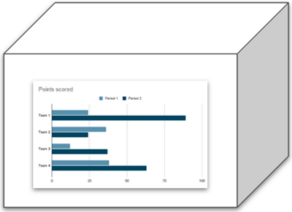
Interpretable Machine Learning
Inherently Interpretable Models - Motivation

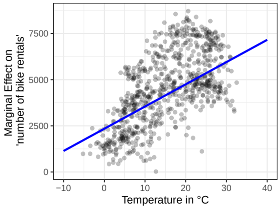


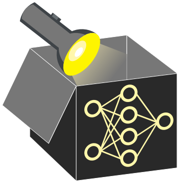
Learning goals

- Why should we use interpretable models?
- Advantages and disadvantages of interpretable models

MOTIVATION

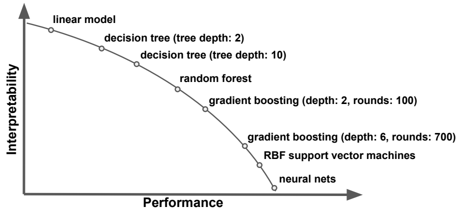
- Achieving interpretability by using interpretable models is the most straightforward approach
- Classes of models deemed interpretable:
  - (Generalized) linear models (LM, GLM)
  - Generalized additive models (GAM)
  - Decision trees
  - Rule-based learning
  - Model-based / component-wise boosting
  - ...





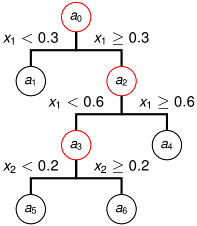
$\rightsquigarrow$ LM provides straightforward interpretation

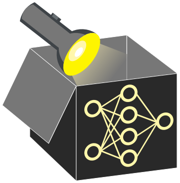
- Often there is a trade-off between interpretability and model performance



ADVANTAGES

- Interpretable models are transparent by design, making many model-agnostic explanation methods unnecessary
  $\rightsquigarrow$ Eliminates an extra source of estimation error





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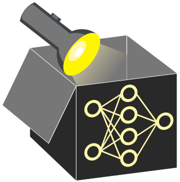

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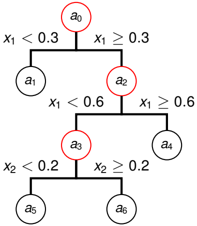
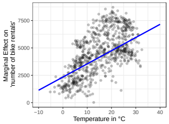
  ⇝ Eliminates an extra source of estimation error

- They often have few hyperparameters and are structurally simple (e.g., linear, additive, sparse, monotonic)
  ⇝ Easy to train, fast to tune, straightforward to explain





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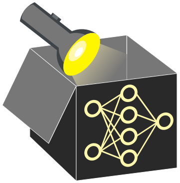

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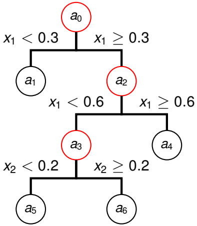
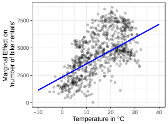
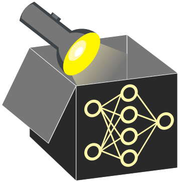
- They often have few hyperparameters and are structurally simple (e.g., linear, additive, sparse, monotonic)
  $\rightsquigarrow$ Easy to train, fast to tune, straightforward to explain
- Many people are familiar with simple interpretable models
  $\rightsquigarrow$ Increases trust, facilitates communication of results

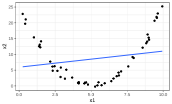




DISADVANTAGES & LIMITATIONS



- Often require assumptions about data / model structure
  $\rightsquigarrow$ If assumptions are wrong, models may perform bad



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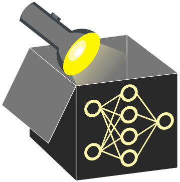

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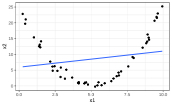

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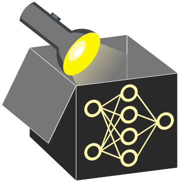

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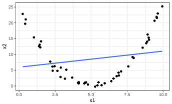

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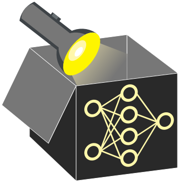

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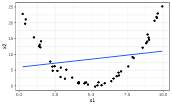

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- Often do not automatically model complex relationships due to limited flexibility
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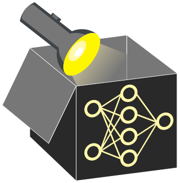
- Inherently interpretable models do not address all explanation needs
  ⇝ Complementary model-agnostic methods (e.g., counterfactuals) remain valuable for specific tasks

FURTHER COMMENTS



- Some researchers advocate for inherently interpretable models instead of explaining black boxes after training ▸ Rudin 2019
  - Built-in interpretation
    $\rightsquigarrow$ fewer risks from misleading post-hoc explanations
  - Good performance possible with effort on preprocessing and/or feature engineering
  - But interpretability depends on meaning of created features
    $\rightsquigarrow$ E.g., PCA keeps models linear, but yields hard-to-interpret components

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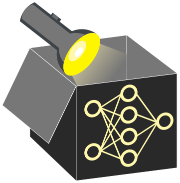

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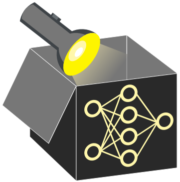
- Limitation: Less suited for complex data complex data requiring end-to-end learning
  - Applies to image, text, or sensor data where features must be learned from raw input
  - Manual extraction of interpretable features is difficult
    $\Rightarrow$ Information loss and lower performance

RECOMMENDATION



- Begin with the simplest model appropriate for the task
- Increase complexity only if necessary to meet performance requirements
  $\rightsquigarrow$ Typically reduces interpretability and requires model-agnostic explanations
- Choose the simplest model with sufficient accuracy $\rightsquigarrow$ Occam's razor

Bike Data, 4-fold CV

Model	RMSE	R^2
LM	800.15	0.83
Tree	981.83	0.74
Random Forest	653.25	0.88
Boosting (tuned)	638.42	0.89