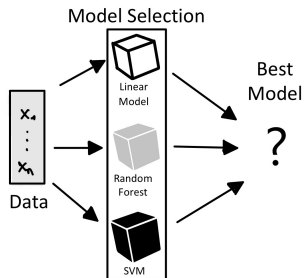


Interpretable Machine Learning

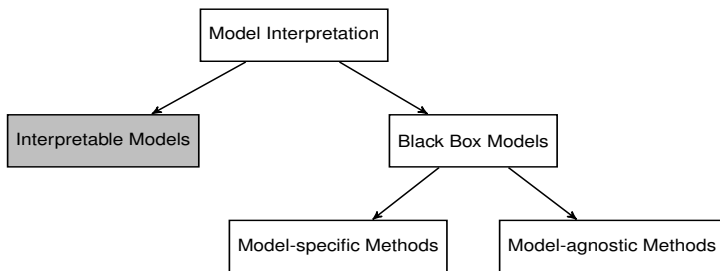
Dimensions of Interpretability



Learning goals

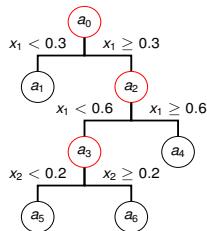
- Intrinsic vs. model-agnostic methods
- Different types of explanations
- Local vs. global methods
- Model or learner explanations – with or without refits
- Levels of interpretability

INTRINSIC VS. MODEL-AGNOSTIC

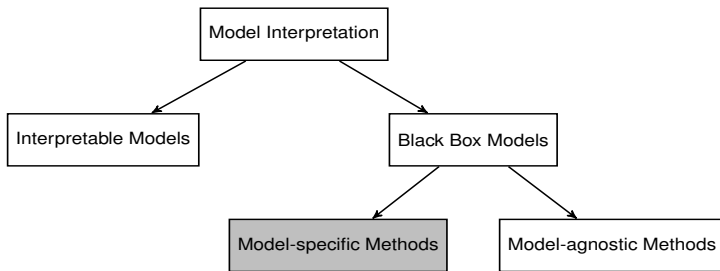


Intrinsically interpretable models:

- 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

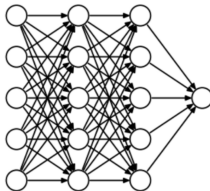


INTRINSIC VS. MODEL-AGNOSTIC

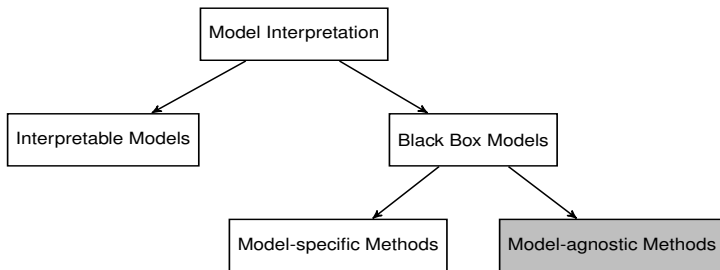


Model-specific methods:

- 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

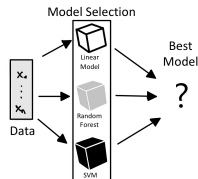


INTRINSIC VS. MODEL-AGNOSTIC

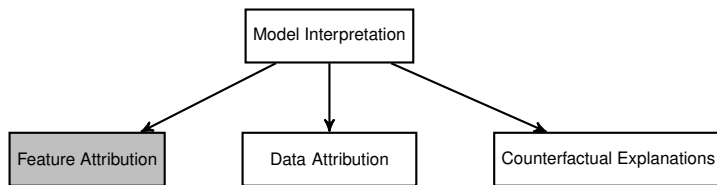


Model-agnostic methods:

- 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



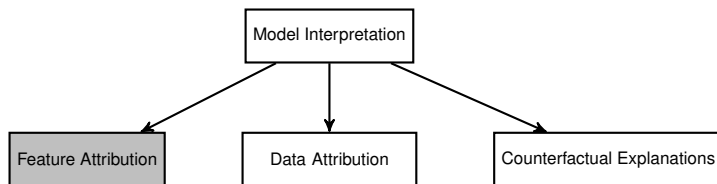
TYPES OF EXPLANATIONS



Feature Attribution:

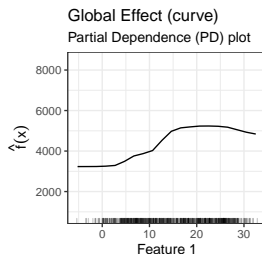
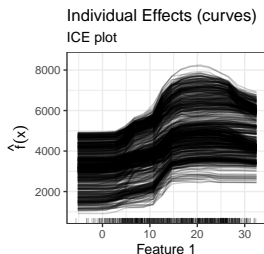
- Produce explanations on a per-feature level, e.g., feature effects or feature importance
- Vary feature values, inspect change of model prediction, model variance or model error

TYPES OF EXPLANATIONS

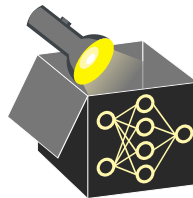
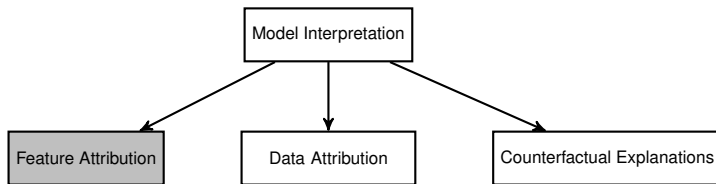


Feature Effects indicate the change in prediction due to changes in feature values.

- 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

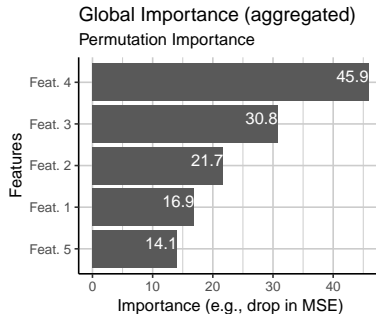


TYPES OF EXPLANATIONS

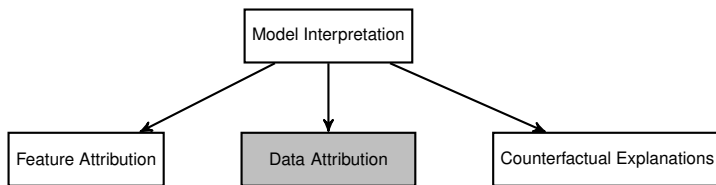


Feature importance methods rank features by how much they contribute to the predictive performance or prediction variance of the model.

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

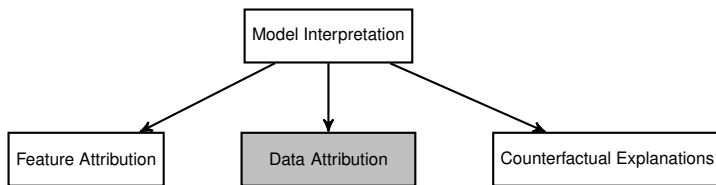


TYPES OF EXPLANATIONS



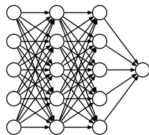
Data Attribution: Identify training instances most responsible for a decision (e.g. Influence Functions)

TYPES OF EXPLANATIONS



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

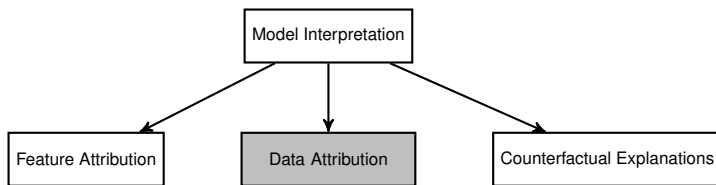
Example: Consider a model which should distinguish muffins and dogs



Muffin

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?



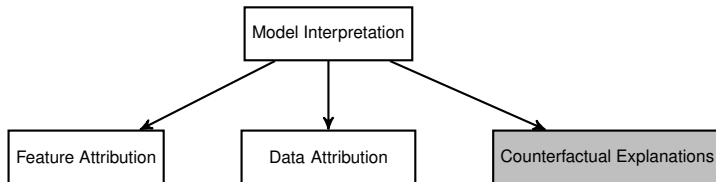
Data Attribution



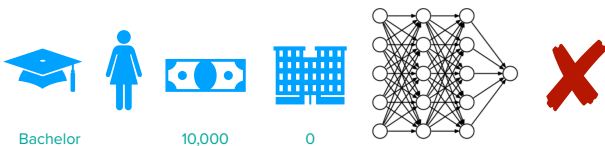
Method searches for the most similar images and bases the decision on them

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

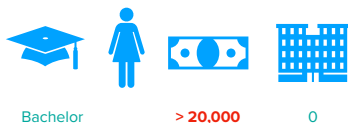
TYPES OF EXPLANATIONS



Example (loan application):



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



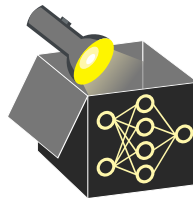
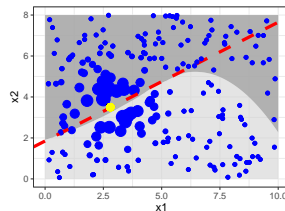
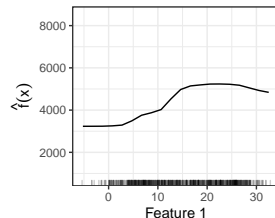
GLOBAL VS. LOCAL

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
- ...

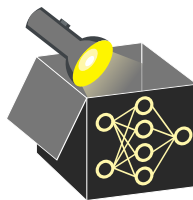
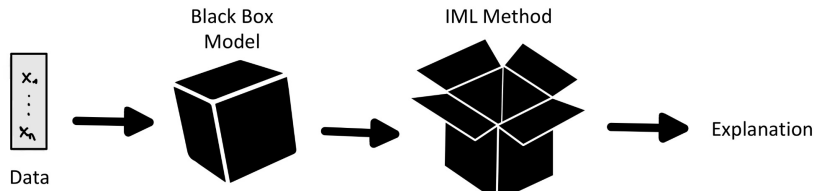
Local interpretation methods explain the model behavior for single data instances:

- 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
~> Explanations can be viewed as statistical estimators



- Situation in ML: Deployed model is trained on all available data
~> No unseen test data left to, e.g., reliably estimate performance
~> IML method could use same data model was trained on
~> 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)
~> Idea: Use resample strategies (e.g., 4-fold CV) as in performance estimation
~> Requires refitting

LEVELS OF INTERPRETABILITY

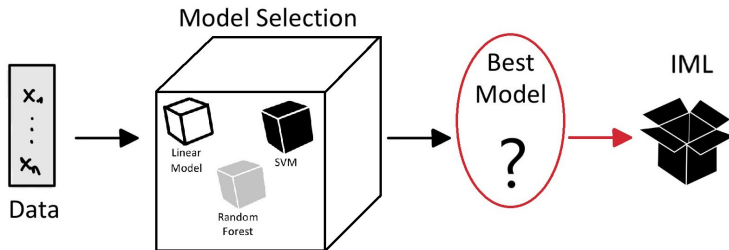
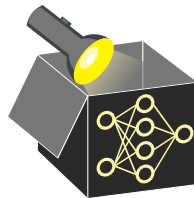
1st
level
view

Research Question

How to explain a given model
fitted on a data set?

Objects of analysis

(deployed) model
 $\theta \mapsto \hat{f}(\theta)$



LEVELS OF INTERPRETABILITY

1st
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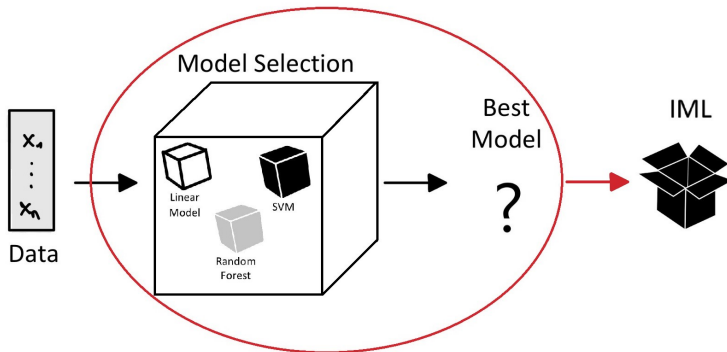
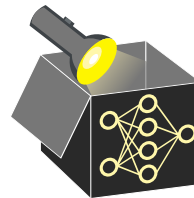
Objects of analysis

(deployed) model
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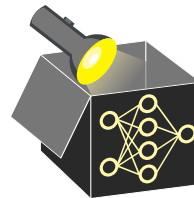
2nd
level
view

How does an optimizer choose
a model based on a data set?

Model selection process (e.g.,
decisions made by AutoML
systems or HPO process)



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 $\theta \mapsto \hat{f}(\theta)$
2 nd level view	How does an optimizer choose a model based on a data set?	Model selection process (e.g., decisions made by AutoML systems or HPO process)
3 rd level view	How do data properties relate to performance of a learner and its hyperparameters?	properties of ML algorithms in general (benchmark)

