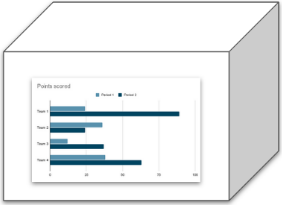
Interpretable Machine Learning

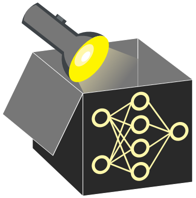
Inherently Interpretable Models - Motivation



Learning goals

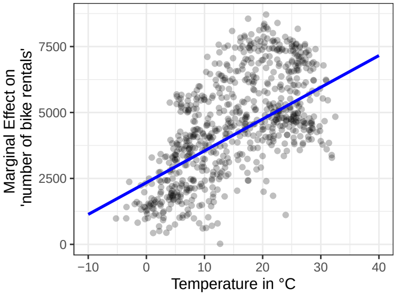
- Why should we use interpretable models?
- Advantages and disadvantages of interpretable models

MOTIVATION



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

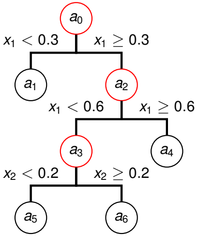
- Classes of models deemed interpretable:
  - (Generalized) linear models (LM, GLM)
  - Generalized additive models (GAM)
  - Decision trees
  - Rule-based learning
  - Model-based boosting / component-wise boosting
  - ...

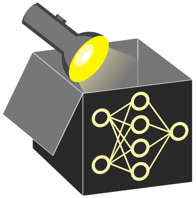


$\rightsquigarrow$ LM provides straightforward interpretation

ADVANTAGES

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

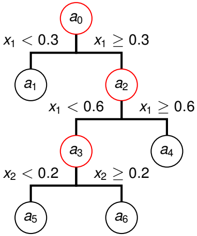


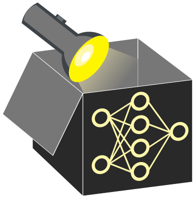


ADVANTAGES

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

- Interpretable models often simple
  $\rightsquigarrow$ training time is fairly small



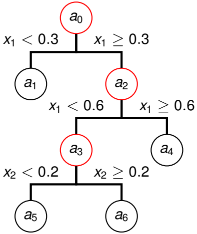


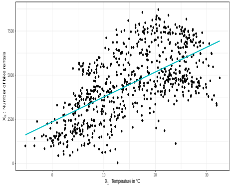
ADVANTAGES

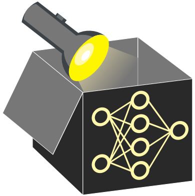
- For inherently interpretable models some additional model-agnostic interpretation methods not required
  $\rightsquigarrow$ Eliminates a source of error

- Interpretable models often simple
  $\rightsquigarrow$ training time is fairly small

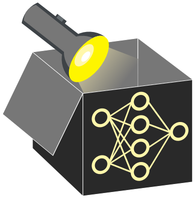
- Some interpretable models estimate monotonic effects
  $\rightsquigarrow$ Simple to explain as larger feature values always lead to higher (or smaller) outcomes (e.g., GLMs)







ADVANTAGES

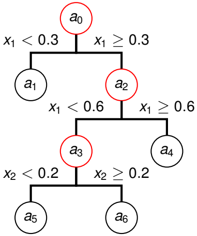


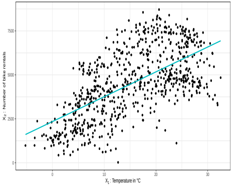
- For inherently interpretable models some additional model-agnostic interpretation methods not required
  $\rightsquigarrow$ Eliminates a source of error

- Interpretable models often simple
  $\rightsquigarrow$ training time is fairly small

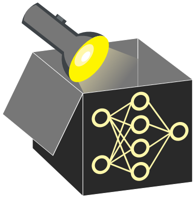
- Some interpretable models estimate monotonic effects
  $\rightsquigarrow$ Simple to explain as larger feature values always lead to higher (or smaller) outcomes (e.g., GLMs)

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

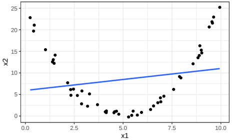




DISADVANTAGES



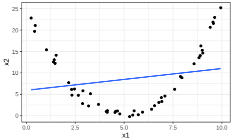
- Often require assumptions about data / model structure
  $\rightsquigarrow$ If assumptions are wrong, models may perform bad

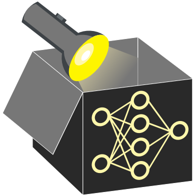


DISADVANTAGES

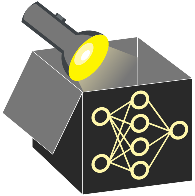
- Often require assumptions about data / model structure
  $\rightsquigarrow$ If assumptions are wrong, models may perform bad

- Interpretable models may also be hard to interpret, e.g.:
  - Linear model with lots of features and interactions
  - Decision trees with huge tree depth

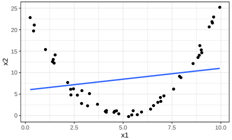




DISADVANTAGES

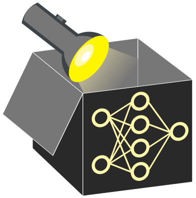


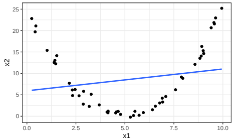
- Often require assumptions about data / model structure
  $\rightsquigarrow$ If assumptions are wrong, models may perform bad



- Interpretable models may also be hard to interpret, e.g.:
  - Linear model with lots of features and interactions
  - Decision trees with huge tree depth
- Often do not automatically model complex relationships due to limited flexibility
  e.g., high-order main or interaction effects need to be specified manually in a LM

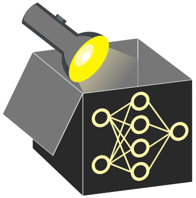
DISADVANTAGES





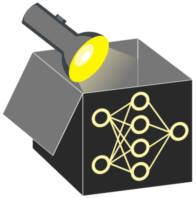
- Often require assumptions about data / model structure
  $\rightsquigarrow$ If assumptions are wrong, models may perform bad
- Interpretable models may also be hard to interpret, e.g.:
  - Linear model with lots of features and interactions
  - Decision trees with huge tree depth
- Often do not automatically model complex relationships due to limited 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
  $\rightsquigarrow$ Methods providing other types of explanations still useful (e.g., counterfactual explanations)

FURTHER COMMENTS



- Some argue that interpretable models should be preferred ▸ Rudin 2019
  - . . . instead of explaining uninterpretable models post-hoc
  - Can sometimes work out by spending enough time and energy on data pre-processing or manual feature engineering

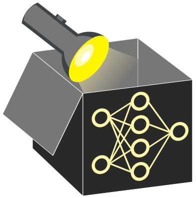
FURTHER COMMENTS



- Some argue that interpretable models should be preferred ▸ Rudin 2019
  - ...instead of explaining uninterpretable models post-hoc
  - Can sometimes work out by spending enough time and energy on data pre-processing or manual feature engineering

$\rightsquigarrow$ 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

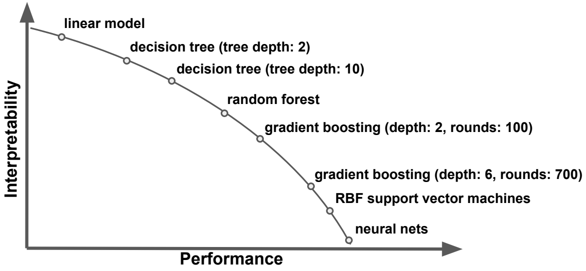
FURTHER COMMENTS



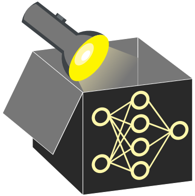
- Some argue that interpretable models should be preferred ▸ Rudin 2019
  - . . . instead of explaining uninterpretable models post-hoc
  - Can sometimes work out by spending enough time and energy on data pre-processing or manual feature engineering

$\rightsquigarrow$ 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

- 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