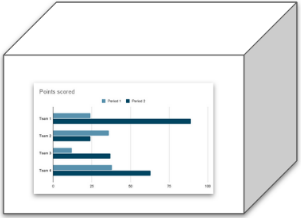
Interpretable Machine Learning

Inherently Interpretable Models - Motivation



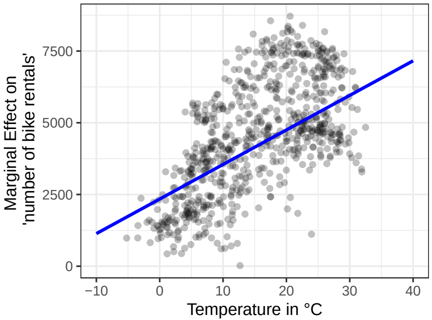
Learning goals

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

MOTIVATION

- Achieving interpretability by using interpretable models is the most straightforward approach

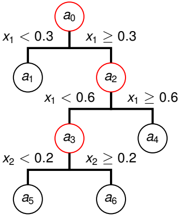
- Classes of models deemed interpretable:
  - (Generalized) linear models (LM, GLM)
  - Generalized additive models (GAM)
  - Decision trees
  - Rule-based learning
  - Model-based boosting / component-wise boosting
  - ...

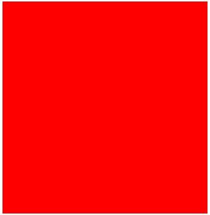


⇝ LM provides straightforward interpretation

ADVANTAGES

- Inherently interpretable - some additional model-agnostic interpretation methods not required
  $\rightsquigarrow$ Eliminates a source of error





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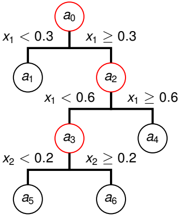
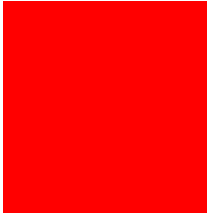
  $\rightsquigarrow$ training time is fairly small





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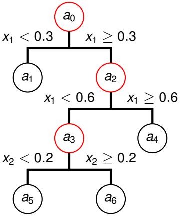

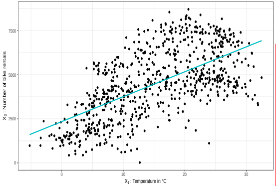

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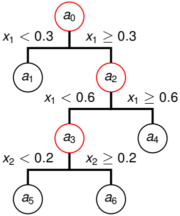
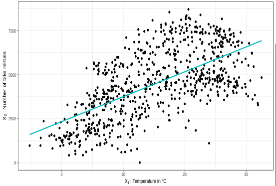
- Many people are familiar with traditional interpretable models
  $\rightsquigarrow$ Increases trust, facilitates communication of results





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- Often certain assumptions about data / model structure required
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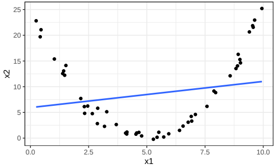

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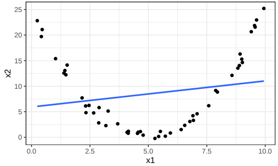
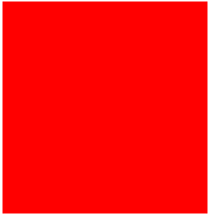
  - Decision trees with huge tree depth





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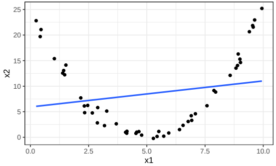

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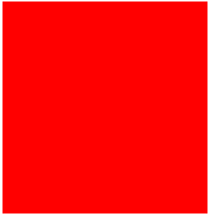
  e.g., high-order main or interaction effects need to be specified manually in a LM



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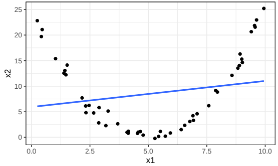

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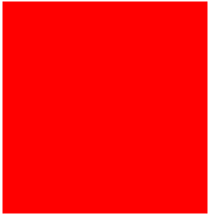
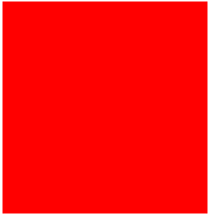
- Inherently interpretable models do not provide all types of explanations
  $\leadsto$ Methods providing other types of explanations still useful (e.g., counterfactual explanations)



FURTHER COMMENTS

- Some argue that one should always use interpretable models in the first place
  ▸ Rudin 2019
  - ...and not try to explain uninterpretable models post-hoc
  - Can sometimes work out by spending enough time and energy on data pre-processing



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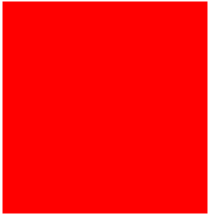
$\rightsquigarrow$ Drawback: Hard to achieve for data for which end-to-end learning is crucial (e.g., hard to extract good features for image / text data $\rightsquigarrow$ information loss = bad performance)



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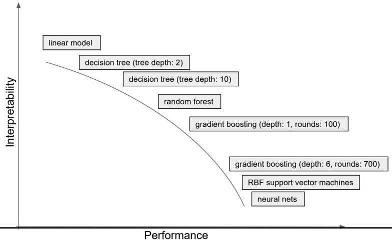
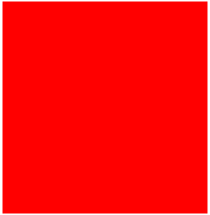
- Often there is a trade-off between interpretability and model performance





RECOMMENDATION

- Start with most simple model that makes sense for application at hand
- Gradually increase complexity if performance is insufficient
  $\rightsquigarrow$ will usually lower interpretability and require additional interpretation methods
- Choose the most simple, sufficient model (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