Interpretable Machine Learning

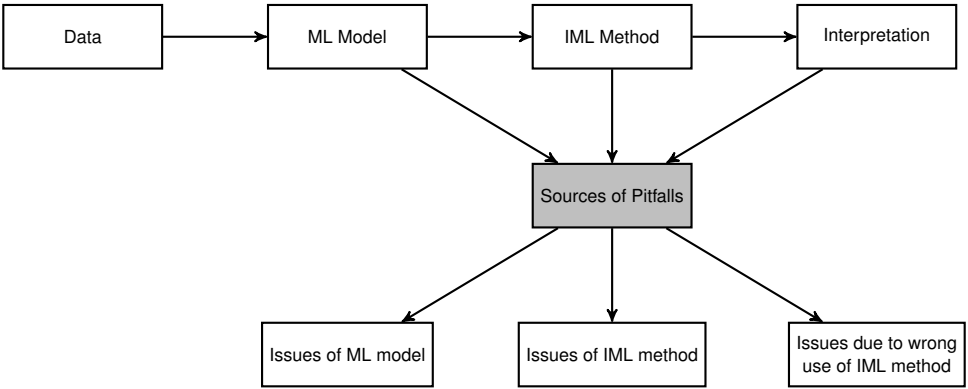
Pitfalls and Best Practices

Learning goals

- General pitfalls of interpretation methods
- Practices to avoid pitfalls

SOURCES OF PITFALLS

▸ Molnar et. al (2021)



ISSUES OF ML MODEL ▸ Molnar et. al (2021)

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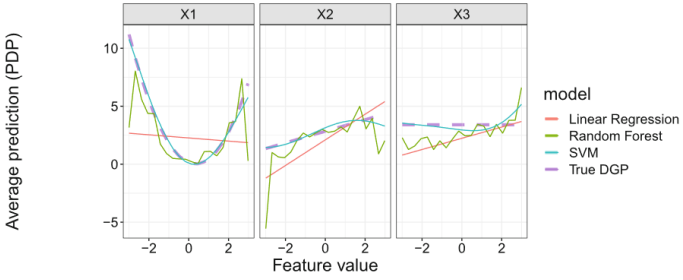

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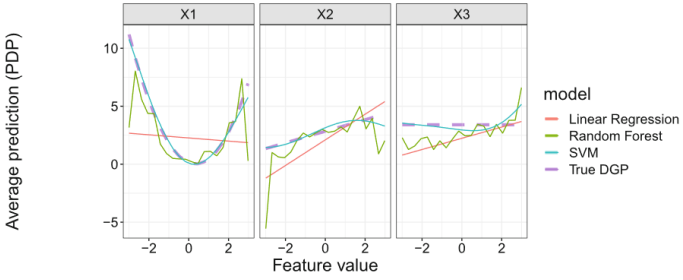

- **Avoid unnecessary complexity**: Prefer simple interpretable models and use them as baseline

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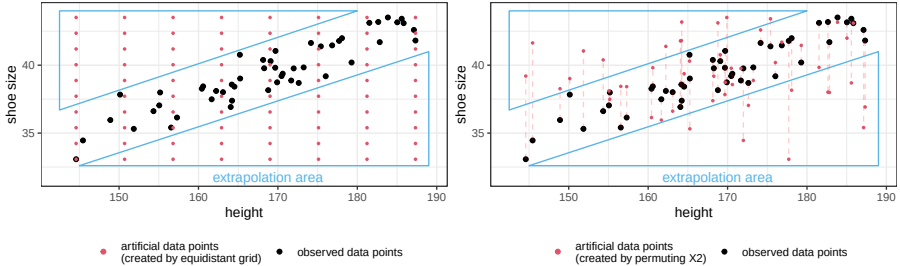

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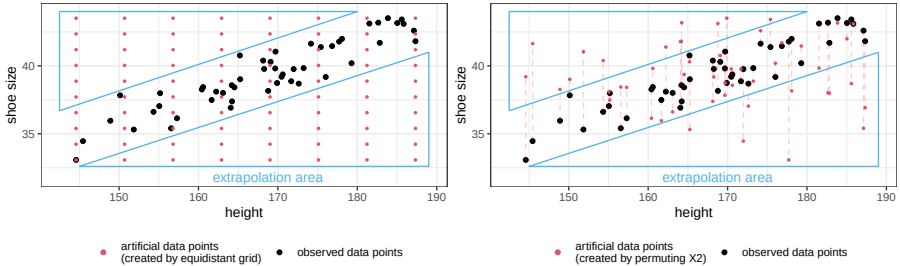

- **Beware of simplifications**: Mapping of complex models to low-dim. explanations
  ⇝ Information loss, e.g., some interpretation methods hide interactions (Figure: PDP and ICE Curves)

slides/03_feature-effects/f

ISSUES DUE TO WRONG USE OF IML METHOD ▸ Molnar et. al (2021)

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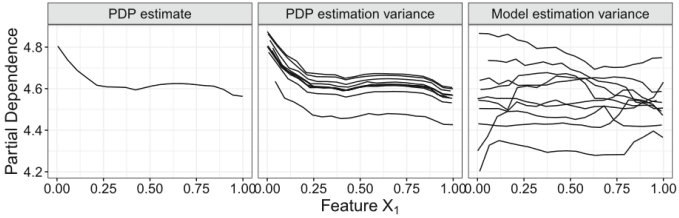

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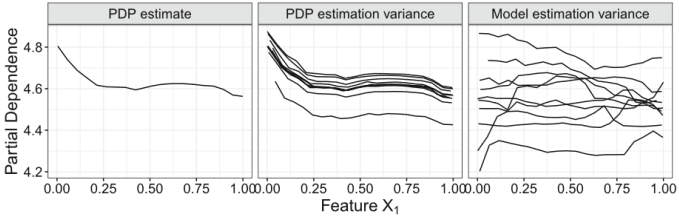

- **Careful with causality**: Do you want to understand the model or the nature of DGP?
  $\rightsquigarrow$ Your goal should guide the choice of interpretation method