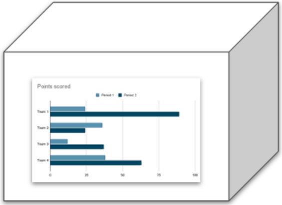
# Interpretable Machine Learning

# Inherently Interpretable Models - Motivation



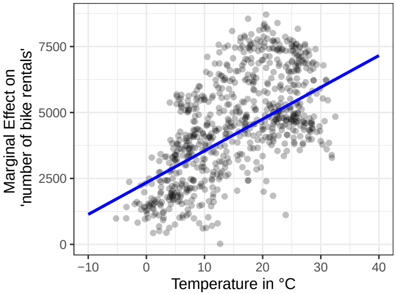

**Learning goals**

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

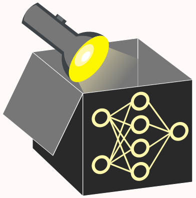
# MOTIVATION

- 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
  - ...




$\rightsquigarrow$ LM provides straightforward interpretation



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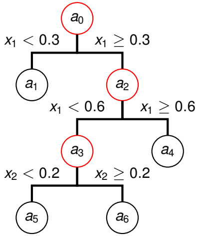
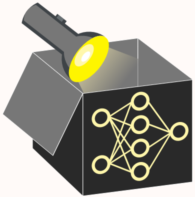
- Inherently interpretable - some additional model-agnostic interpretation methods not required
  $\rightsquigarrow$ Eliminates a source of error



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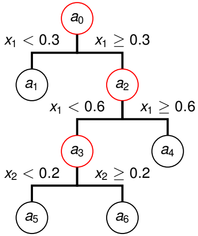


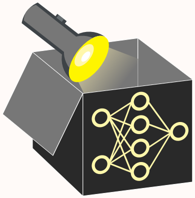

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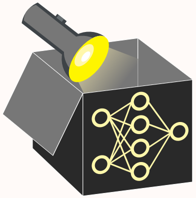

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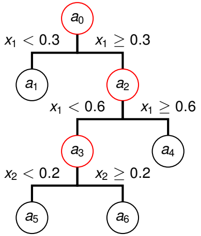


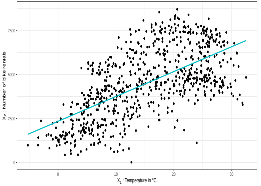

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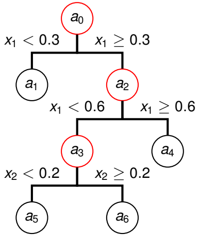
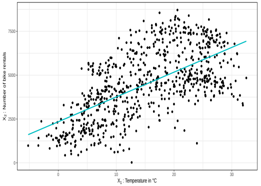
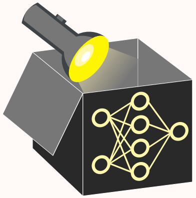
- Many people are familiar with traditional interpretable models
  $\rightsquigarrow$ Increases trust, facilitates communication of results



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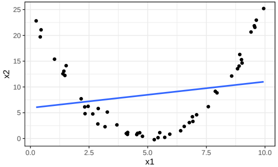
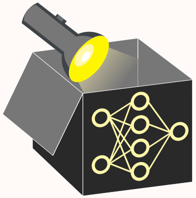
  $\rightsquigarrow$ If assumptions are wrong, models may perform bad



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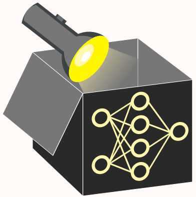

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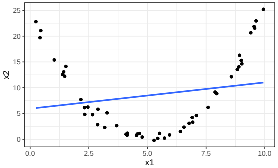


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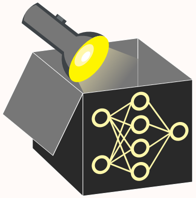

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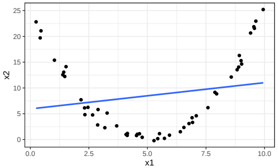


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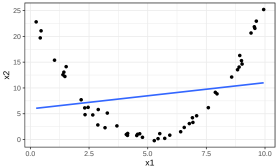


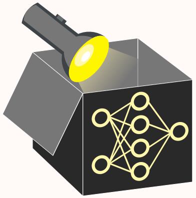

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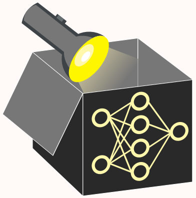
- Inherently interpretable models do not provide all types of explanations
  $\rightsquigarrow$ Methods providing other types of explanations still useful (e.g., counterfactual explanations)

# FURTHER COMMENTS



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  ▸ Rudin 2019
  - . . . and not try to explain uninterpretable models post-hoc
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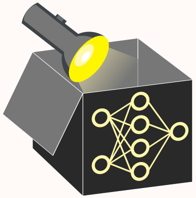
$\rightsquigarrow$ Drawback: Hard to achieve for data for which end-to-end learning is crucial (e.g., hard to extract good features for image / text data $\rightsquigarrow$ information loss = bad performance)



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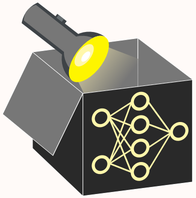

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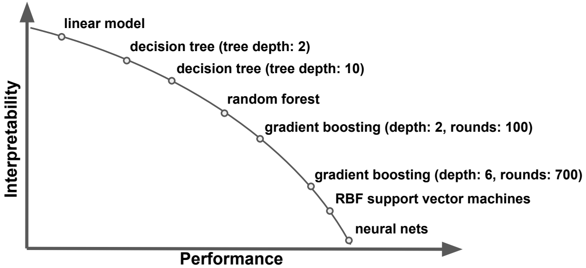
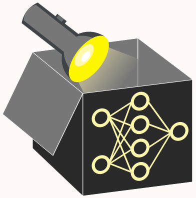
- Often there is a trade-off between interpretability and model performance



# 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 |