_{j=1}^m f_j(x_{ij}) + \sum_{k=1}^l \beta_k z_{ik}$$

- ▶ Adds priors on the common regression coefficients, priors on the standard deviations of the smooth terms.

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- ▶ Approach 1: Bayesian Hierarchical Model
- ▶ Approach 2: Mixed Effect / Random Effect Model
- ▶ Generalized Additive Mixed Model (GAMM)
- ▶ Bayesian GAMM

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- ▶ Including Interactions: Bayesian Factor Analysis (Ferrari, F. and Dunson, D.B. 2019)