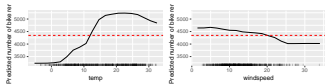
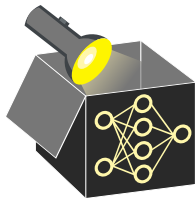


Interpretable Machine Learning

Partial Dependence Feature Importance



Learning goals

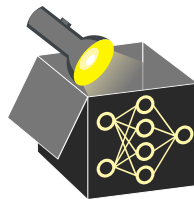
- Introduction to PDP feature importance
- Numerical and Categorical Measures of flatness

PARTIAL DEPENDENCE - REVISION

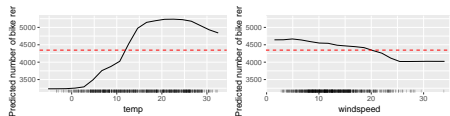
The partial dependence (PD) is the expectation of ICE curves w.r.t. the marginal distribution of complementary features \mathbf{x}_{-S} .

The PD function \hat{f} is estimated by the point-wise average of the ICE curves at \mathbf{x}_S^* :

$$\hat{f}_{S,PD}(\mathbf{x}_S^*) = \frac{1}{n} \sum_{i=1}^n \hat{f}(\mathbf{x}_S^*, \mathbf{x}_{-S}^{(i)})$$

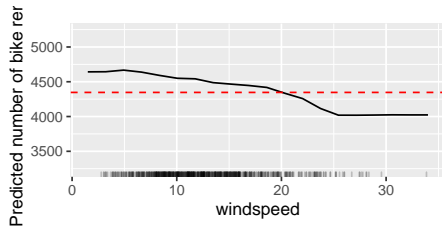
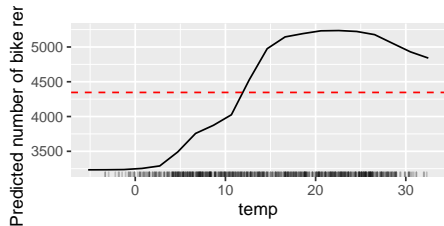
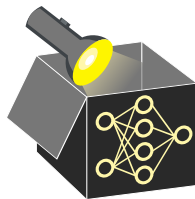


PD plot: Visualizes the **average effect of a feature**, i.e., how the expected prediction changes if the feature value is changed.



PD FEATURE IMPORTANCE - MOTIVATION

- The basic motivation is that a flat PDP indicates that the feature is not important
- The more the PDP varies, the more important the feature is



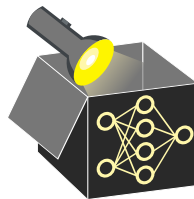
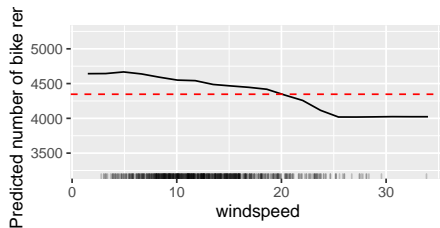
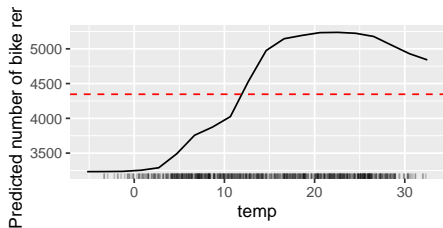
The notion of variable importance is based on any measure of the **flatness** $F(\cdot)$ of the partial dependence function \hat{f} .

$$I(x) = F(\hat{f}_S(\mathbf{z}_S))$$

PD FEATURE IMPORTANCE - IDEA

- Therefore, we focus our attention to the surface that spans between the PDP curve itself and the average of all feature values (red dashed line).

$$\sum_{k=1}^K \hat{f}_S(x_S^{(k)})$$

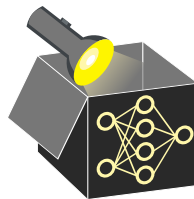
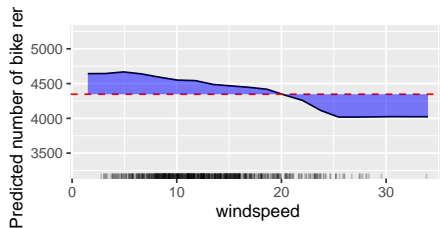
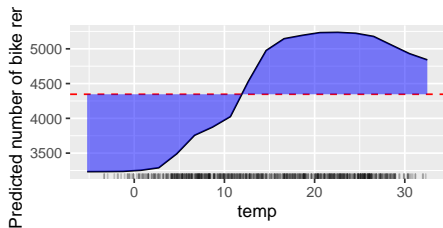


The function $F(\cdot)$ determines the exact quantification of the **flatness** measure.

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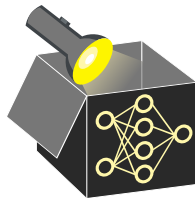
MEASURES OF FLATNESS

For **numerical** features, importance is defined as the deviation of each unique feature value from the average curve

$$I(x_S) = \sqrt{\frac{1}{K-1} \sum_{k=1}^K \left(\hat{f}_S(x_S^{(k)}) - \frac{1}{K} \sum_{k=1}^K \hat{f}_S(x_S^{(k)}) \right)^2}$$

For **categorical** we achieve a rough estimate of the deviation by applying the range rule: This is the range of the PDP values for the unique categories divided by four.

$$I(x_S) = \left(\max_k \left(\hat{f}_S(x_S^{(k)}) \right) - \min_k \left(\hat{f}_S(x_S^{(k)}) \right) \right) / 4$$



DISCUSSION

Advantages

variable importance measure that is...

- suitable for use with any supervised learning algorithm, provided new predictions can be obtained
- model-based and takes into account the effect of all the features in the model
- consistent and has the same interpretation regardless of the learning algorithm employed
- has the potential to help identify possible interaction effects.

Disadvantages

- This PDP-based feature importance should be interpreted with care.
- It captures only the main effect of the feature and ignores possible feature interactions.
- variable importance metric relies on the fitted model; hence, it is crucial to properly tune and train the model to attain the best performance possible.

