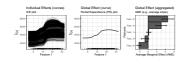
Interpretable Machine Learning

Individual Conditional Expectation (ICE) Plot





- ICE curves as local effect method
- How to sample grid points for ICE curves



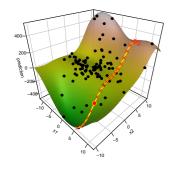
MOTIVATION

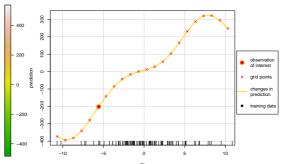
Question: How does changing values of a single feature of an observation affect model prediction?

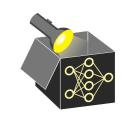
Idea: Change values of observation and feature of interest, and visualize how prediction changes

Example: Prediction surface of a model (left), select observation and visualize changes in prediction for different values of x_2 while keeping x_1 fixed

 \Rightarrow local interpretation







INDIVIDUAL CONDITIONAL EXPECTATION (ICE)

► Goldstein et. al (2013)

Partition each observation ${\bf x}$ into ${\bf x}_S$ (feature(s) of interest) and ${\bf x}_{-S}$ (remaining features)

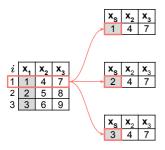


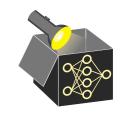
	x _s	X _{-s}	
i	X ₁	X ₂	X ₃
1	1	4	7
2	2	5	8
3	3	6	9

 \leadsto In practice, \mathbf{x}_S consists of one or two features (i.e., $|S| \leq 2$ and $-S = S^\complement$).

Formal definition of ICE curves:

- Choose grid points $\mathbf{x}_S^* = \mathbf{x}_S^{*(1)}, \dots, \mathbf{x}_S^{*(g)}$ to vary \mathbf{x}_S
- For each *k* connect point pairs to obtain **ICE curve**
- \sim ICE curves visualize how prediction of *i*-th observation changes after varying its feature values indexed by S using grid points \mathbf{x}_{S}^{*} while keeping all values in -S fixed

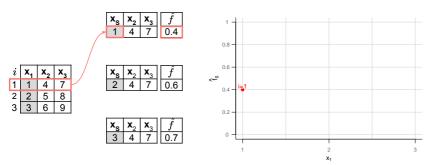


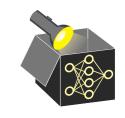


1. Step - Grid points:

Sample grid values $\mathbf{x}_{S}^{*^{(1)}}, \dots, \mathbf{x}_{S}^{*^{(g)}}$ along feature of interest \mathbf{x}_{S} and replace vector $\mathbf{x}^{(i)}$ in data with grid

 \Rightarrow Creates new artificial points for *i*-th observation (here: $\mathbf{x}_S^* = x_1^* \in \{1,2,3\}$ scalar)

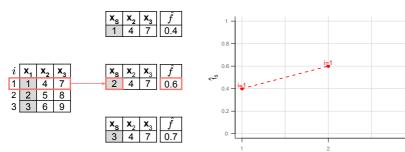


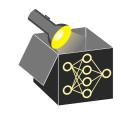


2. Step - Predict and visualize:

For each artificially created data point of *i*-th observation, plot prediction $\hat{f}_{S,ICE}^{(i)}(\mathbf{x}_S^*)$ vs. grid values \mathbf{x}_S^* :

$$\hat{f}_{1,ICE}^{(i)}(x_1^*) = \hat{f}(x_1^*, \mathbf{x}_{2,3}^{(i)}) ext{ vs. } x_1^* \in \{1, 2, 3\}$$

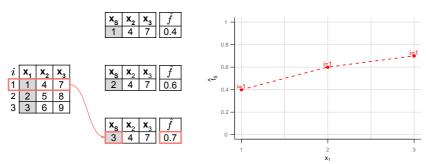


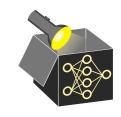


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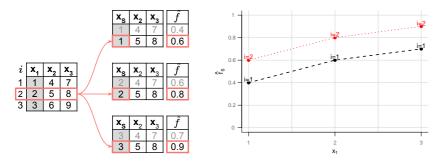




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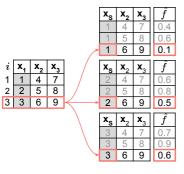
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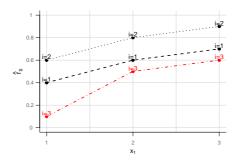


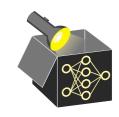


3. Step - Repeat for other observations:

ICE curve for i = 2 connects all predictions at grid values associated to i-th observation.







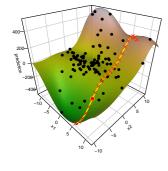
3. Step - Repeat for other observations:

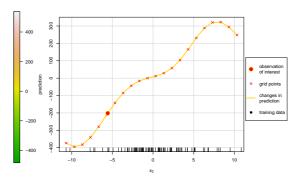
ICE curve for i = 3 connects all predictions at grid values associated to i-th observation.

ICE CURVES - INTERPRETATION

Example: Prediction surface of a model (left), select observation and visualize changes in prediction for different values of x_2 while keeping x_1 fixed

 \Rightarrow local interpretation





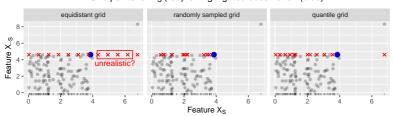


COMMENTS ON GRID VALUES

- Plotting ICE curves involves generating grid values **x**_S*; visualized on x-axis
- Common choices for grid values are
 - equidistant grid values within feature range
 - randomly sampled values or quantile values of observed feature values
- Except equidistant grid, the other two options preserve (approximately) the marginal distribution of feature of interest



Grid points for X_S (red) for highlighted observation (blue)



COMMENTS ON GRID VALUES

- Plotting ICE curves involves generating grid values x_S*; visualized on x-axis
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 - equidistant grid values within feature range
 - randomly sampled values or quantile values of observed feature values
- Except equidistant grid, the other two options preserve (approximately) the marginal distribution of feature of interest
- Correlations/interactions → unrealistic values in all three methods

