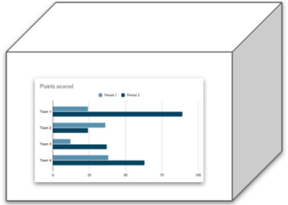
Interpretable Machine Learning

Inherently Interpretable Models - Motivation



Learning goals

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

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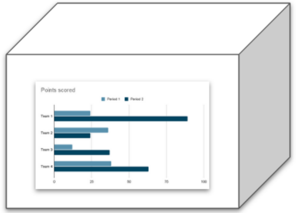

MOTIVATION

- 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
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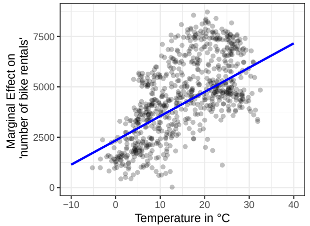
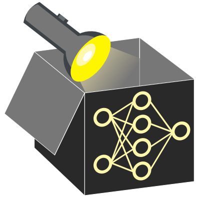
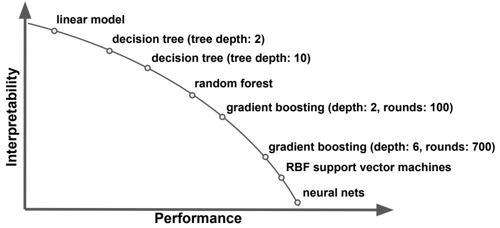




$\rightsquigarrow$ LM provides straightforward interpretation

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



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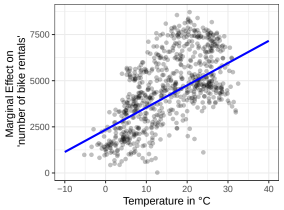

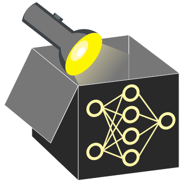

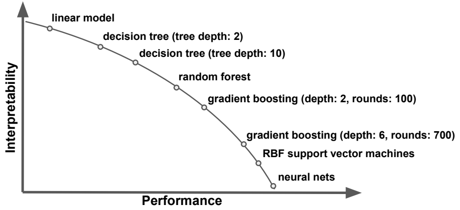

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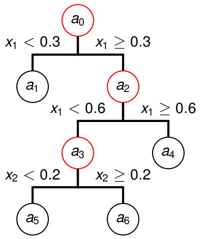
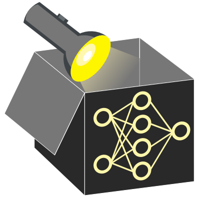
- Interpretable models are transparent by design, making many model-agnostic explanation methods unnecessary
  $\rightsquigarrow$ Eliminates an extra source of estimation error





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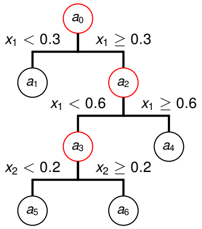

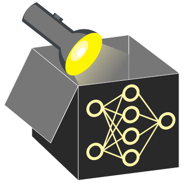

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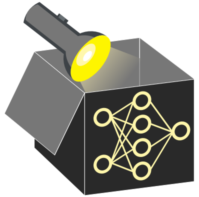

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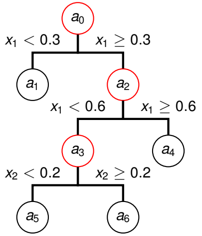

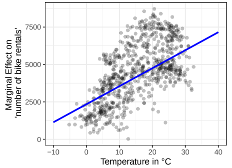

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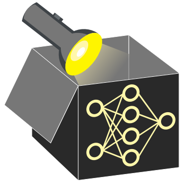

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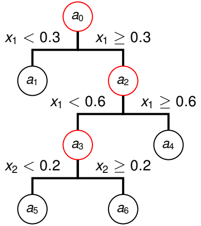

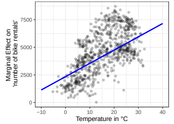

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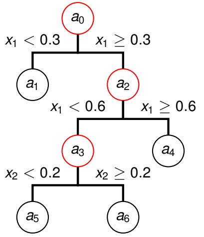

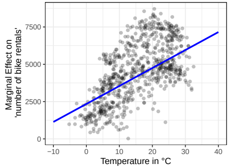

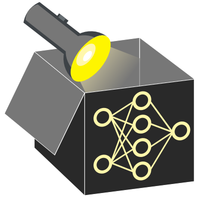

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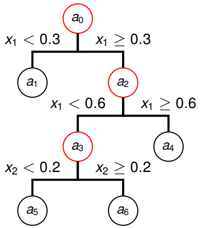

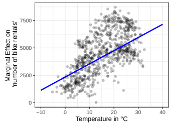

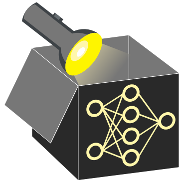

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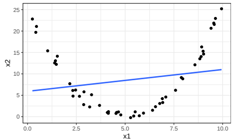
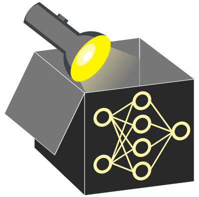
- Often require assumptions about data / model structure
  ⇝ If assumptions are wrong, models may perform bad





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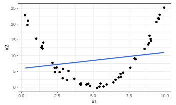

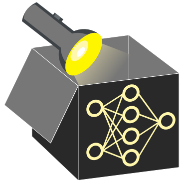

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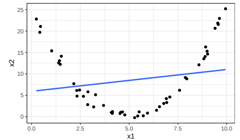

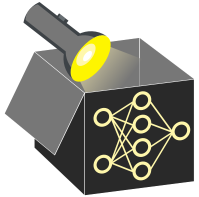

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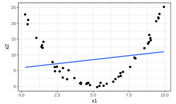

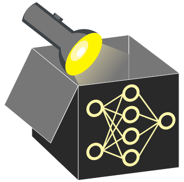

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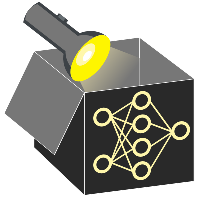

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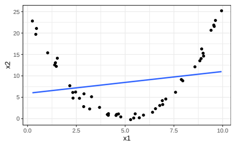

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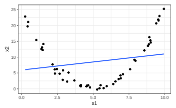

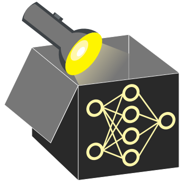

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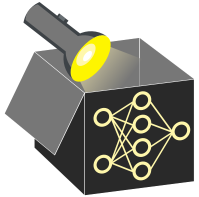

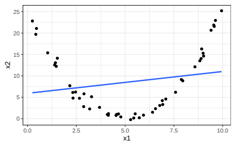

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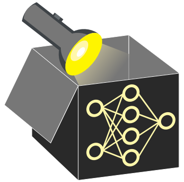
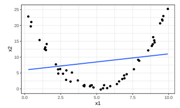
  ⇝ Complementary model-agnostic methods (e.g., counterfactuals) remain valuable for specific tasks





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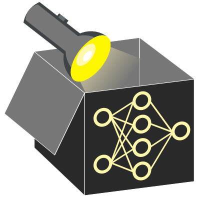

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  - Built-in interpretation ⇒ fewer risks from misleading post-hoc explanations
  - Good performance possible with effort on preprocessing / feat. engineering
  - But interpretability depends on meaning of created features
    $\rightsquigarrow$ E.g., PCA keeps models linear, but yields hard-to-interpret components

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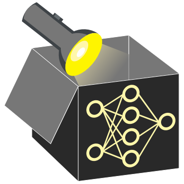

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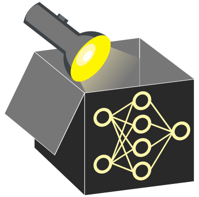

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- Limitation: Less suited for complex data where end-to-end learning is crucial
  - Applies to image, text, or sensor data where features must be learned
  - Manual extraction of interpretable features is difficult
    ⇒ Information loss and lower performance

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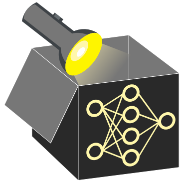

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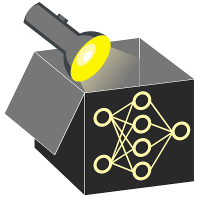

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- Increase complexity only if necessary to meet performance requirements
  ⇝ Typically reduces interpretability and requires model-agnostic explanations
- Choose the simplest model with sufficient accuracy ⇝ Occam's razor

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

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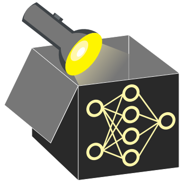

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