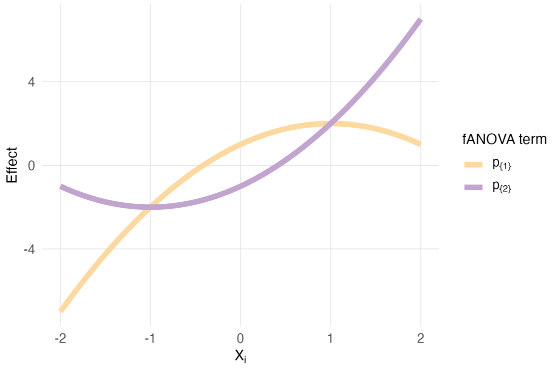
Functional ANOVA Decomposition

Juliet Fleischer

August 12, 2025



Outline

Overview of the fANOVA Research Field

Foundations

Overview of the fANOVA Research Field

Foundations → (Generalized) fANOVA

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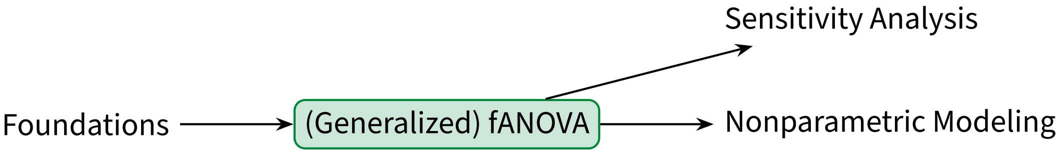
Foundations → (Generalized) fANOVA → Sensitivity Analysis

Overview of the fANOVA Research Field



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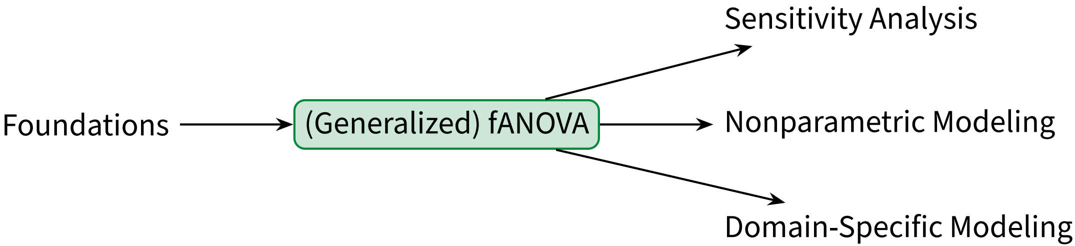

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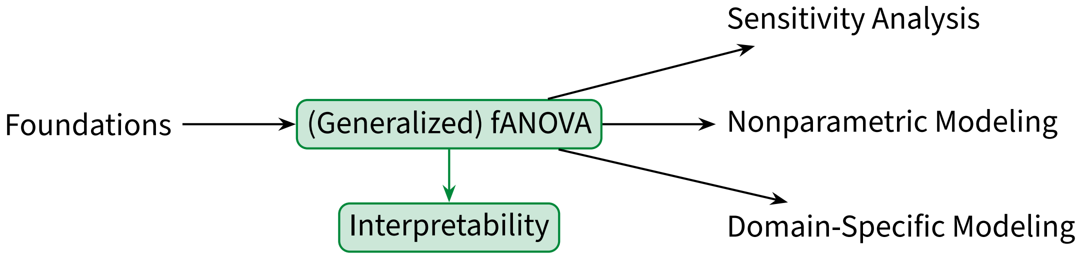

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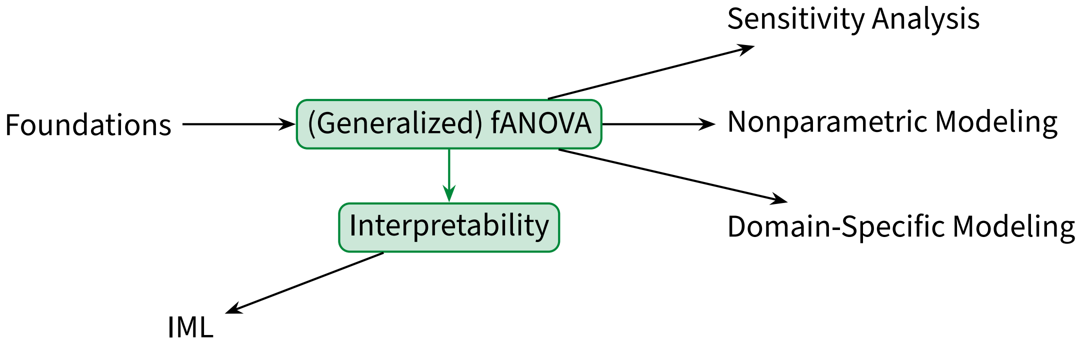

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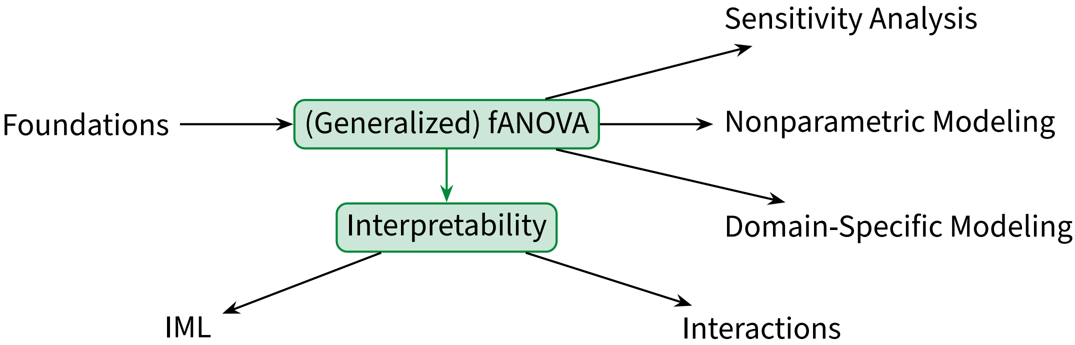

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Decomposition of Model into Interpretable Components

General Form

$$y(\boldsymbol{X}) = \sum_{u \subseteq \{1,\ldots,N\}} y_u(\boldsymbol{X}_u)$$

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- $\boldsymbol{X} = (X_1, \dots, X_N)$: input variables (assumed to be independent in classical fANOVA)

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$$= y_\emptyset + \big(y_{\{1\}}(X_1) + \cdots + y_{\{N\}}(X_N)\big)$$

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Conditions for Interpretability under Independent Inputs

Strong Annihilating Conditions

$$\int_{\mathbb{R}} y_u(\boldsymbol{x}_u) f_{\{i\}}(x_i)\, d\nu(x_i) = 0 \quad \text{for } i \in u \neq \emptyset$$

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$$\mathbb{E}[y_u(\boldsymbol{X}_u) y_v(\boldsymbol{X}_v)] = 0 \quad (u \neq v)$$

Recursive Form of the Components

$$y_\emptyset = \int_{\mathbb{R}^N} y(\boldsymbol{x}) \prod_{i=1}^{N} f_{\{i\}}(x_i)\, d\nu(x_i) = \mathbb{E}[y(\boldsymbol{X})]$$

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\end{aligned}
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Remark: fANOVA components can be seen from the lens of orthogonal projections.

Example with Independent MVN Input

$$y(x_1, x_2) = 2x_1 + x_2^2 + x_1 x_2$$

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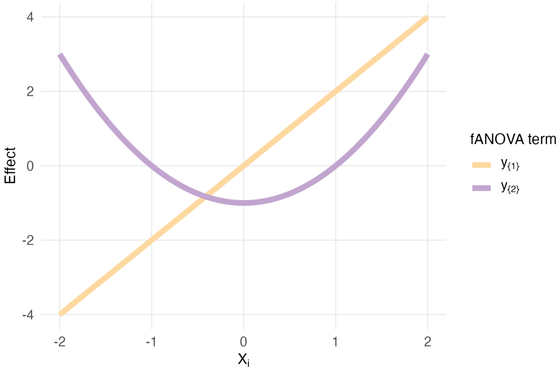
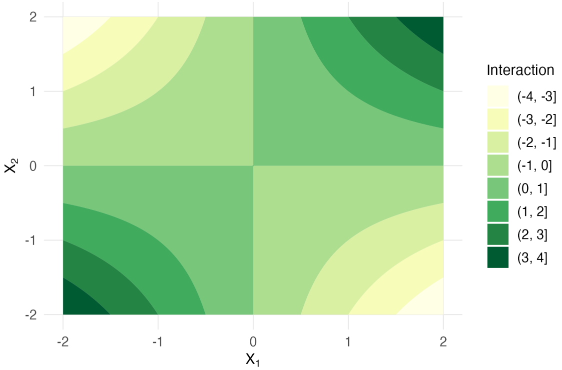
Components:

$$y_\emptyset = 1, \qquad y_{\{1\}}(x_1) = 2x_1, \qquad y_{\{2\}}(x_2) = x_2^2 - 1, \qquad y_{\{1,2\}}(x_1, x_2) = x_1 x_2$$

Visualization of fANOVA components under Independence

$$y(x_1, x_2) = 2x_1 + x_2^2 + x_1 x_2$$

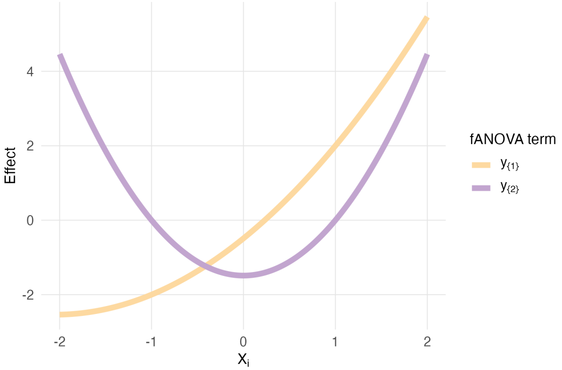


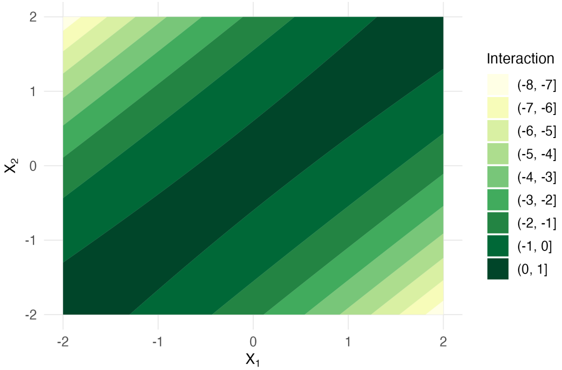


Outline

Visualization of fANOVA components under Dependence

$$y(x_1, x_2) = 2x_1 + x_2^2 + x_1x_2, \qquad \rho = 0.8$$





Conditions for Interpretability under Dependent Inputs

Weak Annihilating Conditions

$$\int_{\mathbb{R}} y_{u,G}(\boldsymbol{x}_u) f_{\boldsymbol{u}}(\boldsymbol{x}_u) d\nu(x_i) = 0 \quad \text{for} \quad i \in u \neq \emptyset$$

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Generalized Components Mirror the Classical Form

$$y_{\emptyset,G} = \int_{\mathbb{R}^N} y(\boldsymbol{x}) f_{\boldsymbol{X}}(\boldsymbol{x}) \, d\nu(\boldsymbol{x})$$

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$$\begin{aligned} y_{u,G}(\boldsymbol{X}_u) = &\int_{\mathbb{R}^{N-|u|}} y(\boldsymbol{X}_u, \boldsymbol{x}_{-u}) f_{-u}(\boldsymbol{x}_{-u})\, d\nu(\boldsymbol{x}_{-u}) - \sum_{v \subsetneq u} y_{v,G}(\boldsymbol{X}_v) \\ &- \sum_{\substack{\emptyset \neq v \subseteq \{1,\ldots,N\} \\ v \cap u \neq \emptyset,\ v \not\subset u}} \int_{\mathbb{R}^{|v \cap -u|}} y_{v,G}(\boldsymbol{X}_{v\cap u}, \boldsymbol{x}_{v\cap -u}) f_{v\cap -u}(\boldsymbol{x}_{v\cap -u})\, d\nu(\boldsymbol{x}_{v\cap -u}) \end{aligned}$$

Generalized Components Mirror the Classical Form

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$$y_{\emptyset,G} = \int_{\mathbb{R}^N} y(\boldsymbol{x}) f_{\boldsymbol{X}}(\boldsymbol{x})\, d\nu(\boldsymbol{x})$$

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Coupled System of Generalized Components

- $N = 3, u = \emptyset$

$$y_{\emptyset,G} = \mathbb{E}[y(\boldsymbol{X})]$$

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$(\emptyset \neq v \subseteq \{1, \ldots, N\},\ v \cap u \neq \emptyset,\ v \not\subset u) \in \{\{1,2\}, \{1,3\}, \{1,2,3\}\}$

$$\begin{aligned} y_{\{1\},G}(\boldsymbol{X}_u) = &\int_{\mathbb{R}^2} y(x_1, x_2, x_3) f_{\{2,3\}}(x_2, x_3)\, d\nu(x_2, x_3) - y_{\emptyset,G} \\ &- \int_{\mathbb{R}} y_{\{1,2\},G}(x_1, x_2) f_{\{2\}}(x_2)\, d\nu(x_2) - \int_{\mathbb{R}} y_{\{1,3\},G}(x_1, x_3) f_{\{3\}}(x_3)\, d\nu(x_3) \\ &- \int_{\mathbb{R}^2} y_{\{1,2,3\},G}(x_1, x_2, x_3) f_{\{2,3\}}(x_2, x_3)\, d\nu(x_2, x_3) \end{aligned}$$

Coupled System of Generalized Components

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- $u = \{1,2\} \to v \subsetneq u \in \{\emptyset, \{1\}, \{2\}\}$ and $(\emptyset \neq v \subseteq \{1, \dots, N\},\ v \cap u \neq \emptyset,\ v \not\subset u) \in \{\{1,2,3\}\}$

$$y_{\{1,2\},G}(\boldsymbol{X}_u) = \int_{\mathbb{R}} y(x_1, x_2, x_3) f_{\{3\}}(x_3)\, d\nu(x_3) - y_{\emptyset,G} - y_{\{1\},G} - y_{\{2\},G}$$

$$- \int_{\mathbb{R}} y_{\{1,2,3\},G}(x_1, x_2, x_3) f_{\{3\}}(x_3)\, d\nu(x_3)$$

Coupled System of Generalized Components

- $u = \{1,2,3\} \rightarrow v \subsetneq u \in \{\emptyset, \{1\}, \{2\}, \{3\}, \{1,2\}, \{1,3\}, \{2,3\}\}$ and
  $\nexists v \subseteq \{1,\ldots,N\}$ s.t. $v \neq \emptyset$, $v \cap u \neq \emptyset$, $v \not\subseteq u$

$$
\begin{aligned}
y_{\{1,2,3\},G}(\boldsymbol{X}_u) = y(x_1, x_2, x_3) &- y_{\emptyset,G} \\
&- y_{\{1\},G} - y_{\{2\},G} - y_{\{3\},G} \\
&- y_{\{1,2\},G} - y_{\{1,3\},G} - y_{\{2,3\},G}
\end{aligned}
$$

Construction of Components via Fourier-polynomial Expansion

$$y(x_1, x_2) = a_0 + a_1 x_1 + a_2 x_2 + a_{11} x_1^2 + a_{22} x_2^2 + a_{12} x_1 x_2$$

Construction of Components via Fourier-polynomial Expansion

$$
\begin{aligned}
y(x_1, x_2) &= a_0 + a_1 x_1 + a_2 x_2 + a_{11} x_1^2 + a_{22} x_2^2 + a_{12} x_1 x_2 \\
&= c_0 + c_{1,1}\, \psi_{1,1}(x_1) + c_{2,1}\, \psi_{2,1}(x_2)
\end{aligned}
$$

Construction of Components via Fourier-polynomial Expansion

$$
\begin{aligned}
y(x_1, x_2) &= a_0 + a_1 x_1 + a_2 x_2 + a_{11} x_1^2 + a_{22} x_2^2 + a_{12} x_1 x_2 \\
&= c_0 + c_{1,1}\, \psi_{1,1}(x_1) + c_{2,1}\, \psi_{2,1}(x_2) \\
&\quad + c_{1,2}\, \psi_{1,2}(x_1) + c_{2,2}\, \psi_{2,2}(x_2) + c_{12,11}\, \psi_{12,11}(x_1, x_2)
\end{aligned}
$$

Construction of Components via Fourier-polynomial Expansion

$$
\begin{aligned}
y(x_1, x_2) &= a_0 + a_1 x_1 + a_2 x_2 + a_{11} x_1^2 + a_{22} x_2^2 + a_{12} x_1 x_2 \\
&= c_0 + c_{1,1}\, \psi_{1,1}(x_1) + c_{2,1}\, \psi_{2,1}(x_2) \\
&\quad + c_{1,2}\, \psi_{1,2}(x_1) + c_{2,2}\, \psi_{2,2}(x_2) + c_{12,11}\, \psi_{12,11}(x_1, x_2) \\
&= \underbrace{c_0}_{y_0} + \underbrace{\left(c_{1,1}\, \psi_{1,1}(x_1) + c_{1,2}\, \psi_{1,2}(x_1)\right)}_{y_1(x_1)}
\end{aligned}
$$

Construction of Components via Fourier-polynomial Expansion

$$
\begin{aligned}
y(x_1, x_2) &= a_0 + a_1 x_1 + a_2 x_2 + a_{11} x_1^2 + a_{22} x_2^2 + a_{12} x_1 x_2 \\
&= c_0 + c_{1,1}\, \psi_{1,1}(x_1) + c_{2,1}\, \psi_{2,1}(x_2) \\
&\quad + c_{1,2}\, \psi_{1,2}(x_1) + c_{2,2}\, \psi_{2,2}(x_2) + c_{12,11}\, \psi_{12,11}(x_1, x_2) \\
&= \underbrace{c_0}_{y_0} + \underbrace{\left(c_{1,1}\, \psi_{1,1}(x_1) + c_{1,2}\, \psi_{1,2}(x_1)\right)}_{y_1(x_1)} \\
&\quad + \underbrace{\left(c_{2,1}\, \psi_{2,1}(x_2) + c_{2,2}\, \psi_{2,2}(x_2)\right)}_{y_2(x_2)}
\end{aligned}
$$

Construction of Components via Fourier-polynomial Expansion

$$
\begin{aligned}
y(x_1, x_2) &= a_0 + a_1 x_1 + a_2 x_2 + a_{11} x_1^2 + a_{22} x_2^2 + a_{12} x_1 x_2 \\
&= c_0 + c_{1,1}\, \psi_{1,1}(x_1) + c_{2,1}\, \psi_{2,1}(x_2) \\
&\quad + c_{1,2}\, \psi_{1,2}(x_1) + c_{2,2}\, \psi_{2,2}(x_2) + c_{12,11}\, \psi_{12,11}(x_1, x_2) \\
&= \underbrace{c_0}_{y_0} + \underbrace{\left(c_{1,1}\, \psi_{1,1}(x_1) + c_{1,2}\, \psi_{1,2}(x_1)\right)}_{y_1(x_1)} \\
&\quad + \underbrace{\left(c_{2,1}\, \psi_{2,1}(x_2) + c_{2,2}\, \psi_{2,2}(x_2)\right)}_{y_2(x_2)} \\
&\quad + \underbrace{c_{12,11}\, \psi_{12,11}(x_1, x_2)}_{y_{12}(x_1, x_2)}
\end{aligned}
$$

Choosing Orthogonal Basis Functions

For Gaussian input variables Hermite polynomial basis functions are proposed:

$$
\begin{aligned}
\psi_{\emptyset}(x_1, x_2) &= 1, \\
\psi_{1,1}(x_1) &= x_1, \\
\psi_{2,1}(x_2) &= x_2, \\
\psi_{1,2}(x_1) &= x_1^2 - 1, \\
\psi_{2,2}(x_2) &= x_2^2 - 1, \\
\psi_{12,11}(x_1, x_2) &= \frac{\rho(x_1^2 + x_2^2)}{1+\rho^2} - x_1 x_2 + \frac{\rho(\rho^2 - 1)}{1+\rho^2}
\end{aligned}
$$

fANOVA Components of a two-degree Polynomial

- Yields fANOVA components for Gaussian Inputs
- Works for polynomials of degree up to $d = 2$

$$y_{\emptyset,G} = a_0 + a_{11} + a_{22} + \rho\, a_{12},$$

$$y_{\{1\},G}(x_1) = a_1\, x_1 + \left(a_{11} + \frac{\rho}{1+\rho^2} a_{12}\right)(x_1^2 - 1),$$

$$y_{\{2\},G}(x_2) = a_2\, x_2 + \left(a_{22} + \frac{\rho}{1+\rho^2} a_{12}\right)(x_2^2 - 1),$$

$$y_{\{1,2\},G}(x_1, x_2) = -a_{12}\left(\frac{\rho(x_1^2 + x_2^2)}{1+\rho^2} - x_1 x_2 + \frac{\rho(\rho^2 - 1)}{1+\rho^2}\right)$$

Decomposition under Weak Correlation

$$z(x_1, x_2) = 2x_1 + x_1^2 + 0.5x_1x_2$$

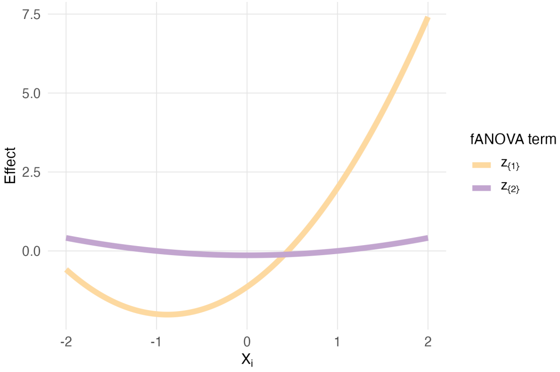

Figure: Main effect for $\rho = 0.3$.

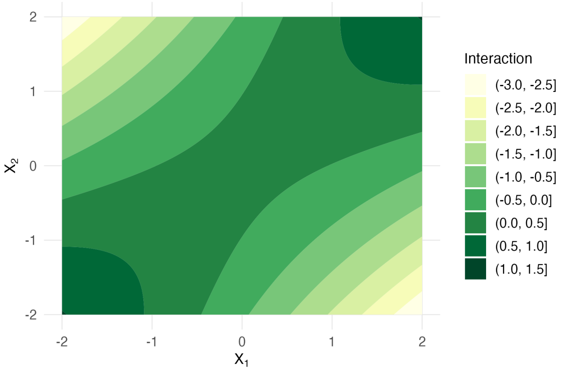

Figure: Interaction effect for $\rho = 0.3$.

Decomposition under Independence

$$z(x_1, x_2) = 2x_1 + x_1^2 + 0.5x_1x_2$$

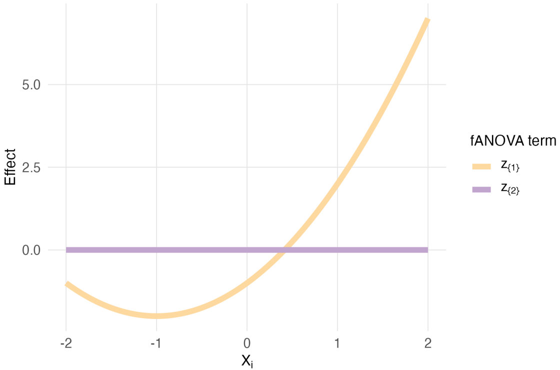

Figure: Main effect for $\rho = 0$.

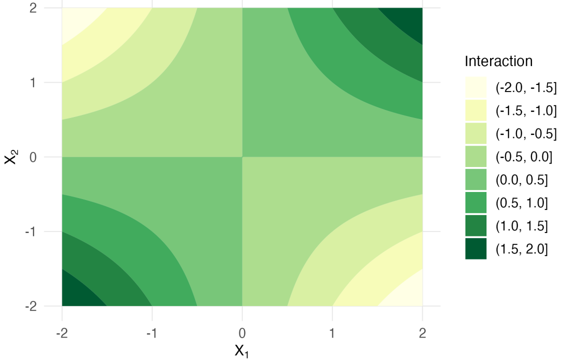

Figure: Interaction effect for $\rho = 0$.

$\rightarrow$ nonzero main effect of X_2 only present under correlation

Variance Decomposition via fANOVA

Not only y, but also its variance can be decomposed:

$$\mu := \mathbb{E}[y(\boldsymbol{X})] = y_{\emptyset,G}$$

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$$= \mathbb{E}\left[\left(y_{\emptyset,G} + \sum_u y_{u,G}(\boldsymbol{X}_u) - y_{\emptyset,G}\right)^2\right]$$

Variance Decomposition via fANOVA

Not only y, but also its variance can be decomposed:

$$\mu := \mathbb{E}[y(\boldsymbol{X})] = y_{\emptyset,G}$$

$$\begin{aligned}\sigma^2 &:= \mathbb{E}\left[(y(\boldsymbol{X}) - \mu)^2\right] \\ &= \mathbb{E}\left[\left(y_{\emptyset,G} + \sum_u y_{u,G}(\boldsymbol{X}_u) - y_{\emptyset,G}\right)^2\right] \\ &= \mathbb{E}\left[\left(\sum_u y_{u,G}(\boldsymbol{X}_u)\right)^2\right]\end{aligned}$$

Variance Decomposition via fANOVA

Not only y, but also its variance can be decomposed:

$$\mu := \mathbb{E}[y(\boldsymbol{X})] = y_{\emptyset,G}$$

$$\begin{aligned}\sigma^2 &:= \mathbb{E}\left[(y(\boldsymbol{X}) - \mu)^2\right] \\ &= \mathbb{E}\left[\left(y_{\emptyset,G} + \sum_u y_{u,G}(\boldsymbol{X}_u) - y_{\emptyset,G}\right)^2\right] \\ &= \mathbb{E}\left[\left(\sum_u y_{u,G}(\boldsymbol{X}_u)\right)^2\right] \\ &= \sum_u \mathbb{E}\left[y_{u,G}^2(\boldsymbol{X}_u)\right] + \sum_{u \not\subseteq v,\, v \not\subseteq u} \mathbb{E}\left[y_{u,G}(\boldsymbol{X}_u) y_{v,G}(\boldsymbol{X}_v)\right]\end{aligned}$$

Alternative Generalization of fANOVA

Different formulations of generalized fANOVA components exists, e.g.:

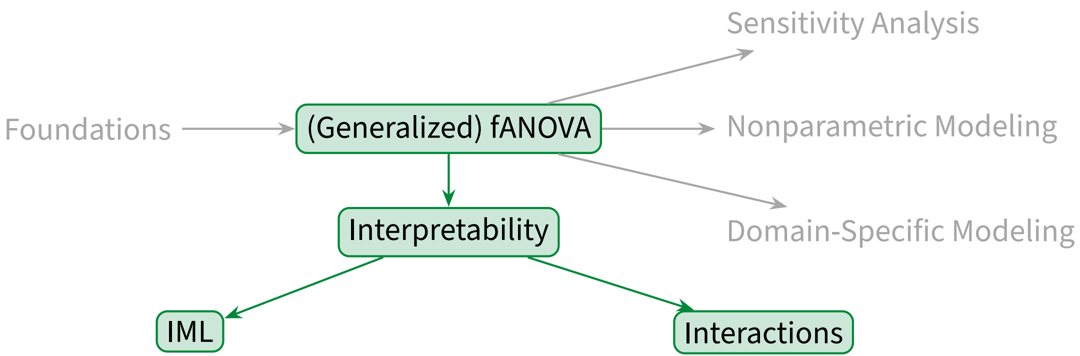
$$\{y_{u,G}(\boldsymbol{x}_u) \mid u \subseteq d\} = \arg \min_{\{g_u \in \mathcal{L}^2(\mathbb{R}^{|u|})\}} \int_{\mathbb{R}^N} \left(\sum_{u \subseteq d} g_u(\boldsymbol{x}_u) - y(\boldsymbol{x}) \right)^2 f_{\boldsymbol{X}}(\boldsymbol{x})\, d\nu(\boldsymbol{x}),$$

subject to hierarchical orthogonality conditions:

$$\forall v \subseteq u,\ \forall g_v : \int_{\mathbb{R}^N} y_u(\boldsymbol{x}_u) g_v(\boldsymbol{x}_v) f_{\boldsymbol{X}}(\boldsymbol{x})\, d\nu(\boldsymbol{x}) = 0.$$

Outline

Summary and Future Research



Reminder: Definition of Orthogonal Projection

$$\Pi_{\mathcal{G}} y = \arg\min_{g \in \mathcal{G}} \|y - g\|^2 = \arg\min_{g \in \mathcal{G}} \mathbb{E}[(y(\boldsymbol{X}) - g(\boldsymbol{X}))^2]$$

- $\mathcal{G}$: linear subspace of $\mathcal{L}^2$ we project onto
- g all functions in the subspace

fANOVA as Orthogonal Projection

$$
\begin{aligned}
y_{\emptyset} &= \mathbb{E}[y(\boldsymbol{X})] \\
&= \arg\min_{a \in \mathbb{R}} \mathbb{E}[(y(\boldsymbol{X}) - a)^2] \\
&= \arg\min_{g_0 \in \mathcal{G}_0} \|y - g_0\|^2 = \Pi_{\mathcal{G}_0} y
\end{aligned}
$$

$$
\begin{aligned}
y_u(.) &= \mathbb{E}[y(\boldsymbol{X}) \mid X_u = .] - \sum_{v \subsetneq u} y_v(.) \\
&= \arg\min_{g_u \in \mathcal{G}_u} \mathbb{E}[(y(\boldsymbol{X}) - g_u(.))^2] - \sum_{v \subsetneq u} y_v(.) \\
&= (\Pi_{\mathcal{G}_u} y)(.) - \sum_{v \subsetneq u} y_v(.)
\end{aligned}
$$

Equality to Hoeffding Decomposition

Hoeffding Decomposition

$$y(\boldsymbol{X}) = \sum_{A \subseteq D} y_A(\boldsymbol{X}_A), \qquad D := \{1, \ldots, N\}, \tag{1}$$

where, for each $A \subseteq D$, the component function y_A is defined by:

$$y_A(\boldsymbol{X}_A) = \sum_{B \subseteq A} (-1)^{|A|-|B|} \, \mathbb{E}[y(\boldsymbol{X}) \mid \boldsymbol{X}_B] \,, \tag{2}$$

where y_u are orthogonal components.

- Classical fANOVA and Hoeffding decomposition yield same components under zero-centered inputs
- Both assume independence of input variables

Hoeffding Decomposition Example

$$y(x_1, x_2) = 2x_1 + x_2^2 + x_1 x_2$$

$$y_\emptyset = \mathbb{E}[y(X_1, X_2)] = 2\,\mathbb{E}[X_1] + \mathbb{E}[X_2^2] + \mathbb{E}[X_1 X_2] = 1,$$

$$\begin{aligned} y_{\{1\}}(x_1) &= \sum_{B \subseteq \{1\}} (-1)^{1-|B|}\,\mathbb{E}[y(\boldsymbol{X}) \mid X_B] = -\,\mathbb{E}[y] + \mathbb{E}[y|X_1 = x_1] \\ &= -1 + (2x_1 + \mathbb{E}[X_2^2] + x_1\mathbb{E}[X_2]) = 2x_1, \end{aligned}$$

$$\begin{aligned} y_{\{2\}}(x_2) &= \sum_{B \subseteq \{2\}} (-1)^{1-|B|}\,\mathbb{E}[y(\boldsymbol{X}) \mid X_B] - \;\mathbb{E}[y] + \mathbb{E}[y|X_2 = x_2] \\ &= -1 + (2\mathbb{E}[X_1] + x_2^2 + x_2\mathbb{E}[X_1]) = x_2^2 - 1. \end{aligned}$$

$$
\begin{aligned}
y_{\{1,2\}}(x_1, x_2) &= \sum_{B \subseteq \{1,2\}} (-1)^{2-|B|}\, \mathbb{E}[y(\boldsymbol{X}) \mid X_B] \\
&= (+1)\,\mathbb{E}[y] - \mathbb{E}[y|X_1 = x_1] - \mathbb{E}[y|X_2 = x_2] + y(x_1, x_2) \\
&= 1 - (2x_1 + 1) - (x_2^2) + (2x_1 + x_2^2 + x_1 x_2) \\
&= x_1 x_2 .
\end{aligned}
$$

$$
y(x_1, x_2) = y_\emptyset + y_{\{1\}}(x_1) + y_{\{2\}}(x_2) + y_{\{1,2\}}(x_1, x_2) = 1 + 2x_1 + (x_2^2 - 1) + x_1 x_2
$$

Substituting the basis functions:

$$
\begin{aligned}
y(x_1, x_2) = \underbrace{c_0}_{y_0} &+ \underbrace{\left(c_{1,1}\, x_1 + c_{1,2}\, (x_1^2 - 1)\right)}_{y_1(x_1)} \\
&+ \underbrace{\left(c_{2,1}\, x_2 + c_{2,2}\, (x_2^2 - 1)\right)}_{y_2(x_2)} \\
&+ \underbrace{c_{12,11} \left(\frac{\rho(x_1^2 + x_2^2)}{1 + \rho^2} - x_1 x_2 + \frac{\rho(\rho^2 - 1)}{1 + \rho^2} \right)}_{y_{12}(x_1, x_2)}.
\end{aligned}
$$

Find weights to recover original polynomial while fulfilling zero-mean and hierarchical orthogonality:

$$
y(x_1, x_2) = a_0 + a_1 x_1 + a_2 x_2 + a_{11} x_1^2 + a_{22} x_2^2 + a_{12} x_1 x_2
$$

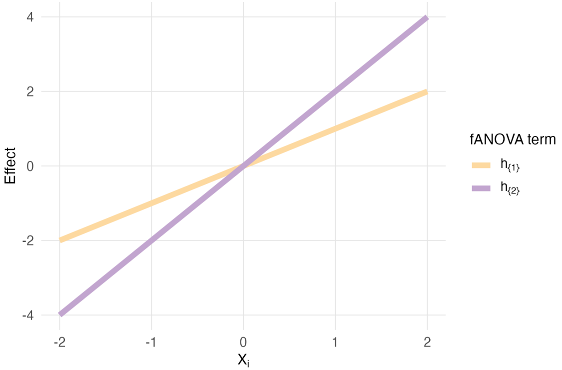
Coefficient Matching

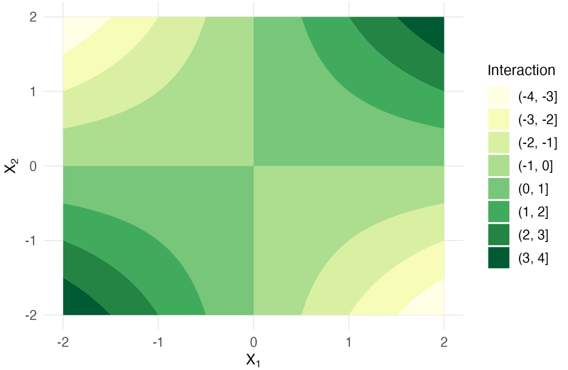
The corresponding weights can be found via coefficient matching. Start from the interaction term:

$$
\begin{aligned}
-c_{12,11} &= a_{12} && \Rightarrow && c_{12,11} = -a_{12} \\
c_{1,2} + c_{12,11}\,\tfrac{\rho}{1+\rho^2} &= a_{11} && \Rightarrow && c_{1,2} = a_{11} + \tfrac{\rho}{1+\rho^2} a_{12} \\
c_{2,2} + c_{12,11}\,\tfrac{\rho}{1+\rho^2} &= a_{22} && \Rightarrow && c_{2,2} = a_{22} + \tfrac{\rho}{1+\rho^2} a_{12} \\
c_{1,1} &= a_1 \\
c_{2,1} &= a_2 \\
c_0 - c_{1,2} - c_{2,2} + c_{12,11}\,\frac{\rho(\rho^2-1)}{1+\rho^2} &= a_0 && \Rightarrow && c_0 = a_0 + a_{11} + a_{22} + \rho\, a_{12}
\end{aligned}
$$

Running Example from Thesis under Independence

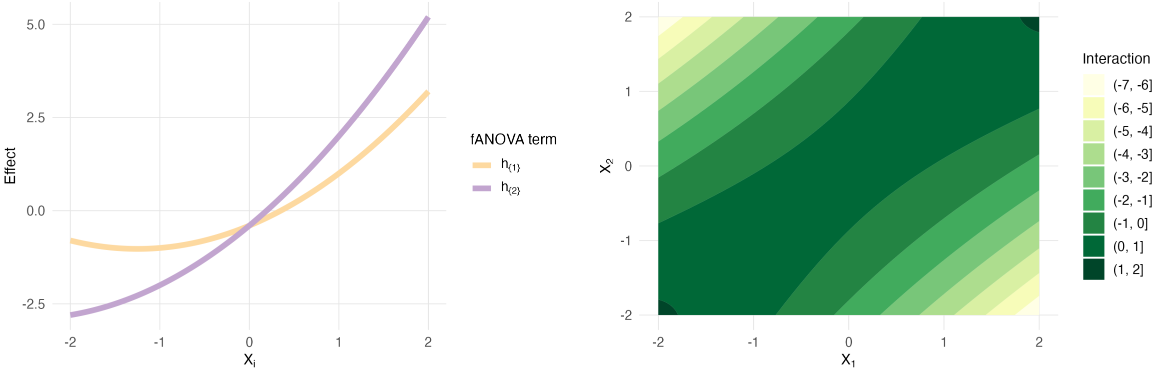
$$h(x_1, x_2) = x_1 + 2x_2 + x_1 x_2 \qquad \rho = 0 \tag{3}$$





Running Example from Thesis under Dependence

$$h(x_1, x_2) = x_1 + 2x_2 + x_1x_2 \qquad \rho = 0.5 \tag{4}$$



Example: Only Linear Terms

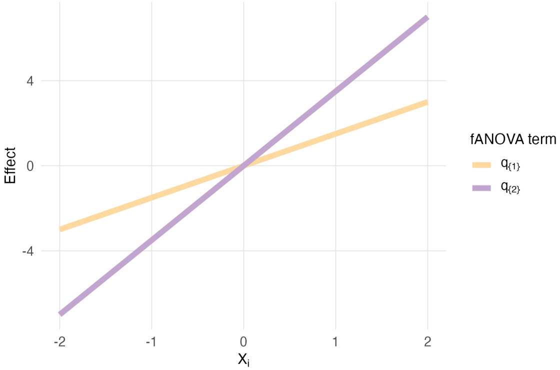


Figure: $q(x_1, x_2) = 1.5x_1 + 3.5x_2$

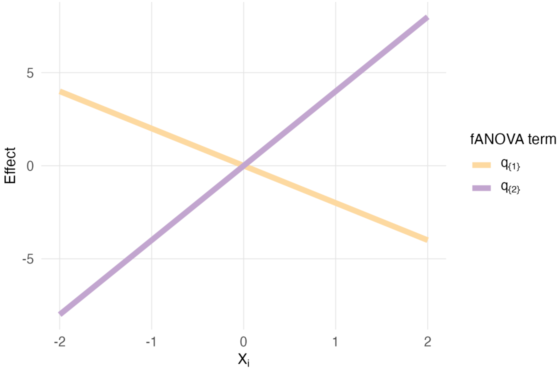
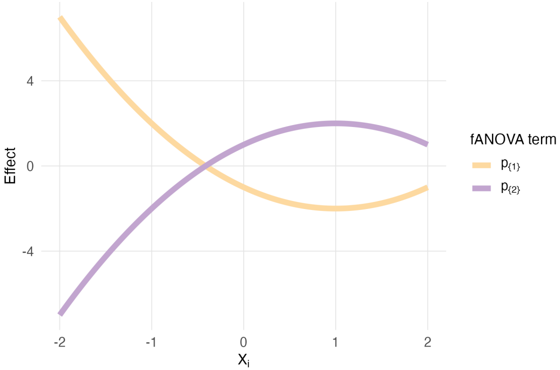
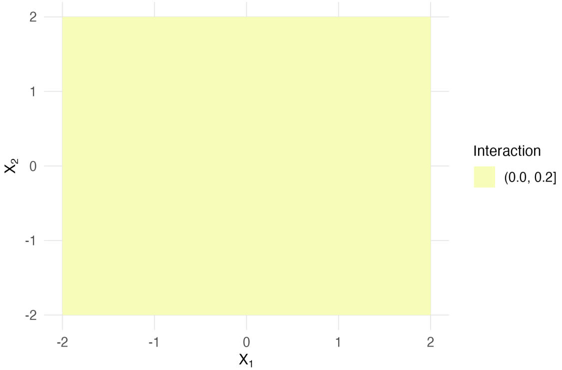


Figure: $q(x_1, x_2) = -2x_1 + 4x_2$

Example: Only Main Terms under Independence

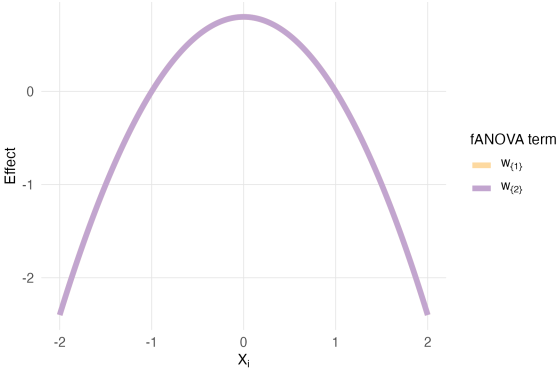
$$y(x_1, x_2) = -2x_1 - 2x_2 + x_1^2 + x_2^2 \qquad \rho = 0$$

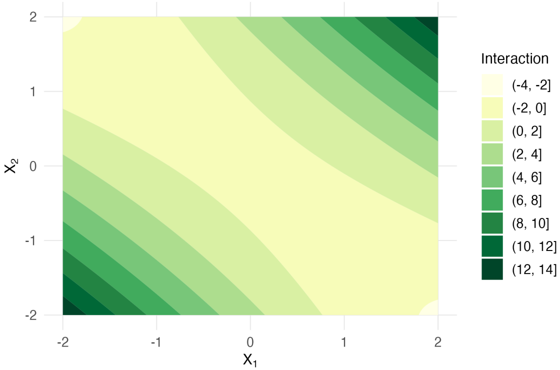




Example: Only Interaction Term under Dependence

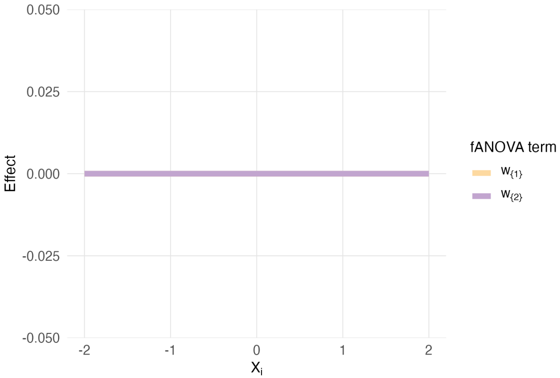
$$y(x_1, x_2) = x_1 x_2 \qquad \rho = -0.5$$

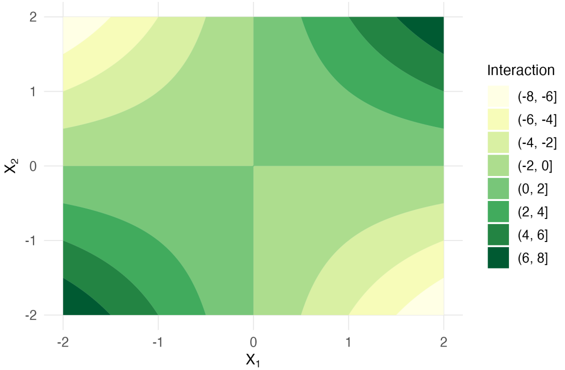




Example: Interaction under Independence

$$y(x_1, x_2) = x_1 x_2 \qquad \rho = 0$$





Proof of Zero-Mean Property for Classical Components

Strong annihilating conditions hold, so:

$$
\begin{aligned}
\mathbb{E}[y_u(\boldsymbol{X}_u)] &:= \int_{\mathbb{R}^N} y_u(\boldsymbol{x}_{\boldsymbol{u}}) f_{\boldsymbol{X}}(\boldsymbol{x})\, d\nu(\boldsymbol{x}) \\
&= \int_{\mathbb{R}^{|u|}} y_u(\boldsymbol{x}_{\boldsymbol{u}}) f_{\boldsymbol{u}}(\boldsymbol{x}_u)\, d\nu(\boldsymbol{x}_u) \\
&= \int_{\mathbb{R}^{|u|}} y_u(\boldsymbol{x}_{\boldsymbol{u}}) \prod_{j \in u} f_{\{j\}}(x_j)\, d\nu(\boldsymbol{x}_u) \\
&= \int_{\mathbb{R}^{|u|-1}} \int_{\mathbb{R}} y_u(\boldsymbol{x}_{\boldsymbol{u}}) f_{\{i\}}(x_i)\, d\nu(x_i) \prod_{j \in u, j \neq i} f_{\{j\}}(x_j)\, d\nu(x_{u \setminus \{i\}}) = 0.
\end{aligned}
$$

Proof of Orthogonality for Classical Components

- $u \neq v$, so pick $i \in u \setminus v$
- $y_v(\boldsymbol{x_v})$ is independent of x_i
- strong annihilating conditions hold by assumption

$$\int_{\mathbb{R}} y_u(\boldsymbol{x}_u) f_{\{i\}}(x_i)\, d\nu(x_i) = 0 \quad \text{for all fixed } \boldsymbol{x}_{u\setminus\{i\}}.$$

Hence,

$$\begin{aligned}
\mathbb{E}[y_u(\boldsymbol{X}_u) y_v(\boldsymbol{X}_v)] &= \int_{\mathbb{R}^N} y_u(\boldsymbol{x_u}) y_v(\boldsymbol{x_v}) f_{\boldsymbol{X}}(\boldsymbol{x})\, d\nu(\boldsymbol{x}) \\
&= \int_{\mathbb{R}^N} y_u(\boldsymbol{x}_u) y_v(\boldsymbol{x}_v) \prod_{j=1}^{N} f_{\{j\}}(x_j)\, d\nu(\boldsymbol{x}) \\
&= \int_{\mathbb{R}^{N-1}} \left(\int_{\mathbb{R}} y_u(\boldsymbol{x}_u) f_{\{i\}}(x_i)\, d\nu(x_i) \right) y_v(\boldsymbol{x}_v) \prod_{j\neq i} f_{\{j\}}(x_j)\, d\nu(\boldsymbol{x}_{-i}) = 0.
\end{aligned}$$

Proof of Zero-Mean Property for Generalized Components

We assume the weak annihilating conditions hold, then:

$$
\begin{aligned}
\mathbb{E}[y_{u,G}(\boldsymbol{X}_u)] &:= \int_{\mathbb{R}^N} y_{u,G}(\boldsymbol{x}_u) f_{\boldsymbol{X}}(\boldsymbol{x})\, d\nu(\boldsymbol{x}) \\
&= \int_{\mathbb{R}^{|u|}} y_{u,G}(\boldsymbol{x}_u) \left(\int_{\mathbb{R}^{N-|u|}} f_{\boldsymbol{X}}(\boldsymbol{x})\, d\nu(\boldsymbol{x}_{-u}) \right) d\nu(\boldsymbol{x}_u) \\
&= \int_{\mathbb{R}^{|u|}} y_{u,G}(\boldsymbol{x}_u) f_u(\boldsymbol{x}_u)\, d\nu(\boldsymbol{x}_u) \\
&= \int_{\mathbb{R}^{|u|-1}} \left(\int_{\mathbb{R}} y_{u,G}(\boldsymbol{x}_u) f_u(\boldsymbol{x}_u)\, d\nu(x_i) \right) \prod_{j \in u, j \neq i} d\nu(\boldsymbol{x}_j) \\
&= 0.
\end{aligned}
$$

Proof of Hierarchical Orthogonality

For any two subsets $\emptyset \neq u \subseteq \{1, \ldots, N\}$ and $\emptyset \neq v \subseteq \{1, \ldots, N\}$, where $v \subsetneq u$, the subset $u = v \cup (u \setminus v)$. Let $i \in (u \setminus v) \subseteq u$. Then we obtain:

$$
\begin{aligned}
\mathbb{E}[y_{u,G}(\boldsymbol{X}_u)\, y_{v,G}(\boldsymbol{X}_v)] &:= \int_{\mathbb{R}^N} y_{u,G}(\boldsymbol{x}_u) y_{v,G}(\boldsymbol{x}_v) f_{\boldsymbol{X}}(\boldsymbol{x})\, d\nu(\boldsymbol{x}) \\
&= \int_{\mathbb{R}^{|u|}} y_{u,G}(\boldsymbol{x}_u) y_{v,G}(\boldsymbol{x}_v) \left(\int_{\mathbb{R}^{N-|u|}} f_{\boldsymbol{X}}(\boldsymbol{x})\, d\nu(\boldsymbol{x}_{-u}) \right) d\nu(\boldsymbol{x}_u) \\
&= \int_{\mathbb{R}^{|u|}} y_{u,G}(\boldsymbol{x}_u) y_{v,G}(\boldsymbol{x}_v) f_u(\boldsymbol{x}_u)\, d\nu(\boldsymbol{x}_u) \\
&= \int_{\mathbb{R}^{|v|}} y_{v,G}(\boldsymbol{x}_v) \int_{\mathbb{R}^{|u\setminus v|}} y_{u,G}(\boldsymbol{x}_u) f_u(\boldsymbol{x}_u)\, d\nu(\boldsymbol{x}_{u\setminus v})\, d\nu(\boldsymbol{x}_v) \\
&= \int_{\mathbb{R}^{|v|}} y_{v,G}(\boldsymbol{x}_v) \int_{\mathbb{R}^{|u\setminus v|-1}} \left(\int_{\mathbb{R}} y_{u,G}(\boldsymbol{x}_u) f_u(\boldsymbol{x}_u)\, d\nu(\boldsymbol{x}_i) \right) \\
&\times \prod d\nu(x_j)\, d\nu(\boldsymbol{x}_v) = 0.
\end{aligned}
$$

Sobol' Indices

$$S_u = \frac{\mathrm{Var}(\mathbb{E}\left[y(\boldsymbol{X}) \mid \mathbf{X}_u = .\right])}{\mathrm{Var}(y(\boldsymbol{X}))},$$

where

- $y(\boldsymbol{X})$ is the probabilistic model, which is decomposed
- $\mathbb{E}[y(\boldsymbol{X}) \mid \mathbf{X}_u = .]$ is the fANOVA component y_u

External Links

- https://docs.google.com/spreadsheets/d/1K5ECL6hDPDnHwM_k342xa29H-vHWzdk27PTgDHUwfFE/edit?usp=sharing - Table with fANOVA-related literature

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