Detecting Evasion Attacks in Deployed Tree Ensembles

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@laudevs

1 Tree Ensembles Can Be **Mislead**

- Susceptible to **Evasion Attacks**
  - Adversarial examples at test time
  - Small carefully crafted changes to inputs fooling the model

Evasion attack

$T($  $) = 7$

$T($  $) = 5?$

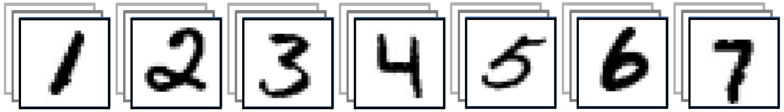
- Many performant attacks exist

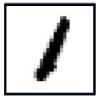
MILP	LT-Attack	Veritas
Kantchelian et al. ICML'16	Chen et al. NeurIPS'19	Devos et al. ICML'21

What we know:

2 Models **Always Make A Prediction**

Model T trained on data:



$T($  $) = 1$

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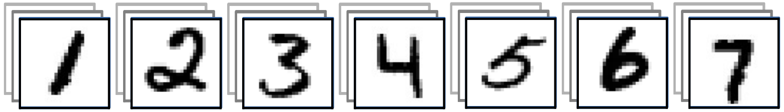

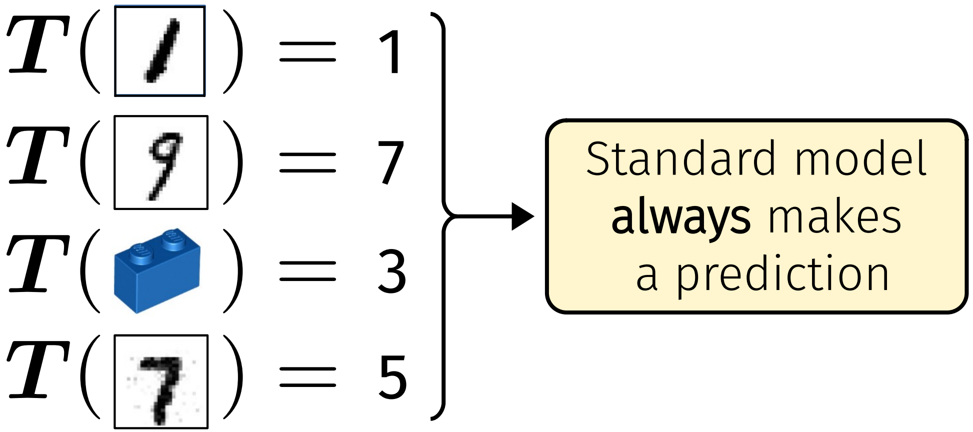

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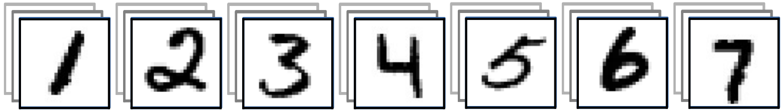
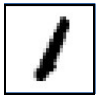


$T($  $) = 1$

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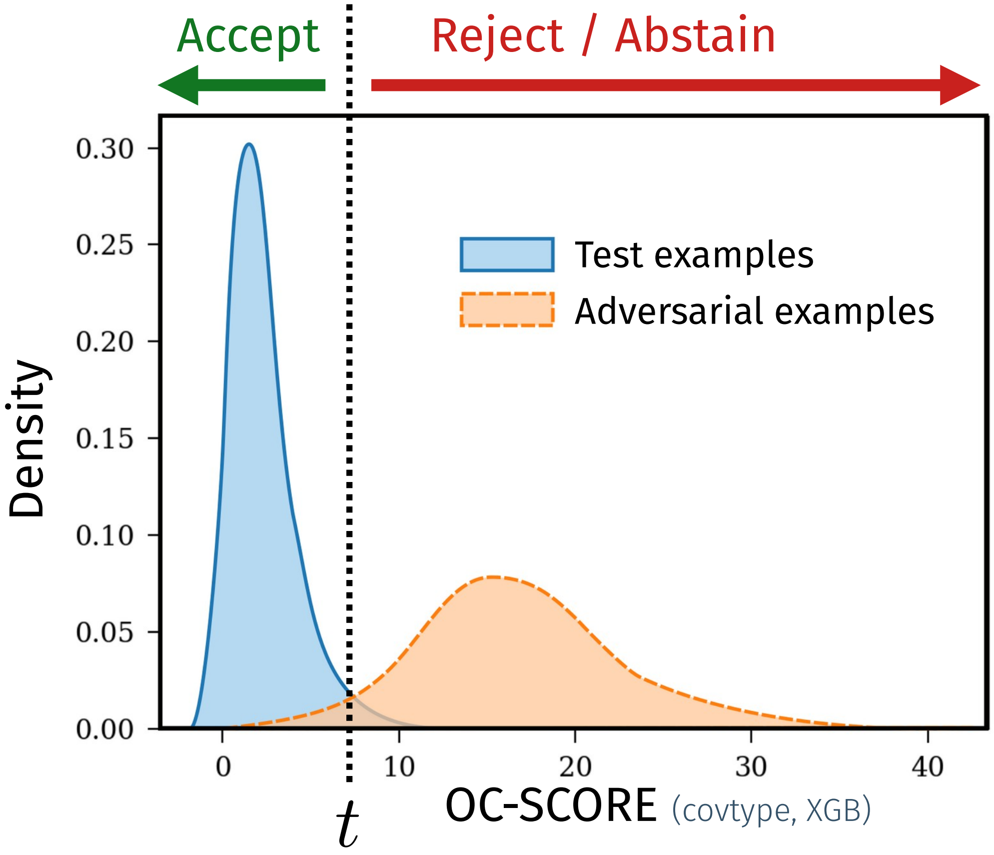
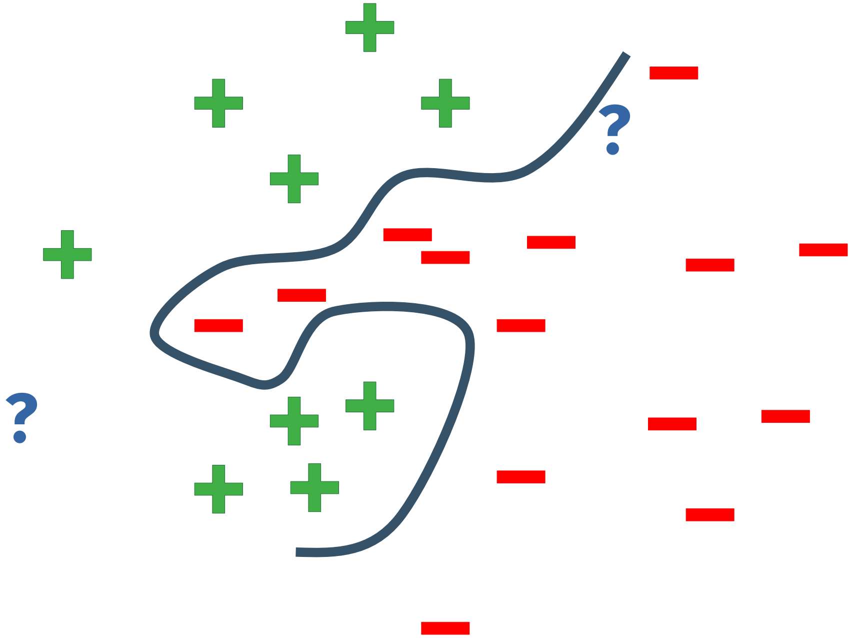


Given a model and a set of ‘*normal*’ examples

- **Assign** a score s to a new example
- **Reject** if $s > t$

Need Insights into **Why Non-Robust**



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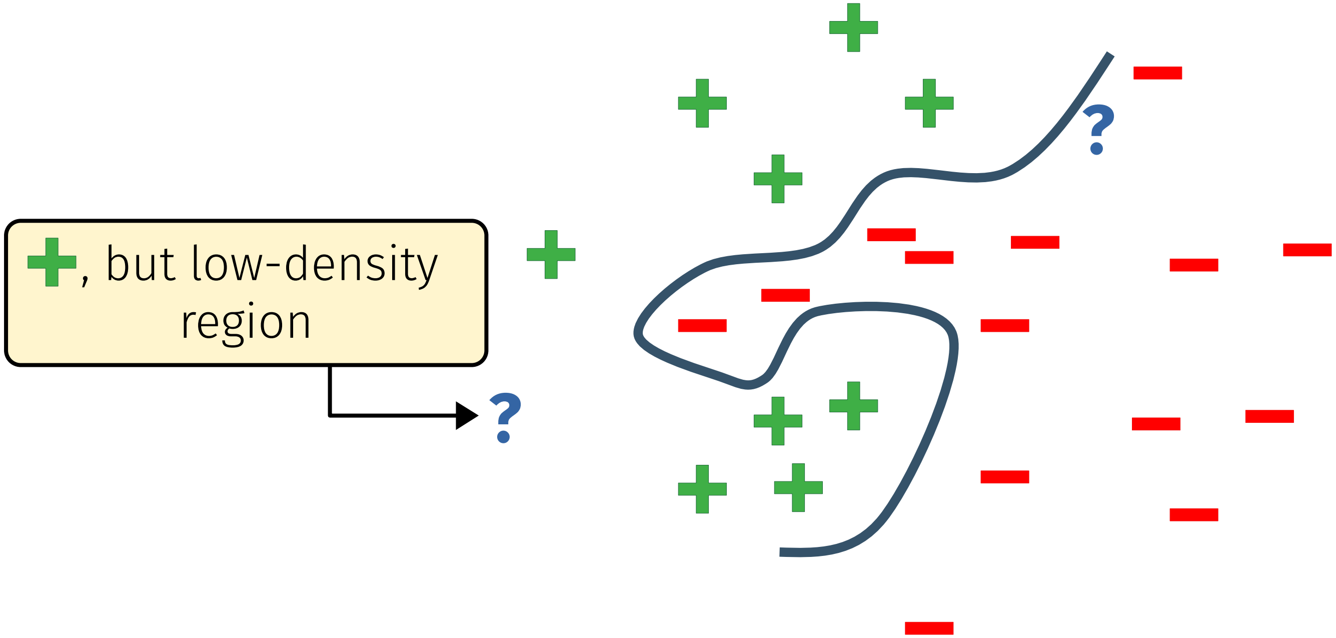

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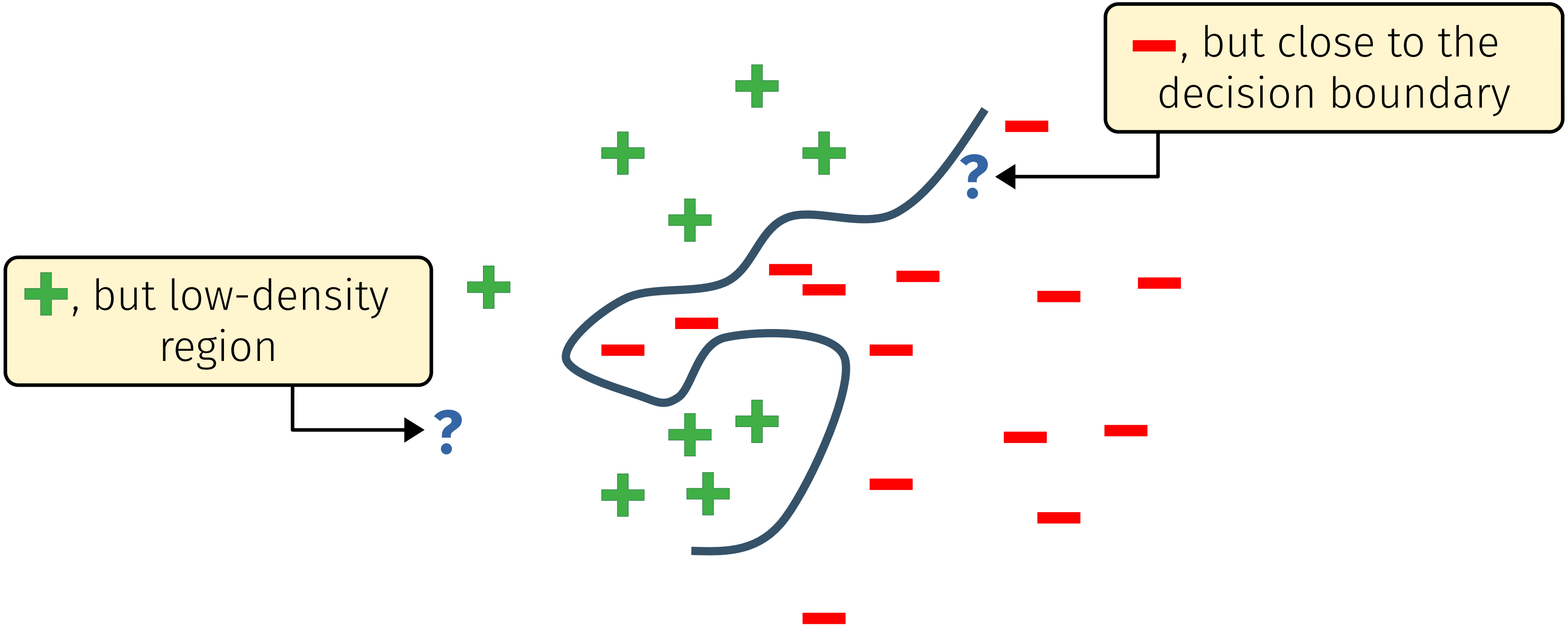

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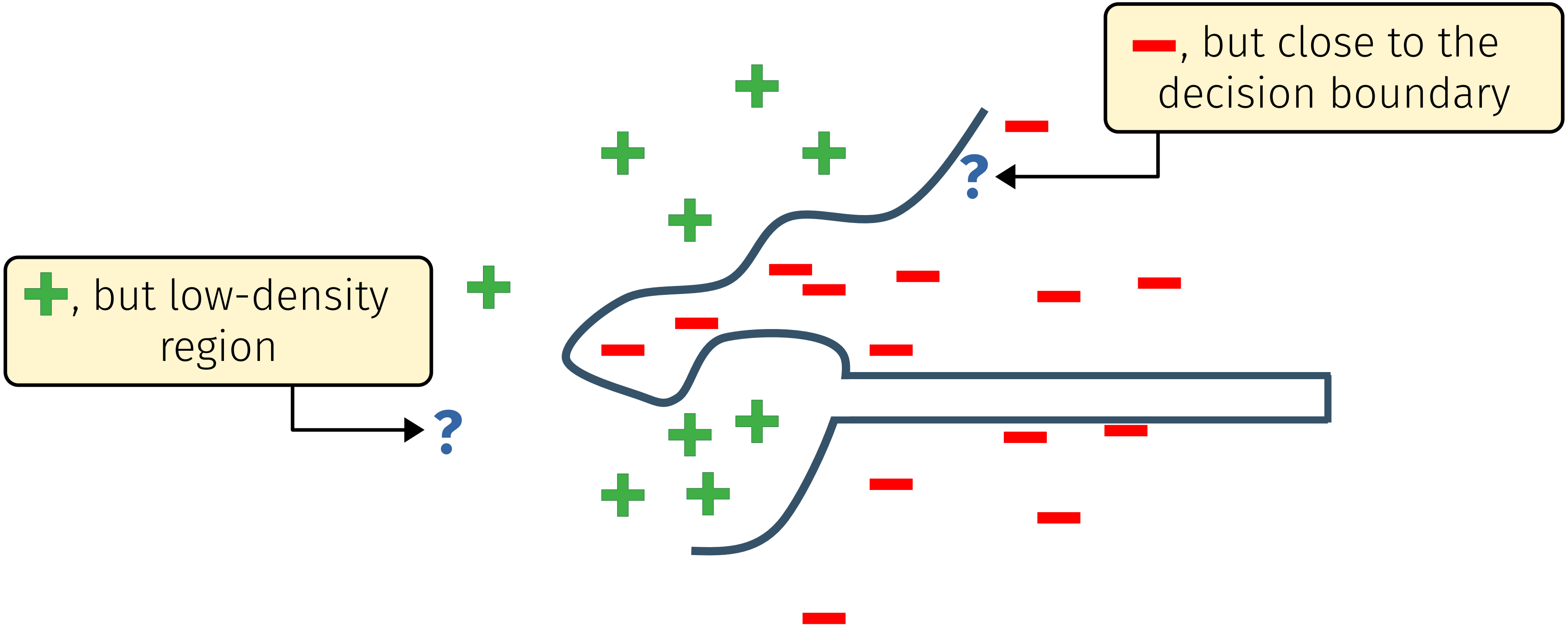

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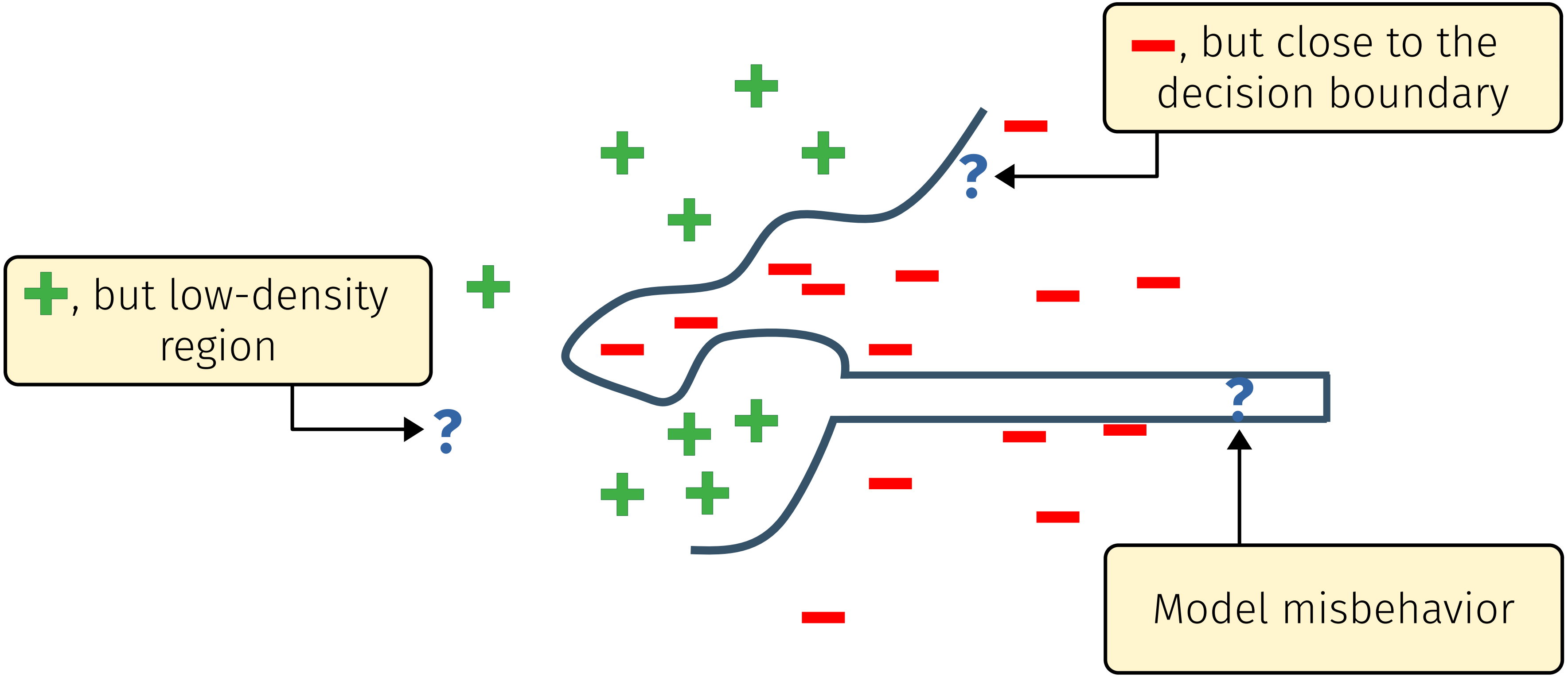

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  - Hardening: generate data automatically
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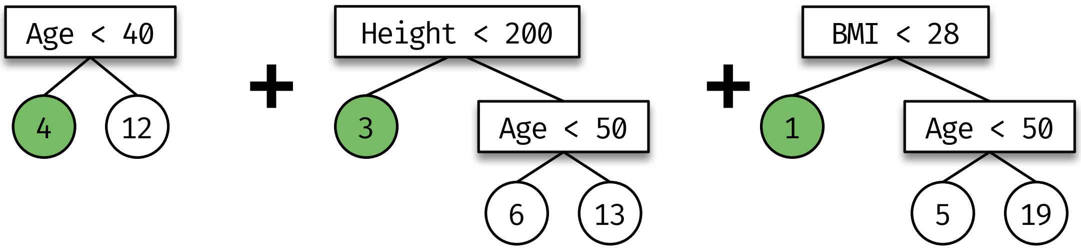
- **Post-deployment detection → OC-SCORE**

This paper

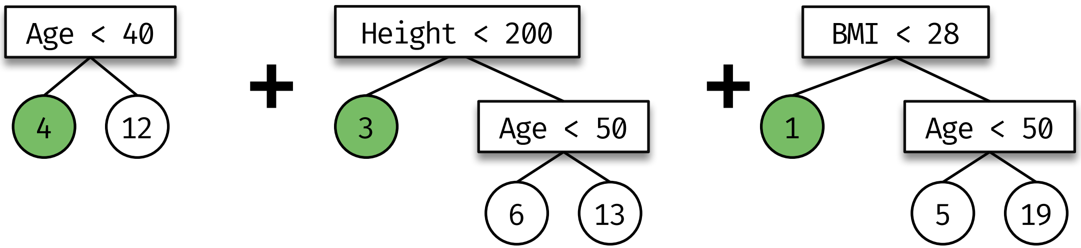
Post-Deployment Detection

The **OC-SPACE**



Age	**Height**	**BMI**
32	176	22

The **OC-SPACE**



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`OC({A=32, H=176, B=22}) = (4,3,1)`

- **OC** = tuple of compatible leaves

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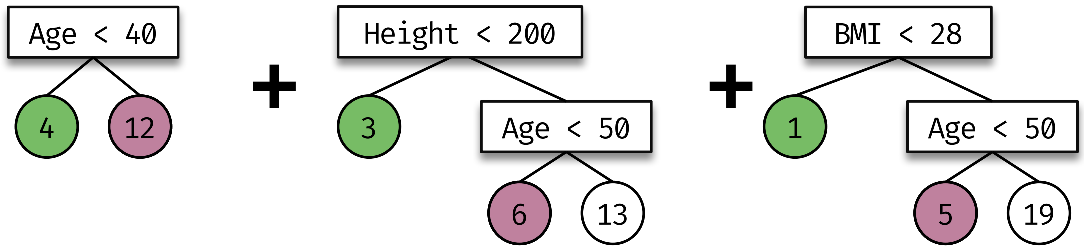

Age	Height	BMI
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OC({A=32, H=176, B=22}) = (4,3,1)
OC({A=55, H=201, B=29}) = (12,6,5)
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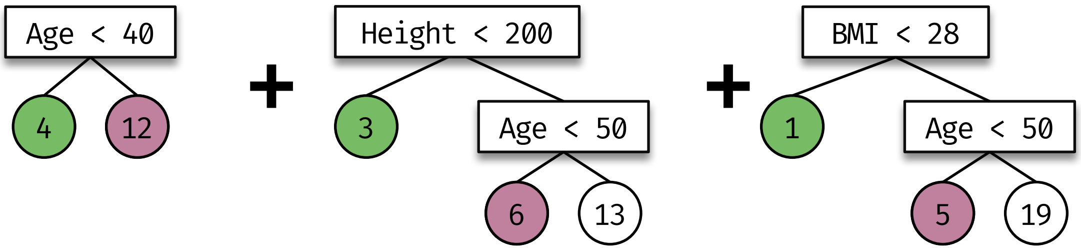

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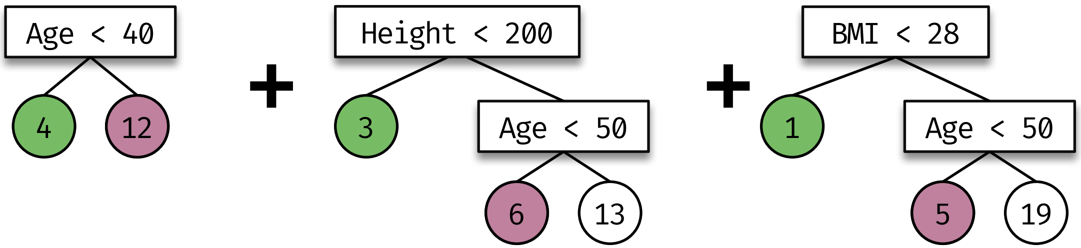

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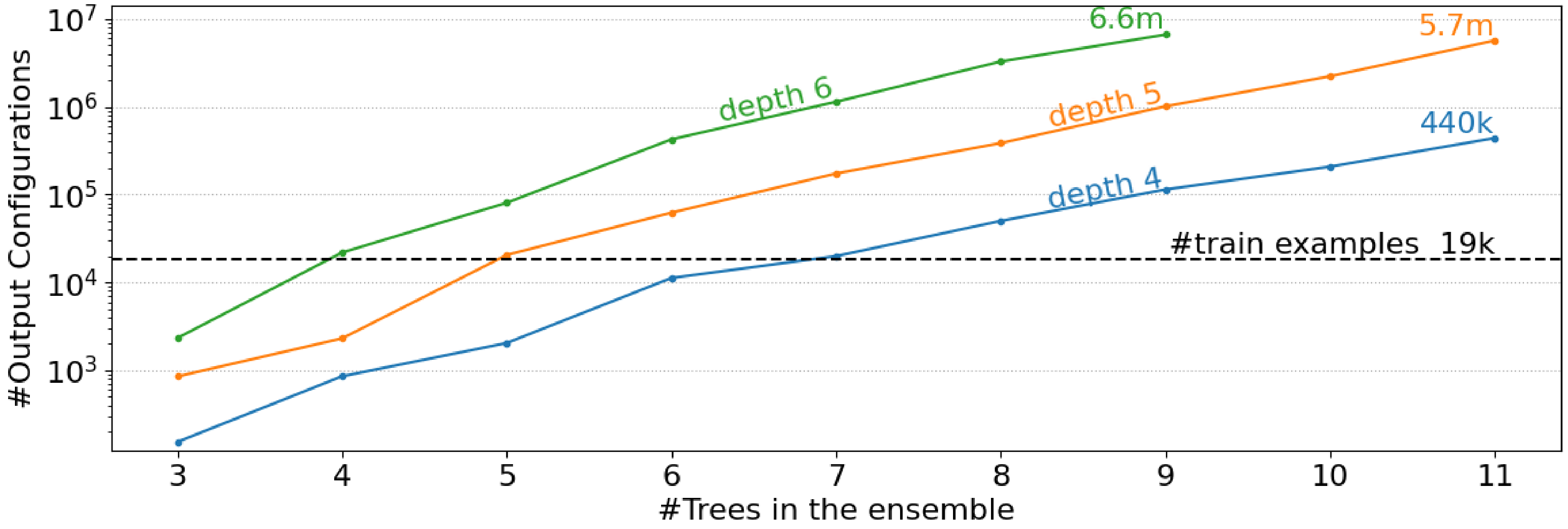
How big is **OC-SPACE**?

OC-SPACE Explodes



Vast majority of OCs **never visited** by a training example

Computed using **Veritas**, XGBoost, California housing; 8 features, 19k examples

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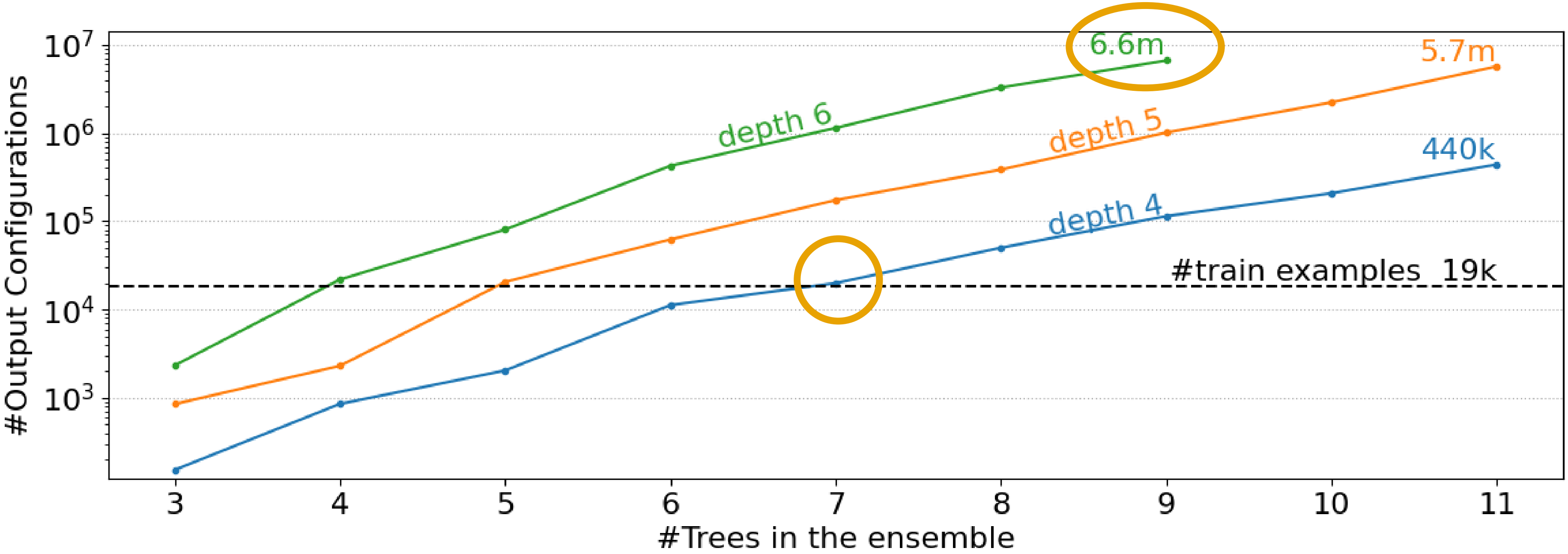

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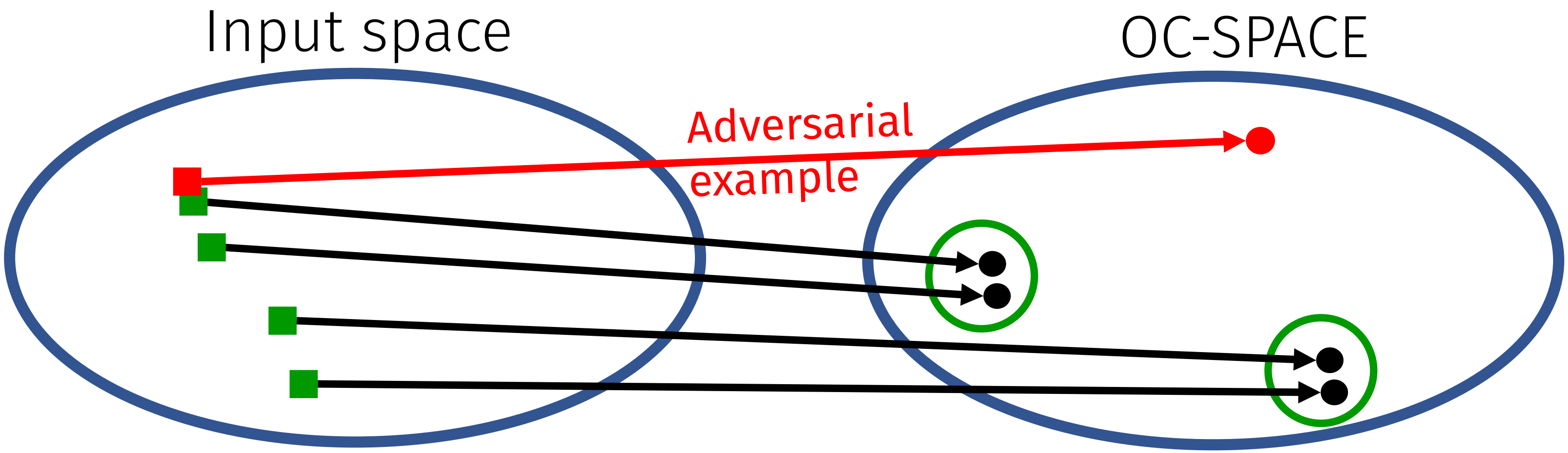
OC-SPACE separates *normal* and *adversarial*



Adversarial example **close to *normal* example in input space**, but **far apart in OC-space**

OC-SCORE Algorithm:

Measuring an example's *adversarialness*

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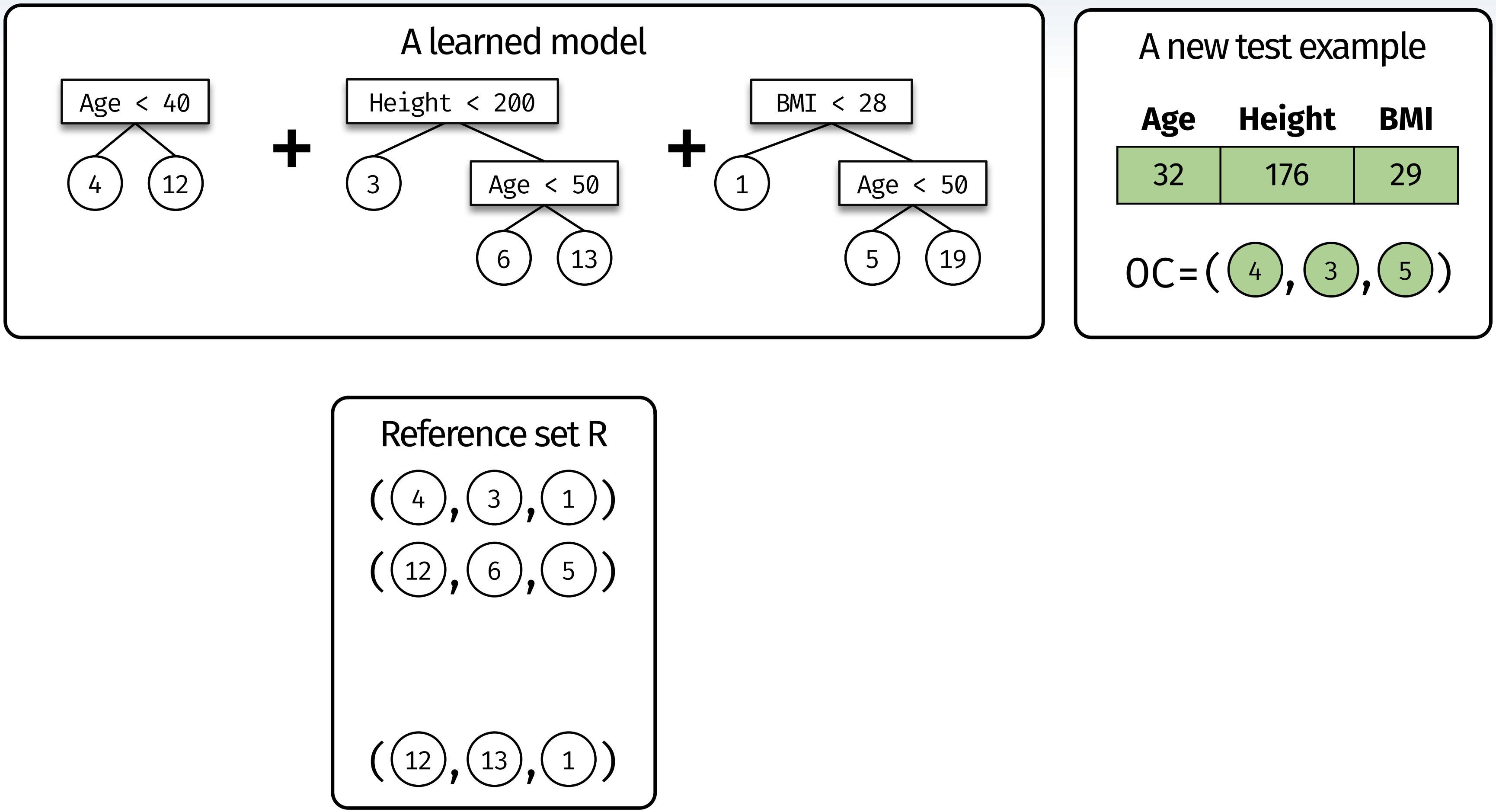
OC-SCORE Algorithm:

Measuring an example's *adversarialness*

- Assign each leaf node an identifier
- Encode reference set examples by their identifiers: R
- Post deployment when you receive an instance $\boldsymbol{x}$
  - Execute ensemble to encode its reached identifiers: $\mathrm{OC}(\boldsymbol{x})$
  - Compute $\min\{\underbrace{\mathrm{hamming}(\mathrm{OC}(\boldsymbol{x}), \mathrm{OC}(\boldsymbol{x}'))}_{\text{Count how many leaves differ}} \mid \underbrace{\boldsymbol{x}' \in R}_{\text{Normal examples}}\}$


A learned model
Age < 40
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Reference set R
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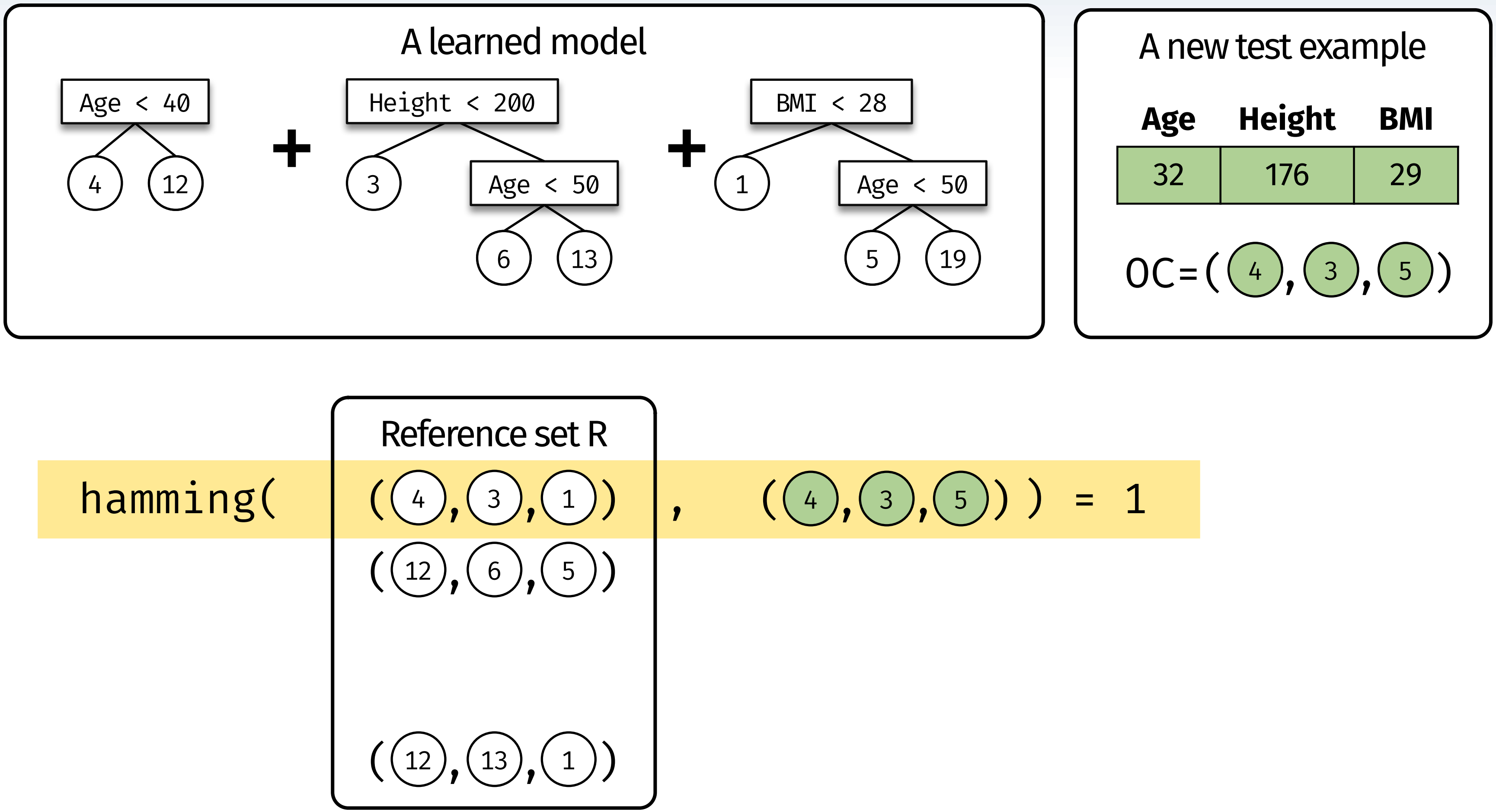
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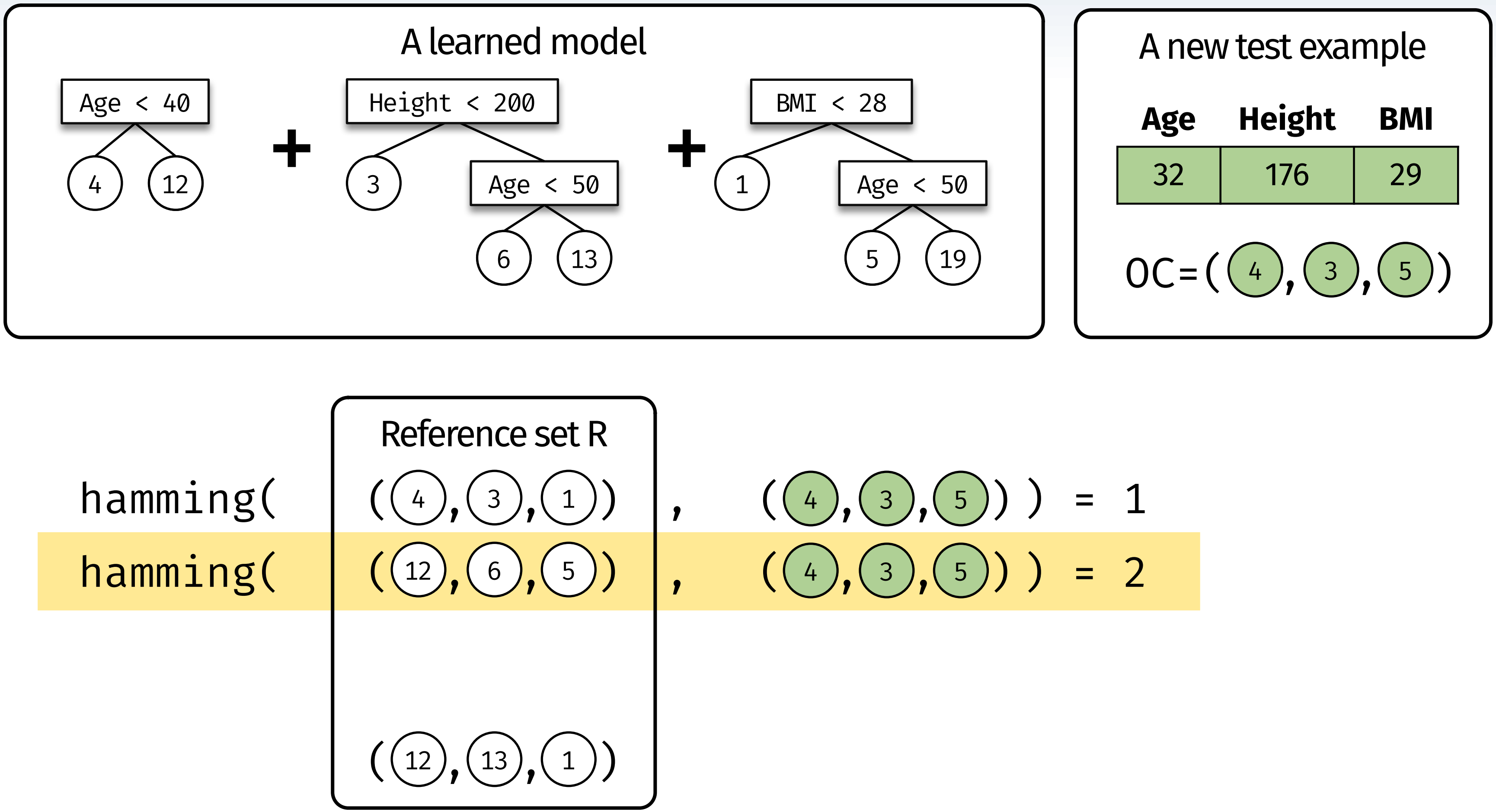
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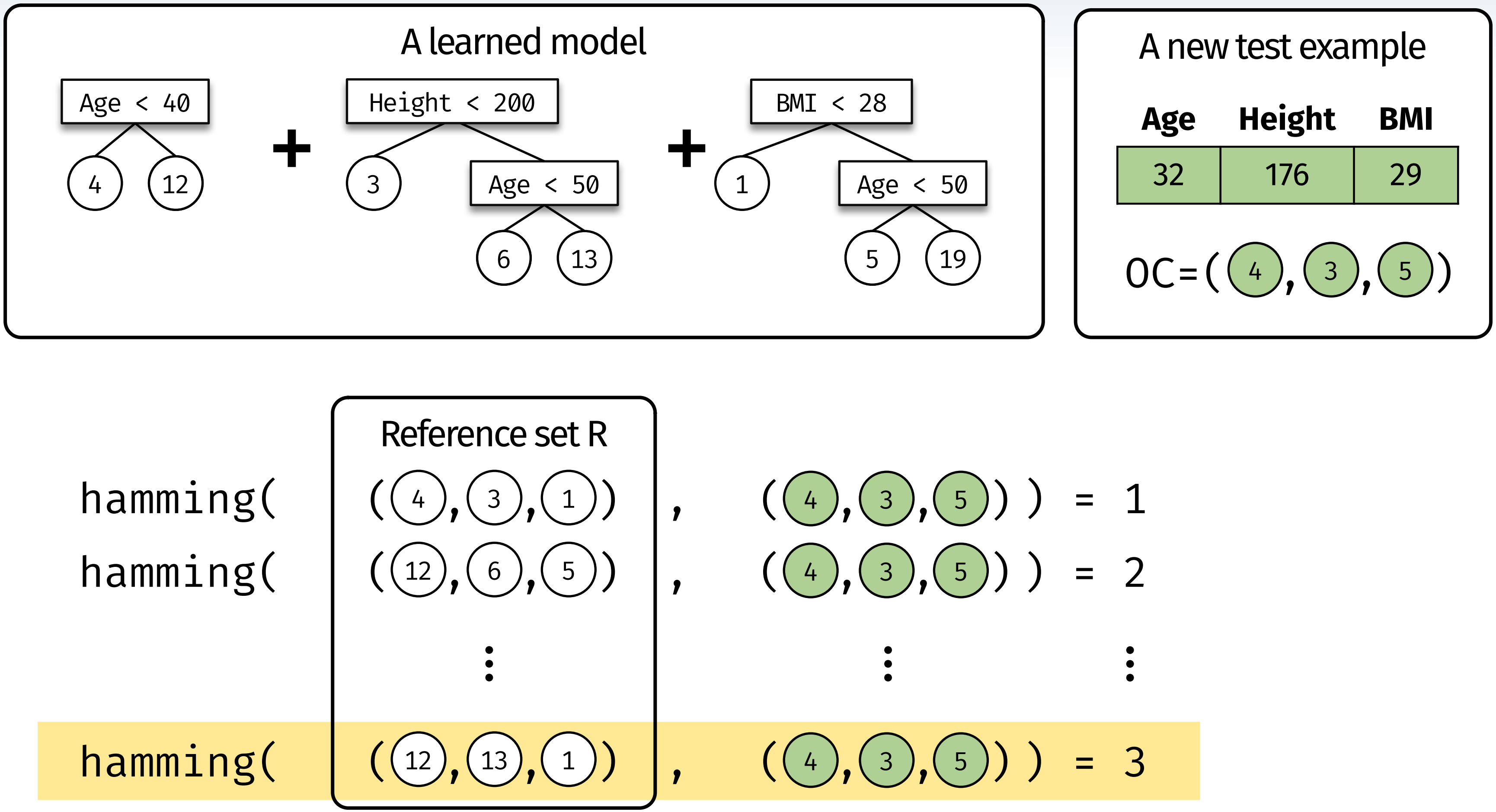
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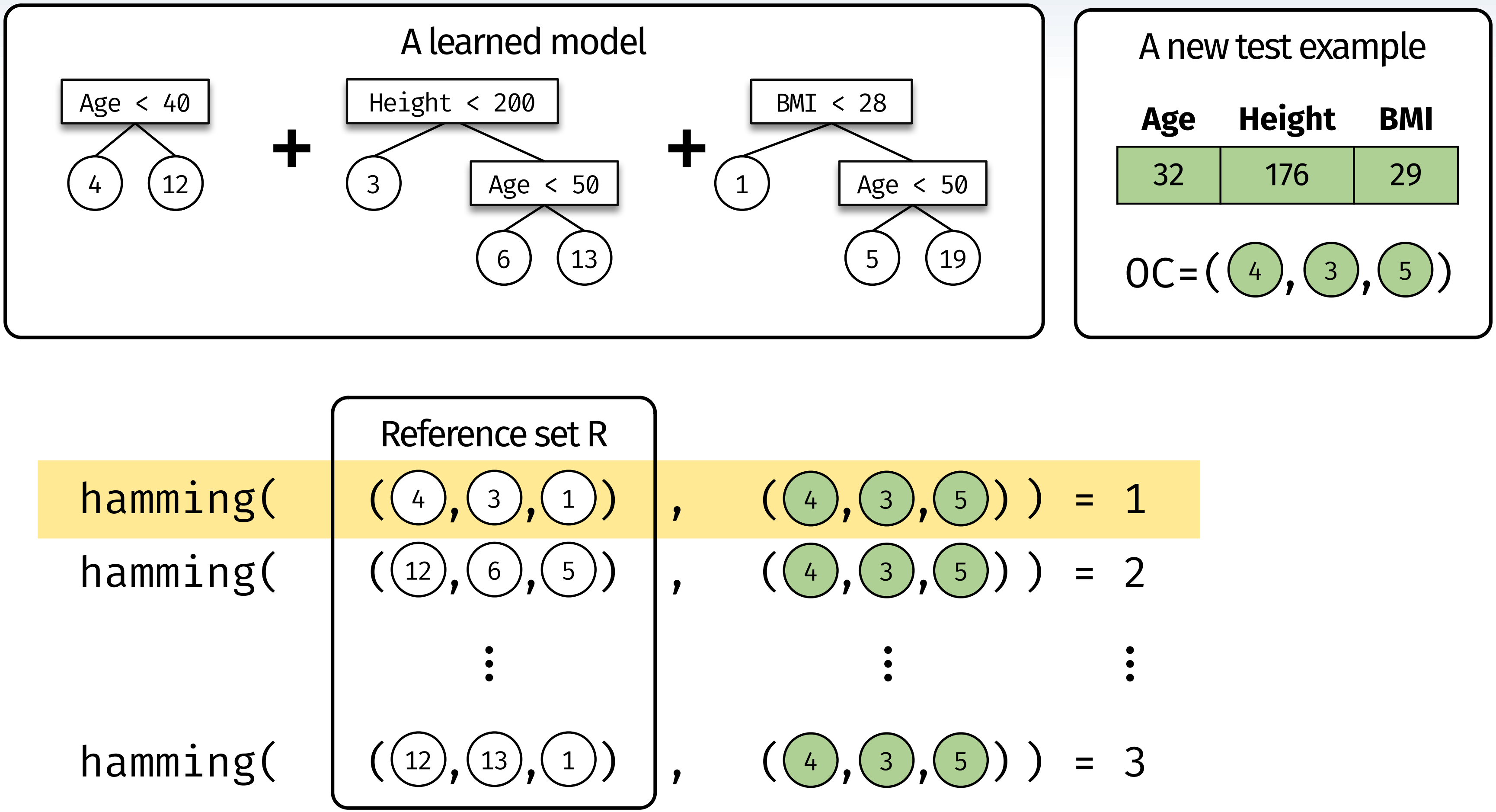
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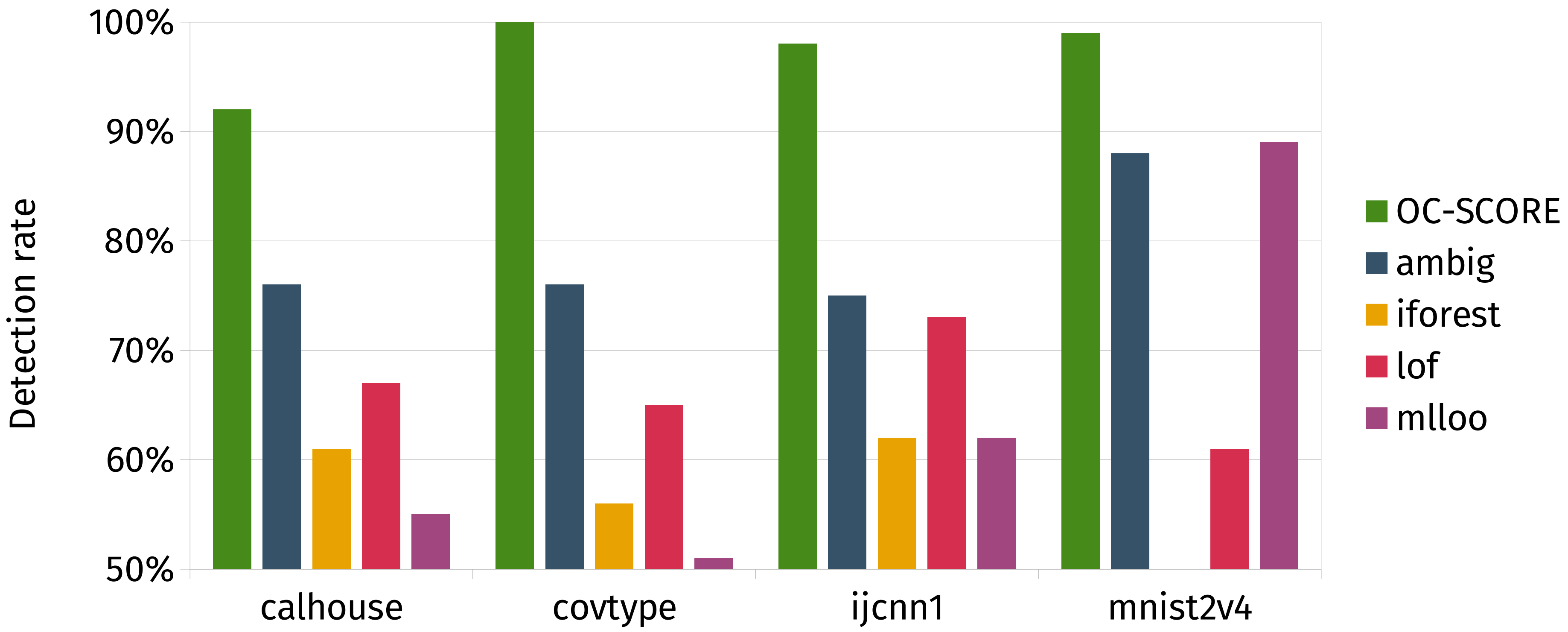
Experimental Setup

How well do we detect adversarial examples?

- **Task:** Distinguish adversarial from normal examples
- **8 dataset**: 4×500 adversarial vs. 2000 normal, 4 adversarial generation methods
- Compare **OC-SCORE** to 4 baselines
  - How accurately can the approaches distinguish between normal and adversarial examples?
  - Does **OC-SCORE** work on real-world data?

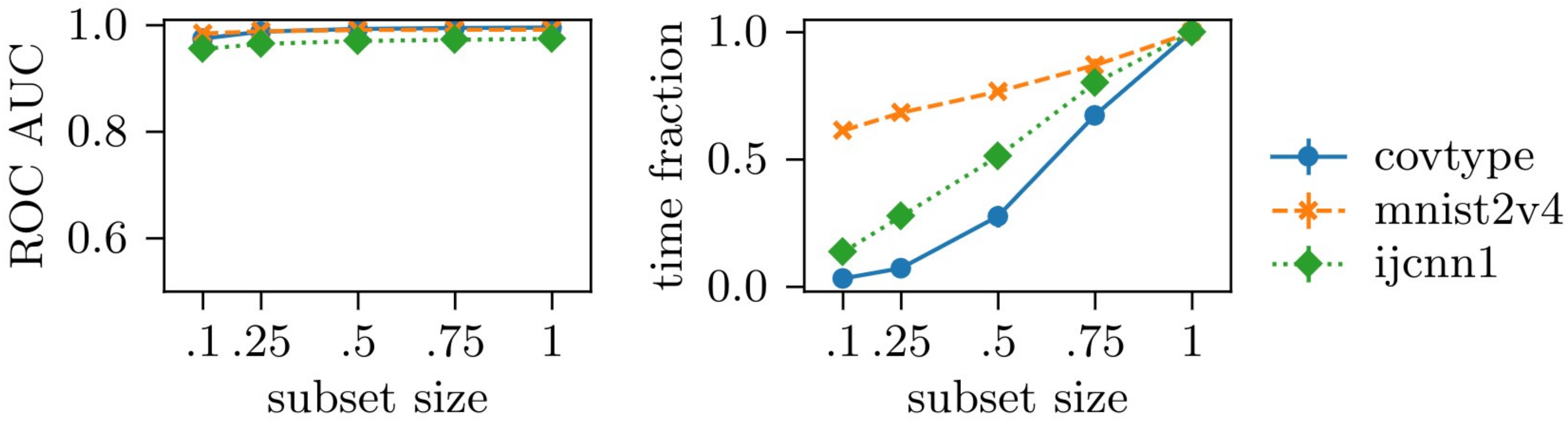
Experimental Results

Good Detection Rate



Reference Set *R* Need Not Be Large

- Random subsets of set of correctly classified training examples
- **Detection performance barely affected**



Applying **OC-SCORE** does not need to be expensive

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Questions?

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