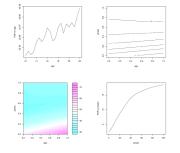
Interpretable Machine Learning

Functional Decompositions Theory of Standard fANOVA



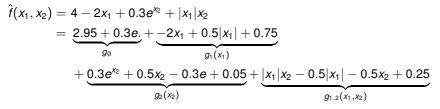
Learning goals

- Properties of classical fANOVA, reason for its popularity
- Equivalent definition of classical fANOVA
- Understand the role constraints play for any functional decomposition



EXAMPLE: FANOVA ALGORITHM

- Remember: Functional decomposition in general not unique
- Standard fANOVA only one possible approach
- Example:



→ seems arbitrarily chosen?

 \longleftrightarrow Show: Standard fANOVA fulfills specific desirable properties or constraints



CONSTRAINTS FOR STANDARD FANOVA ALGO.

Theorem

Features independent \implies The components defined by standard fANOVA fulfill the so-called vanishing conditions:

$$\mathbb{E}_{X_j}[g_S(\mathbf{x}_S)] = \int g_S(\mathbf{x}_S) d\mathbb{P}(x_j) = 0 \quad \text{for any } j \in S \text{ and } S \subseteq \{1, \dots, p\}$$



CONSTRAINTS FOR STANDARD FANOVA ALGO.

Theorem

Features independent \implies The components defined by standard fANOVA fulfill the so-called vanishing conditions:

$$\mathbb{E}_{X_j}[g_S(\mathbf{x}_S)] = \int g_S(\mathbf{x}_S) d\mathbb{P}(x_j) = 0$$
 for any $j \in S$ and $S \subseteq \{1, \dots, p\}$

Implications:

• For any component g_S , all its PD-functions are 0:

$$\mathbb{E}_{X_V}\left[g_S(\mathbf{x}_S)\right] = \int g_S(\mathbf{x}_S) d\mathbb{P}(\mathbf{x}_V) = 0 \quad \text{for any } V \subsetneq S \text{ and } S \subseteq \{1,\dots,p\}$$

 \rightsquigarrow g_S contains no lower-order effects, but only pure interaction term (compare H-statistic)

CONSTRAINTS FOR STANDARD FANOVA ALGO.

Theorem

Features independent \implies The components defined by standard fANOVA fulfill the so-called vanishing conditions:

$$\mathbb{E}_{X_j}[g_S(\mathbf{x}_S)] = \int g_S(\mathbf{x}_S) d\mathbb{P}(x_j) = 0 \quad ext{for any } j \in S ext{ and } S \subseteq \{1,\dots,p\}$$



Implications:

• For any component g_S , all its PD-functions are 0:

$$\mathbb{E}_{X_V}\left[g_S(\mathbf{x}_S)\right] = \int g_S(\mathbf{x}_S) d\mathbb{P}(\mathbf{x}_V) = 0 \quad \text{for any } V \subsetneq S \text{ and } S \subseteq \{1, \dots, p\}$$

 \rightsquigarrow g_S contains no lower-order effects, but only pure interaction term (compare H-statistic)

• All components are orthogonal, i.e., mutually indep. and uncorrelated:

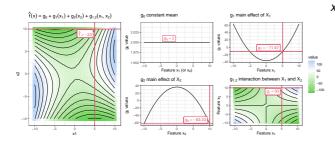
$$\forall V \neq S: \quad \mathbb{E}_{\mathbf{X}}[g_V(\mathbf{x}_V)g_S(\mathbf{x}_S)] = 0$$

• This implies variance decomposition used to define Sobol indices: $Var[\hat{f}(\mathbf{x})] = \sum_{S \subset \{1,...,p\}} Var[g_S(\mathbf{x}_S)]$

EXAMPLES REVISITED

Example: $\hat{f}(\mathbf{x}) = 2 + x_1^2 - x_2^2 + x_1 \cdot x_2$ (e.g., for $x_1 = 5$ and $x_2 = 10$ we have $\hat{f}(\mathbf{x}) = -23$)

• Computation of components using feature values $x_1 = x_2 = (-10, -9, ..., 10)^{\top}$ gives:



For $x_1 = 5$ and $x_2 = 10$:

- g_∅ = 2
- $g_1(x_1) = -9.67$
- $g_2(x_2) = -65.33$
- $g_{1,2}(x_1,x_2) = 50$

$$\Rightarrow \hat{f}(\mathbf{x}) = -23$$

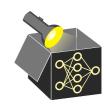
- Vanishing condition means:
 - g_1 and g_2 are mean-centered w.r.t. marginal distribution of x_1 and x_2
 - Integral of $g_{1,2}$ over marginal distribution x_1 (or x_2) is always 0.



EXAMPLES REVISITED

Example

$$\hat{f}(x_1, x_2) = 4 - 2x_1 + 0.3e^{x_2} + |x_1|x_2
= \underbrace{2.95 + 0.3e}_{g_0} + \underbrace{-2x_1 + 0.5|x_1| + 0.75}_{g_1(x_1)}
+ \underbrace{0.3e^{x_2} + 0.5x_2 - 0.3e + 0.05}_{g_2(x_2)} + \underbrace{|x_1|x_2 - 0.5|x_1| - 0.5x_2 + 0.25}_{g_{1,2}(x_1, x_2)}$$



- \implies Main effect terms inside $g_{1,2}$ are chosen exactly such that the one-dimensional PDPs of $g_{1,2}$ vanish
- \implies Same for constant terms inside g_1 and g_2 : Ensure centering

EXAMPLES REVISITED

Example

$$\hat{f}(x_1, x_2) = 4 - 2x_1 + 0.3e^{x_2} + |x_1|x_2$$

$$= \underbrace{2.95 + 0.3e}_{g_{\emptyset}} + \underbrace{-2x_1 + 0.5|x_1| + 0.75}_{g_1(x_1)}$$

$$+ \underbrace{0.3e^{x_2} + 0.5x_2 - 0.3e + 0.05}_{g_2(x_2)} + \underbrace{|x_1|x_2 - 0.5|x_1| - 0.5x_2 + 0.25}_{g_{1,2}(x_1, x_2)}$$



- \implies Main effect terms inside $g_{1,2}$ are chosen exactly such that the one-dimensional PDPs of $g_{1,2}$ vanish
- \implies Same for constant terms inside g_1 and g_2 : Ensure centering

Example

From in-class exercise: $g(x_1, x_2) = \beta_{12} (x_1 - \mu_1)(x_2 - \mu_2)$

• So far: Definition of standard fANOVA implies vanishing conditions



- So far: Definition of standard fANOVA implies vanishing conditions



- So far: Definition of standard fANOVA implies vanishing conditions
- In other words: Vanishing conditions are equivalent characterization



- So far: Definition of standard fANOVA implies vanishing conditions
- In other words: Vanishing conditions are equivalent characterization
- In general: Functional decomp. can be defined by sets of constraints



- So far: Definition of standard fANOVA implies vanishing conditions
- In other words: Vanishing conditions are equivalent characterization
- In general: Functional decomp. can be defined by sets of constraints
- Many other methods to compute decompositions exist, each with their set of constraints

