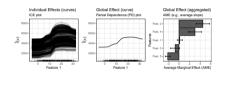
# **Interpretable Machine Learning**

# **Individual Conditional Expectation (ICE) Plot**



#### Learning goals

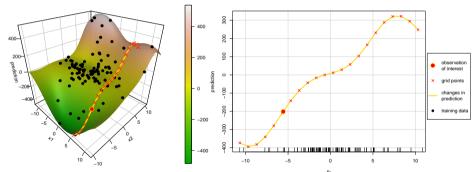
- ICE curves as local effect method
- How to sample grid points for ICE curves

#### **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)

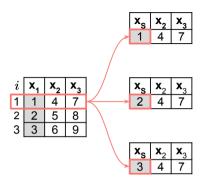
Partition each observation  $\mathbf{x}$  into  $\mathbf{x}_S$  (features of interest) and remaining features  $\mathbf{X}_{-S}$ .

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

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 -Sfixed:

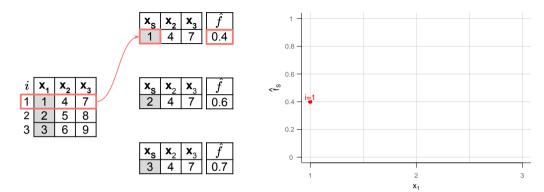
$$\hat{f}_S^{(i)}(\mathbf{x}_S^*)$$
 vs.  $\mathbf{x}_S^*$ 

where  $\hat{f}_{S}^{(i)}(\mathbf{x}_{S}^{*}) = \hat{f}(\mathbf{x}_{S}^{*}, \mathbf{x}_{-S}^{(i)})$  is prediction of *i*-th observation in which original feature value  $\mathbf{x}_{S}^{(i)}$  was replaced by  $\mathbf{x}_{S}^{*}$ 



### 1. Step - Grid points:

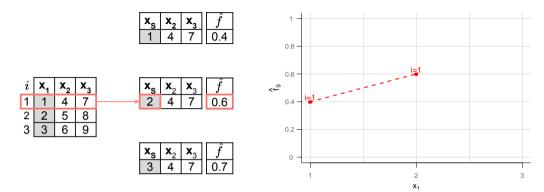
Sample grid values  $\mathbf{x}_S^{*^{(i)}}, \dots, \mathbf{x}_S^{*^{(g)}}$  along feature of interest  $\mathbf{x}_S$  and replace vector  $\mathbf{x}^{(i)}$  in data with grid  $\Rightarrow$  Creates new artificial points for the *i*-th observation (here:  $\mathbf{x}_S^* = x_1^* \in \{1, 2, 3\}$  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  $\mathbf{x}_S^*$ :

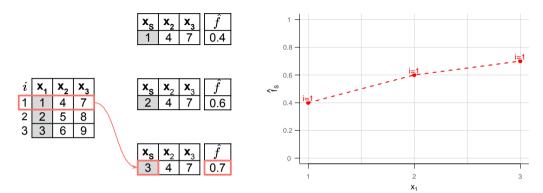
$$\hat{f}_1^{(i)}(x_1^*) = \hat{f}(x_1^*, \mathbf{x}_{2,3}^{(i)})$$
 vs.  $x_1^* \in \{1, 2, 3\}$ 



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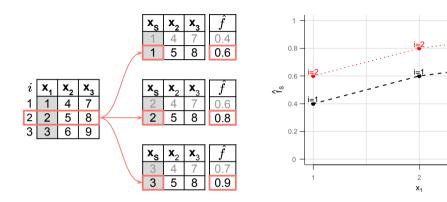
$$\hat{f}_1^{(i)}(x_1^*) = \hat{f}(x_1^*, \mathbf{x}_{2,3}^{(i)}) \text{ vs. } x_1^* \in \{1, 2, 3\}$$



#### 2. Step - Predict and visualize:

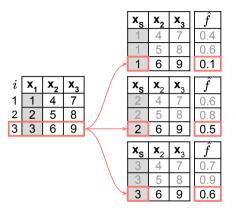
For each artificially created data point of *i*-th observation, plot prediction  $\hat{f}_S^{(i)}(\mathbf{x}_S^*)$  vs. grid values  $\mathbf{x}_S^*$ :

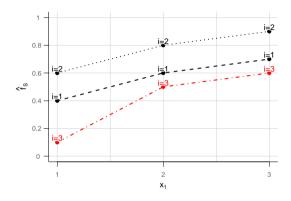
$$\hat{f}_1^{(i)}(x_1^*) = \hat{f}(x_1^*, \mathbf{x}_{2,3}^{(i)})$$
 vs.  $x_1^* \in \{1, 2, 3\}$ 



#### 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<sub>S</sub> 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<sub>S</sub> (red) for highlighted observation (blue)

