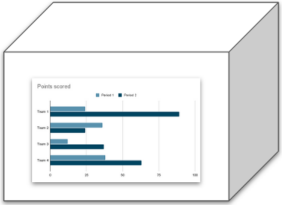
Interpretable Machine Learning

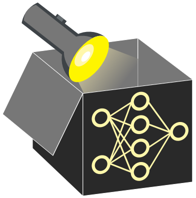
Inherently Interpretable Models - Motivation



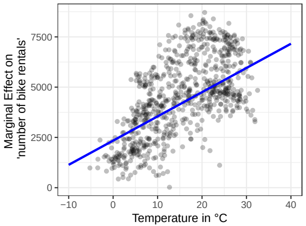
Learning goals

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

MOTIVATION

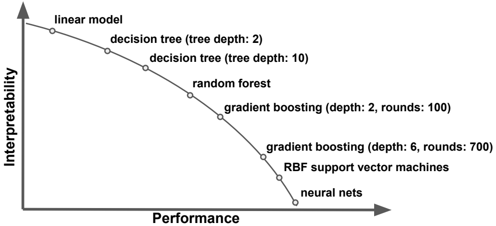


- Achieving interpretability by using interpretable models is the most straightforward approach
- Classes of models deemed interpretable:
  - (Generalized) linear models (LM, GLM)
  - Generalized additive models (GAM)
  - Decision trees
  - Rule-based learning
  - Model-based / component-wise boosting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



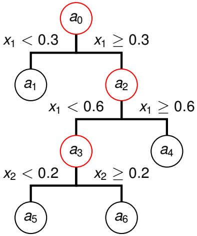
$\rightsquigarrow$ LM provides straightforward interpretation

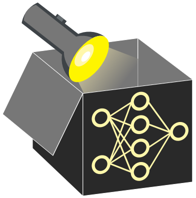
- Often there is a trade-off between interpretability and model performance



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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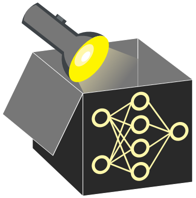

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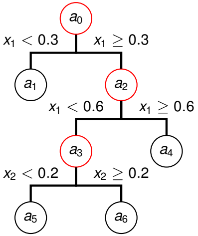
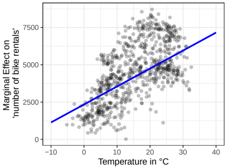
  $\rightsquigarrow$ Easy to train, fast to tune, and straightforward to explain





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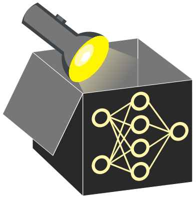
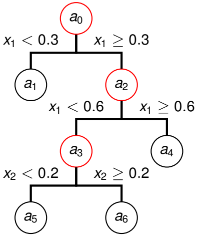
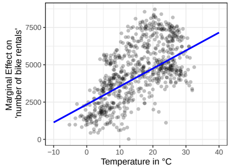
- Many people are familiar with simple interpretable models
  $\rightsquigarrow$ Increases trust, facilitates communication of results

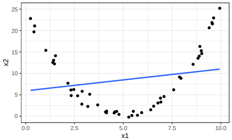


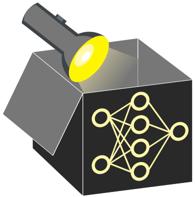




DISADVANTAGES & LIMITATIONS

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





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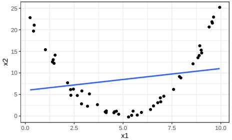
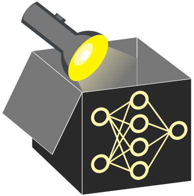
  - LM with lots of features and interactions
  - Decision trees with huge tree depth





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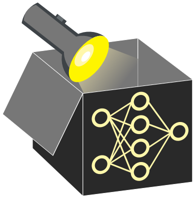

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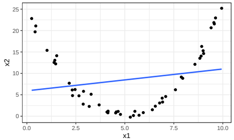

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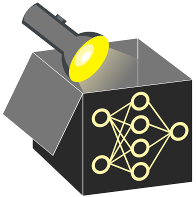

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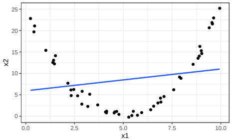

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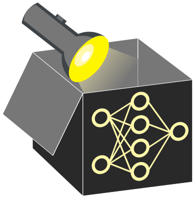
- Inherently interpretable models do not address all explanation needs
  $\rightsquigarrow$ Complementary model-agnostic methods (e.g., counterfactuals) remain valuable for specific tasks

FURTHER COMMENTS



- Some researchers advocate for inherently interpretable models instead of explaining black boxes after training ▸ Rudin 2019
    - Built-in interpretation $\Rightarrow$ fewer risks from misleading post-hoc explanations
    - Good performance possible with effort on preprocessing / feat. 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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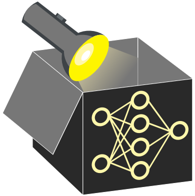

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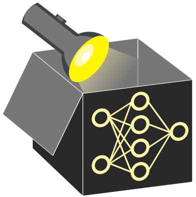
    $\rightsquigarrow$ E.g., PCA keeps models linear, but yields hard-to-interpret components
- Limitation: Less suited for complex data where end-to-end learning is crucial
  - Applies to image, text, or sensor data where features must be learned
  - Manual extraction of interpretable features is difficult
    $\Rightarrow$ 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