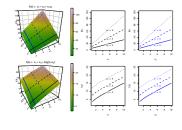
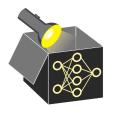
Interpretable Machine Learning

Feature Interactions





- Feature interactions
- Difference to feature dependencies



- Feature dependencies concern data distribution
- Feature interactions may occur in structure of **both** model or DGP (e.g., functional relationship between X and $\hat{f}(X)$ or X and Y = f(X)) \rightsquigarrow Feature dependencies may lead to feature interactions in a model



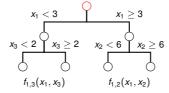
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- No. of potential interactions increases exponentially with no. of features
 Difficult to identify interactions, especially when features are dependent
- Interactions: A feature's effect on the prediction depends on other features \rightsquigarrow Example: $\hat{f}(\mathbf{x}) = x_1 x_2 \Rightarrow$ Effect of x_1 on \hat{f} depends on x_2 and vice versa



No interaction



Interactions: x_1 and x_3 , x_1 and x_2

No interactions: x_2 and x_3



FEATURE INTERACTIONS > Friedman and Popescu (2008)

Definition: A function $f(\mathbf{x})$ contains an interaction between x_i and x_k if a difference in $f(\mathbf{x})$ -values due to changes in x_i will also depend on x_k , i.e.:

$$\mathbb{E}\left[\frac{\partial^2 f(\mathbf{x})}{\partial x_j \partial x_k}\right]^2 > 0$$



 \Rightarrow If x_i and x_k do not interact, $f(\mathbf{x})$ is sum of 2 functions, each independent of x_i , x_k :

$$f(\mathbf{x}) = f_{-j}(x_1, \dots, x_{j-1}, x_{j+1}, \dots, x_p) + f_{-k}(x_1, \dots, x_{k-1}, x_{k+1}, \dots, x_p)$$

Example: $f(\mathbf{x}) = x_1 + x_2 + x_1 \cdot x_2$ (not separable)

$$\mathbb{E}\left[\tfrac{\partial^2(x_1+x_2+x_1\cdot x_2)}{\partial x_1\partial x_2}\right]^2 = \mathbb{E}\left[\tfrac{\partial(1+x_2)}{\partial x_2}\right]^2 = 1 > 0$$

 \Rightarrow interaction between x_1 and x_2

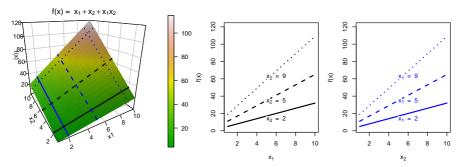


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- Effect of x_1 on $f(\mathbf{x})$ varies with x_2 (and vice versa)
- ⇒ Different slopes

Example of separable function:

$$f(\mathbf{x}) = x_1 + x_2 + \log(x_1 \cdot x_2) = x_1 + x_2 + \log(x_1) + \log(x_2)$$

$$\Rightarrow f(\mathbf{x}) = f_1(x_1) + f_2(x_2) \text{ with } f_1(x_1) = x_1 + \log(x_1) \text{ and } f_2(x_2) = x_2 + \log(x_2)$$

$$\Rightarrow$$
 no interactions due to separability, also $\mathbb{E}\left[\frac{\partial^2 \textit{f}(\textbf{x})}{\partial \textit{x}_1 \partial \textit{x}_2}\right]^2 = 0$

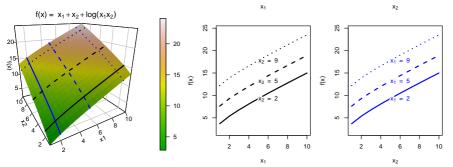


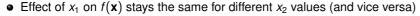
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⇒ Parallel lines at different horizontal (blue) or vertical (black) slices

