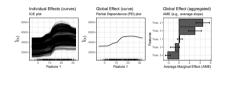
Interpretable Machine Learning

Individual Conditional Expectation (ICE) Plot



Learning goals

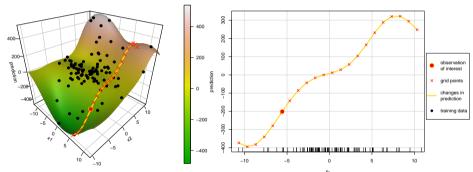
- ICE curves as local effect method
- How to sample grid points for ICE curves

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)

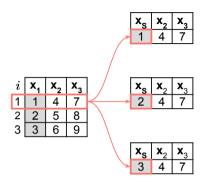
Partition each observation \mathbf{x} into \mathbf{x}_{S} (features of interest) and \mathbf{x}_{S} (remaining feat.)

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



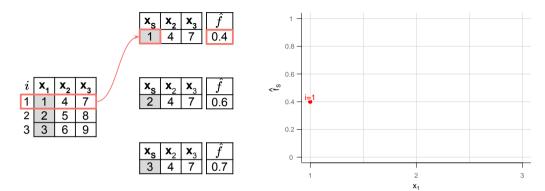
Formal definition of ICE curves:

- Choose grid points $\mathbf{x}_{S}^{*} = \mathbf{x}_{S}^{*(1)}, \dots, \mathbf{x}_{S}^{*(g)}$ to vary \mathbf{x}_{S}
- $\bullet \ \ \mathsf{Plot} \ \mathsf{point} \ \mathsf{pairs} \ \left\{ \left(\mathbf{x}_{S}^{*^{(k)}}, \hat{f}_{S}^{(i)}(\mathbf{x}_{S}^{*^{(k)}})\right) \right\}_{k=1}^{g} \ \ \mathsf{where} \ \hat{f}_{S}^{(i)}(\mathbf{x}_{S}^{*}) = \hat{f}(\mathbf{x}_{S}^{*}, \mathbf{x}_{-S}^{(i)})$
- For each k connect point pairs to obtain ICE curve
- → 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:

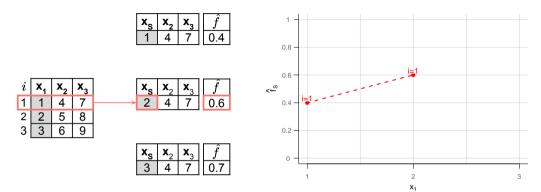
Sample grid values $\mathbf{x}_{S}^{*^{(1)}}, \dots, \mathbf{x}_{S}^{*^{(g)}}$ along feature of interest \mathbf{x}_{S} and replace vector $\mathbf{x}^{(i)}$ in data with grid \Rightarrow Creates new artificial points for the *i*-th observation (here: $\mathbf{x}_{S}^{*} = x_{1}^{*} \in \{1, 2, 3\}$ is a scalar)



2. Step - Predict and visualize:

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

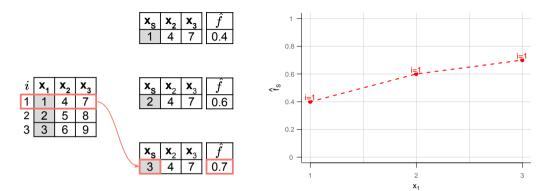
$$\hat{f}_1^{(i)}(x_1^*) = \hat{f}(x_1^*, \mathbf{x}_{2,3}^{(i)})$$
 vs. $x_1^* \in \{1, 2, 3\}$



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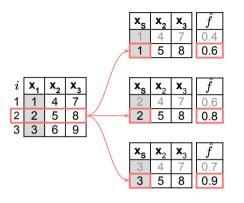
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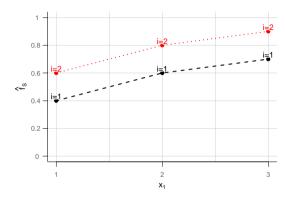


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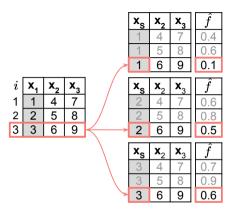
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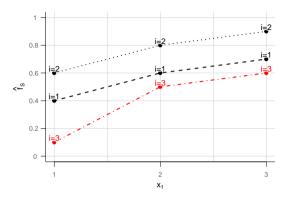




3. Step - Repeat for other observations:

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





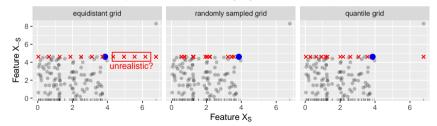
3. Step - Repeat for other observations:

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

COMMENTS ON GRID VALUES

- Plotting ICE curves involves generating grid values x^{*}_S that are visualized on the 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 ⇒ Avoids unrealistic feature values for distributions with outliers

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



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