Machine Learning Interpretability

The Good, the Bad, and the Ugly

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Contents

Obligatory Front Matter

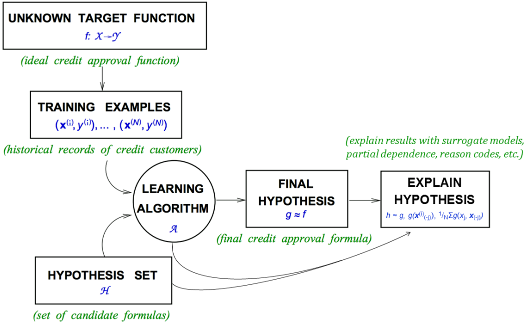
- **What is interpretation?** “The ability to explain or to present in understandable terms to a human.” Doshi-Velez and Kim, 2017
- **What is a good interpretation?** "When you can no longer keep asking why." Gilpin et al., 2018
- **Why should you care?**
  - Understanding of an impactful and quickly expanding set of technologies.
  - Addressing accidental or intentional discrimination.
  - Preventing malicious hacking and adversarial attacks.
  - Enabling regulatory compliance and increased financial margins.

Notation

- **Spaces**.
  - The input features come from a set $\mathcal{X}$ contained in a P-dimensional input space (i.e. $\mathcal{X} \subset \mathbb{R}^P$).
  - The output responses come from a set $\mathcal{Y}$ contained in a C-dimensional output space (i.e. $\mathcal{Y} \subset \mathbb{R}^C$).

- **Dataset**. A dataset $\mathbf{D}$ consists of N tuples of observations: $[(\mathbf{x}^{(0)}, \mathbf{y}^{(0)}), (\mathbf{x}^{(1)}, \mathbf{y}^{(1)}), \ldots, (\mathbf{x}^{(N-1)}, \mathbf{y}^{(N-1)})], \mathbf{x}^{(i)} \in \mathcal{X}, \mathbf{y}^{(i)} \in \mathcal{Y}$.
  - The input data $\mathbf{X}$ is composed of the set of row vectors $\mathbf{x}^{(i)}$.
    - let $\mathcal{P}$ be the set of features $\{X_0, X_1, \ldots, X_{P-1}\}$, where $X_j = \left[x_j^{(0)}, x_j^{(1)}, \ldots, x_j^{(N-1)}\right]^T$.
    - then each i-th observation denoted as $\mathbf{x}^{(i)} = \left[x_0^{(i)}, x_1^{(i)}, \ldots, x_{P-1}^{(i)}\right]$ is an instance of $\mathcal{P}$.

Proposed Updates to the Learning Problem



The learning problem. Adapted from *Learning From Data*, Abu-Mostafa, Magdon-Ismail, and Lin, 2012.

Surrogate Decision Trees (DT)

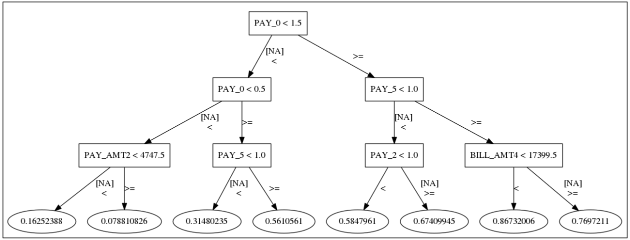


Figure: h_{tree} for Taiwanese credit card data Lichman, 2013, and for machine-learned GBM response function $g(X)$.

- Given a learned function g and set of predictions, $g(\mathbf{X}) = \hat{\mathbf{Y}}$, a surrogate DT can be trained: $\mathbf{X}, \hat{\mathbf{Y}} \xrightarrow{\mathcal{A}_{\text{surrogate}}} h_{\text{tree}}$.
- h_{tree} displays a low-fidelity flow chart of g's decision making process, important features in g, and important interactions in g.

Surrogate Decision Trees (DT)

- Always use error measures to assess the trustworthiness of h_{tree}.
- Prescribed methods (Craven and Shavlik, 1996; Bastani, Kim, and Bastani, 2017) for training h_{tree} do exist. In practice, straightforward cross-validation approaches are typically sufficient.
- Comparing cross-validated error to standard training error can give an indication of the stability of the single tree model, h_{tree}.
- Hu et al., 2018 use local linear surrogate models, h_{glm}, in h_{tree} leaf nodes to increase overall surrogate model accuracy while retaining a high degree of interpretability.
- h_{tree} can provide low-fidelity explanations for model mechanisms in the original feature space if g is defined to include feature extraction.

Partial Dependence (PD) and Individual Conditional Expectation (ICE)

- Following Friedman, Hastie, and Tibshirani, 2001 a single feature $X_j \in \mathcal{P}$, a P-dimensional feature space, and its complement set $\mathcal{P}_{(-j)}$ (where $X_j \cup \mathcal{P}_{(-j)} = \mathcal{P}$) is considered.
- $\text{PD}(X_j, g)$ for a given feature X_j is estimated as the average of the output of the learned function g, where all the components of X_j are set to a constant $x_j^{(i)} \in X_j$, and $\mathcal{P}_{(-j)}$ is left untouched.
- $\text{ICE}(\mathbf{x}_j^{(i)}, g)$ for a given row $\mathbf{x}^{(i)}$ and feature X_j is estimated as the output of the learned function g where $x_j^{(i)}$ is set to a constant $x_j^{(i)} \in X_j$ and $\mathbf{x}^{(i)} \in \mathcal{P}_{(-j)}$ are left untouched.
- PD and ICE are usually plotted over some set of interesting $x_j^{(i)} \in X_j$.

Partial Dependence (PD) and Individual Conditional Expectation (ICE)

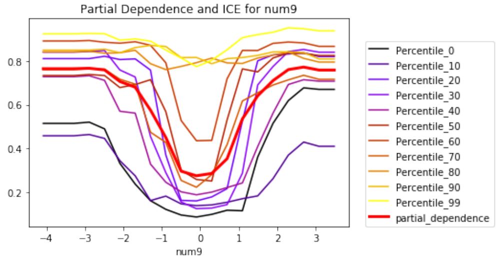


Figure: PD and ICE curves for $X_j = \text{num}_9$, for known signal generating function $f(X) = \text{num}_1 * \text{num}_4 + |\text{num}_8| * \text{num}_9^2 + e$, and for machine-learned GBM response function $g(X)$.

Overlaying PD and ICE curves is a succinct method for describing global and local prediction behavior and can be used to detect interactions. Goldstein et al., 2015

Partial Dependence (PD) and Individual Conditional Expectation (ICE)

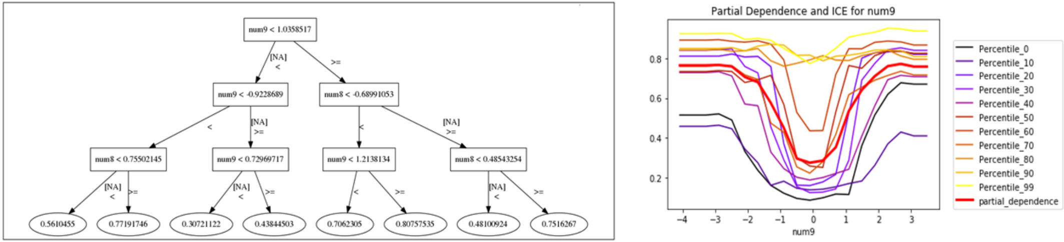


Figure: Surrogate DT, PD, and ICE curves for $X_j = \text{num}_9$, for known signal generating function $f(X) = \text{num}_1 * \text{num}_4 + |\text{num}_8| * \text{num}_9^2 + e$, and for machine-learned GBM response function $g(X)$.

Combining Surrogate DT models with PD and ICE curves is a convenient method for detecting, confirming, and understanding important interactions.

Local Interpretable Model-agnostic Explanations (LIME) - *Description*

Local Interpretable Model-agnostic Explanations (LIME) - *Recommendations*

Tree Shap - *Description*

Tree Shap - *Recommendations*

Closing Recommendations

- Monotonically constrained XGBoost, Surrogate DT, PD and ICE plots, and Tree Shap are a direct and open source way to create an interpretable nonlinear model.
- Global and local explanatory techniques are often necessary to explain a model.
- Simpler low-fidelity or sparse explanations should help in understanding more accurate and complex high-fidelity explanations.
- Seek consistency in results across multiple explanatory techniques.
- Methods that rely on generated data are sometimes unpalatable to users. They want to understand *their* data.
- Beware of uninterpretable features.
- Consider production deployment of explanatory techniques.

Software Examples and Resources

Comparison of Explanatory Techniques on Simulated Data:
https://github.com/h2oai/mli-resources/tree/master/lime_shap_treeint_compare

In-depth Explanatory Technique Examples:
https://github.com/jphall663/interpretable_machine_learning_with_python

"Awesome" Machine Learning Interpretability Resource List:
https://github.com/jphall663/awesome-machine-learning-interpretability

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