Interpretable Machine Learning

Introduction to loss-based feature importance

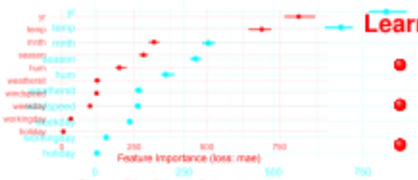

Figure: Bike Sharing Dataset

Learning goals

- Understand motivation for feature importance
- Develop an intuition for possible use-cases
- Know characteristics of feature importance methods

MOTIVATION

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  - requires one plot per feature
  - does not take the true target y into account

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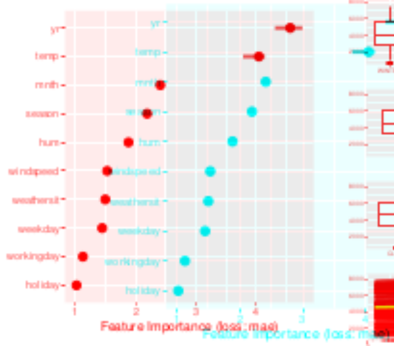
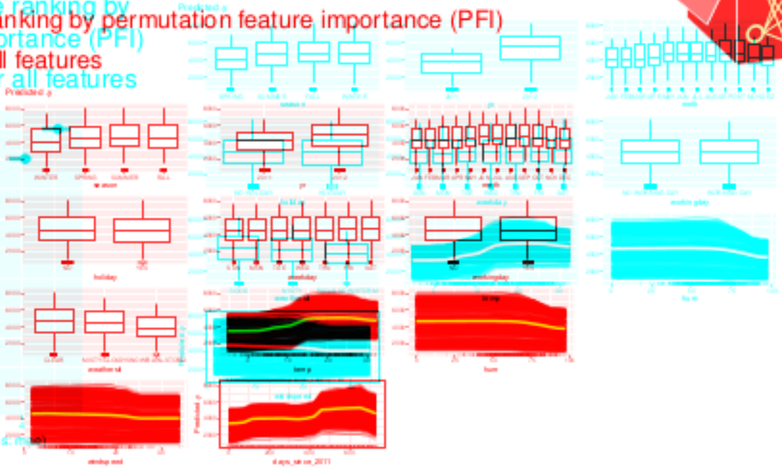
  - provides insight into the relationship with y
- **N.B.:** Here, we use the term feature importance to describe loss-based feature importance methods. In the literature, you may find other notions of "feature importance" (e.g., variance-based methods derived from feature effect methods, see also ▸ Greenwell et al. (2020))

EXAMPLE

Feature importance offers condensed summary of feat. relevance w.r.t. performance

- Fit random forest on bike sharing data
- Left: Feature importance ranking by permutation feature importance (PFI)
- Right: Feature effects for all features





FEATURE IMPORTANCE SCHEME

Loss-based feature importance methods are often based on two concepts

1. **Perturbation/Removal:**
   Generate predictions for which the feature of interest has been perturbed or removed
2. **Performance Comparison:**
   Compare performance under perturbation/removal with the original model performance

Depending on the type of perturbation/removal, feature importance methods provide insight into different aspects of model and data.

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POTENTIAL INTERPRETATION GOALS

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For example, one may be interested in getting insight into whether the ...

(1) feature x_j is causal for the prediction?

(2) feature x_j contains prediction-relevant information about y?

(3) model requires access to x_j to achieve it's prediction performance?

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- Changing feature value x_j has an effect on prediction $\hat{y} = \hat{f}(x)$
- In LM: non-zero coefficient, in ML: present feature effect
- **Note:** If x_j is causal for prediction $\hat{y} \not\Rightarrow$ causal for the ground truth y, e.g.:
  - A disease symptom may be used in a model to predict disease status $\rightsquigarrow$ causal for prediction $\hat{y}$
  - But intervening on disease symptom does not have an effect on the disease $\rightsquigarrow$ not causal for the ground truth y

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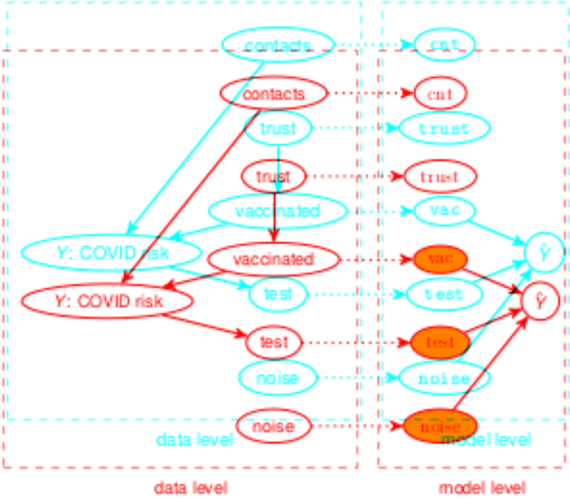

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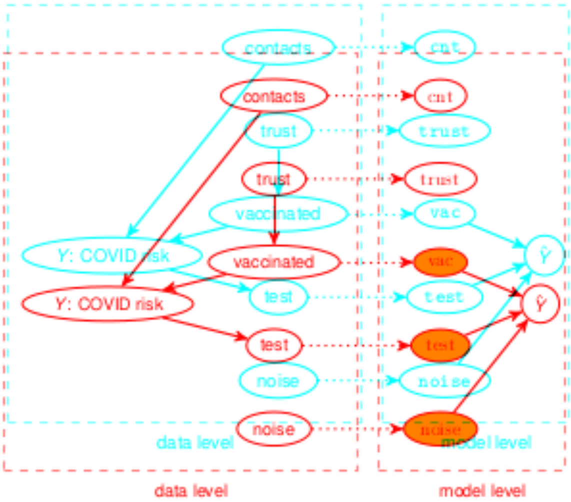

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Examples: overfitting due noisy features

- All features used by the model are of interest
- Here: Model uses feature `noise`, although it does not contain prediction-relevant information about y (data level)

⇒ Overfitted models may use many noise features which are deemed relevant on model level (but not on data level)

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(1) feature x_j is causal for the prediction?

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- Feature x_j helps to predict the target y (e.g., conditional expectation) w.r.t. performance
- If $x_j \perp\!\!\!\perp y$ (independent) then x_j and y have zero mutual information (since $\mathbb{E}[y|x_j] = \mathbb{E}[y]$)
  $\rightsquigarrow$ x_j has no prediction-relevant information

(3) model requires access to x_j to achieve it's prediction performance?

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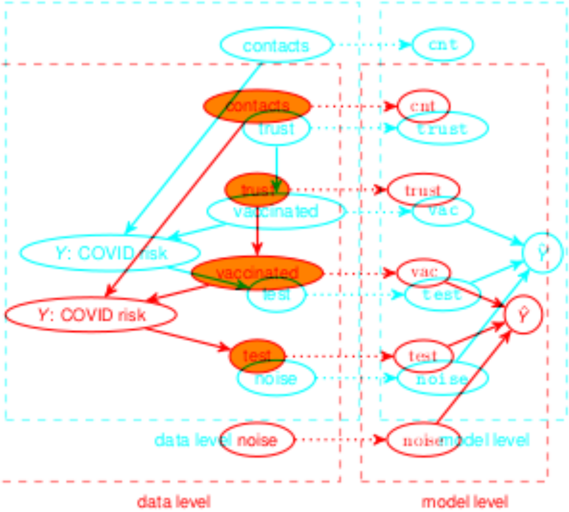

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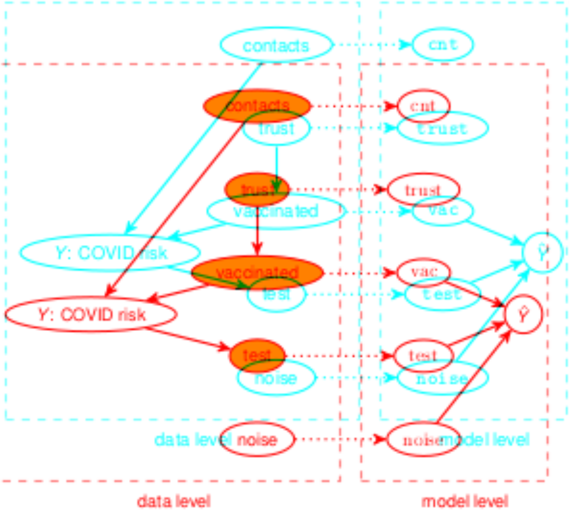

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- All prediction-relevant features for y are of interest
- Example: All features that are directly or indirectly (i.e., via another feature) connected to y

⇒ Underfitted models may ignore prediction-relevant features such as contacts here

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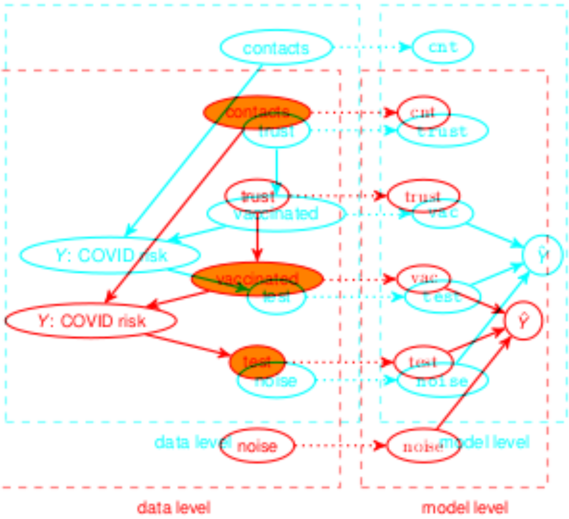
- Feature x_j helps to predict the target y w.r.t. performance, compared to using only x_{-j}
- If $x_j \perp y | x_{-j}$ (independent) then $\mathbb{E}[y|x_{-j}] = \mathbb{E}[y|x_j, x_{-j}]$ $\leadsto$ x_j does not contribute unique prediction-relevant information about y
- **Note:** A model may rely on features that can be replaced with others, e.g., a random forest fitted on data with $\mathbb{E}[y|x_1] \neq \mathbb{E}[y]$ and $\mathbb{E}[y|x_1] = \mathbb{E}[y|x_1, x_2]$ where x_1 was not used as split variable may rely on x_2

EXAMPLE: UNIQUE PREDICTION RELEVANT INFORMATION (3)



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Examples: correlated features, confounding

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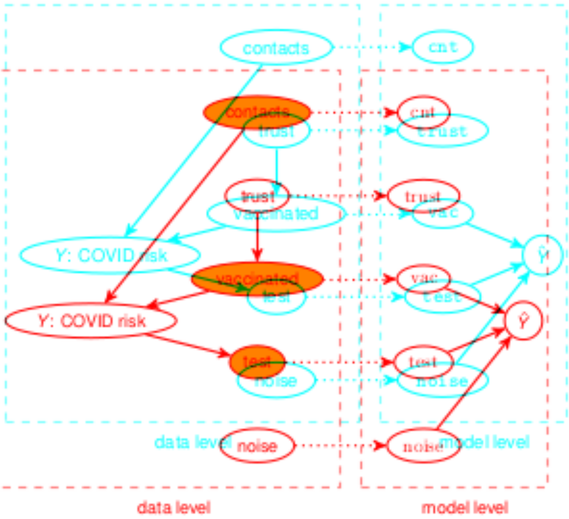

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- Example: All features that are directly connected to y

$\Rightarrow$ trust and vaccinated may be correlated but only vaccinated is directly connected to y

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