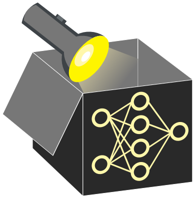
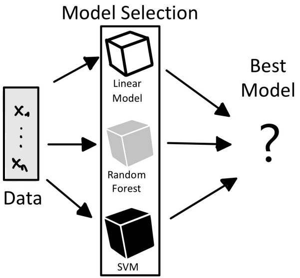
Interpretable Machine Learning

Dimensions of Interpretability

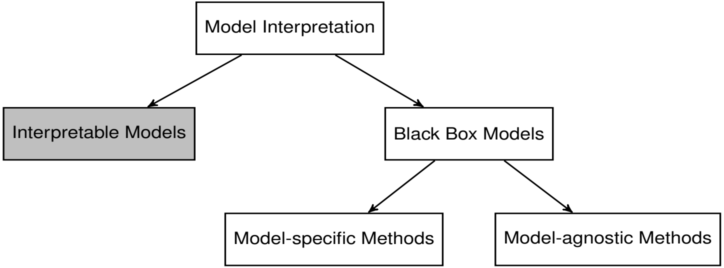


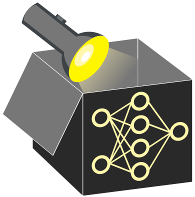


Learning goals

- Intrinsic vs. model-agnostic methods
- Different types of explanations
- Local vs. global methods
- Model or learner explanations – with or without refits
- Levels of interpretability

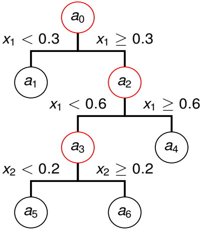
INTRINSIC VS. MODEL-AGNOSTIC





Intrinsically interpretable models:

- Examples: linear model, decision tree, decision rule, GLMs
- Interpretable because of simple model structure,
  e.g., weighted combination of feature values or tree structure
- Difficult to interpret with many features / complex interactions



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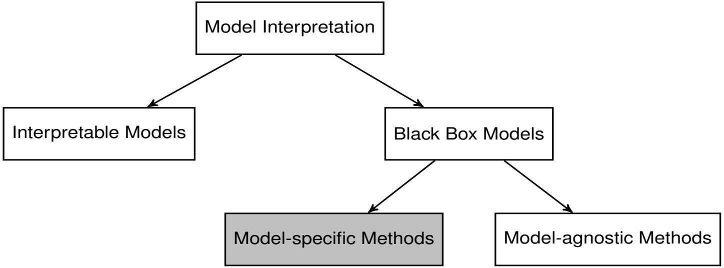
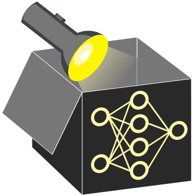
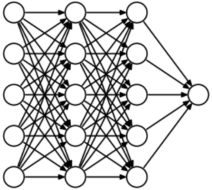




Model-specific methods:

- Interpretation method applicable to a specific ML model
- Example: implicitly integrated feature interpretation methods in tree based models, e.g., Gini Importance
- Advantage: Can exploit model structure
- Visualize activations of NNs



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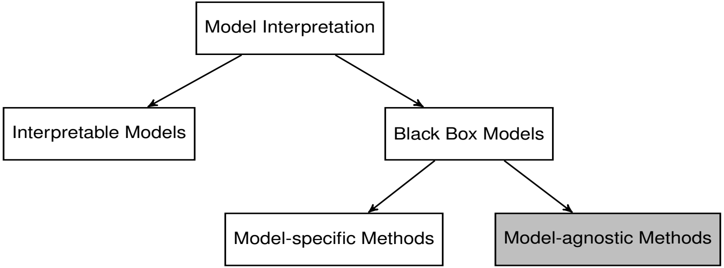
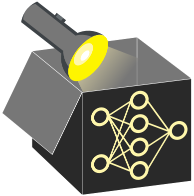
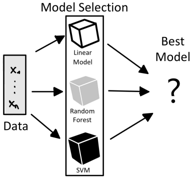


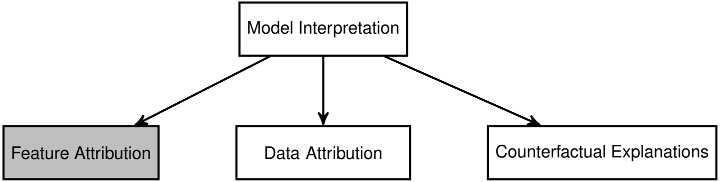


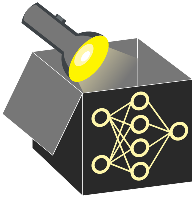
Model-agnostic methods:

- In ML: Tune over many model classes
  ⇝ Unknown which model is best / deployed
  ⇝ Need for interpretation methods applicable to any model
- Applied after training (post-hoc)
- Applicable to intrinsically interpretable models
  ⇝ provides insights into other types of explanations



TYPES OF EXPLANATIONS

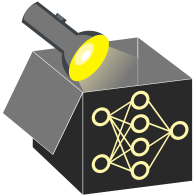


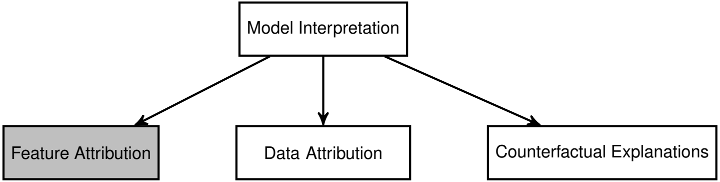


Feature Attribution:

- Produce explanations on a per-feature level, e.g., feature effects or feature importance
- Vary feature values, inspect change of model prediction, model variance or model error

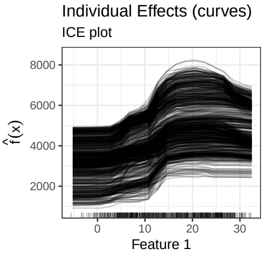
TYPES OF EXPLANATIONS

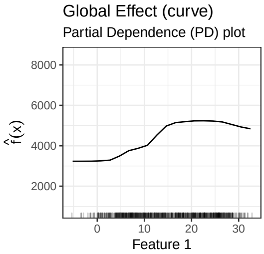




Feature Effects indicate the change in prediction due to changes in feature values.

- Model-agnostic methods: ICE curves, PD plots . . .
- Pendant in linear models: Regression coefficient θ_j
- Further examples: Saliency Maps, model-agnostic methods such as SHAP and LIME





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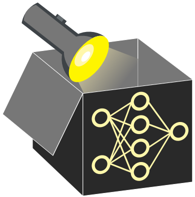
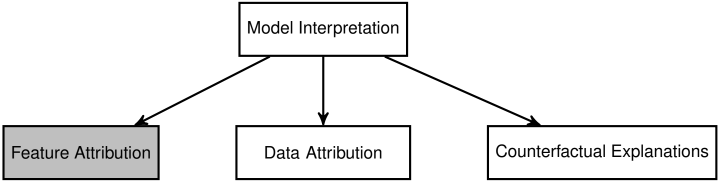
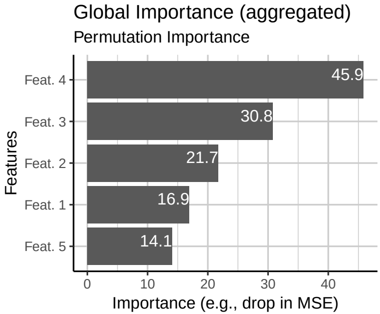




Feature importance methods rank features by how much they contribute to the predictive performance or prediction variance of the model.

- Model-agnostic methods: PFI, . . .
- Pendant in linear models: t-statistic, p-value (significant effect)



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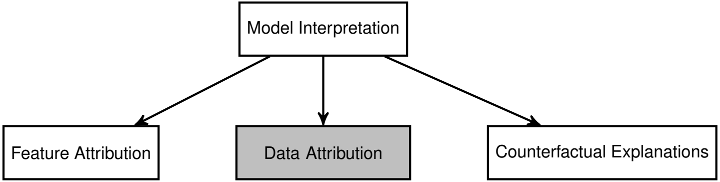

Data Attribution: Identify training instances most responsible for a decision (e.g. Influence Functions)

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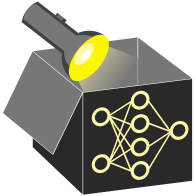
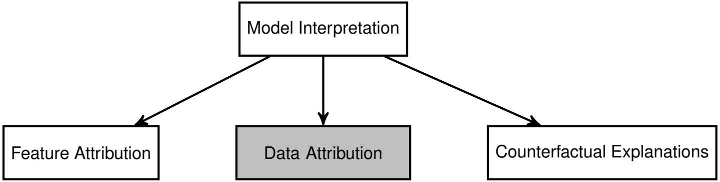
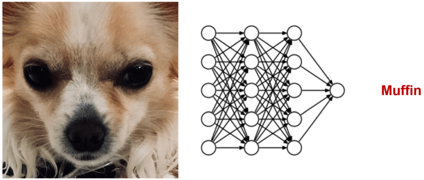




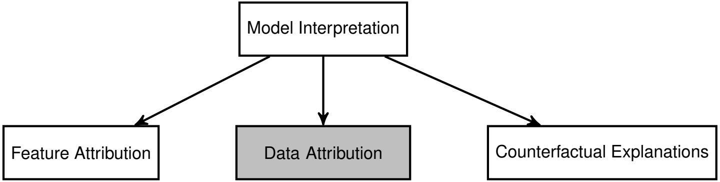
Data Attribution: Identify training instances most responsible for a decision (e.g. Influence Functions)

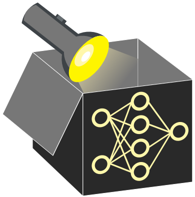
Example: Consider a model which should distinguish muffins and dogs



How does this incorrect prediction come about?

TYPES OF EXPLANATIONS





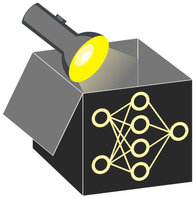
Data Attribution: Identify training instances most responsible for a decision (e.g. Influence Functions)

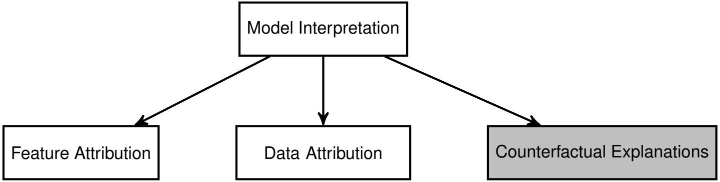
Look at training data: Which data points caused the model prediction?

Method searches for the most similar images and bases the decision on them

- $\rightsquigarrow$ Training images looking most like new input show a muffin
- $\rightsquigarrow$ Wrong output (muffin instead of dog)

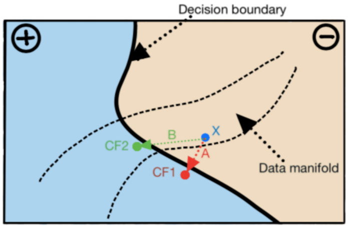
TYPES OF EXPLANATIONS





Counterfactual Explanations:

- Identify smallest necessary change in feature values so that a desired outcome is predicted
- Contrastive explanations
- Diverse counterfactuals
- Feasible & actionable explanations



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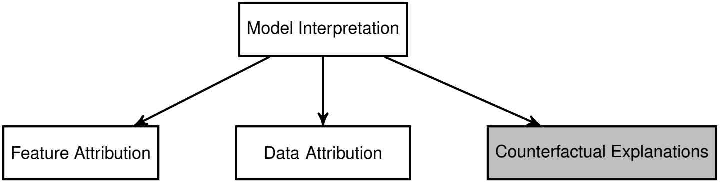
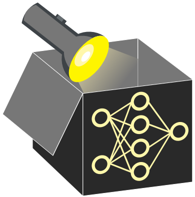
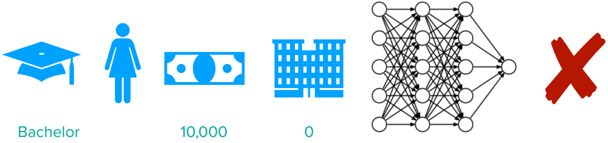
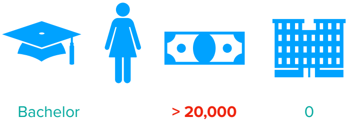




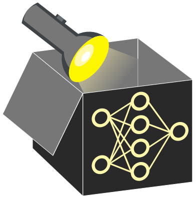
Example (loan application):



What can a person do to obtain a favorable prediction from a given model ?

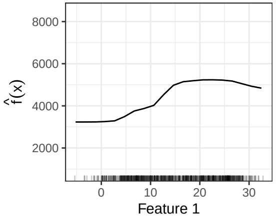


GLOBAL VS. LOCAL



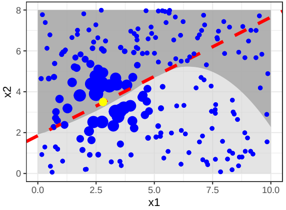
Global interpretation methods explain the model behavior for the entire input space by considering all available observations:

- Permutation Feature Importance (PFI)
- Partial Dependence (PD) plots
- Accumulated Local Effect (ALE) plots
- ...

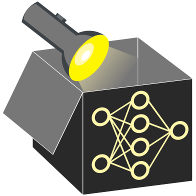


Local interpretation methods explain the model behavior for single data instances:

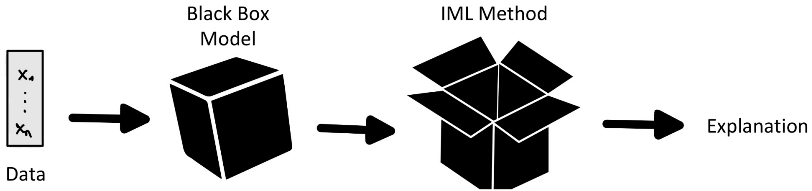
- Individual Conditional Expectation (ICE) curves
- Local Interpretable Model-Agnostic Explanations (LIME)
- Shapley values, SHAP
- ...



FIXED MODEL VS. REFITS

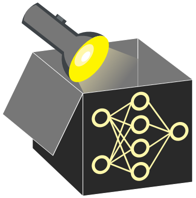


- Input of global interpretation methods: model + data, output: explanations
  $\leadsto$ Explanations can be viewed as statistical estimators

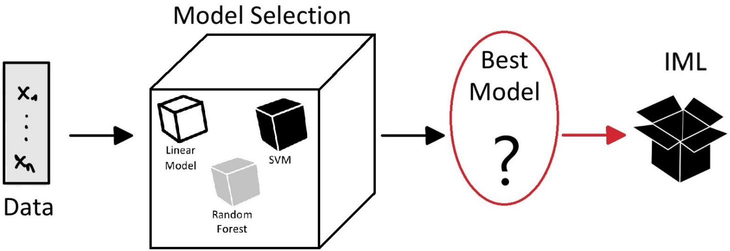


- Situation in ML: Deployed model is trained on all available data
  $\leadsto$ No unseen test data left to, e.g., reliably estimate performance
  $\leadsto$ IML method could use same data model was trained on
  $\leadsto$ But: Some IML methods rely on measuring loss requiring unseen test data
- Alternative: Explain the inducer that created the model (instead of a fixed model)
  $\leadsto$ Idea: Use resample strategies (e.g., 4-fold CV) as in performance estimation
  $\leadsto$ Requires refitting

LEVELS OF INTERPRETABILITY



	Research Question	Objects of analysis
1^{st} level view	How to explain a given model fitted on a data set?	(deployed) model $\theta \mapsto \hat{f}(\theta)$



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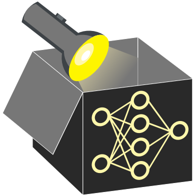

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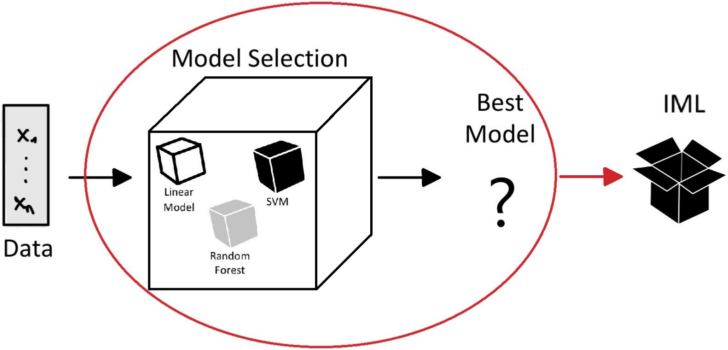

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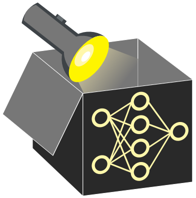

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3rd level view	How do data properties relate to performance of a learner and its hyperparameters?	properties of ML algorithms in general (benchmark)