

# From Counterfactuals to Trees: Competitive Analysis of Model Extraction Attacks

Awa Khouna<sup>1,2</sup> Julien Ferry<sup>1,2</sup> Thibaut Vidal<sup>1,2</sup>

<sup>1</sup>Department of Mathematical and Industrial Engineering, Polytechnique Montréal, Montréal, Canada

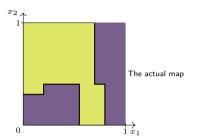
<sup>2</sup>CIRRELT & SCALE-AI Chair in Data-Driven Supply Chains,

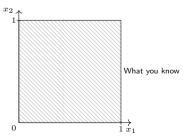




# The Map Riddle

**Setup.** Imagine a hidden map (a colored map). You can't see the full map.



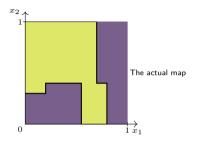


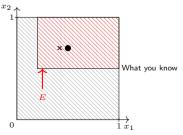
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**Oracle.** For any point  $\mathbf{x}$  and rectangle E, the oracle returns the *nearest* point  $\mathbf{x}'$  of a different color within E if it exists.

**Question.** Can repeated queries *exactly* reconstruct the entire map?



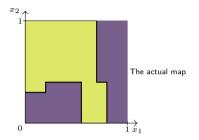


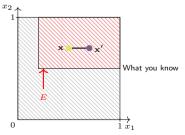
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#### Model Extraction Attack

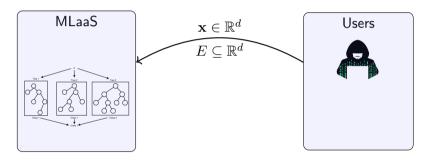


Figure: Model extraction attacks framework.

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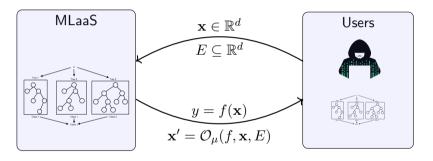


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#### From the Riddle to the Attack

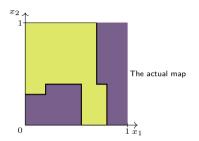
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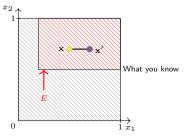
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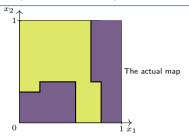
Our analogy: the colored map  $\leftrightarrow$  classifier decision regions; oracle  $\leftrightarrow$  counterfactual explanation.

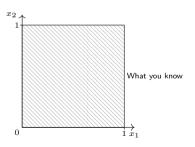
**Takeaway:** Counterfactuals reveal *where* the nearest boundary is. With a smart querying strategy, this can be enough to reconstruct the model.





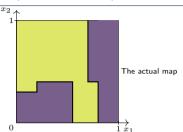


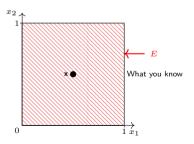




The algorithm in 3 steps:

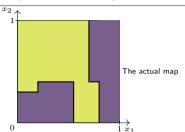
1. Probe center: query  $(\mathbf{x}, E)$ .

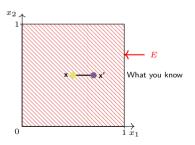




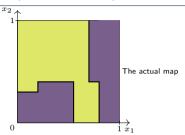
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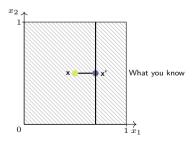
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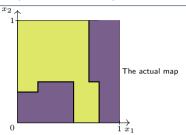


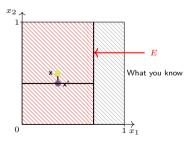
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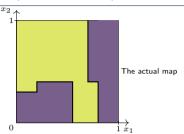


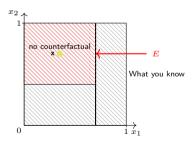
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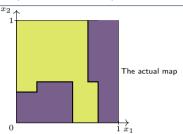


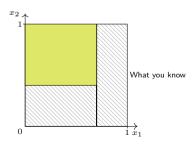
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# Theory: Query Complexity & Competitiveness

Let n be the number of split levels and  $s_i$  splits on feature i,  $\sum_i s_i = n$ .

- Worst-case queries:  $O\!\!\left(\prod_{i=1}^m (s_i+1)\right) \le O\!\!\left((1+\frac{n}{m})^m\right)$ .
- Competitive ratio:

$$C_{\mathsf{TRA}}^{(n,m)} = \frac{2\prod_{i=1}^{m}(s_i+1)-1}{n+1} \le \frac{2(1+\frac{n}{m})^m-1}{n+1}.$$

• **Tight for D&C:** no pure divide-and-conquer method can beat  $C_{\mathsf{TRA}}^{(n,m)}$ .

#### Key Insight

CFs provide *precise local boundary* information; TRA converts local probes into a *global reconstruction* with provable efficiency.



# Anytime Performance (Fidelity vs Queries)

- TRA reaches 100% fidelity faster (orders of magnitude fewer queries).
- Outperforms CF / DualCF (no functional equivalence) and PathFinding (equivalence but many queries).
- Also works with non-optimal CFs (practical APIs).

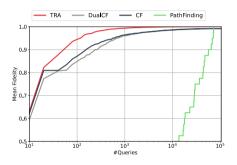
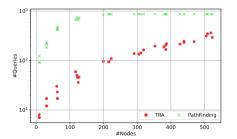


Figure: Mean Fidelity vs Number of queries over 40 trained classifier on Adult dataset

#### Functional Equivalence: Trees & Forests

- **Decision Trees:** TRA extracts exact decision boundaries with far fewer queries than PathFinding.
- Random Forests: TRA reconstructs an equivalent *tree* with perfect fidelity; *sub-linear* query growth vs nodes (empirically).



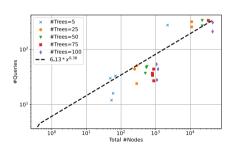


Figure: # Queries vs # Nodes for 40 classifiers.

Figure: # Queries vs # Nodes for 25 trained Random forests.



# **Implications**

- Counterfactual explanations can fully expose tree/ensemble decision boundaries.
- Design challenge: preserve recourse and explainability while limiting leakage.

#### Towards Safer Explanations

IP-preserving CFs by rate-limiting the oracle, region restrictions or query auditing.

#### **Takeaway**

Once you can ask "where is the nearest boundary?", you can reconstruct the **entire map**.

Explainability and Security must be co-designed.

# Thank you!

Meet us at our poster at NeurIPS 2025!



Scan for the paper on arXiv

Poster: From Counterfactuals to Trees
Competitive Analysis of Model Extraction
Attacks

₩ednesday, December 3, 2025
 4:30-7:30 p.m. PST
 Exhibit Hall C,D,E - San Diego Convention