Antidistillation Fingerprinting

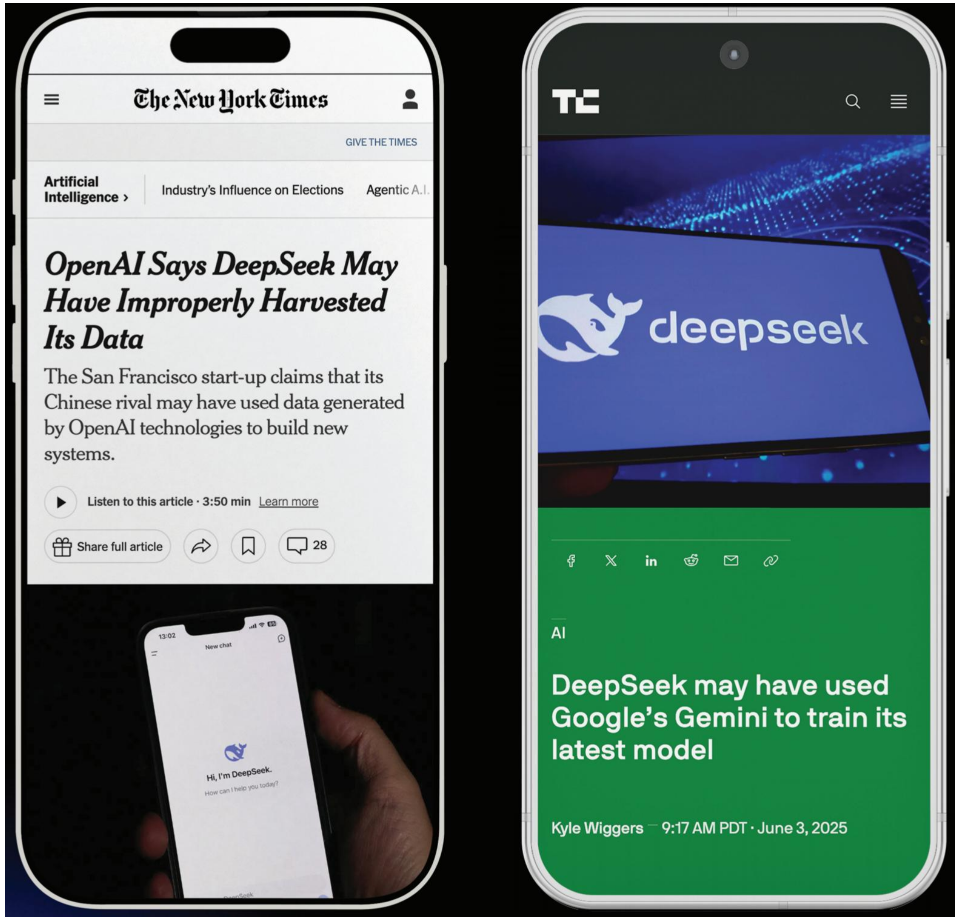
Yixuan (Even) Xu John Kirchenbauer Yash Savani Asher Trockman
Alexander Robey Tom Goldstein Fei Fang J. Zico Kolter

Carnegie Mellon University
University of Maryland

Model Distillation

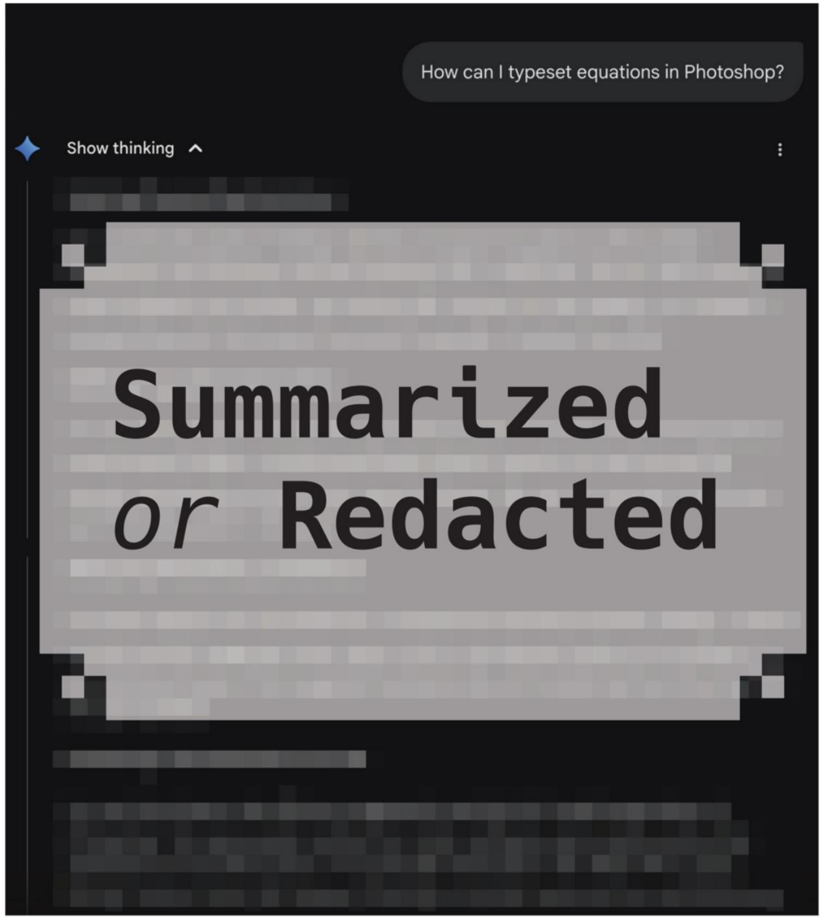
- **Distillation:** Using a trained model to generate training signals for another model
  - For LMs: Usually via data

- Distilling a model is **easier than** training from scratch
  - Less effort for data curation
  - Better and denser signals



Negative Externalities of Distillation

- Frontier models are hiding their reasoning **against distillation**
- This is less ideal for users
  - The model is solving problems or even making decisions for them
  - Less transparent
- Also for the model owners
  - Such a defense can be broken



The Research Question

How can we ***tell if another model*** *has* ***trained on*** *a* ***teacher model's outputs****?*

We name this task ***fingerprinting*** for this work.

From the Model Owner's Perspective

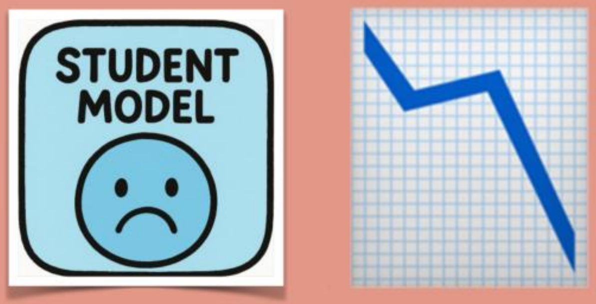
- There are three models
  - **Teacher $\boldsymbol{\theta_T}$:** The owner's trained model
  - **Student $\boldsymbol{\theta_S}$:** A model to be trained on the teacher's outputs
  - **Proxy $\boldsymbol{\theta_P}$:** An ***"imaginary"*** student model
    - From the teacher's perspective, the student model is unknown
    - If the method needs to use a "student model", it can only use a proxy model

- Antidistillation is **NOT** everything
  - We still would like the method to be **lightweight**
  - We would like to **preserve the model's performance**

Antidistillation Sampling (Savani et al. 2025)

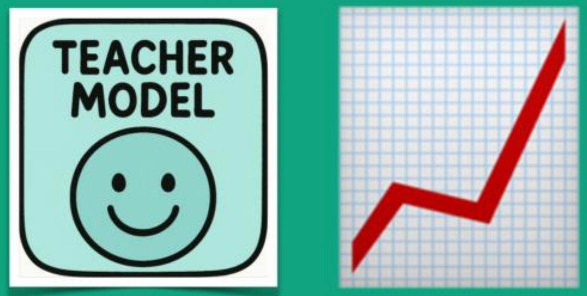
Non-distillability

Student models should not benefit from training on the reasoning traces



Nominal utility

Teacher model's performance should not fall significantly as a result of using the method



The Basic Idea

- Suppose the teacher generates the next token as t after $x_{1:l}$
  - The student / proxy will do one step of **Gradient Descent** on t
  - Assume a **downstream evaluation loss** of the the proxy $\boldsymbol{L(\theta_P)}$
  - Define the **delta vector** as Δ_t = The increase in $\boldsymbol{L(\theta_P)}$ after the **GD** step

- ***Antidistillation sampling***
  - We have a logits vector $z = z(x_{1:l}, \theta_T)$, and a **delta vector** Δ
  - We will sample according to **softmax**$(\boldsymbol{z} + \boldsymbol{\lambda}\Delta)$
    - Parameter λ controls the trade-off between nominal utility and non-distillability
    - $\lambda = 0$ falls back to normal sampling, while $\lambda \to \infty$ causes maximum poisoning

Fast Computation

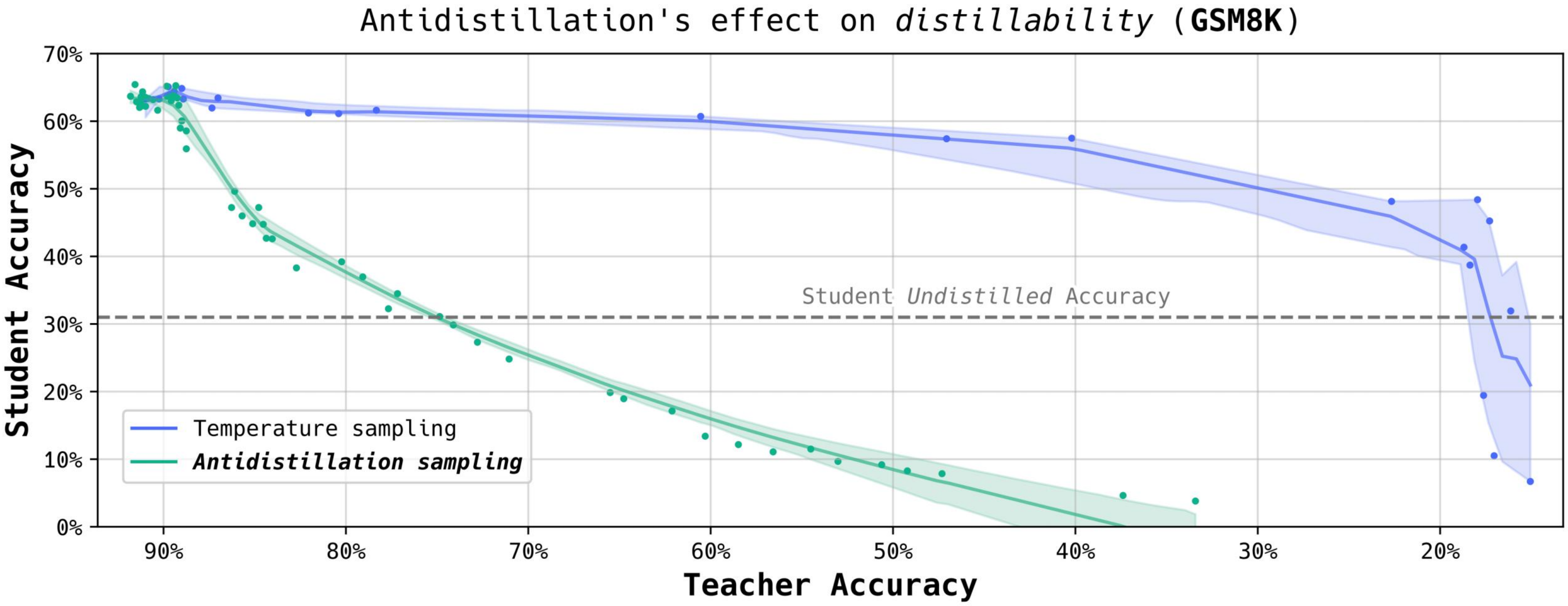
- Really enumerating the next token to compute Δ is expensive
  - Requires $\boldsymbol{\Omega(|V|)}$ **backward passes** per token

- We use **finite difference method** to estimate Δ
  - Assume differentiable loss $L(\theta_P)$, we compute $\boldsymbol{G = \nabla L(\theta_P)}$
  - Then, we approximate Δ by

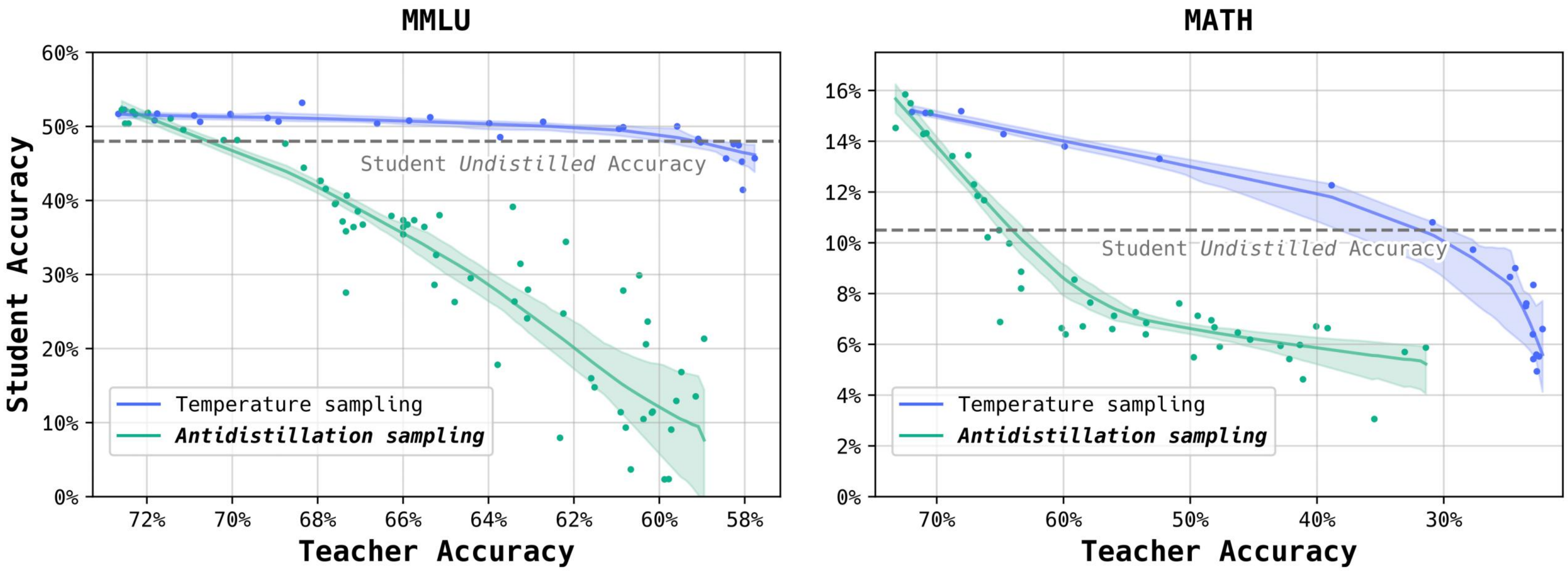
$$\Delta = \frac{z(x_{1:l}, \theta_P + \boldsymbol{\varepsilon G}) - z(x_{1:l}, \theta_P - \boldsymbol{\varepsilon G})}{2\boldsymbol{\varepsilon}}$$

  - $\boldsymbol{O(1)}$ **forward passes** per token, compatible with KV-caching

Empirical Results



Empirical Results



Antidistillation Fingerprinting

- *When you think about it…*
  - Antidistillation sampling essentially **injects biases** to the traces, so that for the student, a specific loss function $L(\cdot)$ **increases**
  - The function $L(\cdot)$ can actually be ***anything*** we choose

- ***Fingerprinting*** a model's output
  - Leave specific structures (fingerprints) in the output traces
  - So that when students train on them, it is detectable statistically
    - i.e., can say with statistical guarantee, the student trained on the teacher's output

Fingerprinting Before Antidistillation

- The red-and-green list watermark (Kirchenbauer et al. 2023)
  - For context $x_{1:l}$, define a **green list** computed as $\boldsymbol{H(x_{1:l}, k)}$
  - H is a hash function keyed by k that outputs half of the vocabulary
  - Change the logits at sampling by increasing all green tokens by δ
  - Normal texts will have a **green-list ratio** of concentrated around 0.5
  - Watermarked texts' **green-list ratio** will be higher

- Idea of ***antidistillation fingerprinting***
  - Use antidistillation sampling bias the **green-list ratio** of the student

Deriving Antidistillation Fingerprinting

- For context $x_{1:l}$, let the **green list** be $\boldsymbol{S} = \boldsymbol{H}(\boldsymbol{x}_{1:l}, \boldsymbol{k})$
  - Define the **per-step loss** $\boldsymbol{L}$ as

$$\boldsymbol{L} = \text{The probability that } \theta_p \text{ outputs a token in } \boldsymbol{S}$$

  - Note that $\boldsymbol{S}$ is context-**dependent**, thus $\boldsymbol{L}$ is also context-**dependent**
  - Recall in antidistillation sampling, $\boldsymbol{L}$ is context-**independent**

- We generalize antidistillation sampling to this setting
  - Using similar derivation, to maximize $\boldsymbol{L}$, the **perturbation** Δ is

$$\Delta_t = \langle \nabla_{\theta_p} \log \Pr[\text{The next token from } \theta_p \text{ is } t], \nabla_{\theta_p} \boldsymbol{L} \rangle$$

Deriving Antidistillation Fingerprinting

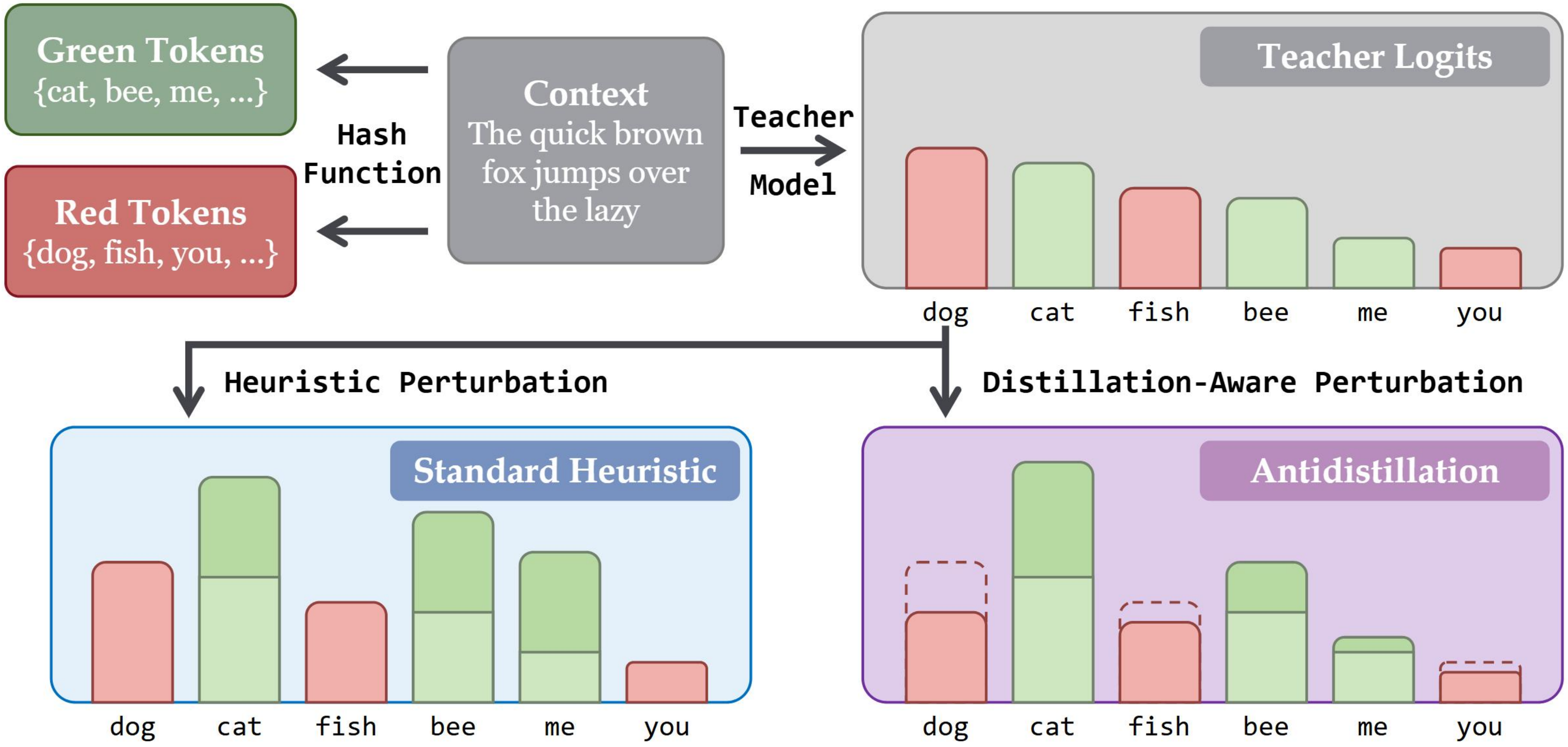
- For context $x_{1:l}$, **green list S**, **per-step loss L**
  - After calculation and approximation, the **perturbation** Δ becomes

$$\Delta_t = \Pr\left[\text{The next token from } \theta_p \text{ is } t\right] \cdot ([t \in \boldsymbol{S}] - \boldsymbol{L})$$

  - Computable with only one additional forward pass with the proxy

- The form admits nice interpretation without antidistillation
  - $([t \in \boldsymbol{S}] - \boldsymbol{L})$ can be considered as an advantage of token t
    - For green tokens, it is positive, and for red tokens, it is negative
  - It is then weighted by $\Pr\left[\text{The next token from } \theta_p \text{ is } t\right]$
    - Intuitively, we perturb likely tokens more than unlikely tokens

Antidistillation Fingerprinting



Experiments

- Models
  - **Teacher:** deepseek-ai/DeepSeek-R1-Distill-Qwen-7B
  - **Proxy:** Qwen/Qwen2.5-3B
  - **Student:** Qwen/Qwen2.5-3B / meta-llama/Llama-3.2-3B

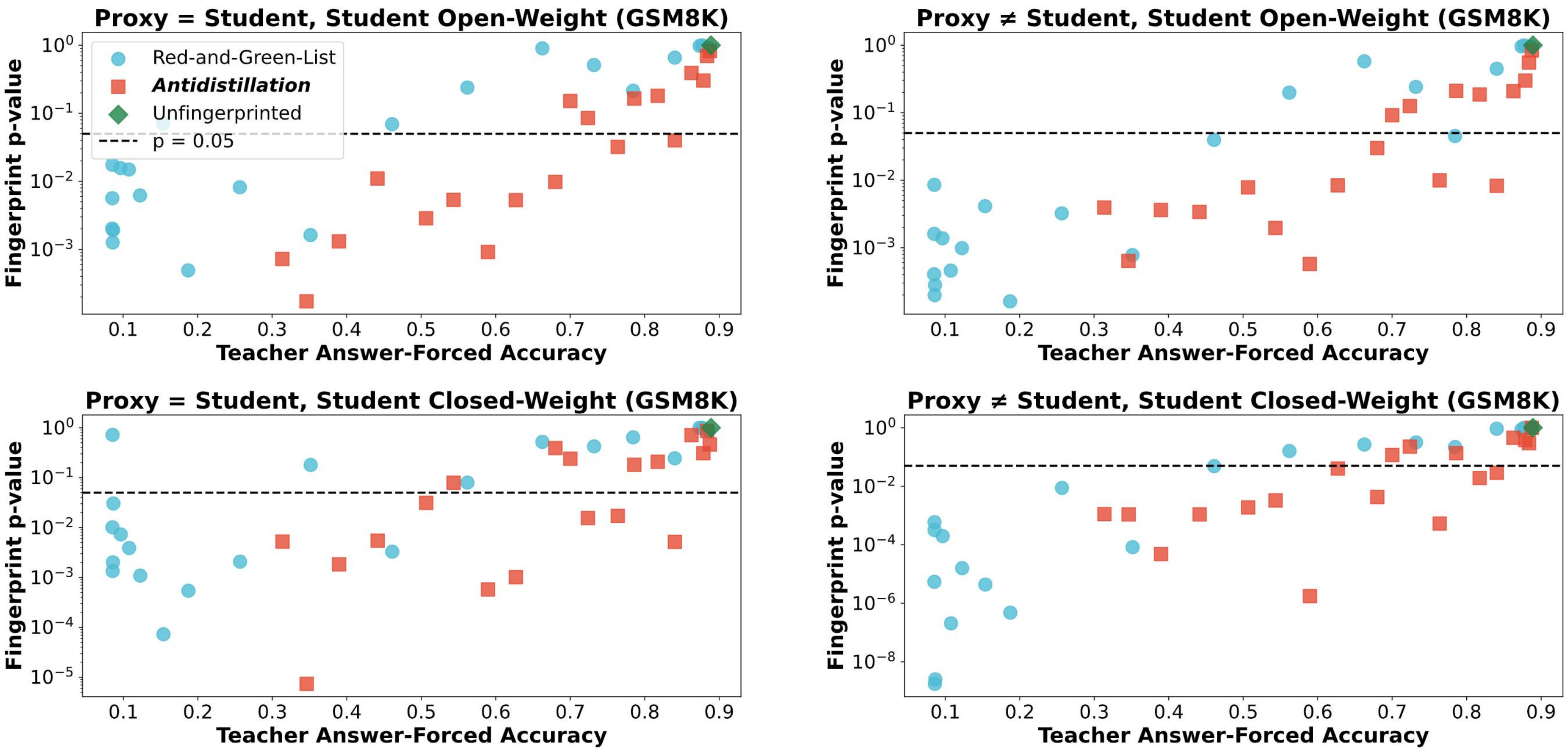
- Datasets & metrics
  - GSM8K (math reasoning), OASST1 (conversational fine-tuning)
  - The **trade-offs** we are looking at
    - Teacher utility vs detectability
    - Fine-tuning quality vs detectability

Four Different Evaluation Settings

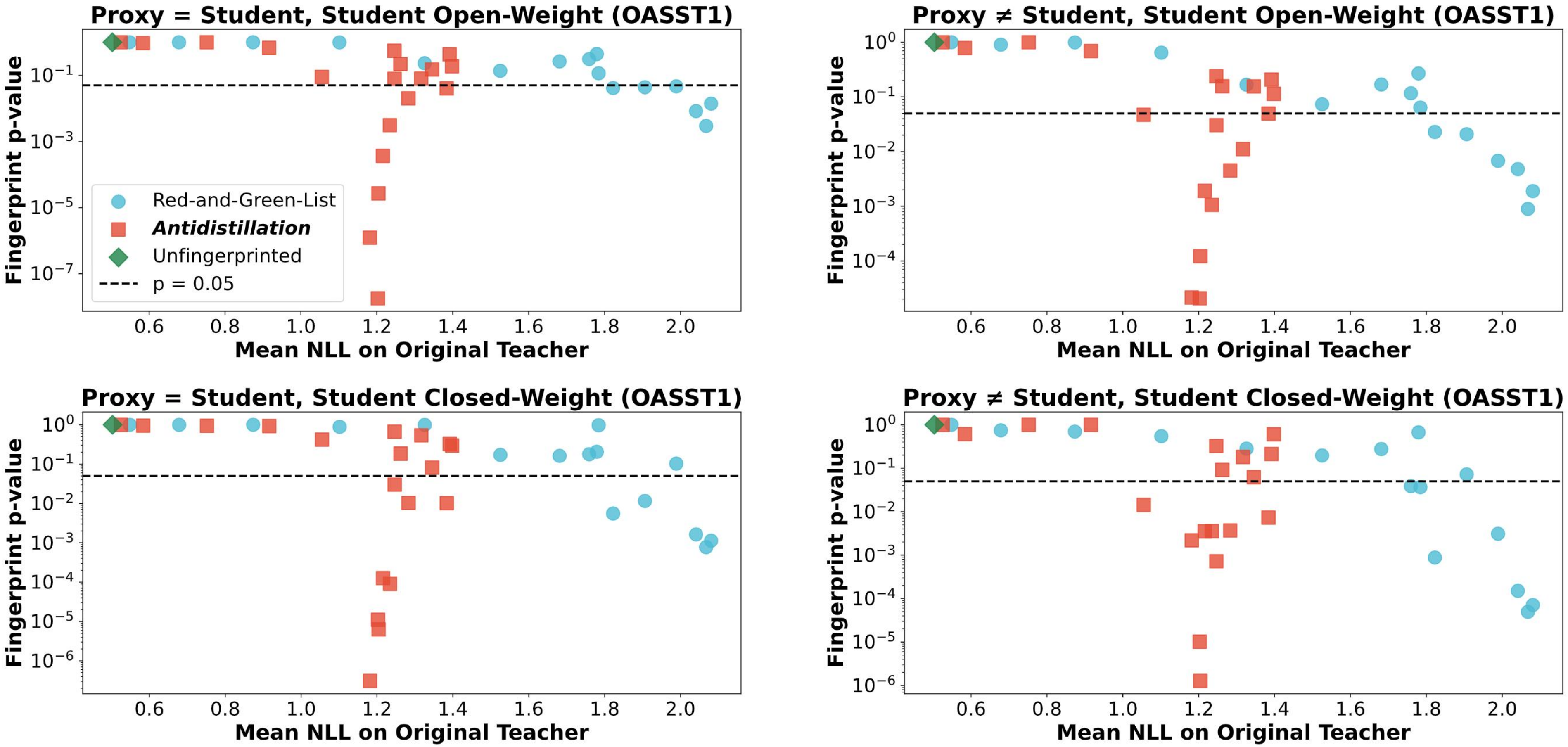
- Do we have access to student logits?
  - **Open:** Yes. We will use the logits to compute statistics
  - **Closed:** No. We only sample one token and use it to compute statistics
  - *Mainly affects the cost of evaluation, but effect is largely the same*

- Do we know the student's fine-tuning data?
  - **Supervised:** Yes. We can use it for evaluation
  - **Unsupervised:** No. We have to generate new data for evaluation
  - *Unsupervised it much harder, so we only present unsupervised results*

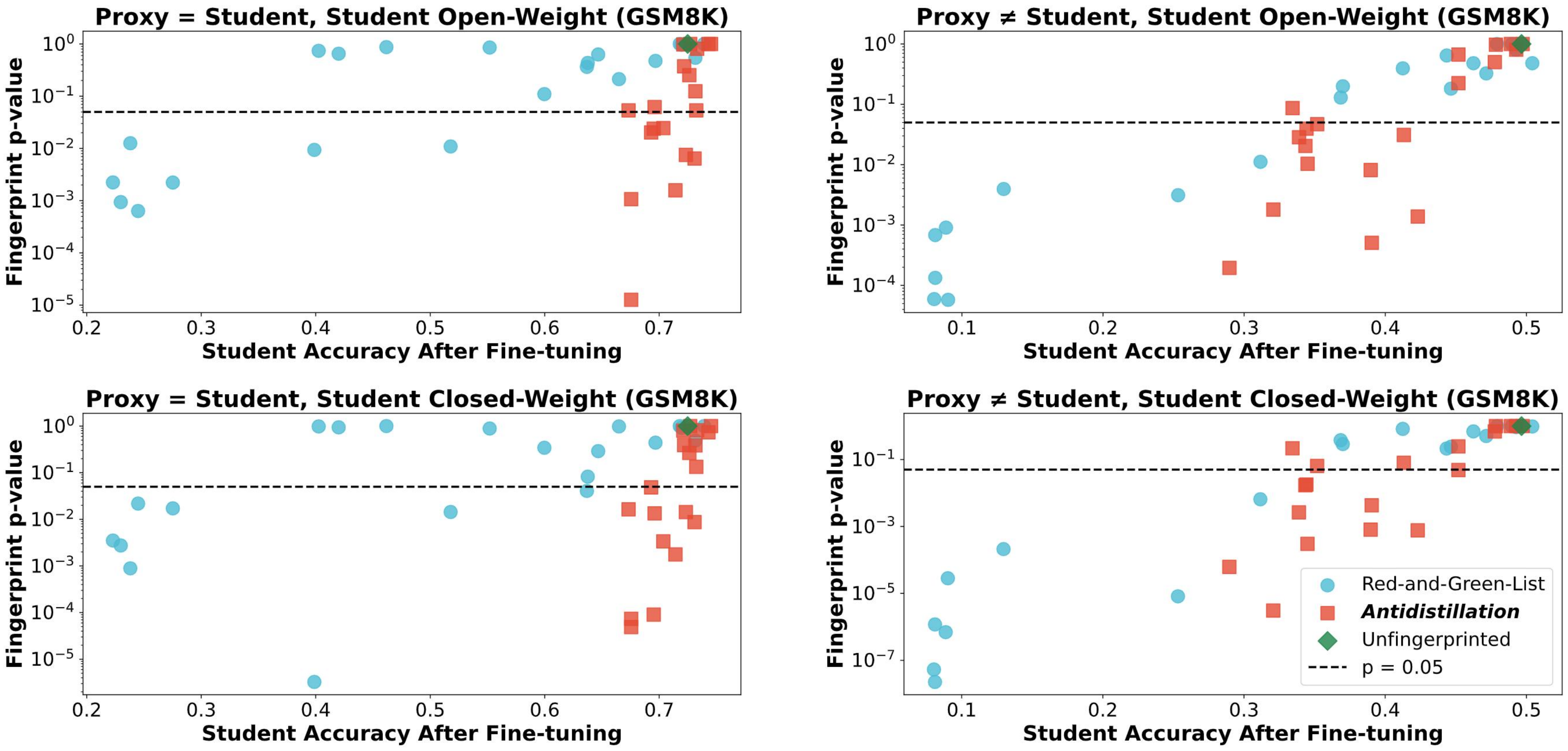
GSM8K (Teacher Utility vs Detectability)



OASST1 (Teacher Utility vs Detectability)



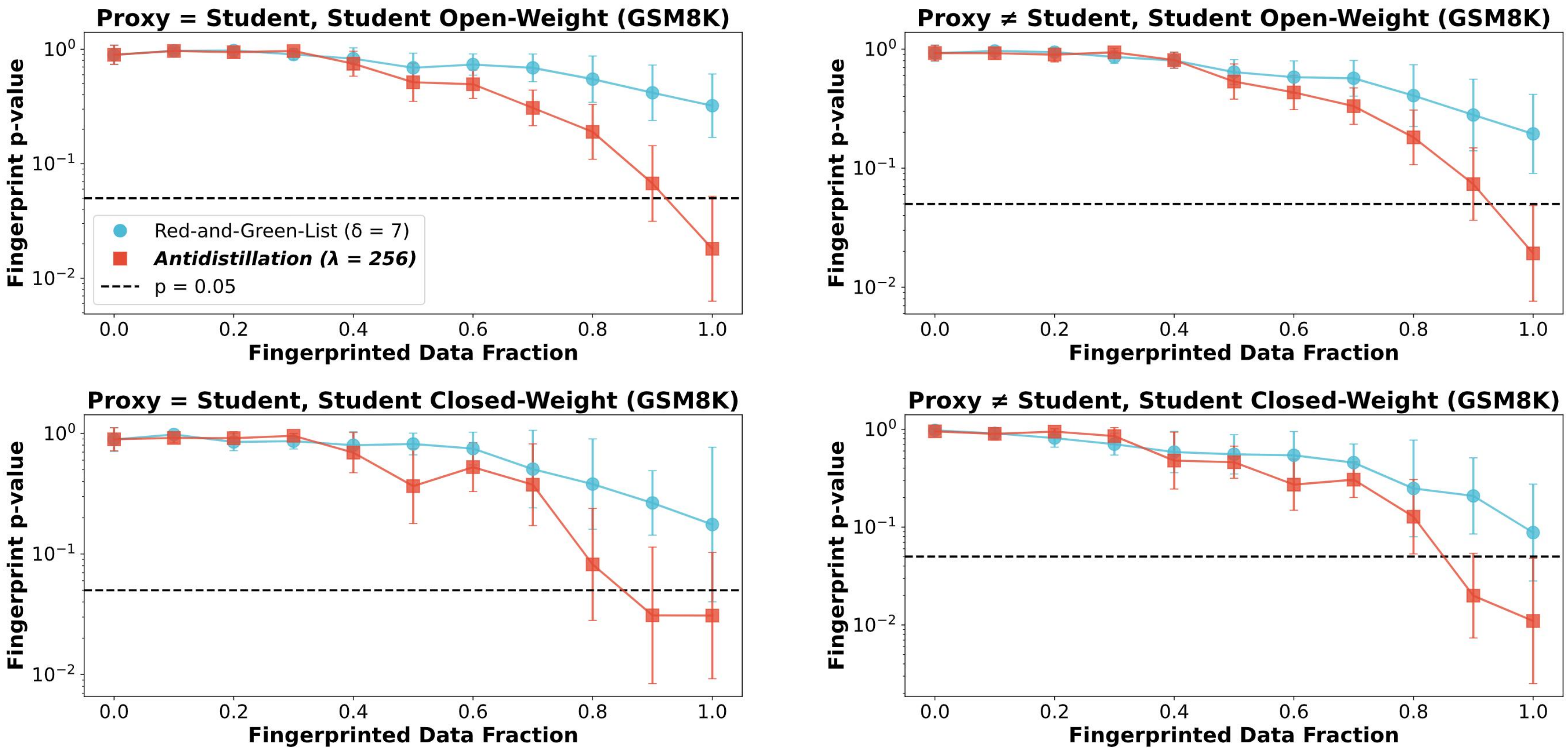
GSM8K (FT Quality vs Detectability)



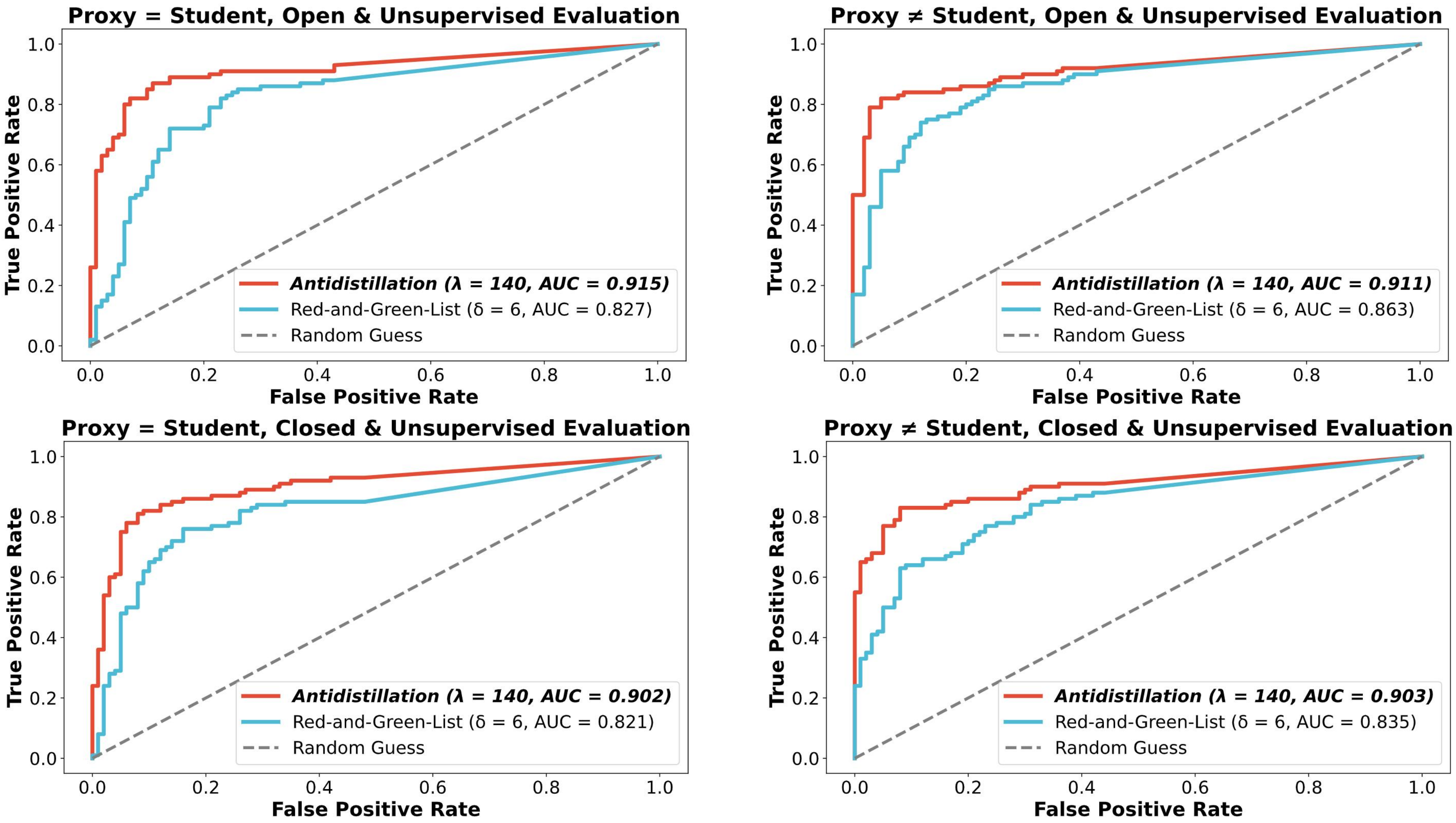
Case Studies for the Same Trace Quality

- Both fingerprinting methods have a strength parameter
  - Increasing it causes the traces' quality to degrade
  - But also increases detectability of the fingerprint
- We fix a level of trace quality for both methods and study:
  - What if only a fraction of the data is fingerprinted?
  - Does the advantage in p-value translate to an advantage in TPR vs FPR?
  - Does the computed p-value constitute an upper bound in FPR?

Effect of Fingerprint Fraction

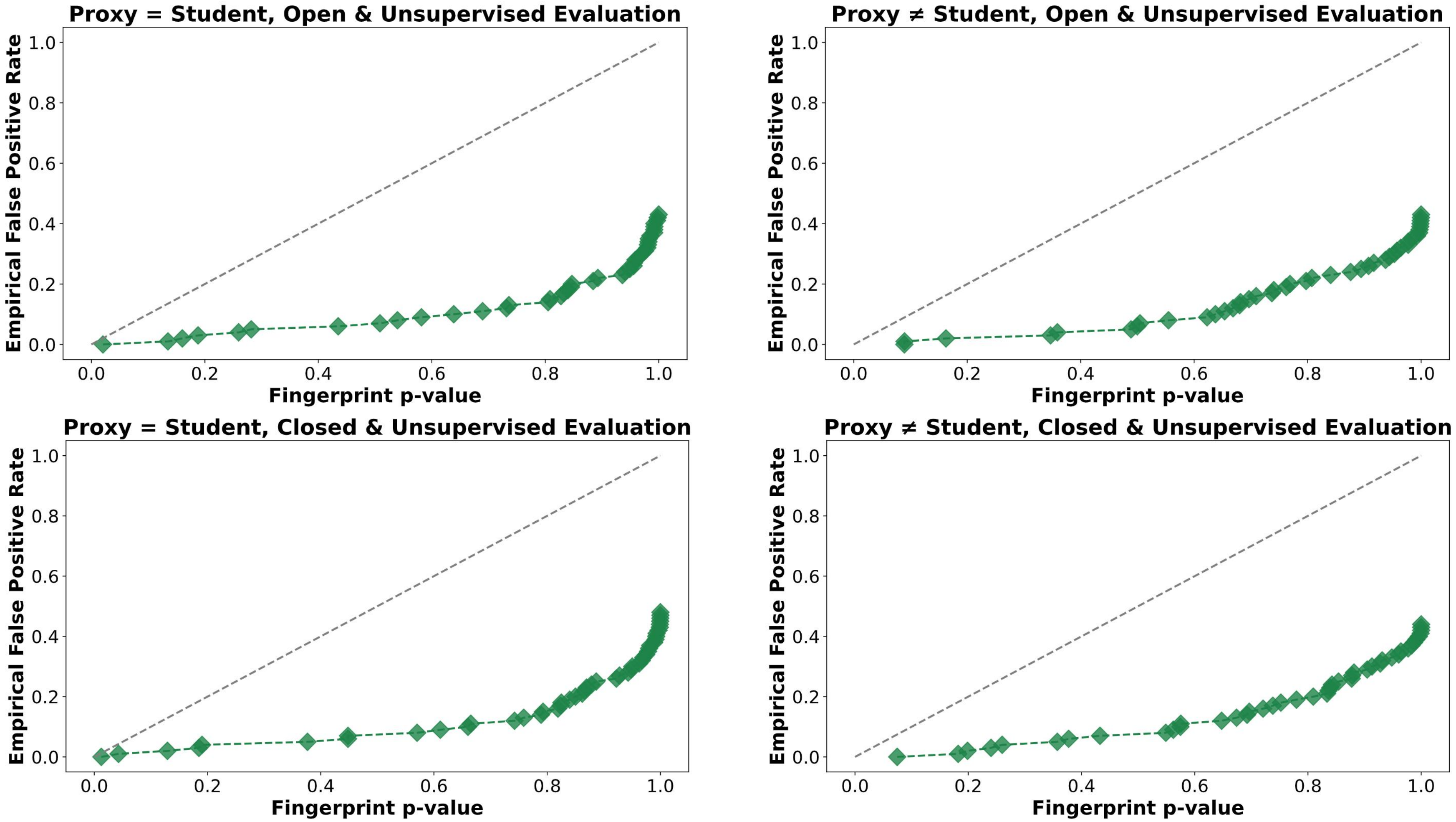


TPR vs FPR



Proxy = Student, Open & Unsupervised Evaluation
Proxy ≠ Student, Open & Unsupervised Evaluation
Proxy = Student, Closed & Unsupervised Evaluation
Proxy ≠ Student, Closed & Unsupervised Evaluation
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
Antidistillation (λ = 140, AUC = 0.915)
Red-and-Green-List (δ = 6, AUC = 0.827)
Antidistillation (λ = 140, AUC = 0.911)
Red-and-Green-List (δ = 6, AUC = 0.863)
Antidistillation (λ = 140, AUC = 0.902)
Red-and-Green-List (δ = 6, AUC = 0.821)
Antidistillation (λ = 140, AUC = 0.903)
Red-and-Green-List (δ = 6, AUC = 0.835)
Random Guess

P-value vs FPR



Our Contributions

- We introduce **antidistillation fingerprinting (ADFP)**, a principled framework for detecting model distillation
- We conduct a thorough theoretical and empirical study
  - On common fine-tuning tasks, ADFP achieves a **Pareto improvement** over state-of-the-art baseline in trading-off trace quality & detectability
  - Theoretically, we **align** detection with student's **learning dynamics**
    - This not only justifies ADFP's superior performance but also offers a theoretical lens to understand why previous heuristic watermarks persist during fine-tuning
  - Results show ADFP is a statistically grounded tool for fingerprinting