Measuring the Reliability of Causal Probing Methods: Tradeoffs, Limitations, and the Plight of Nullifying Interventions

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*Equal Contribution

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Summary

Which features do LLMs use to perform a given task?

– **Causal interventions** on feature representations

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How ***reliable*** are interventions?

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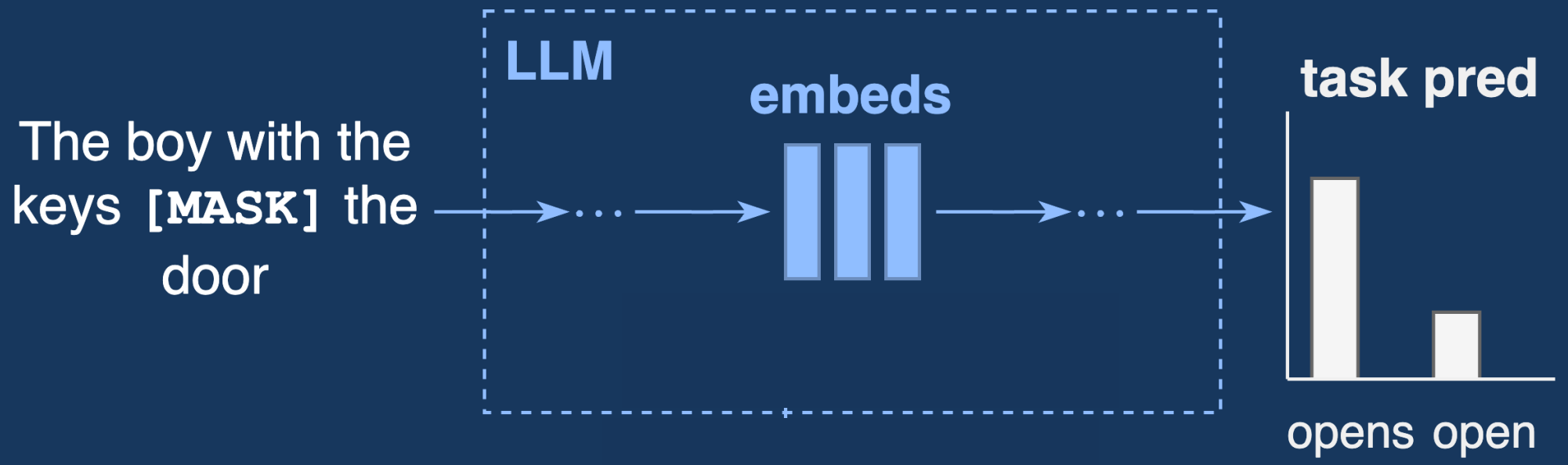
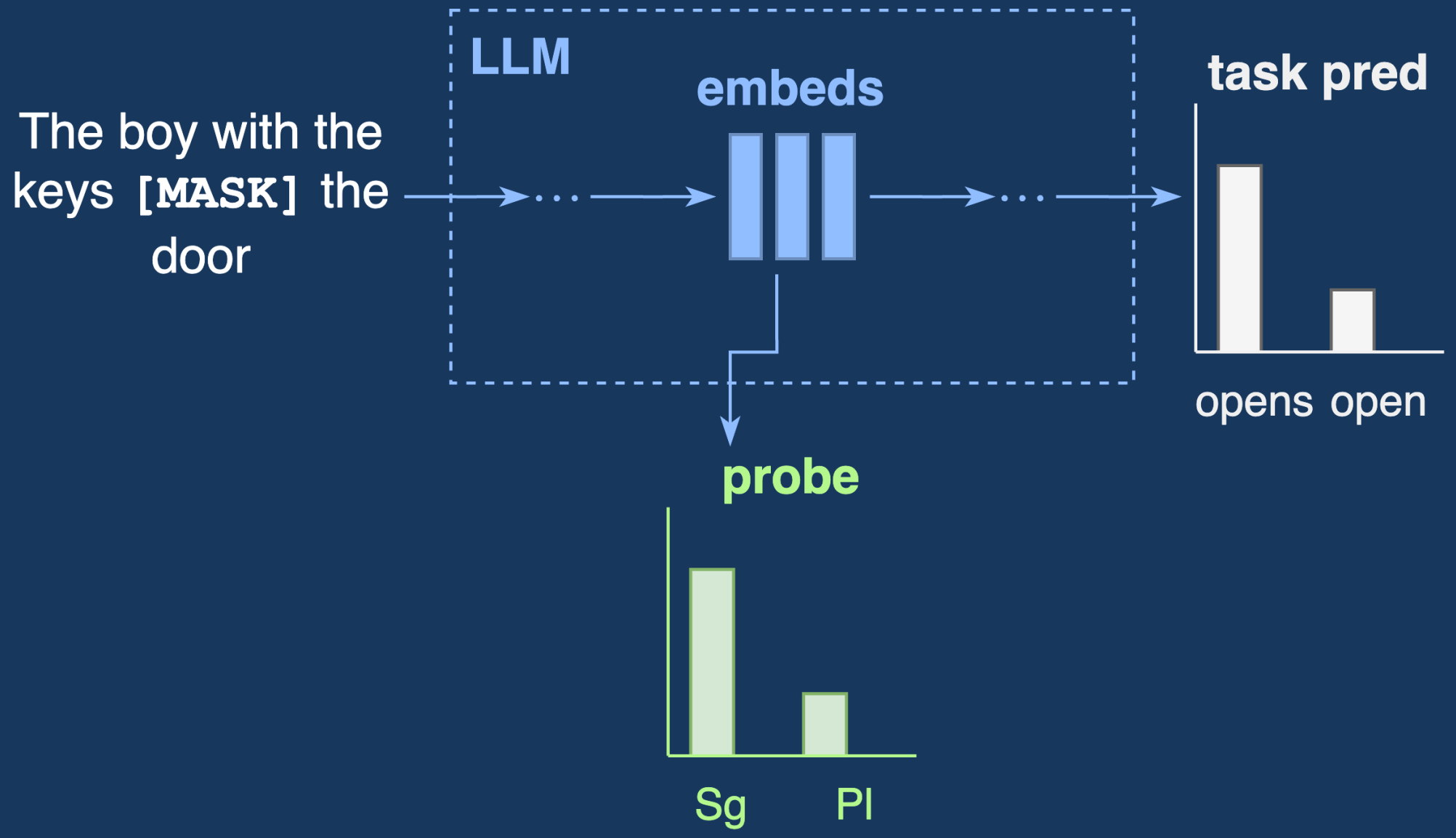
We define an **evaluation framework** to compare *different classes* of interventions

Causal Probing



Causal Probing



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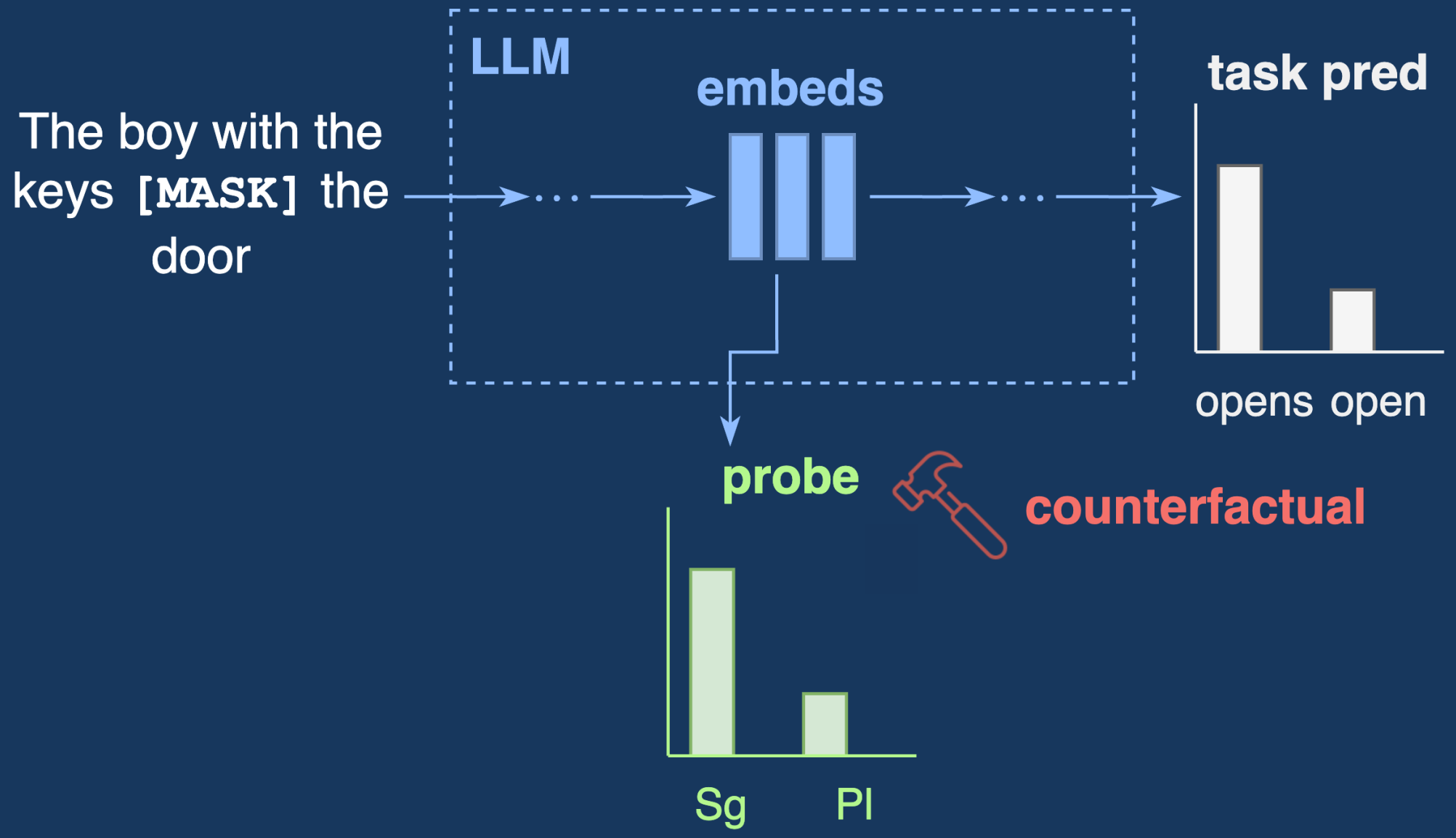

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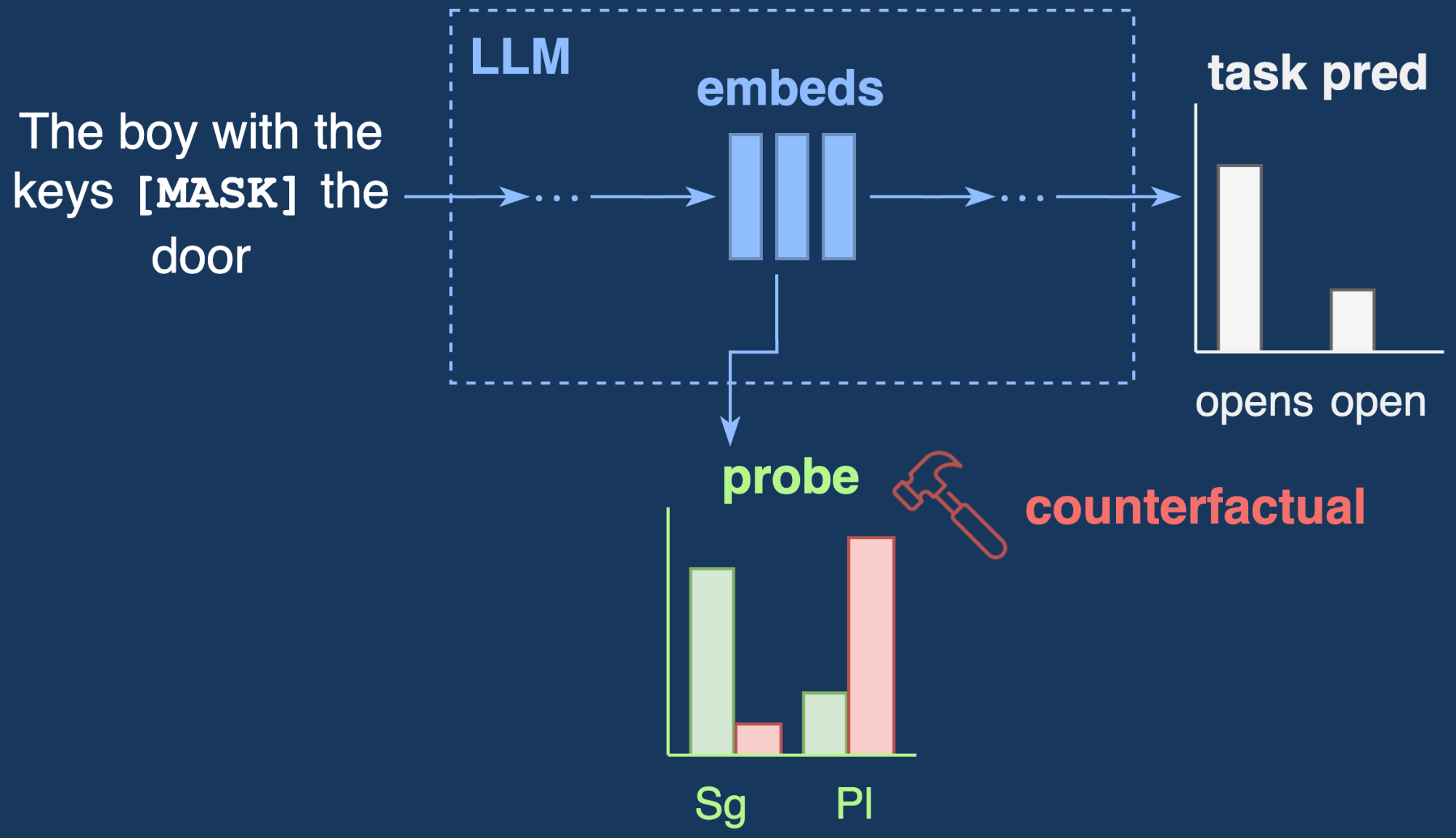

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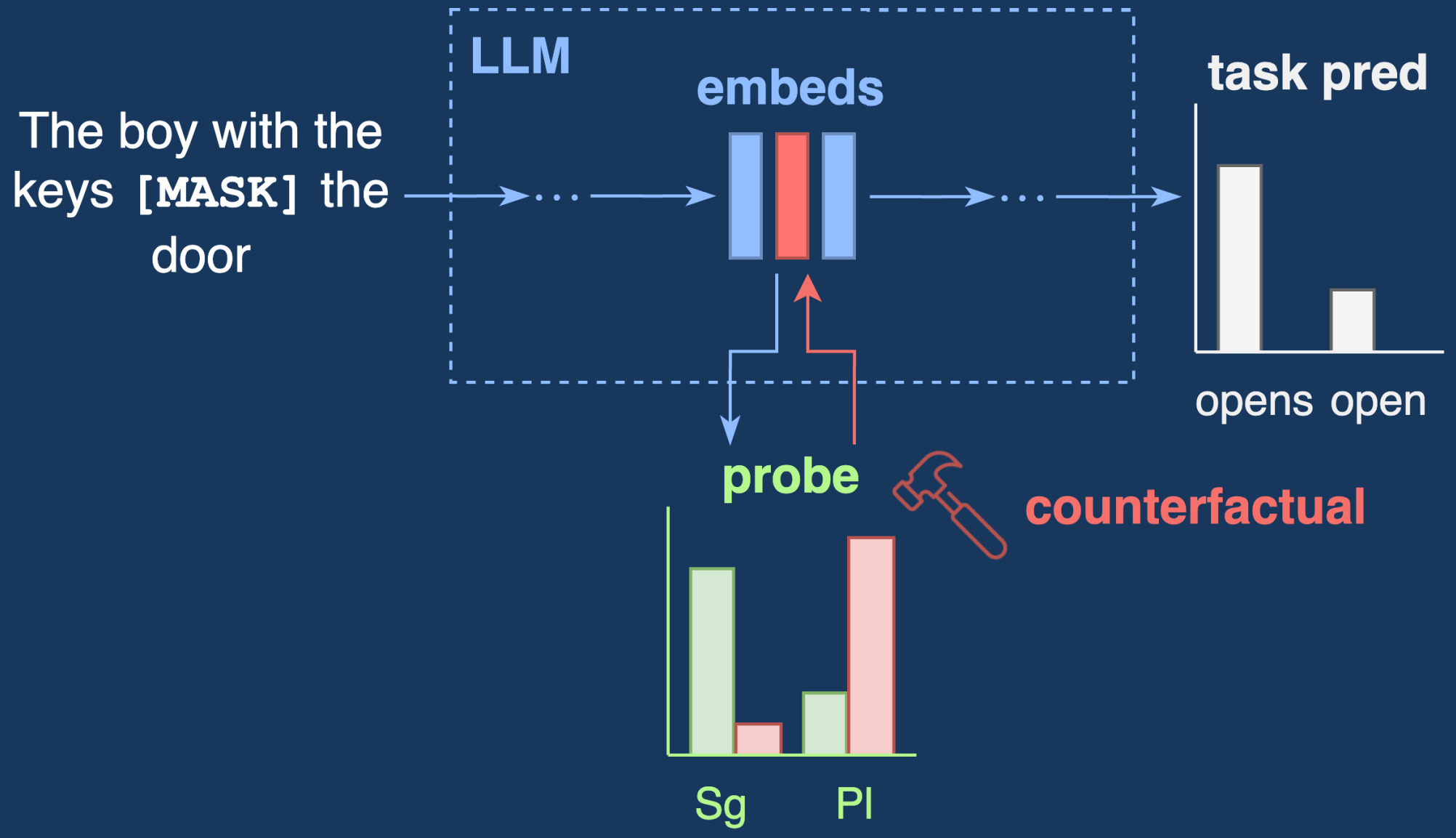

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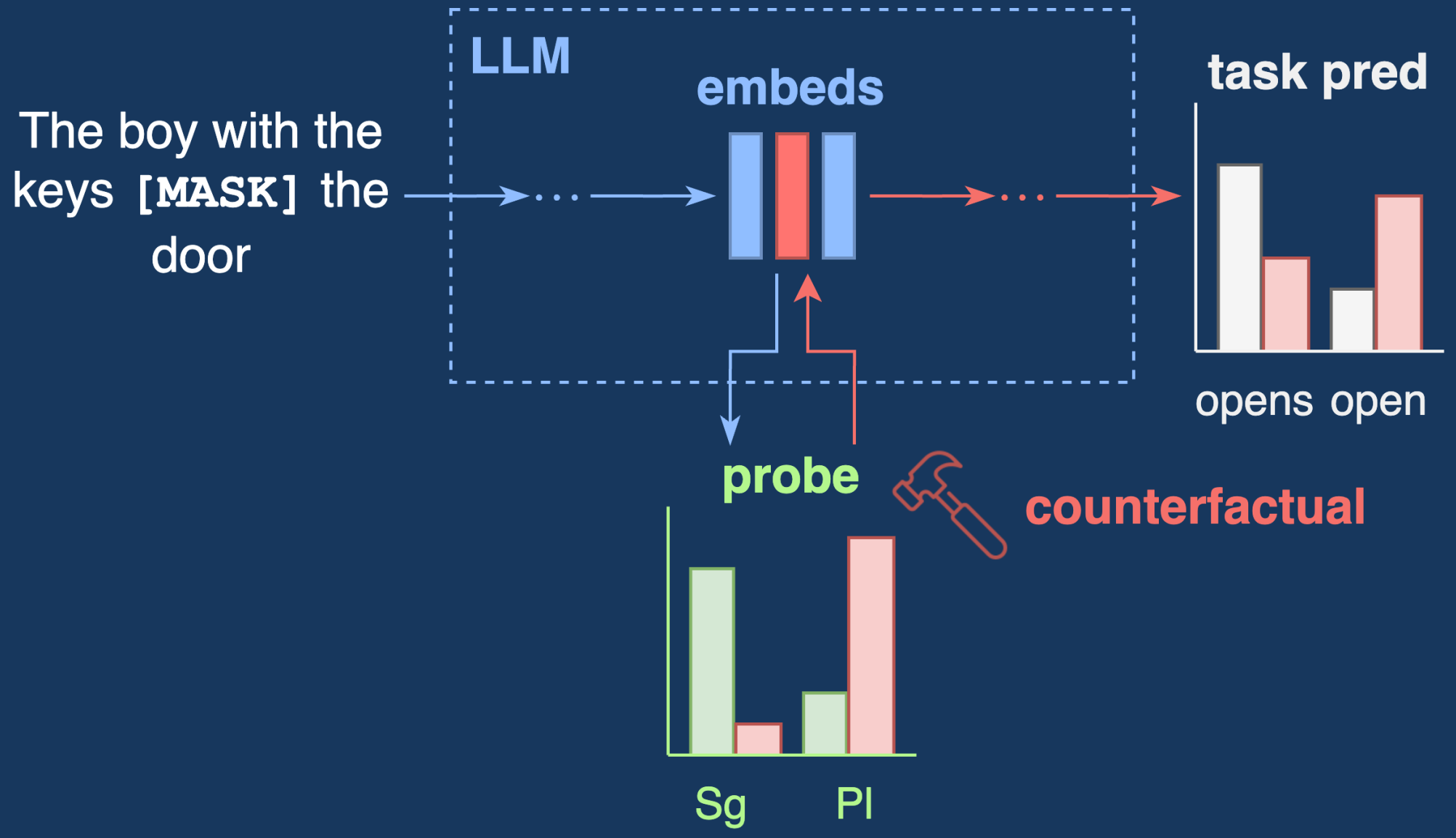

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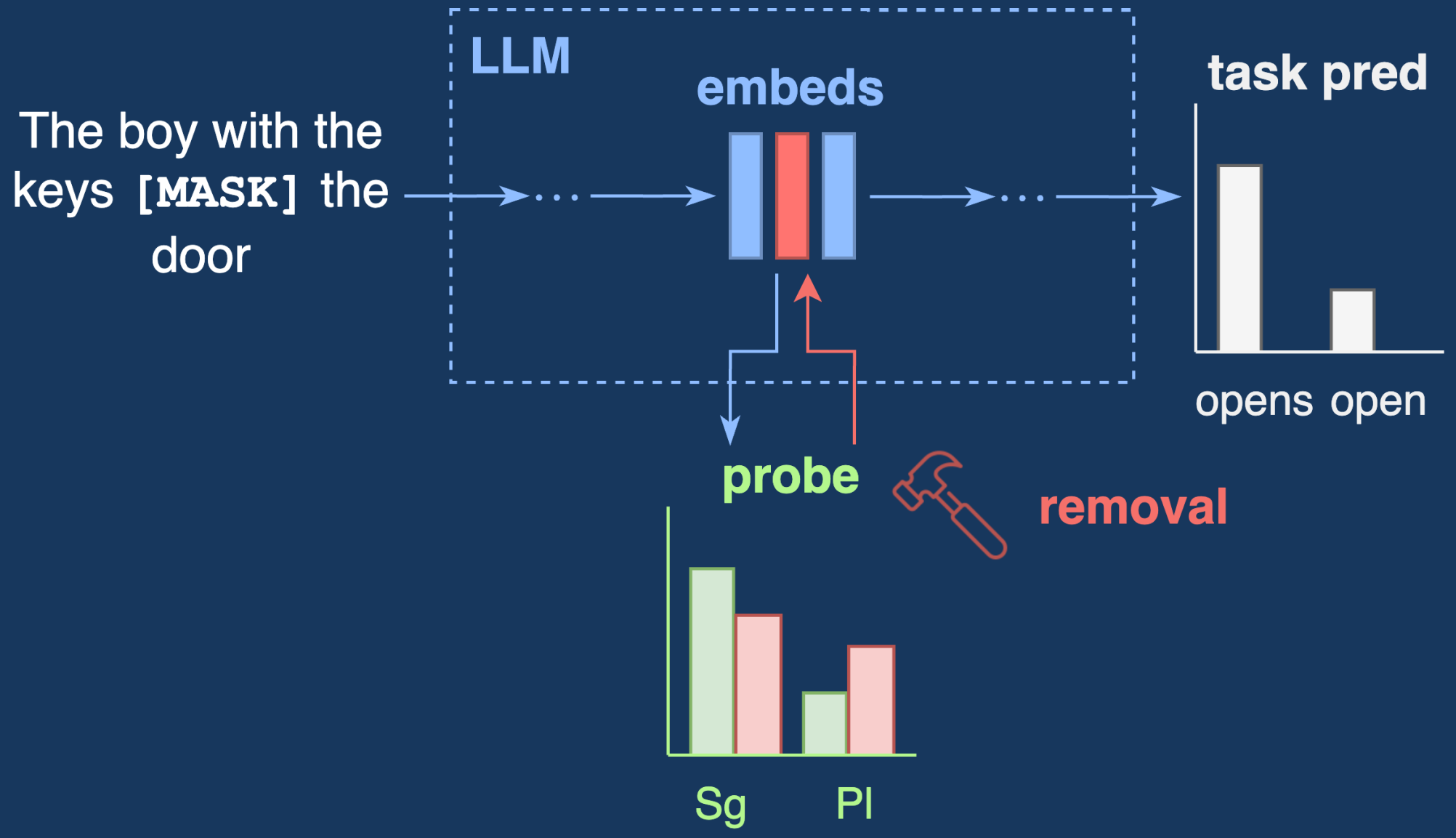

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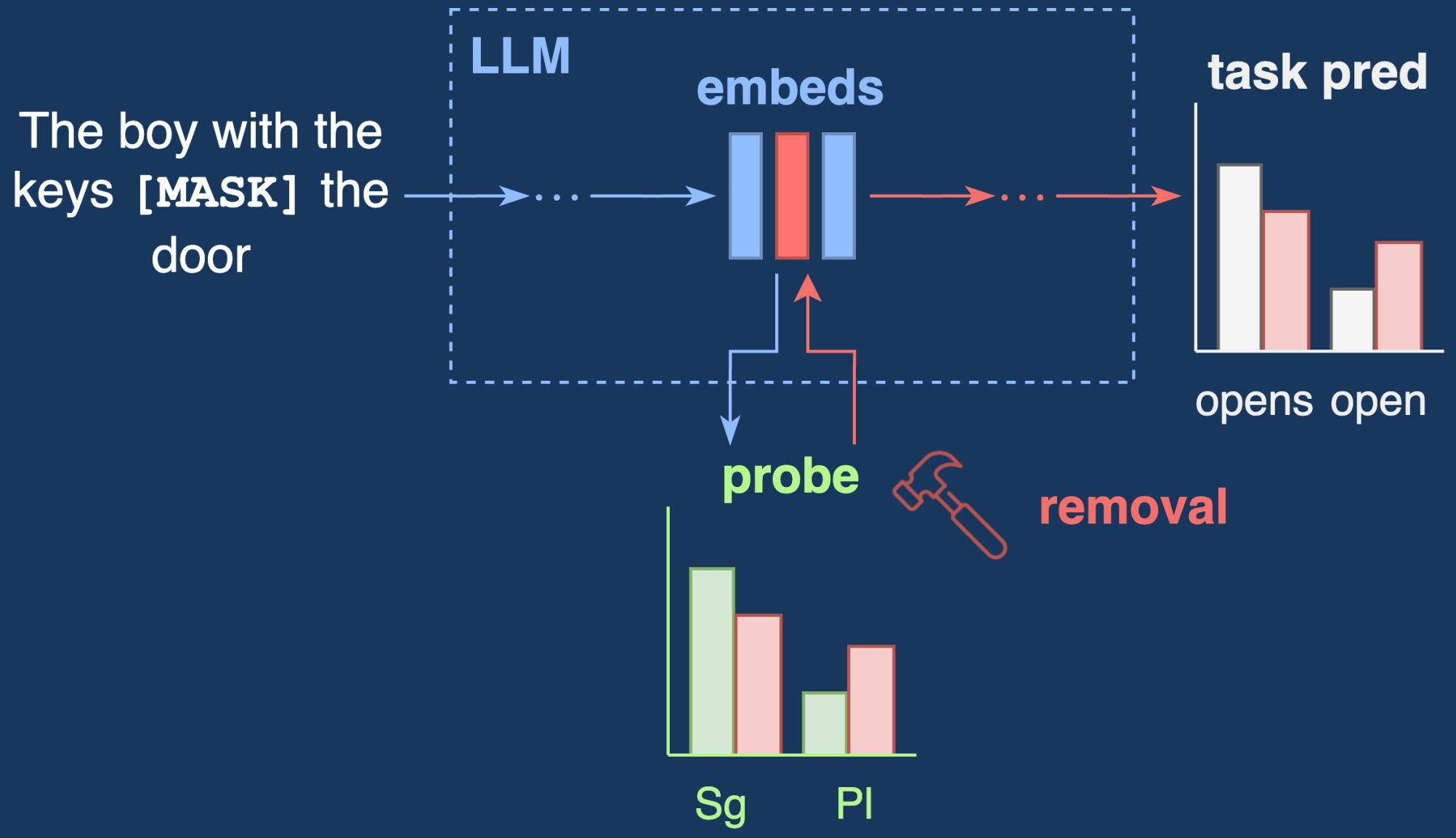

Our Evaluation Framework

oracle

probes

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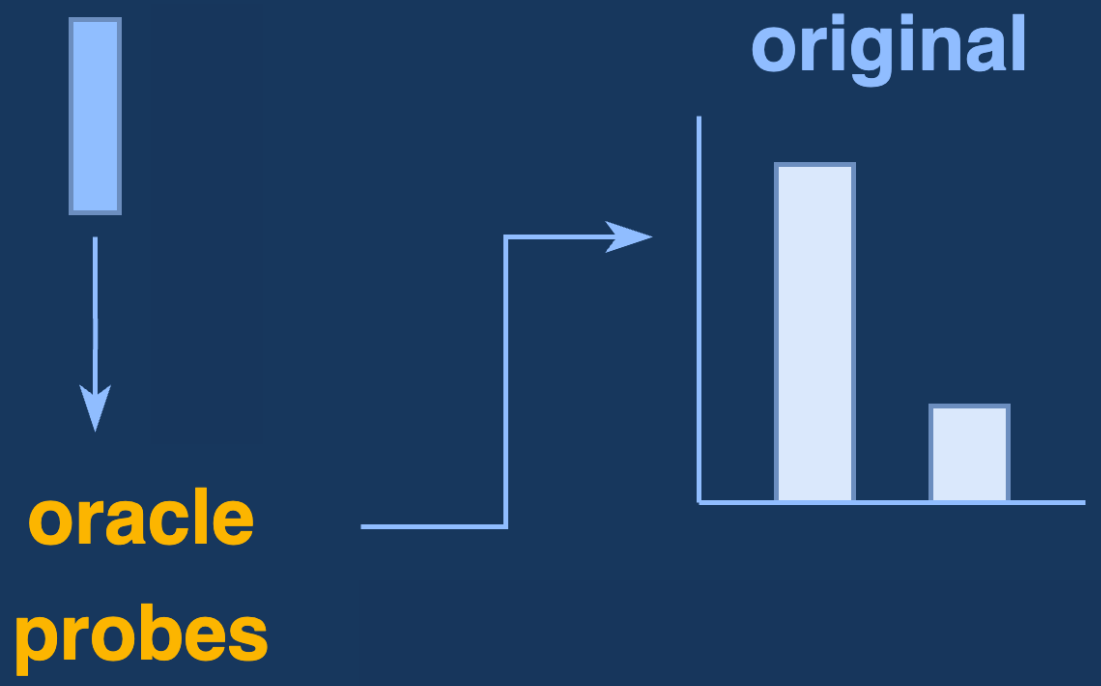

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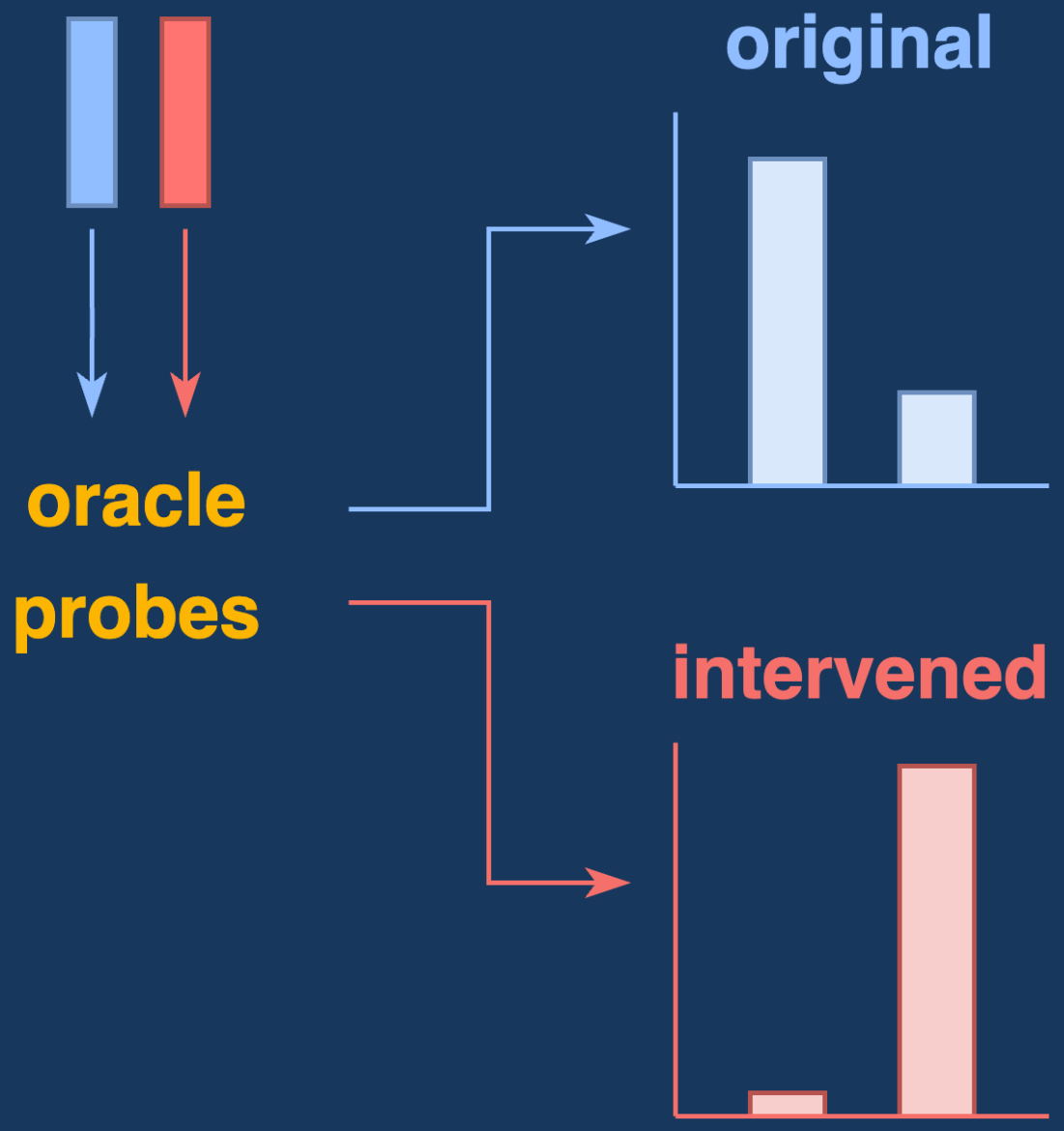

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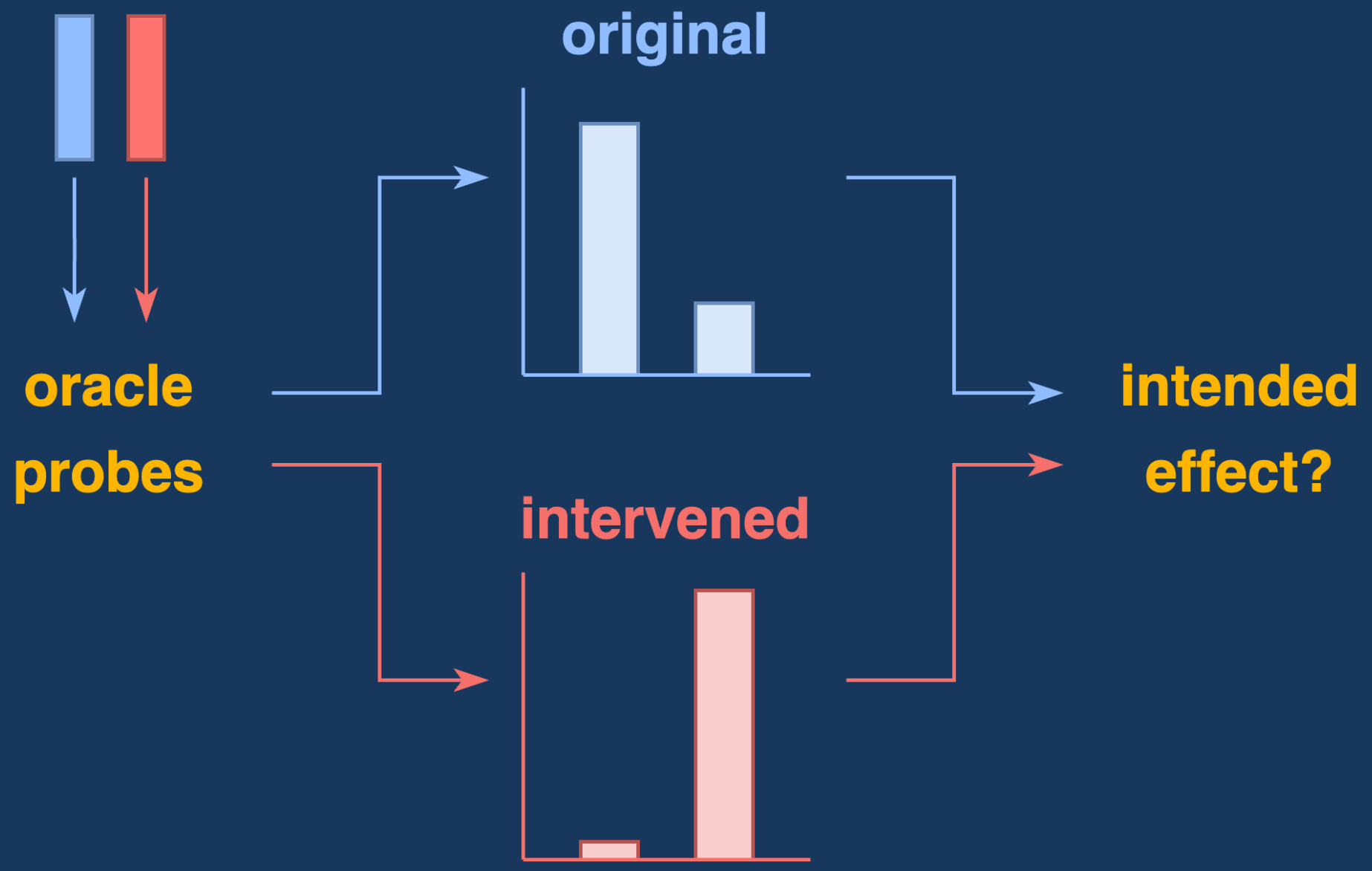

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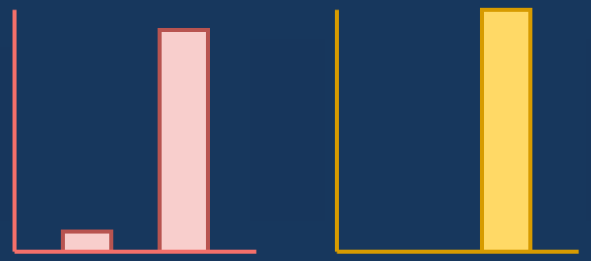

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$1 - \mathrm{dist}\Big($  $,$  $\Big)$

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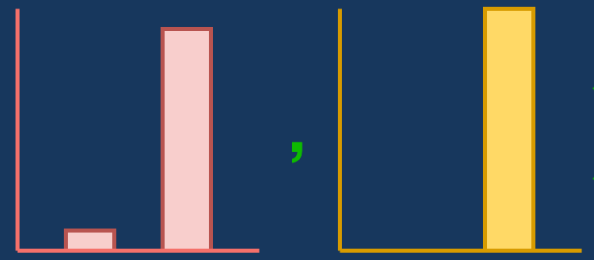
$1 - \mathrm{dist}\Big($  $\Big) \in [0, 1]$

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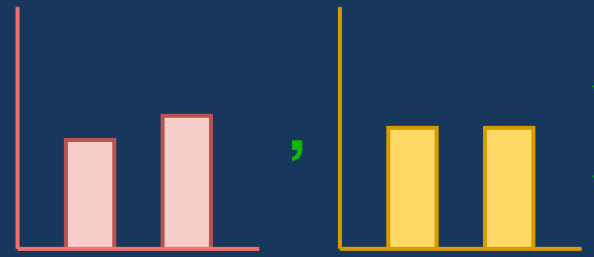
$1 - \mathrm{dist}\Big($  $\Big) \in [0, 1]$

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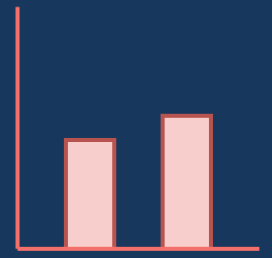
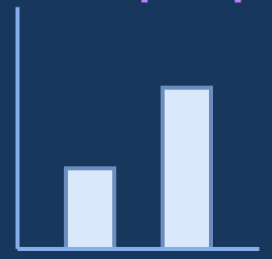
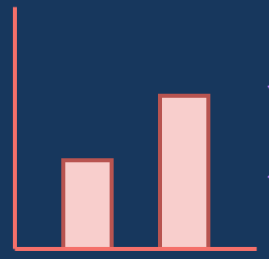
$1 - \mathrm{dist}\Big($  $,$  $\Big) \in [0, 1]$

selectivity

different properties

$1 - \mathrm{dist}\Big($  $,$  $\Big) \in [0, 1]$

Causal Probing Interventions

Concept Removal: *Remove* representation of target feature

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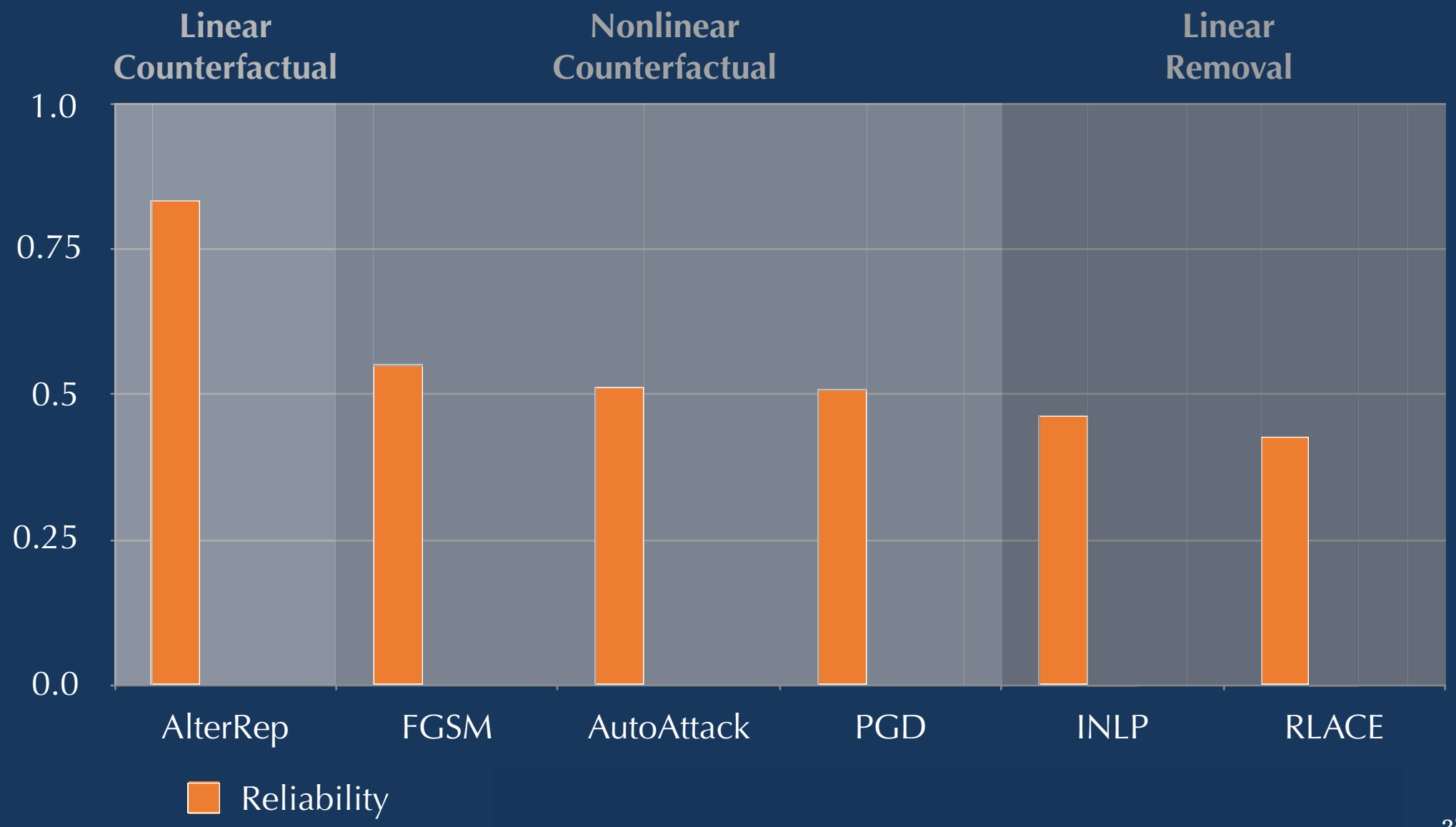
Intervene on `[MASK]` token in final layer of BERT

Our Evaluation Framework

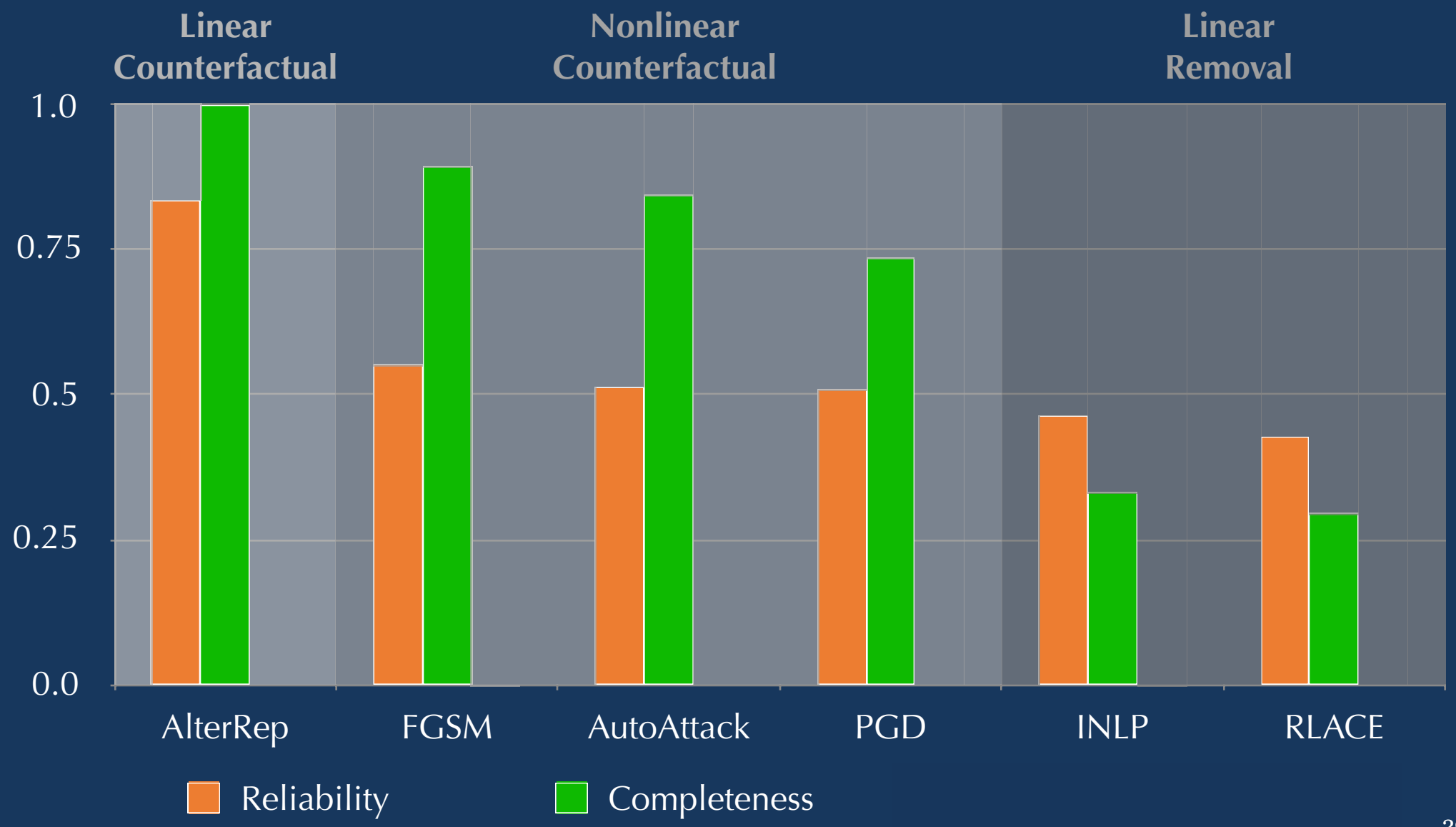
Evaluate interventions according to

- **Completeness:** Is the intended intervention carried out?
- **Selectivity:** Are we damaging non-targeted features?
- **Reliability:** Harmonic mean of completeness and selectivity

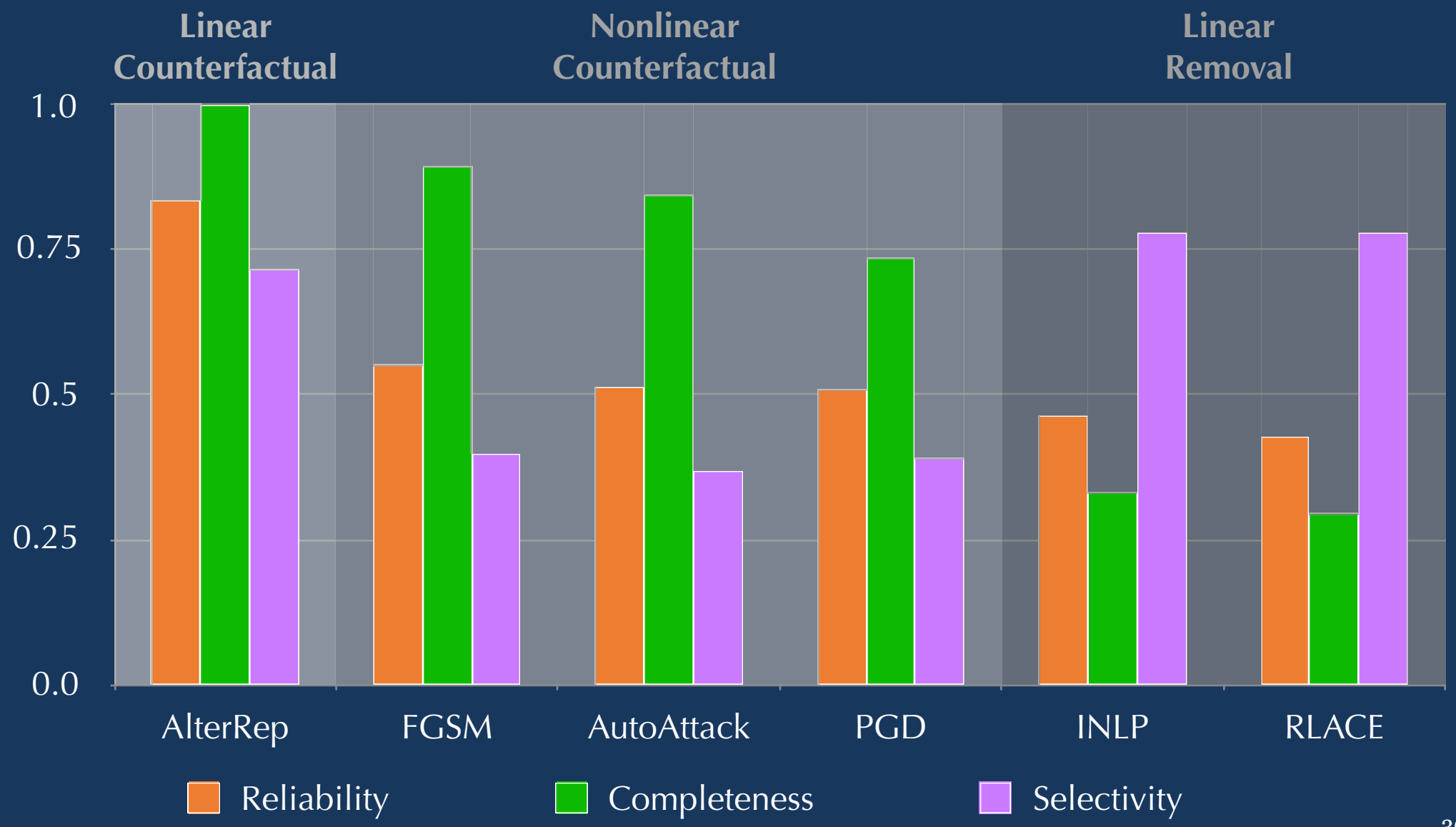
Reliability: AlterRep is most reliable!



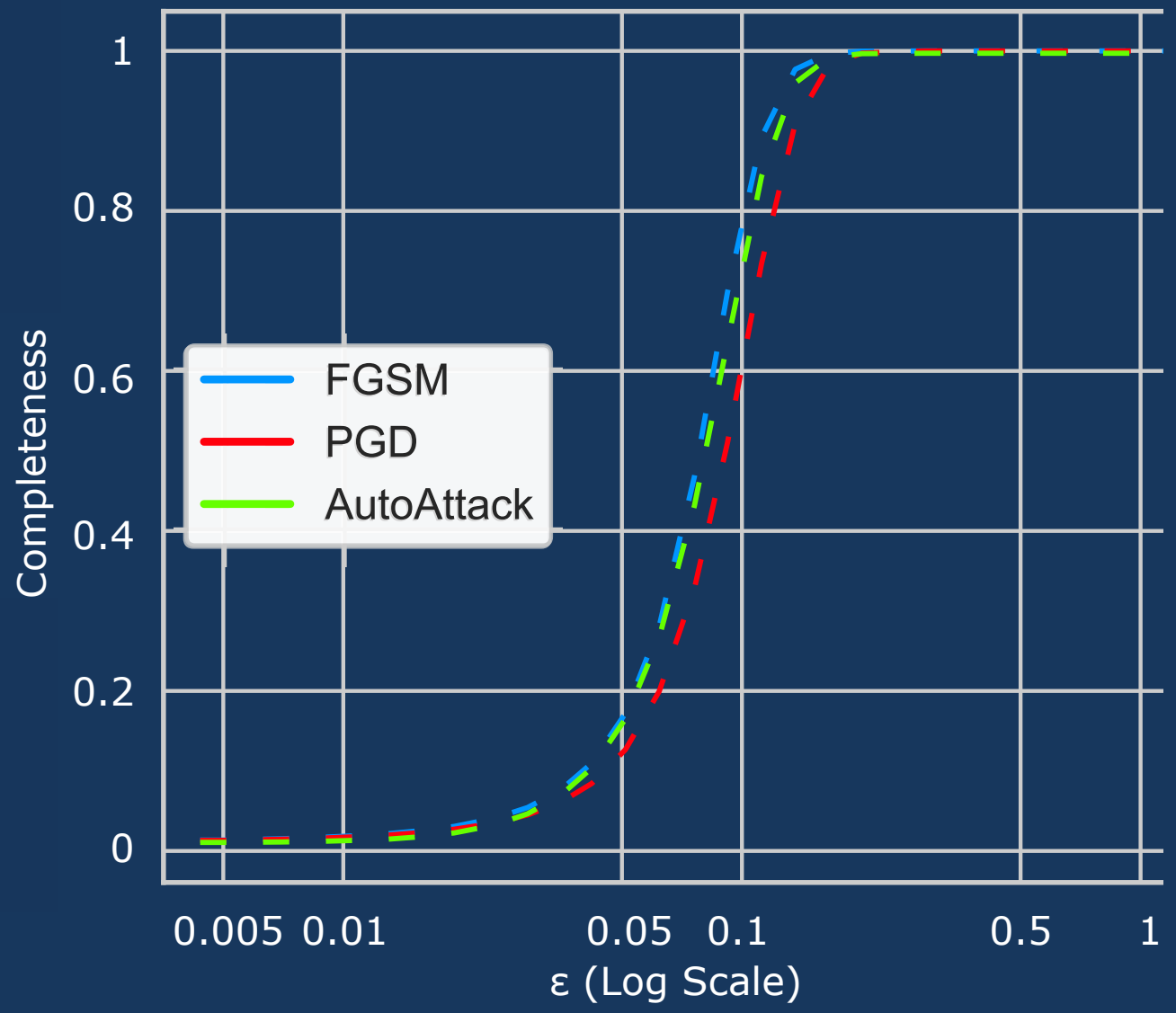
Completeness: Removal Methods are not complete!



SELECTIVITY: GBIs ARE NOT SELECTIVE; LINEAR METHODS ARE



Completeness and Selectivity are a tradeoff!



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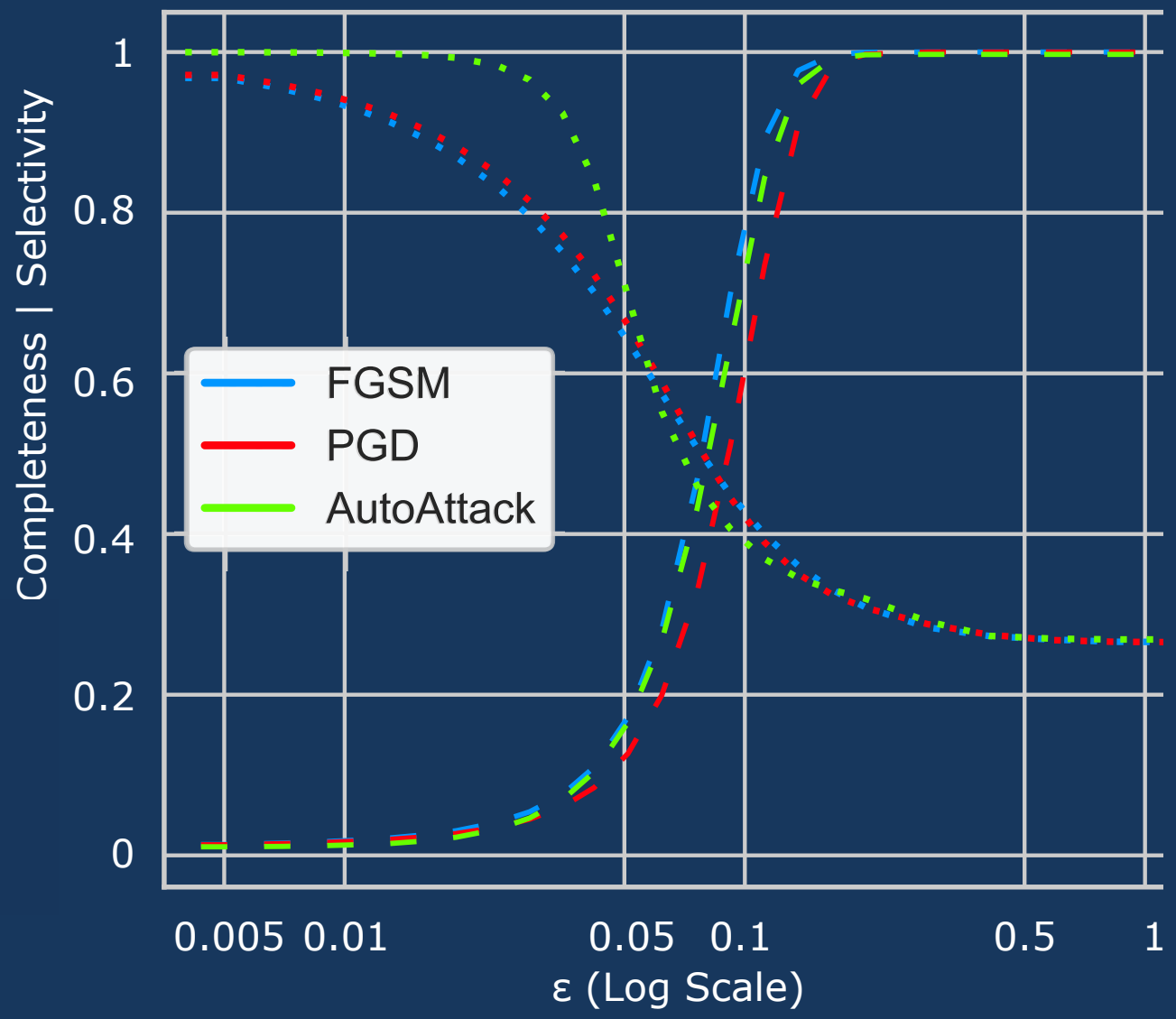

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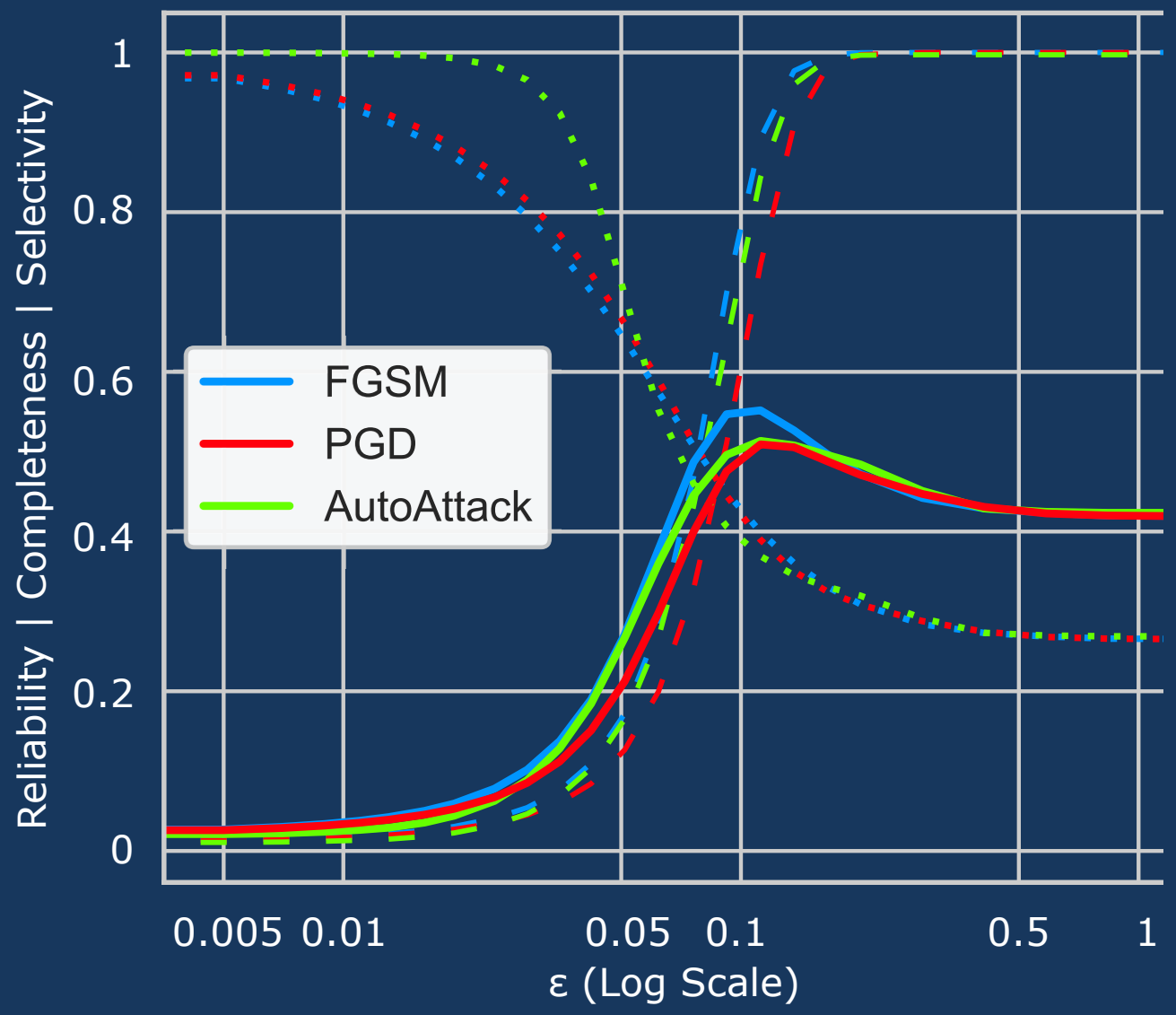
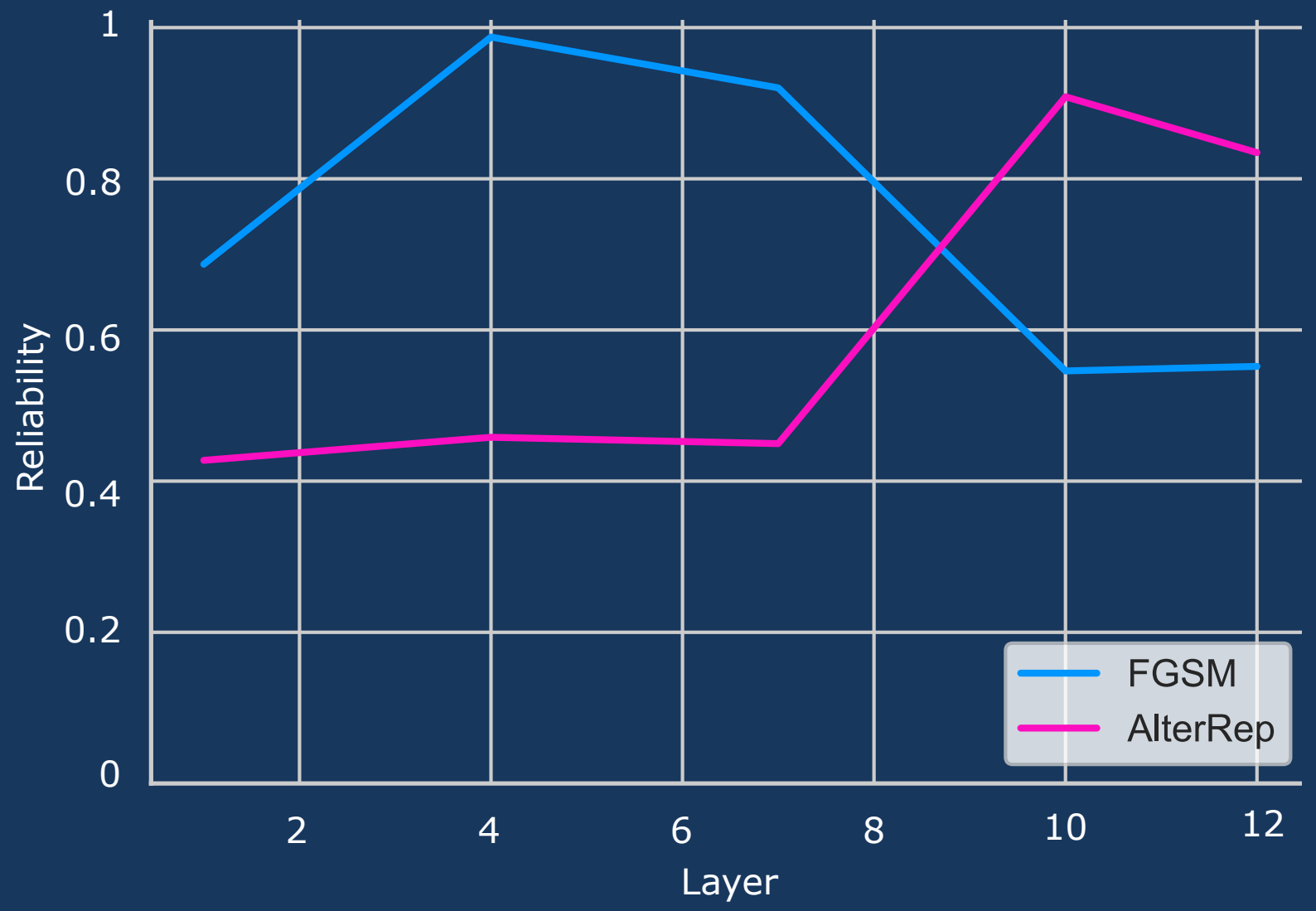


FGSM (NONLINEAR) MORE RELIABLE IN EARLIER LAYERS
ALTERREP (LINEAR) MORE RELIABLE IN LATER LAYERS



Takeaways

We introduce an **evaluation framework** to compare different classes of causal probing interventions

- **Tradeoff** between *completeness* and *selectivity*
- Concept removal is **not reliable** (for causal probing)
- Linear interventions better in later layers (less collateral damage)

Questions?

Supplementary Materials for QA

More Reliable methods → Greater Δ in task accuracy