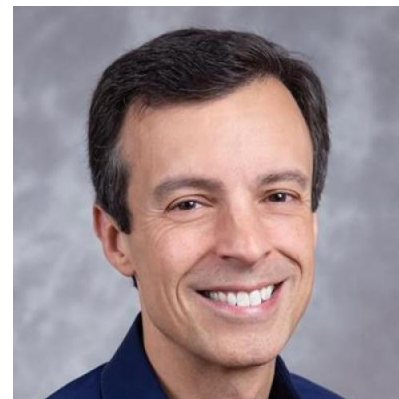


# Using Noise to Infer Aspects of Simplicity Without Learning



Zachary Boner\*, Harry Chen\*, Lesia Semenova\*, Ronald Parr, Cynthia Rudin

# Tabular dataset in high stakes domains

sparse decision trees

## Recidivism datasets

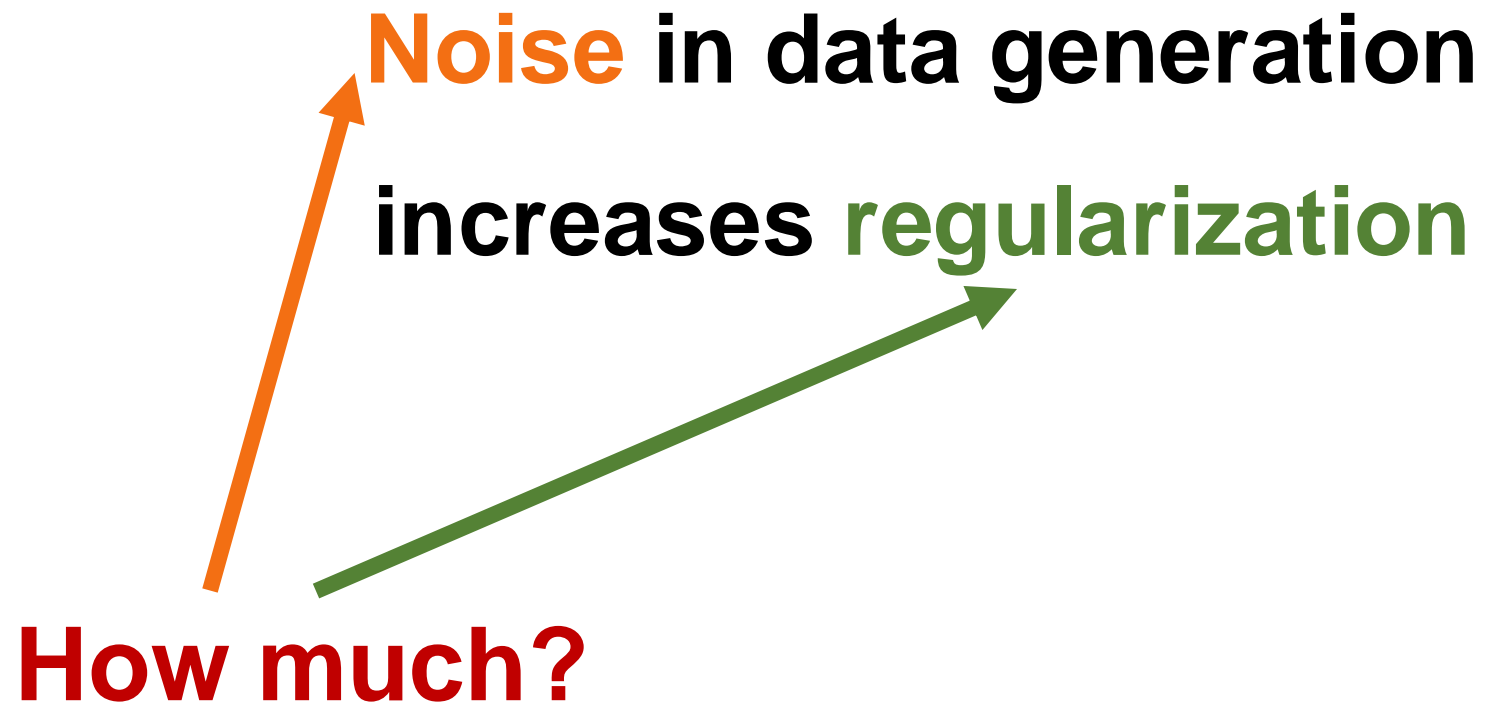
Amsterdam	7 leaves
Broward	9 leaves
COMPAS	5 leaves
NIJ	10 leaves

## Credit default datasets

Australian	5 leaves
German	4 leaves
GMSC	5 leaves
FICO	5 leaves

These are the number of leaves for trees that achieve black-box accuracy

**Noise in data generation  
increases regularization**



## KEY QUESTION:

Given **the noise level  $\rho$** , how much **simpler can ML models** get as compared to the **non-noisy case** while still maintaining similar generalization performance?

# Noise increases regularization

Optimizing

0-1 loss with regularization penalty  $\lambda$  and random label noise  $\rho$

is equivalent to optimizing

0-1 loss with regularization penalty  $\frac{\lambda}{1-2\rho}$  over clean data

# Noise increases regularization

Optimizing for linear models

Exponential loss with additive attribute noise  $\rho$

is equivalent to optimizing for linear models

Exponential loss with  $l_2$  regularization penalty  $\frac{1}{2}\rho^2$  over clean data

# Feedback for policymakers and ML practitioners

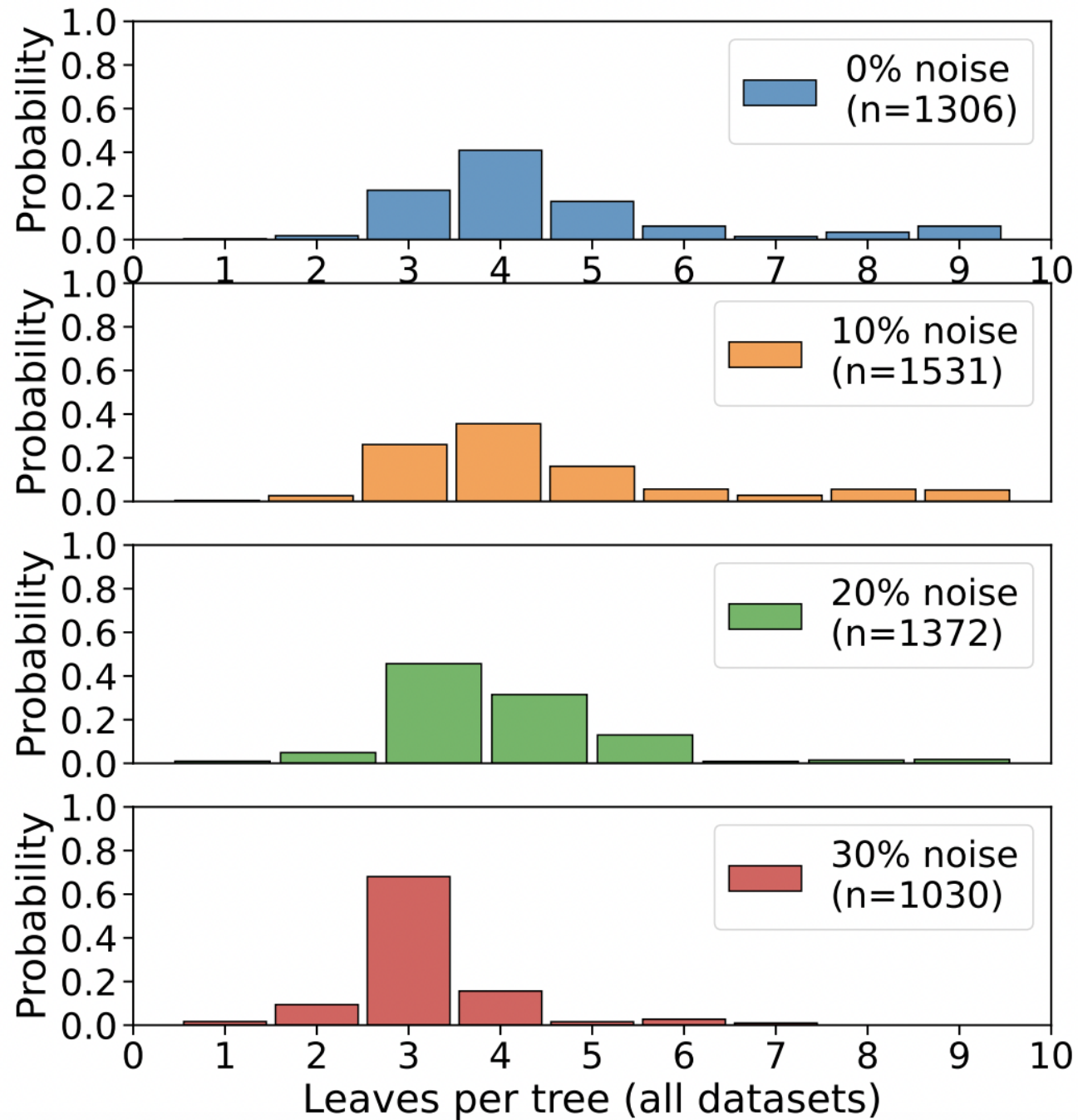
Our results are **the initial steps**

that will help to **reason about the simplicity of models**

encountered for many **high-stakes** decision domains.

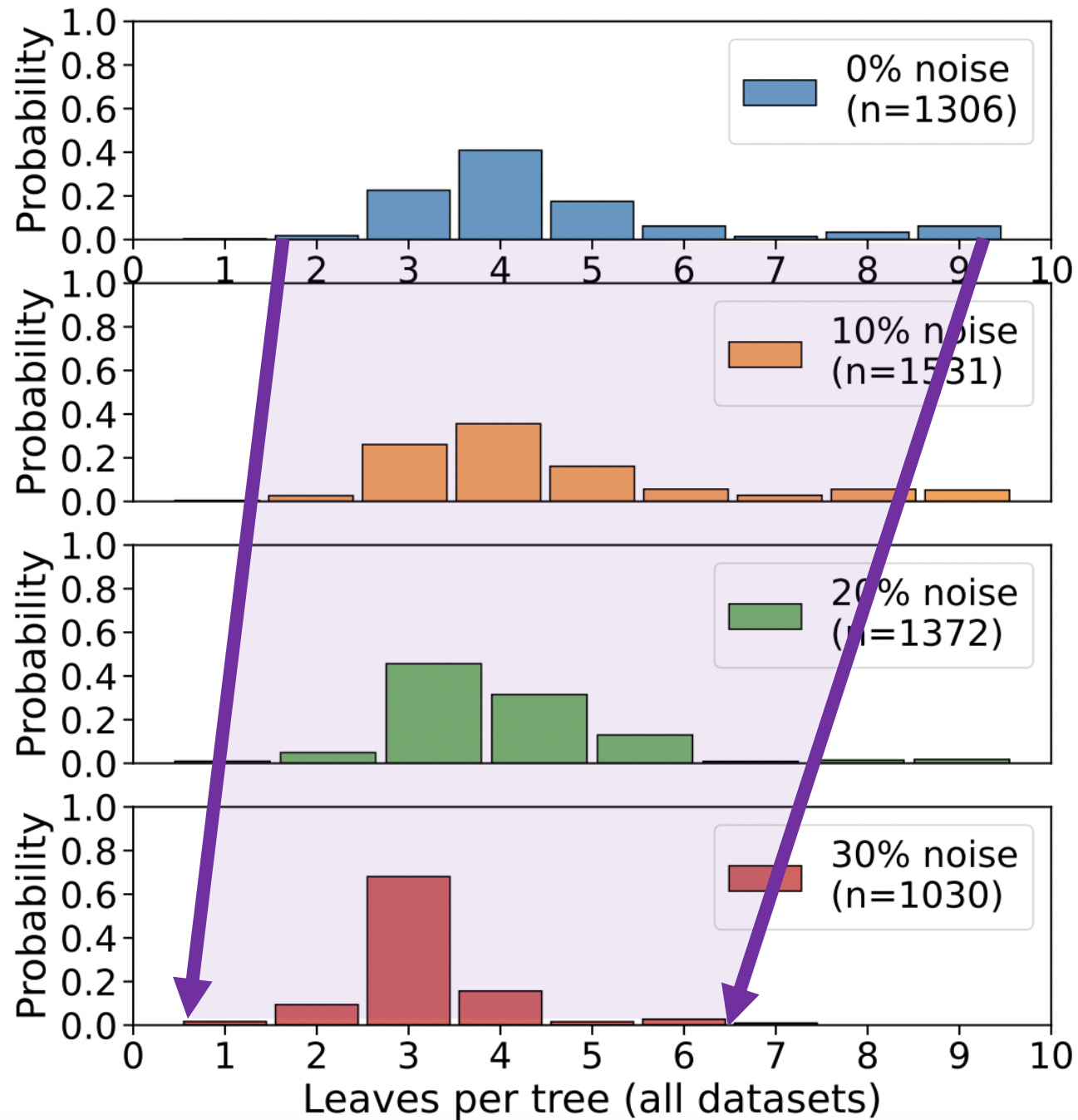


**Noise in data generation  
increases regularization,  
simplifies the set of near-optimal models,**



Not only optimal,  
 but **all near-optimal models**  
 (as know as the Rashomon set)  
**become simpler**  
 under reasonable conditions

Theorems 3, 11



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 but **all near-optimal models**  
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Theorems 3, 11

**Noise in data generation**  
**increases regularization,**  
**simplifies the set of near-optimal models,**  
**increases the set of (relatively) good features**

Under the same amount of uniform random **label noise  $\rho$** ,  
the expected AUC of features with **higher value**  
**decreases faster than**  
the expected AUC of features with **lower value**

Theorem 5, Corollary 6, 7

## Noise in data generation

- ❖ increases regularization,
- ❖ simplifies the set of near-optimal models,
- ❖ increases the set of (relatively) good features

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