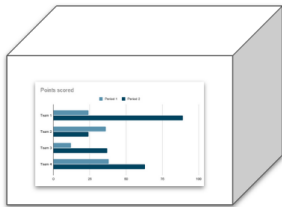


Interpretable Machine Learning

Inherently Interpretable Models - Motivation

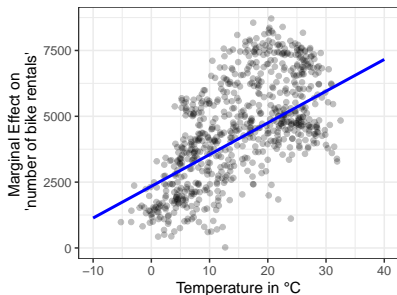


Learning goals

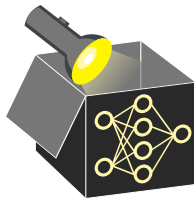
- Why should we use interpretable models?
- Advantages and disadvantages of interpretable models

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
 - ...

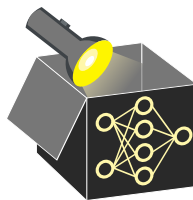
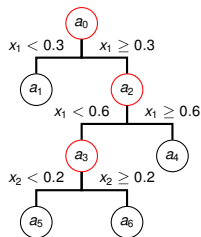


↪ LM provides straightforward interpretation



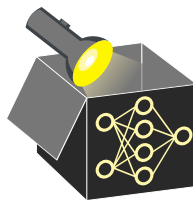
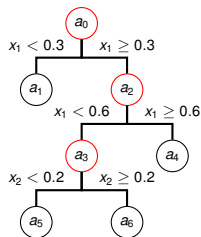
ADVANTAGES

- Inherently interpretable - some additional model-agnostic interpretation methods not required
~> Eliminates a source of error



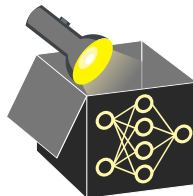
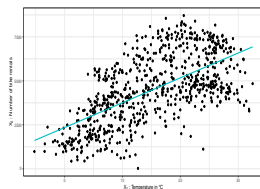
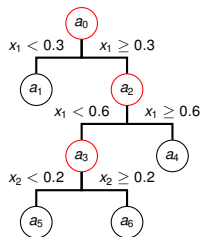
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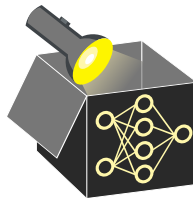
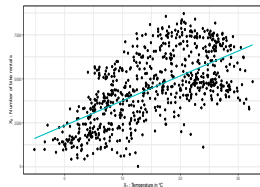
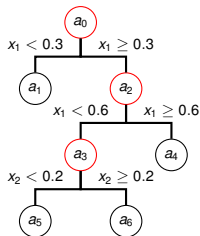
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~> Larger feature values always lead to higher (or smaller) outcomes (e.g., GLMs)



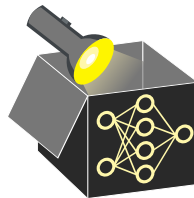
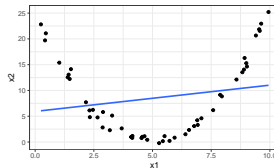
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- Many people are familiar with traditional interpretable models
~> Increases trust, facilitates communication of results



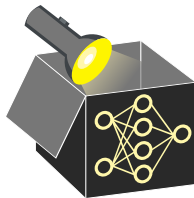
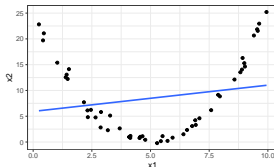
DISADVANTAGES

- Often certain assumptions about data / model structure required
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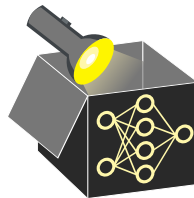
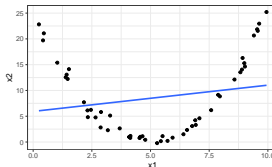
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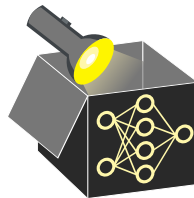
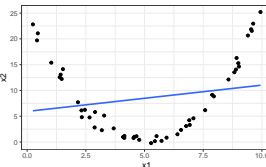
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- Often not able to automatically model complex relationships due to limited model flexibility
e.g., high-order main or interaction effects need to be specified manually in a LM
- Inherently interpretable models do not provide all types of explanations
~> Methods providing other types of explanations still useful (e.g., counterfactual explanations)

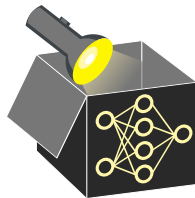


FURTHER COMMENTS

- 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



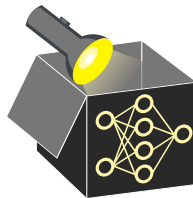
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(e.g., hard to extract good features for image / text data
↪ information loss = bad performance)



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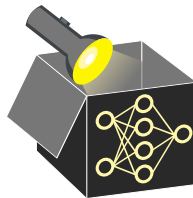
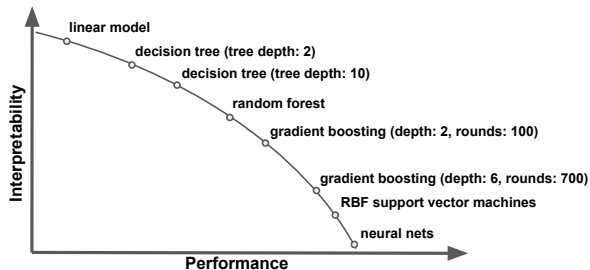
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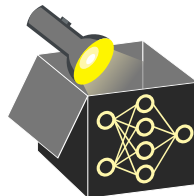
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- Often there is a trade-off between interpretability and model performance



RECOMMENDATION

- Start with most simple model that makes sense for application at hand
- Gradually increase complexity if performance is insufficient
 ~> 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