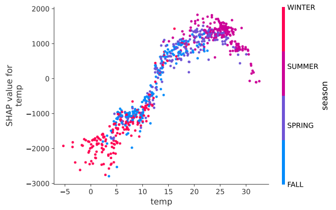
# Interpretable Machine Learning

## Global SHAP

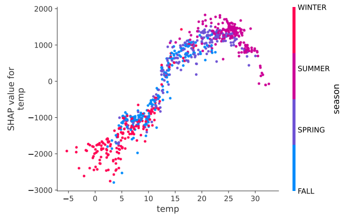



### Learning goals

- Understand how SHAP values can be aggregated for global model interpretation
- Learn global SHAP visualizations: feature importance, summary, and dependence plots
- Recognize advantages and limitations of global SHAP explanations

# Interpretable Machine Learning

## Shapley
## Global SHAP

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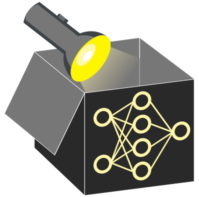
# GLOBAL SHAP ▸ Lundberg et al. 2018



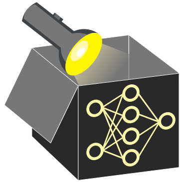
**Idea:**

- Run SHAP for every observation and thereby get a matrix of Shapley values
- The matrix has one row per data observation and one column per feature
- We can interpret the model globally by analyzing the Shapley value matrix

$$\Phi = \begin{bmatrix} \phi_{11} & \phi_{12} & \phi_{13} & \cdots & \phi_{1p} \\ \phi_{21} & \phi_{22} & \phi_{23} & \cdots & \phi_{2p} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \phi_{n1} & \phi_{n2} & \phi_{n3} & \cdots & \phi_{np} \end{bmatrix}$$



# GLOBAL SHAP ▸ LUNDBERG_2018



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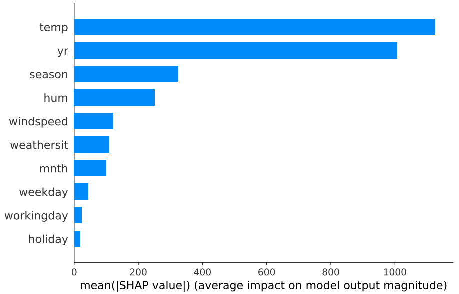
# FEATURE IMPORTANCE

**Idea:** Average the absolute Shapley values of each feature over all observations.
This corresponds to calculating averages column by column in matrix $\Phi$

$$I_j = \frac{1}{n} \sum_{i=1}^{n} \left| \phi_j^{(i)} \right|$$



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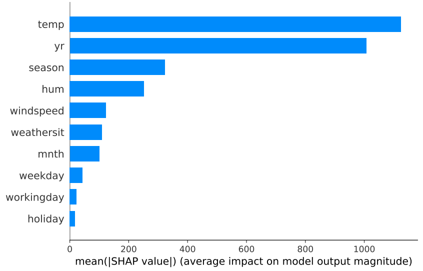
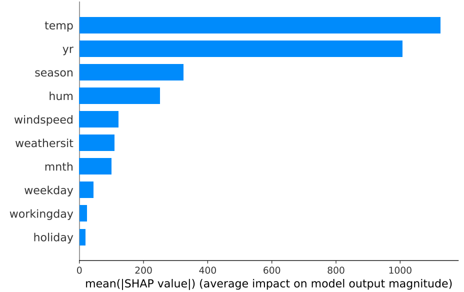


# FEATURE IMPORTANCE

**Interpretation:**

- Features “temp” and “year” have highest influence on the model’s prediction
- Shapley FI does not provide information on direction of the effect
  ⇝ Provides a feature ranking based on the magnitude of the Shapley values
- Shapley FI is based only on model predictions
  Note: Other FI measures are based on model’s performance (loss)



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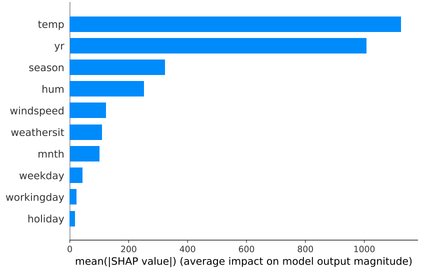
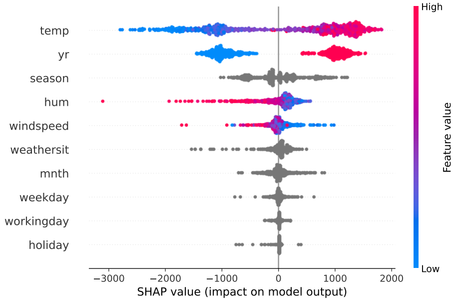


# SUMMARY PLOT

Combines feature importance with feature effects

- Each point is a Shapley value for a feature and an observation
- The color represents the value of the feature from low to high
- Overlapping points are jittered in y-axis direction







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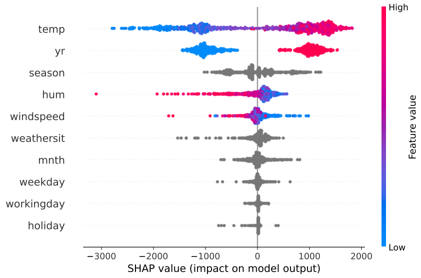




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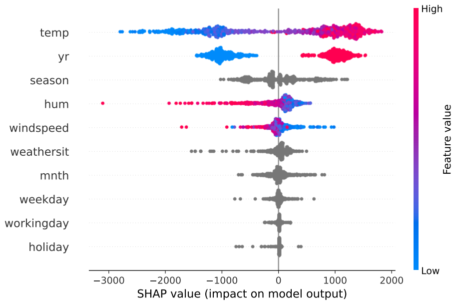
# SUMMARY PLOT

**Interpretation:**

- Low temp have a negative impact; high temp lead to more bike rentals
- Year: two point clouds for 2011 (low value) and 2012 (high value)
- Categorical features are gray (no low/high value)
- High humidity has a huge negative impact on bike rentals
- Low humidity has a rather minor positive impact on bike rentals



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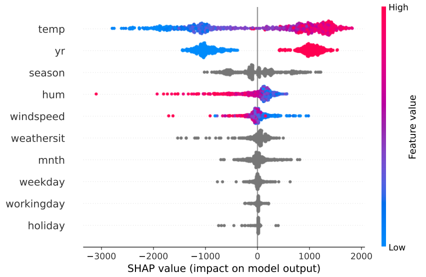
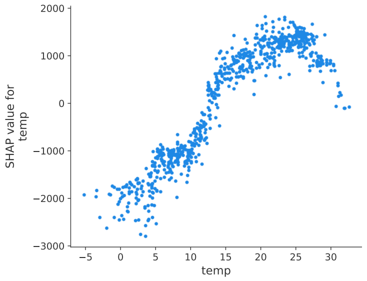


# DEPENDENCE PLOT: EFFECT + INTERACTION

### Interpretation of SHAP Dependence Plot (Feature = Temperature)

- Plot points with feature value on x-axis and corresponding SHAP value on y-axis



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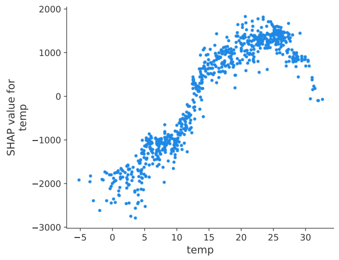

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**Interpretation of SHAP Dependence Plot (Feature = Temperature)**

- Plot points with feature value on x-axis and corresponding SHAP value on y-axis
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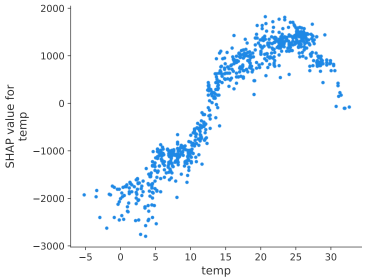
- SHAP values increase with temp until $\approx$25℃: higher temp $\rightsquigarrow$ higher predictions
- After $\approx$25℃, SHAP values decrease slightly



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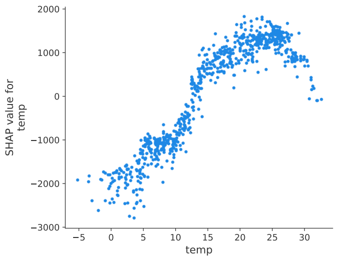

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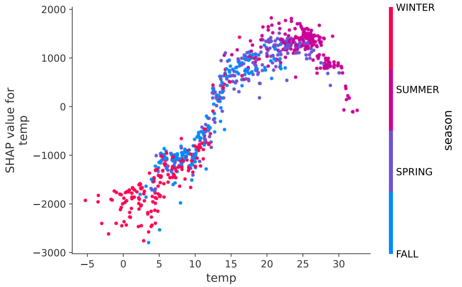
  - In summer, higher temperatures decrease bike rentals
  - In winter, higher temperatures increase bike rentals



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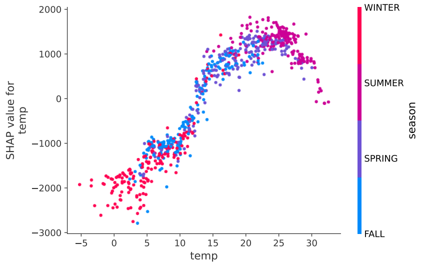

# DISCUSSION

### Advantages

- Retains local accuracy: SHAP values exactly decompose predictions
- Aggregating local SHAP values yields global model insights
  ⇝ Visual diagnostics: feature importance, summary plot, dependence plots
- Efficient for tree-based models via TreeSHAP
  (See ▸ Lundberg et al 2018 and for intuitive explanation ▸ Sukumar: TreeSHAP)
- Unifies feature attribution under a consistent additive framework
- Can be used for images ▸ SHAP image examples and text ▸ SHAP text examples

### Disadvantages

- KernelSHAP is inefficient for large datasets or complex models
- Ignores feature dependencies in marginal sampling (interventional SHAP)
- Conditional sampling (observational SHAP) is difficult in practice (would require estimating a conditional distribution)



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