A Path to Simpler Models Starts with Noise

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Machine Learning, 11, 63–91 (1993)

Very Simple Classification Rules Perform Well on Most Commonly Used Datasets

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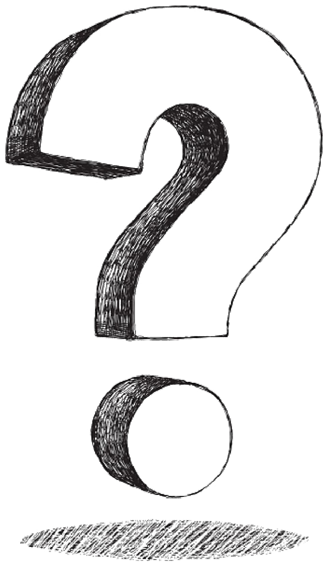
Larger
Rashomon ratios

Correlate with

Existence of simpler
(or interpretable)
models

$$\textbf{Rashomon ratio} = \frac{\text{Size of }\{\text{models that perform equally well}\}}{\text{Size of the hypothesis space}}$$

Semenova et al. On the existence of simpler machine learning models. FaccT, 2022



Leads to →

Larger
Rashomon ratios

Correlate with ↔

Existence of simpler
(or interpretable)
models

Noise
in data generation

Leads to →

Larger
Rashomon ratios

↔ **Correlate with**

Existence of simpler
(or interpretable)
models

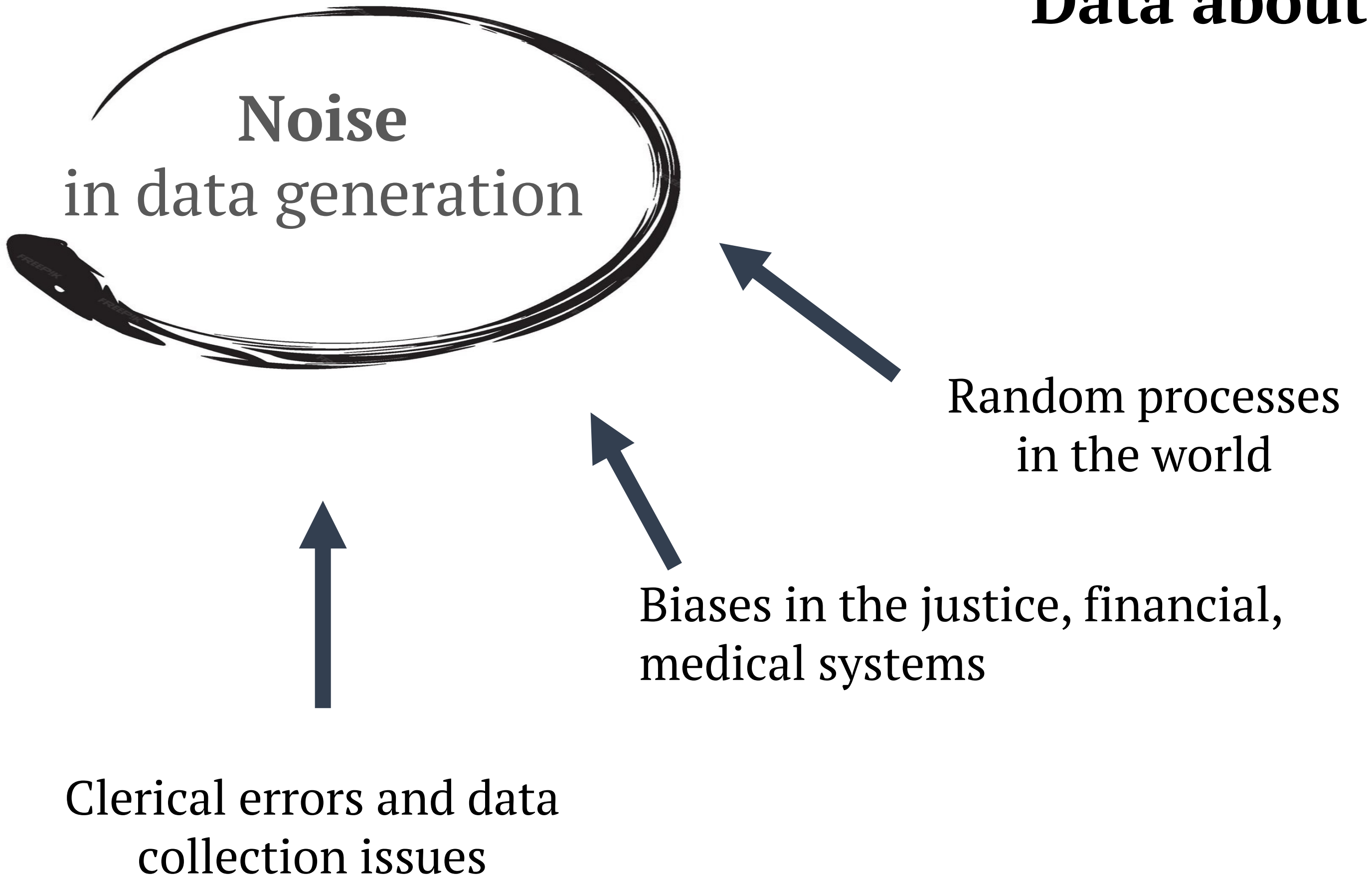
Noise
in data generation

Larger
Rashomon ratios

Existence of simpler
(or interpretable)
models

decisions made by analysts
to compensate for the noise
(think cross-validation and
regularization)

Data about humans are noisy!



Noise in high-stakes decision domains

leads to ***technical justification***

for demanding

simpler (interpretable) models

- COMPAS recidivism risk score prediction dataset
- Space of decision trees

noise

- COMPAS recidivism risk score prediction dataset
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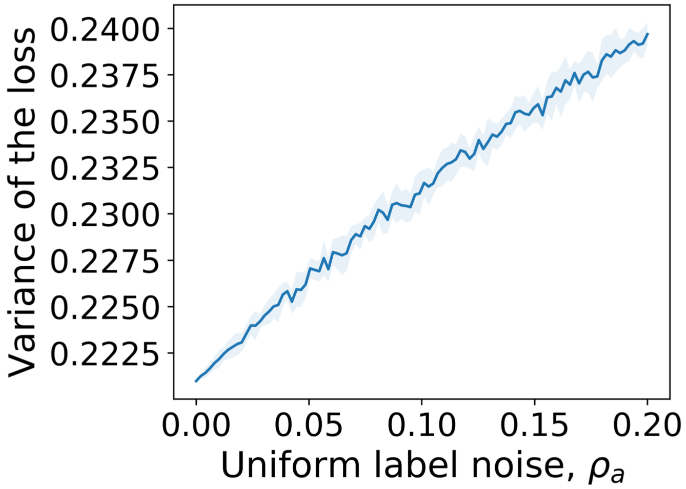
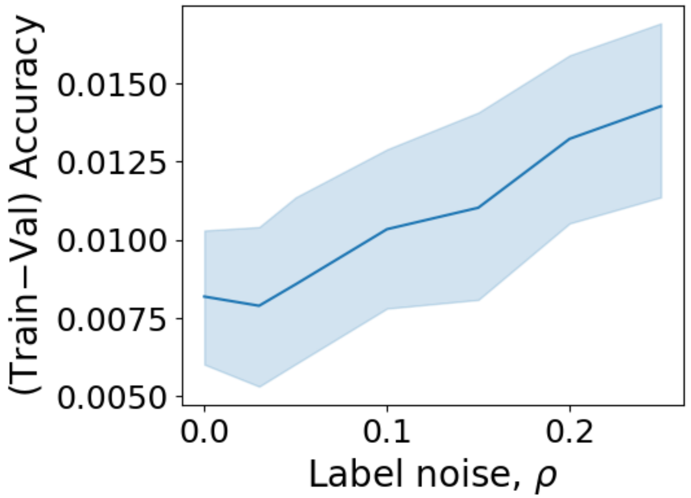


↗ variance of the loss

noise

Uniform random label noise (Theorem 2)
Labels flip with probability p(x) (Theorem 12)
Margin noise (Theorem 15)

- COMPAS recidivism risk score prediction dataset
- Space of decision trees



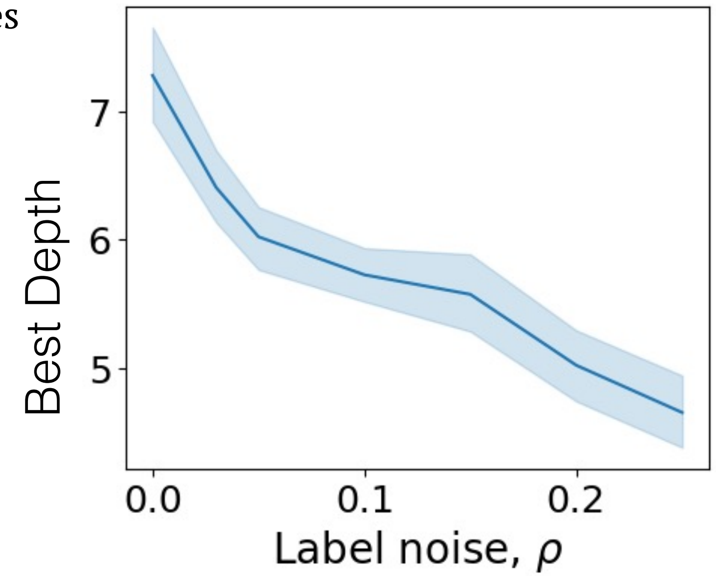
generalization

variance of the loss

noise

Generalization bounds for continuous and discrete hypothesis spaces

- COMPAS recidivism risk score prediction dataset
- Space of decision trees



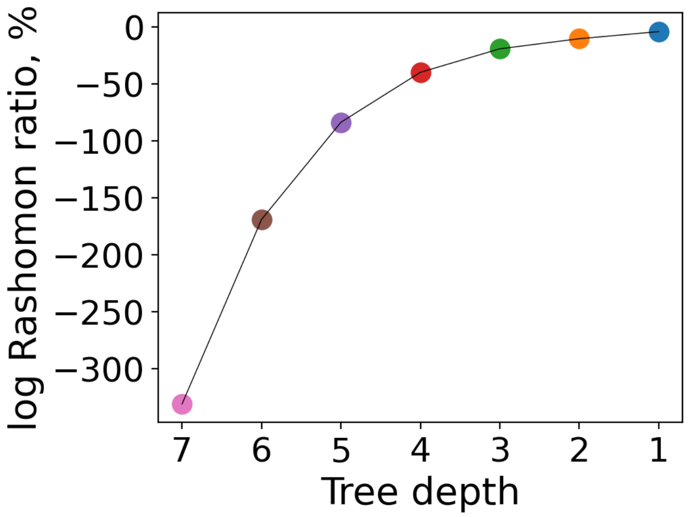
↘ complexity of the space

↘ generalization

↗ variance of the loss

noise

- COMPAS recidivism risk score prediction dataset
- Space of decision trees



↗ the Rashomon ratio

↘ complexity of the space

↘ generalization

↗ variance of the loss

noise

Rashomon ratio is larger for decision trees of smaller depth (Proposition 6)
Rashomon ratio increases with noise for ridge regression (Theorem 7)

Path

- noise
- ↗ variance of the loss
- ↘ generalization
- ↘ complexity of the space
- ↗ the Rashomon ratio

$\nearrow$ **the Rashomon ratio**

Our results *explain* **why** on *noisier* datasets **simpler models often tend to perform as well as black boxes**

noise

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https://arxiv.org/pdf/2310.19726.pdf