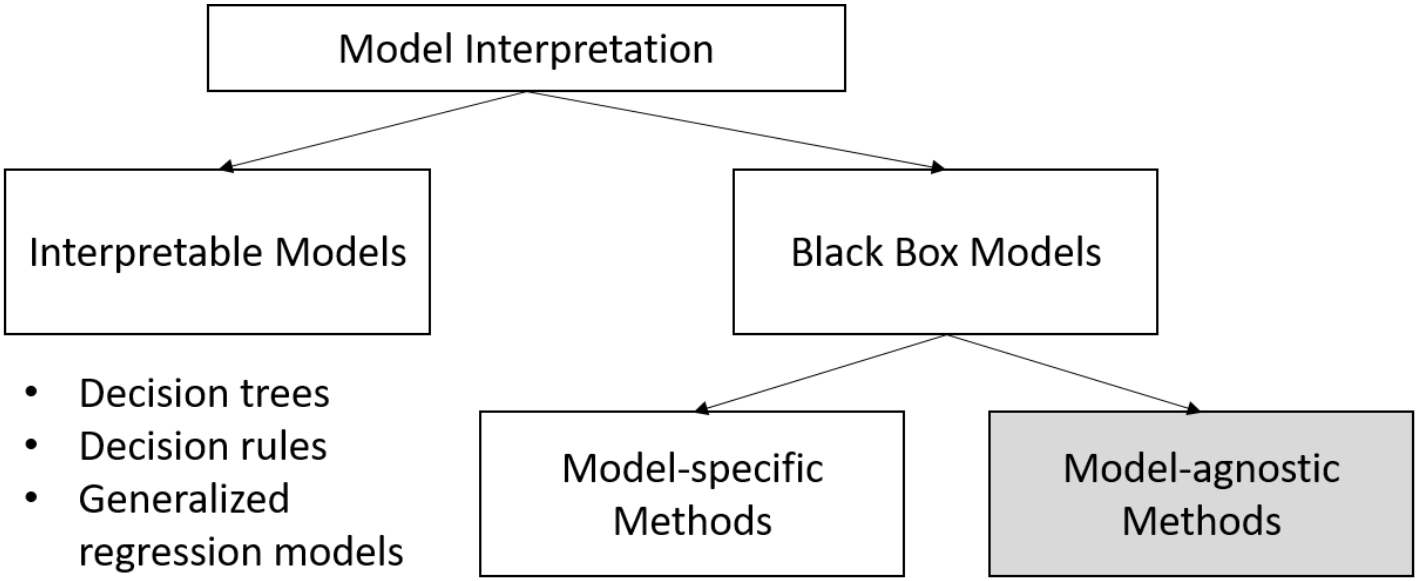
# Interpretable Machine Learning

# Fundamental Terms and Concepts

**Learning goals**

- What is interpretable machine learning (IML)?
  What is the purpose of IML?

# WHAT TOOLS DO WE HAVE?




- Decision trees
- Decision rules
- Generalized regression models

- Random Forest Explainer
- Visualizing activations of neural networks

Advantage: Flexibility

- Underlying models can be exchanged
- Several IML Visualizations can be used

$\Rightarrow$ We will focus on model-agnostic interpretability!

# INTRINSIC AND MODEL-AGNOSTIC INTERPRETATION

- Intrinsically interpretable models:
  - Examples are linear models and decision trees.
  - They are interpretable because of their simple structures, e.g. weighted combination of feature values or tree structure.
  - They are difficult to interpret with many features or complex interaction terms.

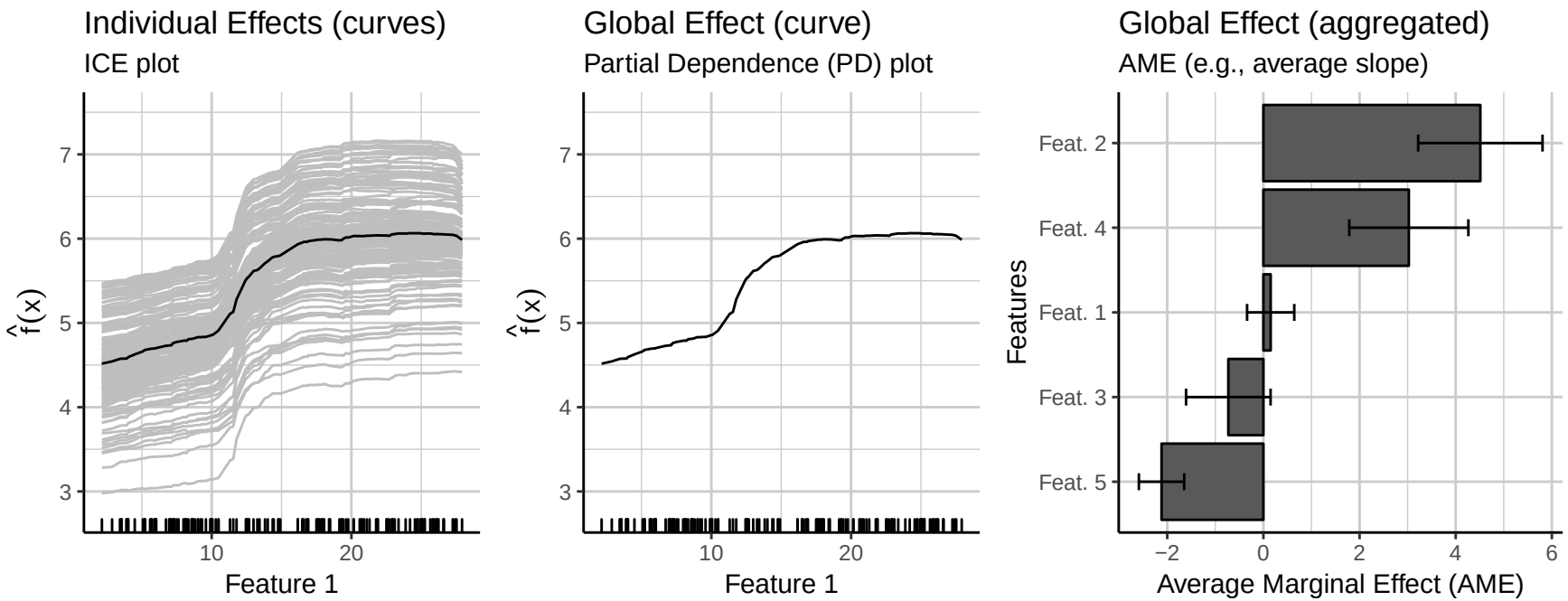
- Model-agnostic interpretation methods:
  - They are applied after training (post-hoc).
  - They also work for more complex black box models.
  - They can also be applied to intrinsically interpretable models, e.g. feature importance for decision trees.

# MODEL-AGNOSTIC INTERPRETABILITY

- Model-agnostic interpretability methods work for **any** kind of machine learning model.
- Explanation type is not tied to the underlying model type.
- Often, only access to data and fitted predictor is required. No further knowledge about the model itself is necessary.
- We usually distinguish between **feature effect** and **feature importance** methods.

# FEATURE EFFECTS VS. FEATURE IMPORTANCE

**Feature Effects** visualize or quantify the (average) relationship or contribution of a feature to the model prediction.

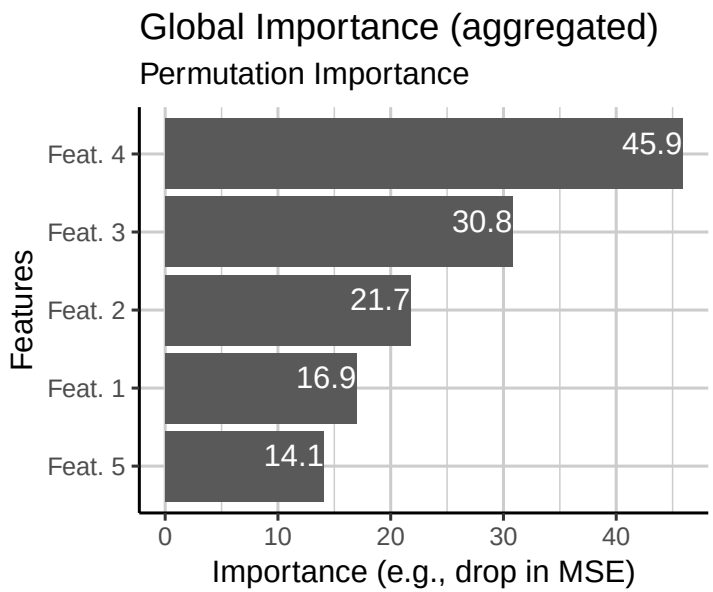



- Methods: Partial Dependence Plots, Individual Conditional Expectation, Accumulated Local Effects (ALE)
- Pendant in linear models: Regression coefficient $\hat{\theta}_j$

# FEATURE EFFECTS VS. FEATURE IMPORTANCE

**Feature importance** methods rank features by how much they contribute to the predictive performance or prediction variance of the model.

- Methods: Permutation Feature Importance, Functional Anova
- Analog in linear models: Absolute t-statistic $\left| \frac{\hat{\theta}_j}{SE(\hat{\theta}_j)} \right|$



# GLOBAL AND LOCAL INTERPRETABILITY

Global interpretability methods explain the expected model behavior for the entire input space by considering all available observations (or representative subsets). For example:

- Permutation Feature Importance
- Partial Dependence Plot
- Functional Anova
- ...

Local interpretability methods explain single predictions or a group of similar observations. For example:

- Individual Conditional Expectation (ICE) Plots
- Local Interpretable Model-Agnostic Explanations (LIME)
- Shapley Values
- ...

# FIXED MODEL VS. REFITS

- Most methods presented in this lecture analyze a fixed, trained model (e.g., permutation feature importance).
- Some methods require refitting the model (e.g., PIMP).
- Trained model $\Rightarrow$ Model is the object of analysis.
- Refitting $\Rightarrow$ Learning process is the object of analysis.
- The advantage of refitting is that it includes information about the variability in the learning process.