Beyond axis-alignment: BART w/ categorical variables & oblique decision rules

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Nonparametric network-linked regression

- Observe data on a network $\mathcal{G} = (V, E)$
- n_v pairs $(\mathbf{x}_{vt}, y_{vt})$ at vertex v
- $\mathbb{E}[y|\mathbf{x}]$ may vary across network
- I.e. $\mathbf{x} \in [0,1]^p$ interacts w/ v



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- Idea: introduce vertex label v as covariate
- Model: $y_{vt} \sim \mathcal{N}(f(\mathbf{x}_{vt}, v), \sigma^2)$
- - Encourage network smoothness so f(x, v) ≈ f(x, v') if v ~ v'?

Pitfalls of one-hot encoding

- $X \in \{c_1,\ldots,c_K\}$
- One-hot encoding: $X o (ilde{X}_1, \dots, ilde{X}_{\mathcal{K}})$
 - $\bullet \quad \tilde{X}_k = \mathbb{1}(X = c_k)$
 - Treat \tilde{X}_k 's as continuous



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• Decision trees built w/ \tilde{X}_k 's can induce $2^K - K$ partitions of the form

k singletons set with K - k elements

$$\{c_1\}\cup\cdots\{c_k\}\cup\{c_{k+1},\ldots,c_K\}$$

 \circledast Bell number $B_k \gg (K/2)^{K/2} \gg 2^K - K$

Zero prior probability on overwhelming majority of partitions of levels
 One-hot encoding can't leverage network structure...

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Decision rule prior

- 1. Draw $j \sim \text{Multinomial}(\theta_1, \dots, \theta_p)$ where $\theta_j = \mathbb{P}(\text{split on } X_j)$
- 2. Compute set of all available values A_i
 - A_j determined by rules at ancestors
 - X_j continuous $\rightarrow A$ is an interval
 - X_j categorical $\rightarrow \mathcal{A}$ is discrete set
- **3**. Draw random subset C from A_j
 - X_j continuous: set $C = [0, c), c \sim U(A_j)$
 - ► X_j categorical: assign elements of A_j to C with probability 0.5



Example: Partitions of Philadelphia's census tracts



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 ... but partially pools data across geographically disparate regions

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- © One-hot encoding: no "borrowing strength" across tracts
- © Uniformly partitioning levels: pools many tracts together ...
- $\ensuremath{\textcircled{\ensuremath{\Theta}}}$. . . but partially pools data across geographically disparate regions
- How can we leverage adjacency and achieve spatial smoothness???

Cutting spanning trees



- Goal: partition $\mathcal{G}[\mathcal{A}]$ into two connected components
 - 1 Draw uniform spanning tree of $\mathcal{G}[\mathcal{A}]$ (Wilson's algorithm)
 - 2 Delete an edge from spanning tree to partition into two components
- Full support: positive prior prob. on every partition of G into connected components

Example: prior draws of f(v, t)

 Conjecture: infinite-tree limit is Gaussian process GP(0, k)

$$k((\pmb{x}, \pmb{v}), (\pmb{x}', \pmb{v}')) \propto$$

 $\mathbb{P}((\pmb{x}, \pmb{v}) \text{ and } (\pmb{x}', \pmb{v}') \text{ in same leaf})$

• *k* determined implicitly by a *recursive partitioning process*



Prior draw of M = 100 regression tree ensemble

Other ways to partition networks



Deleting uniform edge from spanning tree can create singletons

- Idea 1: form "hot spots" based on a random ball
 - © Simpler to implement: pick a vertex & take all within random distance
 - Ooes not maintain connectivity
- Idea 2: use second smallest eigenvector of graph Laplacian
- Network partitioning processes determines degree of smoothness
 - Conjecture: infinite tree limit is a GP w/ kernel k
 - ▶ $k(v, v') = \mathbb{P}(v \& v' \text{ co-clustered in random recursive partitioning}).$

Multiple resolutions



- Idea: run BART w/ additional network-structured predictors
- Challenge: how strictly do we enforce the hierarchical structure?
 - Split on high resolution after exhausting all lower resolutions?
 - Allow splits on lower resolution after splitting on higher resolution?

Oblique BART



- Categorical rule $\{X_j \in \mathcal{C}\}$ equivalent to $\left\{\sum_{c \in \mathcal{C}} \mathbb{1}(X_j = c) < 0.5
 ight\}$
- Oblique trees: decision rules based on *linear combinations* of x_i's
- Implementation: easier to use rules of form $\{\phi^{\top}(\mathbf{x} \mathbf{x}_0) < 0\}$
- x_0 drawn from polytope and normal direction ϕ draw from a prior

Parting thoughts & other on-going projects

- Don't one-hot encode categorical predictors w/ regression trees!
- BART with random basis expansion in leafs for interrupted time series
- BART with image input
- Extending BART to more complex input space involves implementing
 - Recipe to randomly split $X \subseteq \mathcal{X}$ into two disjoint pieces
 - Efficient representation of subsets of $\mathcal X$
 - Fast way to check whether x is in a given subset

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Thanks, y'all!

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