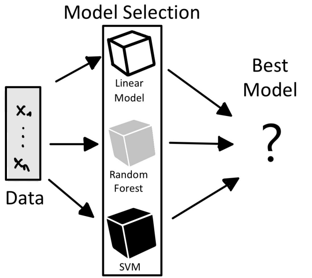
Interpretable Machine Learning

Dimensions of Interpretability



Learning goals

- Difference between intrinsic, model-specific, and model-agnostic interpretability
- Different types of explanations
- Local, global, and regional explanations
- Model/learner explanation (without/with refits)
- Levels of interpretability

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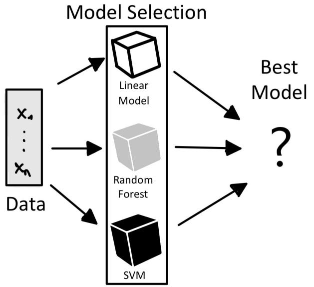

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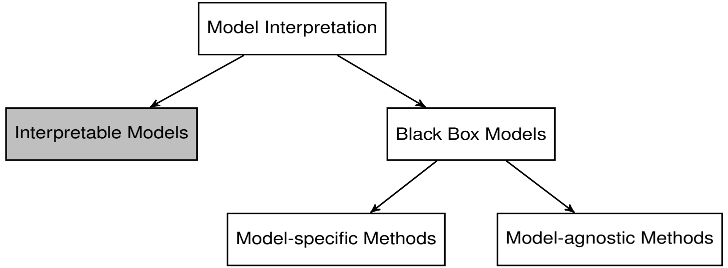
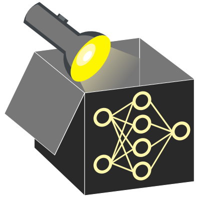
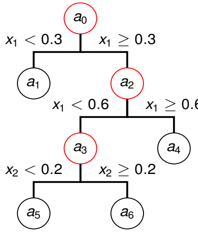
INTRINSIC, MODEL-SPECIFIC, MODEL-AGNOSTIC





Intrinsically Interpretable Models:

- Simple model structure (e.g., weighted sum or tree)
- Examples: GLMs, decision trees
- Pro: Additional IML methods not necessarily required
- Con: Limited model complexity can reduce performance; can still be hard to interpret with many features /interactions



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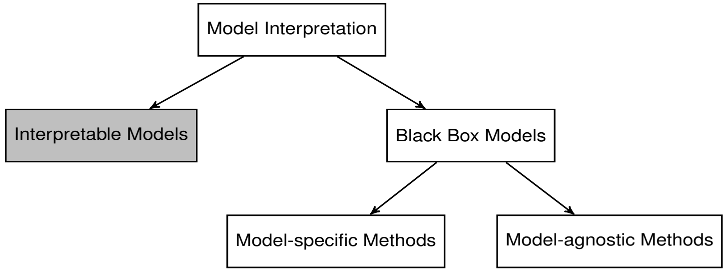

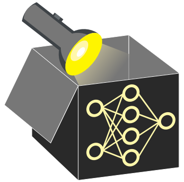

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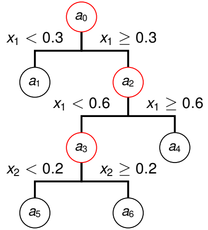

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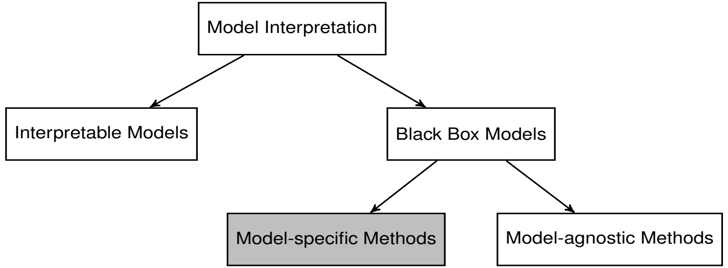
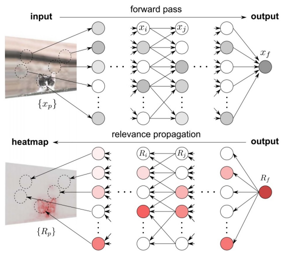


Model-specific Methods:

- Designed for specific model types (e.g., NNs)
- Examples: Gini importance of tree-based models, Layer-wise relevance propagation (LRP)
- Pro: Exploit model structure
- Con: Restricted to specific model class



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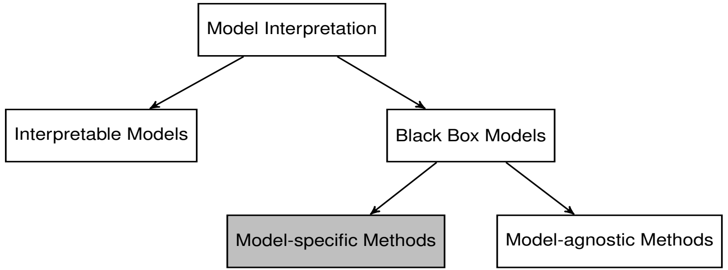

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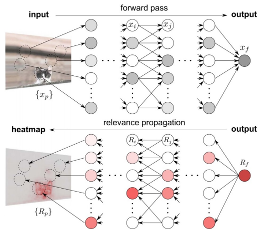

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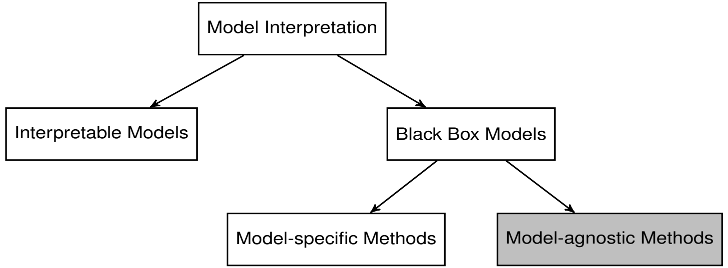
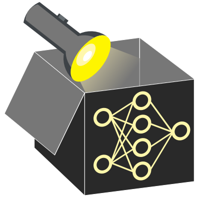
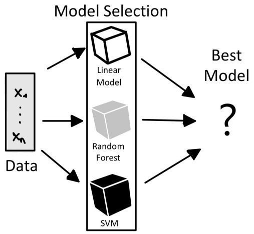




Model-agnostic Methods:

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



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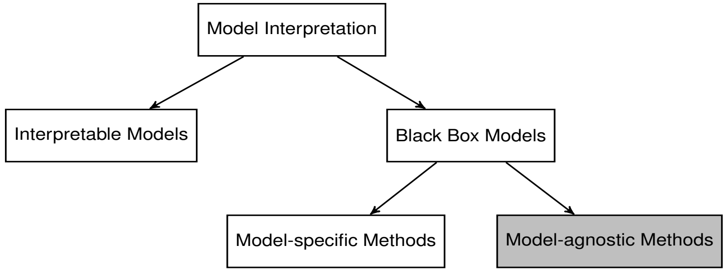

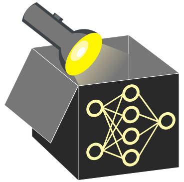

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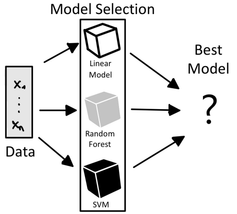
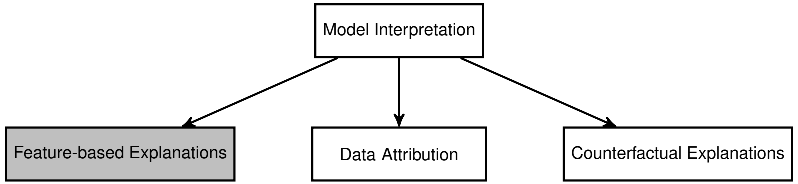
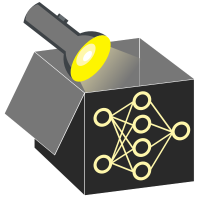


TYPES OF EXPLANATIONS





Feature-based Explanations:

- Analyze the role of individual features in model behavior.
- Types of feature-based explanations:
  - Feature Importance
  - Feature Effects
  - Feature Interactions
- Common principle: Vary or perturb feature values and observe changes in predictions, variance, or performance.

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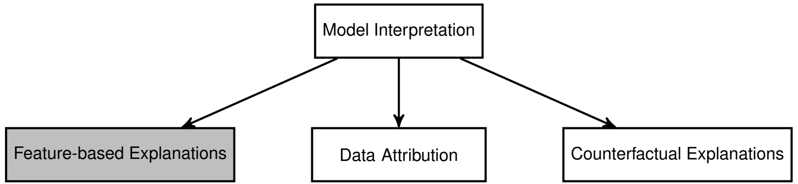

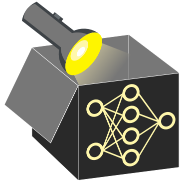

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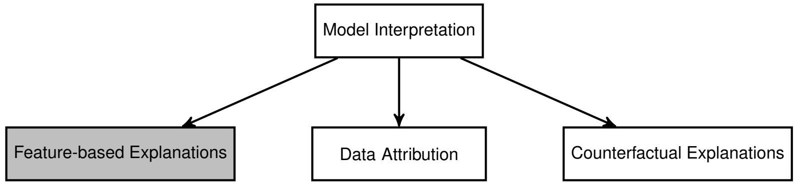
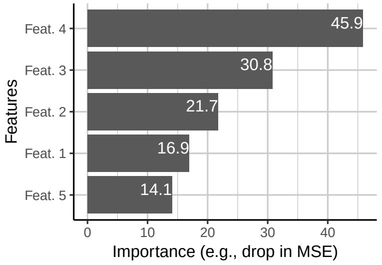


Feature Importance quantifies relevance of features, e.g., their contribution to model prediction, predictive performance, or prediction variance.

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



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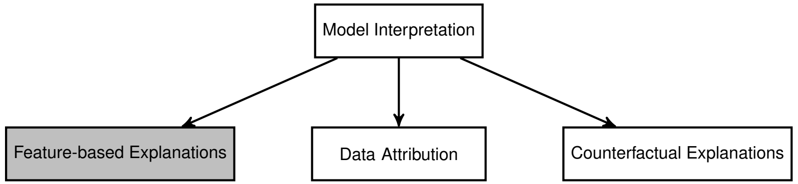

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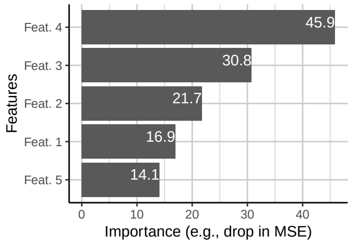

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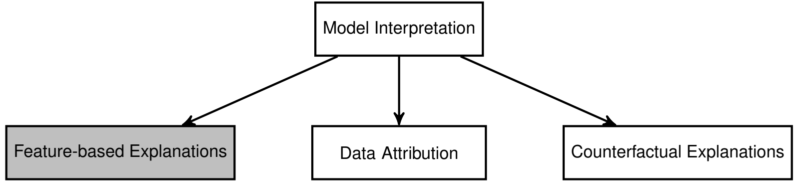
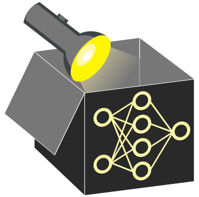
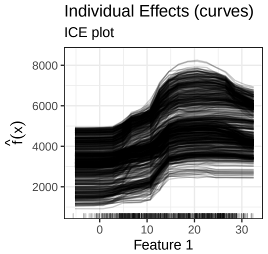
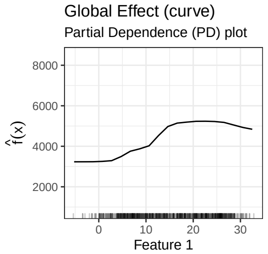




Feature Effects indicate changes (direction and magnitude) in model prediction due to changes in feature values.

- Model-agnostic methods: ICE curves, PD plots . . .
- Pendant in linear models: Weights / coefficients θ_j
- Further examples: ALE, SHAP, and LIME





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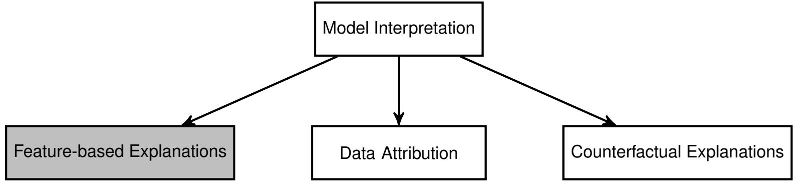
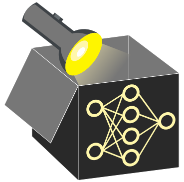
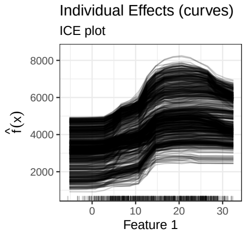
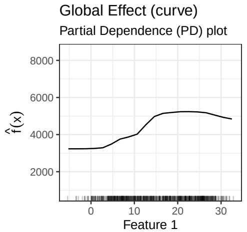

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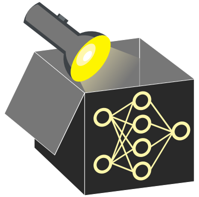
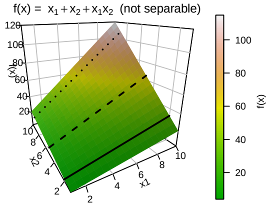


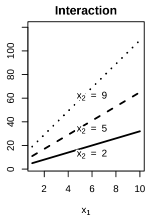
Model Interpretation

Feature-based Explanations | Data Attribution | Counterfactual Explanations

Feature Interaction: How combinations of features jointly affect predictions.

- Model-agnostic methods: Friedman's H-statistic
- Pendant in linear models: Coefficients of interaction terms θ_{jk}





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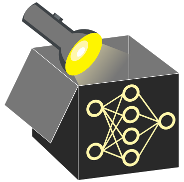

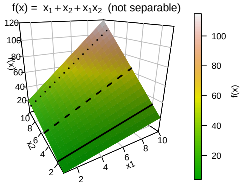

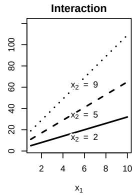

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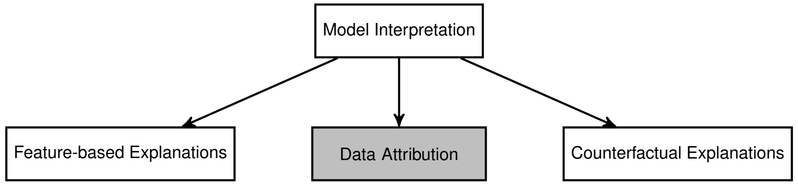
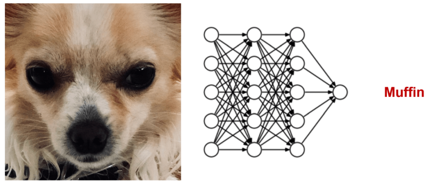


Data Attribution: Identify which training instances most influenced a prediction.

Example: A model should distinguish muffins and dogs.

Question: Why does it misclassify this dog image (test point) as a muffin?



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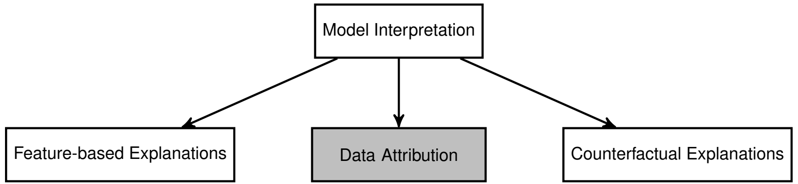

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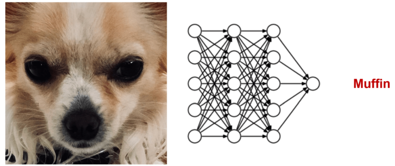

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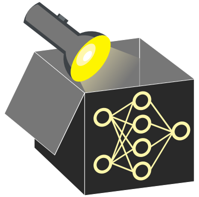

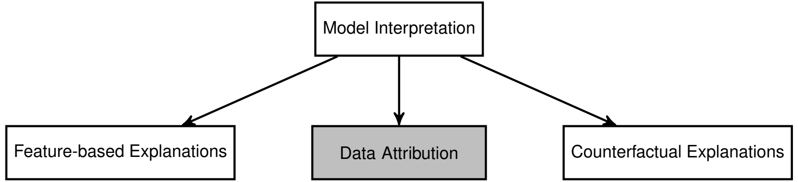

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Approach: Measure how perturbations to training instances affect prediction or loss.

- ⇝ Influential training instances drive prediction of test points.
- ⇝ If these resemble muffins, the model may predict muffin instead of dog.

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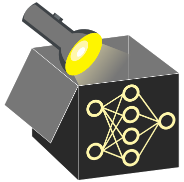

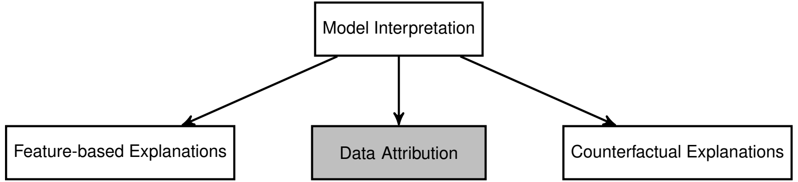

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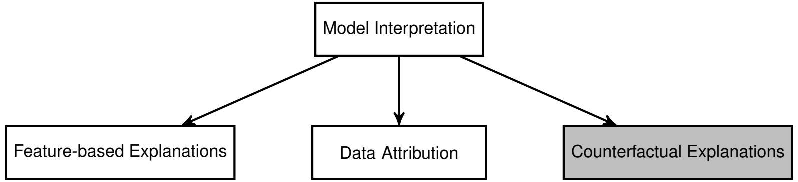
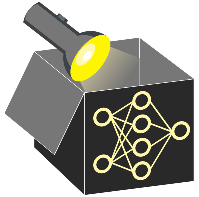
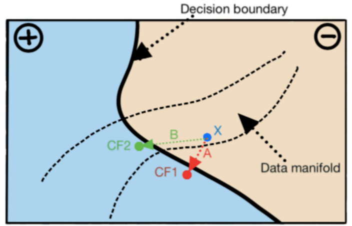




Counterfactual Explanations:

- 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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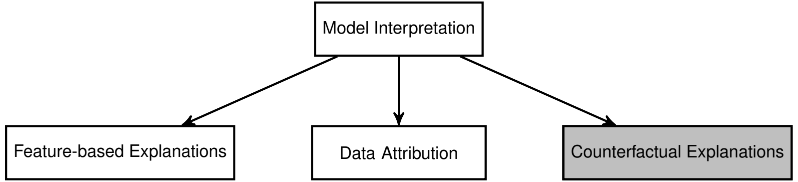

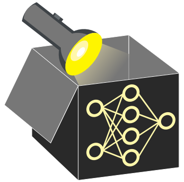

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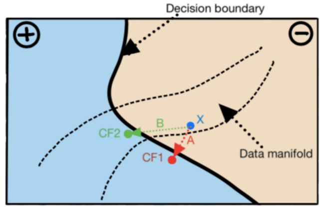

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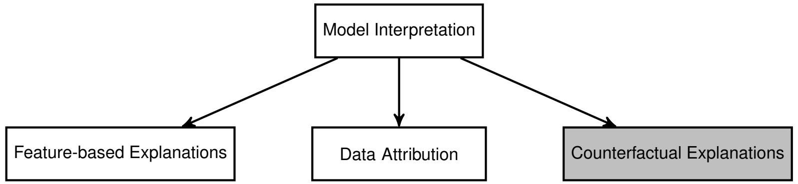
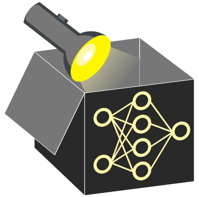
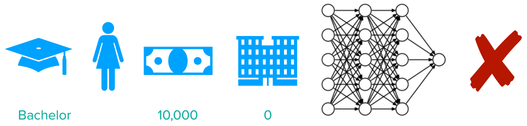
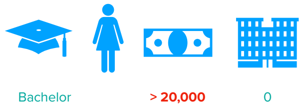




Example (loan application):



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



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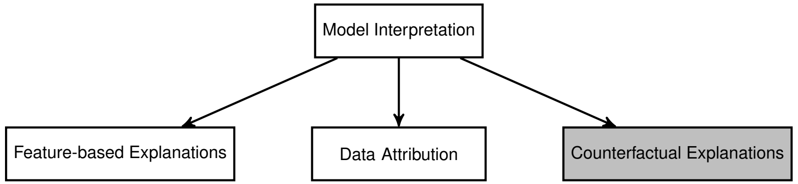

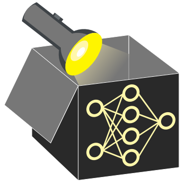

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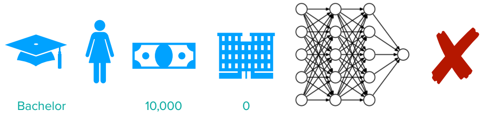
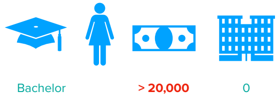


What can a person do to obtain a favorable prediction from a given model ?



LOCAL, GLOBAL, AND REGIONAL EXPLANATIONS

Local – Explain model behavior for **single instances**:

- Provide nuanced instance-specific insights
- Crucial for complex models where features typically affect instances differently (due to interactions)
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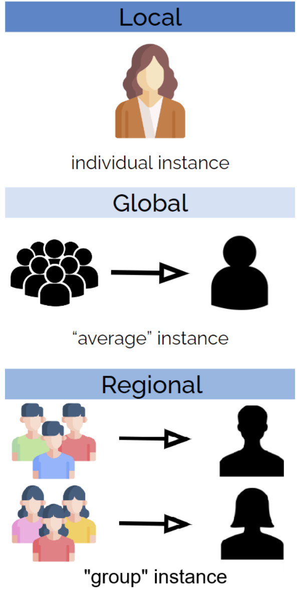

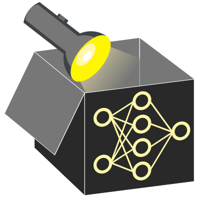

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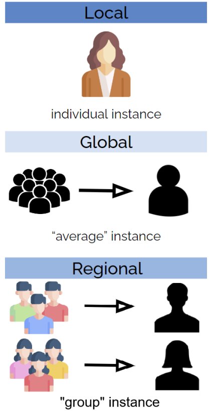

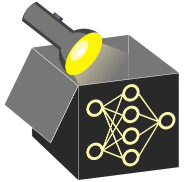

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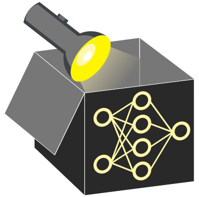

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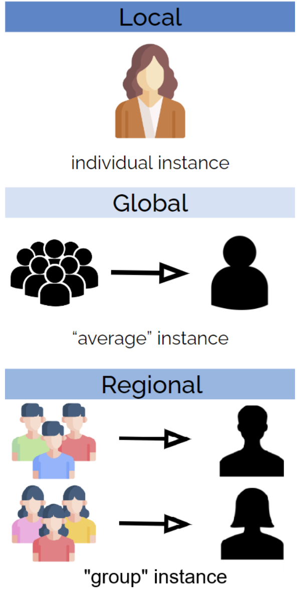

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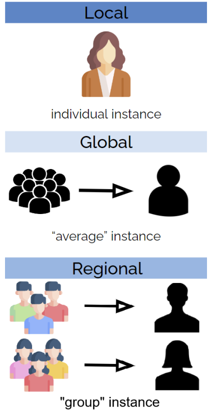

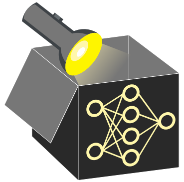

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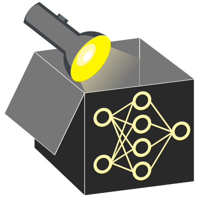

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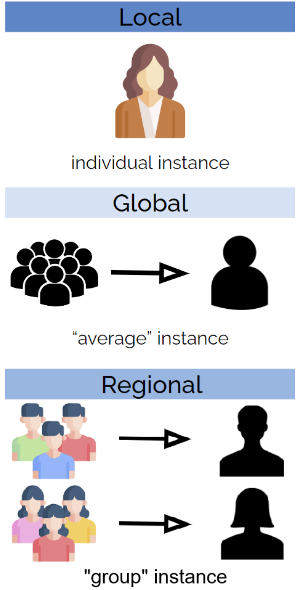

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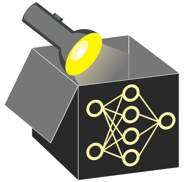

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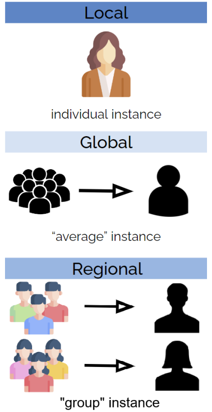

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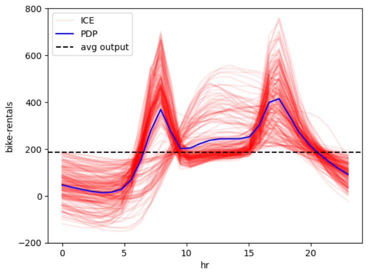

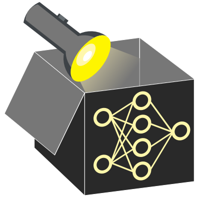

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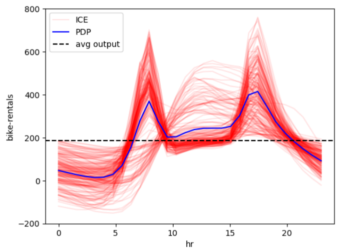

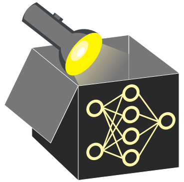

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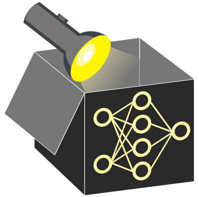

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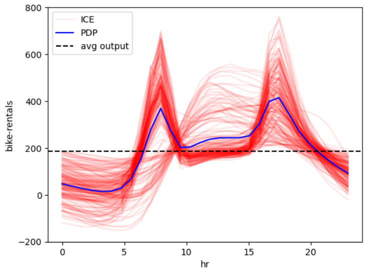

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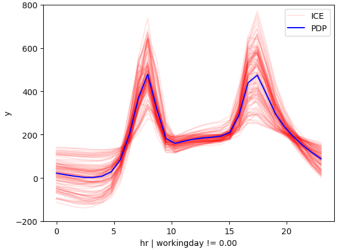

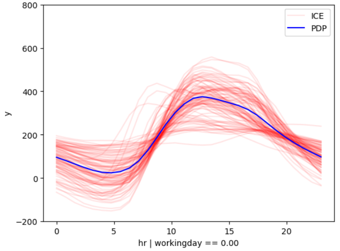

Region 2 (non-working day)

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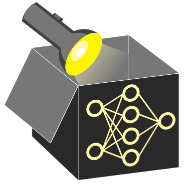

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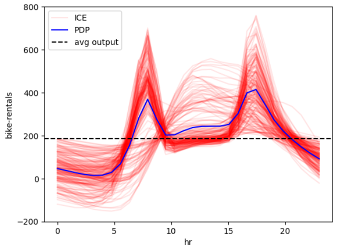

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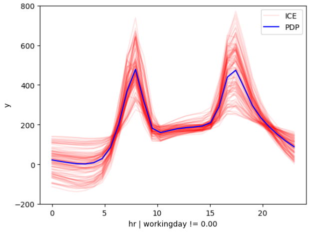

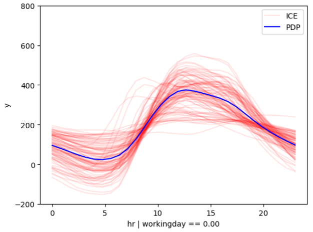

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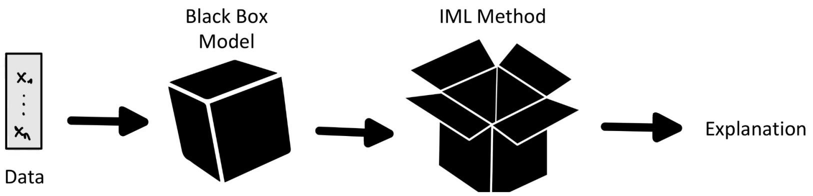
FIXED MODEL VS. REFITS

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



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- Alternative: Explain the inducer that created the model (instead of a fixed model)
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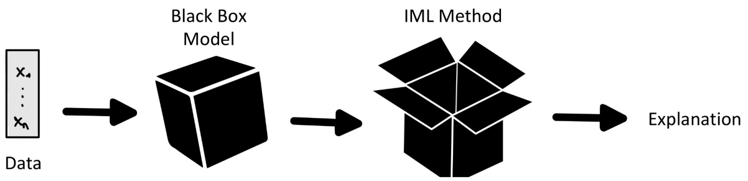

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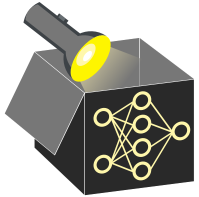

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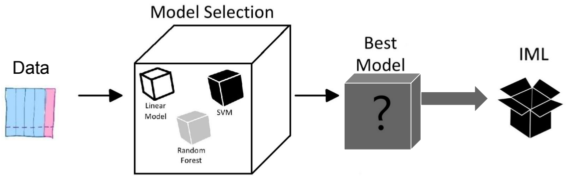

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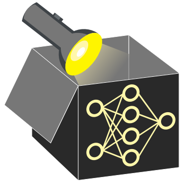

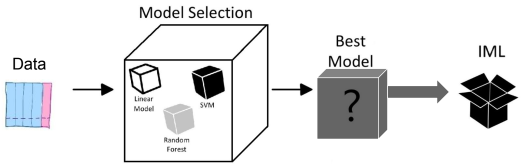

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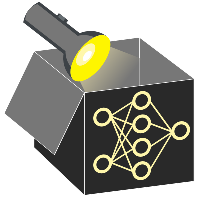

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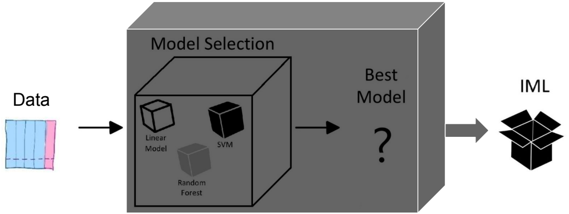

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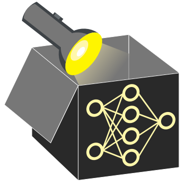

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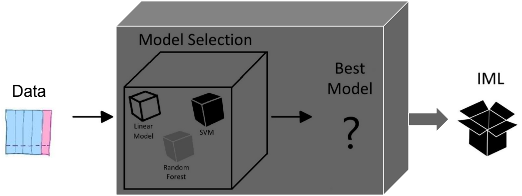

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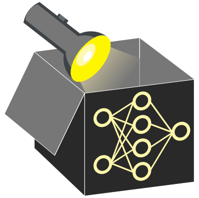

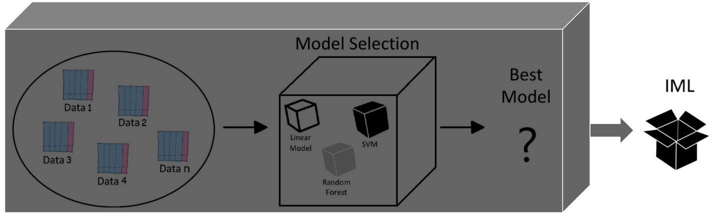

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