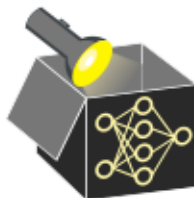
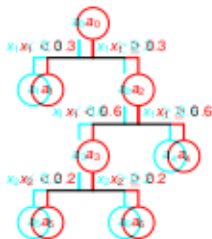


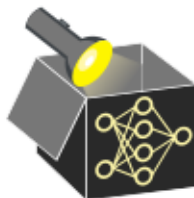
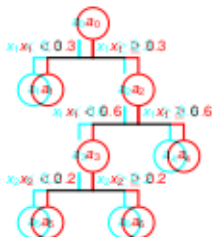
ADVANTAGES

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



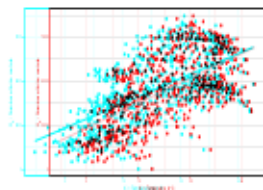
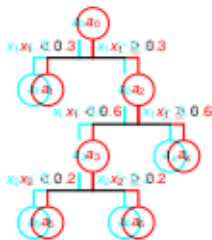
ADVANTAGES

- For inherently interpretable models some additional model-agnostic interpretation methods not required
~> Eliminates a source of error
- Interpretable models often simple
~> training time is fairly small



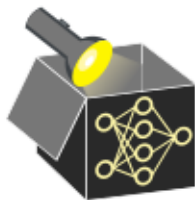
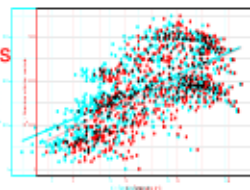
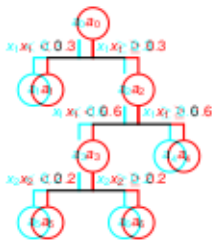
ADVANTAGES

- For inherently interpretable models some additional model-agnostic interpretation methods not required
~> Eliminates a source of error
- Interpretable models often simple
~> training time is fairly small
- Some interpretable models estimate monotonic effects
○ Simple to explain as larger feature values always lead to higher (or smaller) outcomes (e.g., GLMs)
○ Larger (or smaller) outcomes (e.g., GLMs)



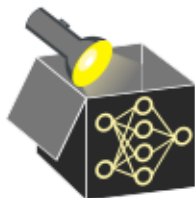
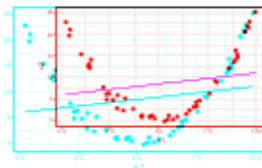
ADVANTAGES

- For inherently interpretable models some additional model-agnostic interpretation methods not required
~> Eliminates a source of error
- Interpretable models often simple
~> training time is fairly small
- Some interpretable models estimate monotonic effects
 - 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
- Increases trust, facilitates communication of results models
~> Increases trust, facilitates communication of results



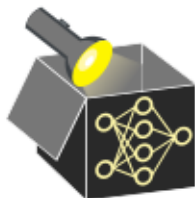
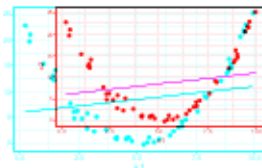
DISADVANTAGES

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



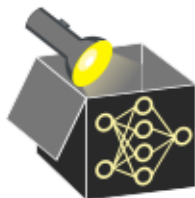
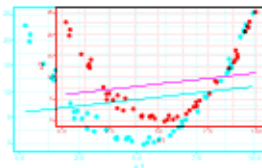
DISADVANTAGES

- Often require assumptions about data / model structure
 - If assumptions are wrong, models may perform bad
 - ↪ If assumptions are wrong, models may perform bad
- Interpretable models may also be hard to interpret, e.g.:
- Interpretable models may also be difficult to interpret
 - Linear model with lots of features and interactions
 - Decision trees with huge tree depth
 - Linear model with hundreds of features and interactions
 - Decision trees with huge tree depth



DISADVANTAGES

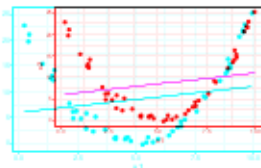
- Often require assumptions about data / model structure
 - If assumptions are wrong, models may perform bad
 - ~> If assumptions are wrong, models may perform bad
- Interpretable models may also be hard to interpret, e.g.:
 - Linear model with lots of features and interactions
 - Decision trees with huge tree depth
 - Linear model with hundreds of features and interactions
- 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
 - Decision trees with huge tree depth
- 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



DISADVANTAGES

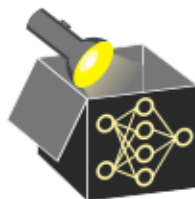


- Often require assumptions about data / model structure
 - ↳ If assumptions are wrong, models may perform bad
 - ↳ If assumptions are wrong, models may perform bad
- Interpretable models may also be hard to interpret, e.g.:
 - Linear model with lots of features and interactions
 - Decision trees with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



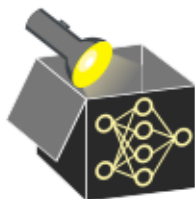
FURTHER COMMENTS

- Some argue that interpretable models should be preferred in the first place
 - ... 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

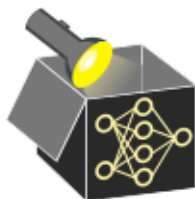


FURTHER COMMENTS

- Some argue that interpretable models should be preferred in the first place
 - ... 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
- ↪ 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
- (= information loss = bad performance)
- ↪ information loss = bad performance)



FURTHER COMMENTS



- Some argue that interpretable models should be preferred in the first place

• 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

↪ 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 and learning is crucial

(\leftarrow information loss = bad performance)

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

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

