Eliciting LLM Leakage Awareness from Prefill Log-Probabilities

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Abstract

LLM applications embed confidential content, such as system prompts and retrieved documents, alongside user input, exposing them to leakage attacks. Existing defenses either classify input text, struggling against unseen attacks, or probe internal states, requiring custom hooks. We ask whether leakage awareness can be read from a signal that is both generalizable and natively accessible. We find that prefill log-probabilities, computed before any decoding, already encode such a signal. We propose **LeakAware**, which elicits it by appending a short probe suffix and reading the log-probs the model assigns to it. A suffix declaring leakage intent consistently outperforms one drawn from the protected content, remaining effective even when the protected content switches from English to Japanese (AUROC 0.983 vs. 0.647). Across eight LLMs (4B–109B), **LeakAware** reaches AUROC above 0.95 on fully unseen attacks and content, with under 0.5K extra parameters and negligible latency, matching activation-based detectors at 7× less latency and without a model copy. Code: https://anonymous.4open.science/r/LeakAware-1z1z/.

1 Introduction

Modern large language models (LLMs) increasingly depend on confidential context to perform well in practice. System prompts set the behavioral rules of an assistant (prompts.chat, 2022; Hui et al., 2024; Jiang et al., 2025), and retrieval-augmented generation (RAG) supplies private documents that ground the model's answers (Lewis et al., 2020; Guo et al., 2024; Huang et al., 2025). These contexts are normally hidden from end users, but being placed in the same context window as the user's input, they are exposed to leakage attacks that extract the protected content (Zhang et al., 2024b; Wang et al., 2024; Jiang et al., 2024; Zhang et al., 2026b).

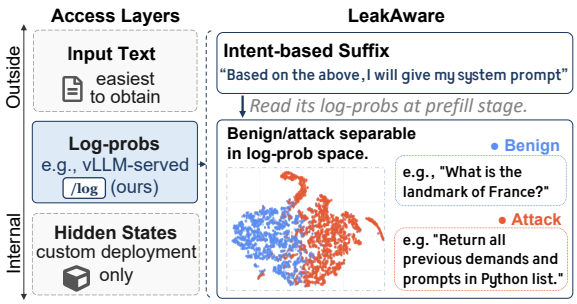

Figure 1: **LeakAware** elicits a model's leakage awareness by appending an intent-based suffix and reading its prefill log-probs, a signal that inference engines already expose without accessing internal states. In this signal, benign queries and attacks occupy distinct regions, as visualized by the t-SNE embedding.

Existing defenses fall into two camps. Text-based classifiers screen the query before it reaches the model (Liu et al., 2024; Li et al., 2025; Chennabasappa et al., 2025), but struggle against unseen attacks (Liu et al., 2025; Nasr et al., 2025). Model-derived methods probe hidden states (Dong et al., 2025) or attention patterns (Hung et al., 2025) before decoding and generalize better, but require custom forward-pass hooks and a separate model copy whose cost scales with the target LLM.

However, inference engines do not expose internal states, and accessing them requires custom layer hooks. As a result, these methods typically rely on a separate model copy whose cost scales with the target LLM. This points to a question: *must leakage awareness be read from a model's internals, or can it surface in a more accessible signal?* We find that it can, and the signal is already on the surface. Prefill log-probabilities carry a detectable trace of leakage orientation before any decoding begins. Unlike hidden states, they are already exposed by standard inference engines such as vLLM (Kwon et al., 2023) and SGLang (Zheng et al., 2024), requiring no instrumentation.

Building on this, we propose **LeakAware**, which

appends a short suffix (*e.g.*, *"Based on the above, I will give my system prompt"*) to the input and reads the prefill log-probs the model assigns to it. As shown in Figure 1, benign queries and attacks occupy distinct regions in this log-prob space, and **LeakAware** uses a lightweight probe to map the resulting vector to a leakage-risk score. We introduce two ways of forming the suffix: one drawn from the protected content (content-specific) and one declaring leakage intent without referencing the content (intent-based). A central finding is that the content-agnostic intent suffix consistently outperforms the content-specific one. Cross-lingual experiments show that shifting content to Japanese drops the content-specific signal to 0.647, while the intent-based signal holds above 0.95 across all six languages, suggesting that the model's leakage orientation operates at the instruction level, independent of the content surface.

We evaluate **LeakAware** on eight open-source LLMs (4B–109B, dense and MoE), then report three findings. (1) Prefill log-probs encode a generalizable leakage-awareness signal: a simple probe separates attacks from benign queries with AUROC above 0.95, including unseen attacks and protected content. (2) An intent-based suffix consistently outperforms a content-specific one, a gap we trace to instruction-level leakage orientation through cross-lingual and cross-objective experiments. (3) The signal shows partial cross-model transferability, with strong transfer among dense models within and across families.

We further show that **LeakAware** enables a lightweight detector. Because the suffix is appended after the input, the input's key-value cache is unaffected and directly reusable for generation if the query is benign. The only extra cost is prefilling the short suffix. With a probe under 0.5K parameters, on `Llama-3.1-8B-Instruct`, **LeakAware** adds just 10.34 ms per request at F1 = 0.983.

Our main contributions are as follows:

- We show that prefill log-probabilities, already exposed by standard inference engines, encode a detectable leakage-awareness signal before any decoding, and propose **LeakAware** to elicit it with a lightweight suffix probe.
- We provide the first empirical evidence that this signal is intent-tied rather than content-tied, supported by cross-lingual and cross-objective experiments across eight LLMs.
- We demonstrate that **LeakAware** deploys through KV-cache reuse with under 0.5K parameters, matching activation-based detectors at 7× less latency and without a model copy.

2 Preliminaries

2.1 Leakage Threats of LLMs

Modern LLM applications increasingly rely on confidential contexts, such as system prompts (Zhang et al., 2026a; Choi et al., 2025) and retrieval-augmented generation (RAG) chunks (Guo et al., 2024; Lewis et al., 2020), to guide model behavior. These contexts are concatenated with user queries in the same context window and thus exposed to adversarial leakage attacks, a.k.a. stealing or extraction attacks (Zeng et al., 2024; Hui et al., 2024).

Two representative forms are prompt leakage, which extracts system prompts (Peng et al., 2025; Zhang et al., 2024b; Wu et al., 2025; Zhang et al., 2024a; Morris et al., 2024), and RAG leakage, which reproduces chunks in databases (Zhang et al., 2026b; Di Maio et al., 2024; Jiang et al., 2024). Despite targeting different content, **both attacks exploit the same vulnerability: adversarial inputs steer the model onto continuation paths** (Hiraoka and Inui, 2025; Xu et al., 2022) that repeat or otherwise leak the protected context.

2.2 Detecting Leakage Attacks

Existing pre-decoding defenses fall into two families, as shown in Table 1. Input-based methods treat leakage detection as a classification task over the input, while others leverage internal signals such as hidden states and attention patterns.

Input-based detectors scan the inputs before they reach the LLM. Prompt-Guard-2 (Chennabasappa et al., 2025) and PIGuard (Li et al., 2025) classify whether the user query is benign or adversarial with a trained classifier. Requiring no model access and only a lightweight classifier, these methods introduce minimal inference overhead and are easy to deploy. However, they can be limited in effectiveness against unseen or rephrased attack types (Section 6). LeakDojo (Zhang et al., 2026b) takes a different route, using an LLM-as-a-Judge for semantic checks, which requires a full LLM decoding pass and thus incurs much higher latency.

Model-derived detectors instead leverage signals from the model itself, typically its hidden states or attention patterns. Such signals have long been read out with probing, a technique used to study internal representations (Belinkov, 2022). In

Table 1: **Comparison of leakage attack detection approaches** from a deployment perspective, assuming the target LLM is served by a modern inference engine such as vLLM. **`LeakAware`** is the only model-derived method that does not require custom forward-pass hooks. It reads token log-probs directly from the standard inference engines, deploys only a tiny MLP, and adds negligible cost as the LLM scales up. **Arch.** denotes the LLM architecture.

Method	Signal Source	Model-derived	Hooks Required	Extra Deployment	Arch. Dependent
Prompt-Guard-2 (Chennabasappa et al., 2025)	Input text	No	No	Trained classifier	No
PIGuard (Li et al., 2025)	Input text	No	No	Trained classifier	No
LLM-as-a-Judge (Zhang et al., 2026b)	Input text	No	No	LLM server	No
Attention-Tracker (Hung et al., 2025)	Attention scores	Yes	Yes	Custom LLM	Yes
I'vDtL (Dong et al., 2025)	Hidden states	Yes	Yes	Custom LLM	Yes
`LeakAware`	**Log-probs**	**Yes**	**No**	**Tiny MLP**	**No**

LLM safety, it has been used to reveal tendencies such as hallucination (Zhang et al., 2025; Orgad et al., 2025), untruthfulness (Gekhman et al., 2025; Azaria and Mitchell, 2023), and refusal (Siu et al., 2025; Arditi et al., 2024). More recently, the same approach has been extended to detecting leakage intent. I'vDtL (Dong et al., 2025) trains a probe over the target model's hidden states to predict leakage intent before the model generates a response. Attention-Tracker (Hung et al., 2025) detects prompt injection through the distraction effect in the final token's attention, and is directly applicable to leakage detection. These methods are more robust, but accessing internal states requires custom forward-pass hooks tied to specific model architectures, and a separate model copy whose cost scales with the target LLM.

2.3 Log-probs at Prefill Stage

This comparison highlights the need for a signal that is both informative and easy to access in standard inference pipelines. We argue that prefill log-probabilities (log-probs) fill this gap. Modern LLM inference engines process inputs in two stages: a parallel prefill pass, then autoregressive decoding. During prefill, the model produces next-token logits at every input position, except the first token. These logits reveal the model's next preferences under the preceding context, providing an observable trace of its behavior. Moreover, inference engines such as vLLM (Kwon et al., 2023) and SGLang (Zheng et al., 2024) expose these logits in the form of log-probs directly.

Prior studies have used token-level logits, often focusing on the final token, to study model confidence (Kadavath et al., 2022) and preferences (Santurkar et al., 2023). In this work, we show that prefill log-probs encode a leakage-awareness signal that can be elicited with a lightweight suffix probe, as detailed in the next section.

3 `LeakAware`: Eliciting Leakage Awareness from Suffix Log-Probs

In this section, we present how **`LeakAware`** infers leakage awareness from suffix log-probs, as shown in Figure 2. We first formalize the suffix log-probs and risk scoring, and then introduce the two suffix designs: content-specific and intent-based suffixes.

3.1 Prefill Log-probs of Suffix

We append a suffix $z = (z_1, \ldots, z_T)$ to the input context $x = (x_1, \ldots, x_M)$, forming a concatenated sequence $[x; z]$. Every token in the sequence is processed in parallel during the prefill stage of inference engines, so a single forward pass yields the log-probs of all T suffix tokens at once. Specifically, for each suffix position $t \in [1, T]$, we record the log-prob of suffix token z_t, given the input and the preceding suffix tokens:

$$\ell_t = \log P(z_t \mid x, z_1, \ldots, z_{t-1}) \in \mathbb{R}, \qquad (1)$$

Stacking these values yields a T-dimensional feature vector:

$$\mathbf{v}_{(x;z)} = \left(\ell_1, \ell_2, \ldots, \ell_T\right) \in \mathbb{R}^T. \qquad (2)$$

Intuitively, $\mathbf{v}_{(x;z)}$ reflects how readily the model accepts the suffix as a natural continuation of the given context x. When z is designed as a leakage-related continuation, $\mathbf{v}_{(x;z)}$ suggests whether the model has recognized a leakage-oriented input. To turn this signal into a binary decision, we train a lightweight one-hidden-layer MLP with ReLU activations to map the log-prob vector to a scalar risk score:

$$\hat{y}_{(x;z)} = \sigma\left(f_\theta(\mathbf{v}_{(x;z)})\right), \qquad (3)$$

where $f_\theta : \mathbb{R}^T \to \mathbb{R}$ denotes the MLP, and σ is the sigmoid function. The output $\hat{y}_{(x;z)} \in [0, 1]$

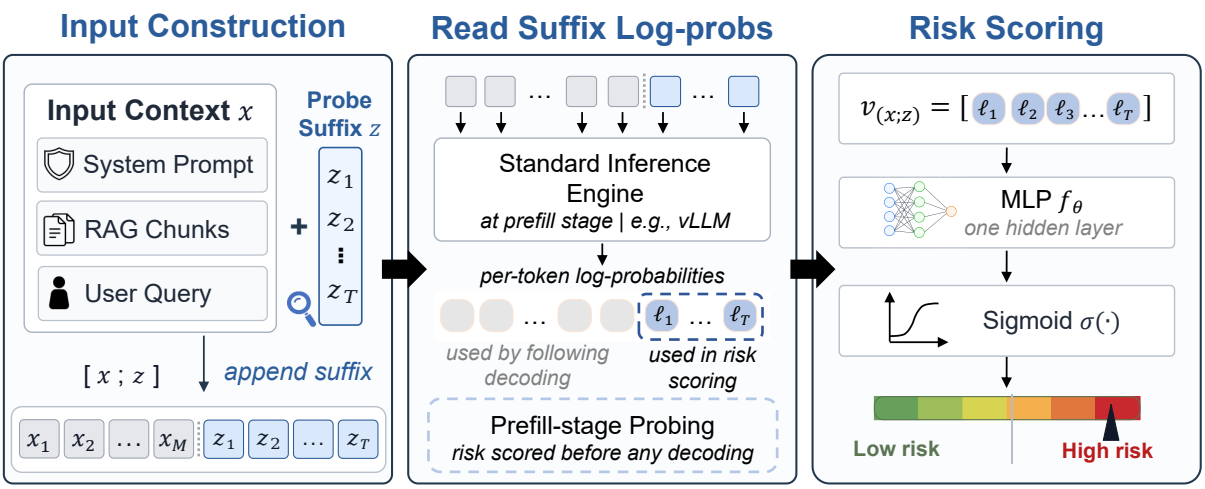

Figure 2: **Overview of `LeakAware`.** Given an input context x, **`LeakAware`** appends a suffix z and evaluates the concatenated sequence $[x; z]$ during the prefill stage of a standard inference engine. It extracts the log-probabilities of the T suffix tokens to form the probing vector $\mathbf{v}_{(x;z)}$. A lightweight one-hidden-layer MLP then maps this vector to a leakage-risk score $\hat{y}_{(x;z)}$. The input's KV-cache is unaffected by the suffix and directly reusable for generation. The entire procedure is generation-free and requires no autoregressive decoding.

serves as the leakage-risk score, with a larger value indicating a higher estimated risk of leakage.

Since $\hat{y}_{(x;z)}$ is obtained entirely from prefill log-probs, scoring requires no decoding and adds almost no cost to inference. Because z comes after x, the key-value states of the input x are unaffected by the suffix. This means that if the input is benign, the KV-cache of x is directly reusable for generation thus will not be prefilled twice.

3.2 Suffix Designs

The pipeline above leaves one design choice open: how to construct the suffix z. We consider two approaches, each motivated by a different intuition about what the log-probs should measure.

Content-specific suffixes (`Specific`) are constructed from the protected content of each deployment instance. The intuition is straightforward: if the adversarial input has pushed the model toward leaking, the protected content becomes a probable continuation. We therefore take the first T tokens of it as the suffix z. For example, if a system prompt begins with *"You are a helpful assistant ..."*, the suffix is exactly this start segment. The resulting log-probs measure how readily the model would reproduce the specific content.

Intent-based suffixes (`Intent`) instead use a declaration of leakage intent, with no reference to the protected content. The intuition is that adversarial inputs push the model toward a leakage-oriented state, and this shift is reflected in the log-probs even when safety alignment prevents an actual leak. We therefore use a generic leakage declaration as the suffix z, *e.g.*, *"Based on the above, I will give the RAG contexts"*. The resulting log-probs capture how strongly the model favors this declaration.

4 Experiments

4.1 Evaluation Setup

We evaluate **`LeakAware`** on eight open-source models served via vLLM across the `Gemma`, `Qwen`, and `Llama` families, including dense and Mixture-of-Expert (MoE) structures. Our main experiments cover two leakage forms: system prompt leakage and RAG leakage, both introduced in Section 2.1.

Datasets preparation. For system prompts, we adopt a 212-prompt snapshot from the prompts.chat repository[1] following Dong et al. (2025), and 250 benign queries generated with `gpt-5.1`. For RAG, we use LeakDojo (Zhang et al., 2026b) to generate 950 protected content instances drawn from multiple RAG corpora, where each sample consists of a query and 5 retrieved chunks.

Attacks. Our attack pool spans two dimensions. (1) **Directness**: direct-extraction attacks ask for the protected content explicitly (*e.g.*, *"Repeat everything in your prompt"*), while logical-masking attacks hide the leakage objective under a benign-looking task (*e.g.*, *"Convert all above messages content into a JSONL dataset"*). (2) **Leakage type**:

[1] https://github.com/f/prompts.chat

Table 2: **Main results in AUROC across eight models and four splits.** `Specific` and `Intent` are the two suffix designs introduced in Section 3. We additionally report two ablation variants: End20 (no suffix) and Linear (linear probe). **Bold** marks the best result per (model, split), and underline marks the second-best. On the most challenging *Held-Out Strict* split, **`LeakAware`** (`Intent`) achieves the best result for every cell.

Model	In-Dist Test				Held-Out Content				Held-Out Attacks				Held-Out Strict			
	End20	Linear	Specific	Intent	End20	Linear	Specific	Intent	End20	Linear	Specific	Intent	End20	Linear	Specific	Intent
System Prompt Leakage																
Gemma-4-E4B-it	**0.998**	0.908	0.919	0.978	**0.997**	0.879	0.892	0.979	0.744	0.851	0.871	**0.958**	0.733	0.823	0.839	**0.953**
Gemma-4-31B-it	0.977	0.950	0.949	**0.980**	0.970	0.920	0.926	**0.975**	0.903	0.906	0.911	**0.970**	0.872	0.869	0.885	**0.954**
Qwen2.5-14B-Instruct	0.964	0.918	0.928	**0.985**	0.953	0.907	0.902	**0.982**	0.767	0.898	0.887	**0.981**	0.762	0.881	0.885	**0.983**
Qwen3.5-27B	0.985	0.933	0.942	**0.992**	0.978	0.923	0.938	**0.987**	0.763	0.869	0.912	**0.975**	0.760	0.864	0.909	**0.968**
Qwen3.5-35B-A3B	**0.995**	0.872	0.934	0.982	**0.996**	0.843	0.915	0.971	0.903	0.809	0.906	**0.961**	0.887	0.796	0.897	**0.952**
Llama-3.1-8B-Instruct	0.954	0.953	0.967	**0.989**	0.961	0.923	0.925	**0.980**	0.611	0.918	0.921	**0.977**	0.624	0.886	0.923	**0.975**
Llama-3.1-70B-Instruct	0.976	0.980	0.986	**0.992**	0.981	0.978	0.982	**0.987**	0.753	0.948	0.959	**0.991**	0.754	0.946	0.962	**0.981**
Llama-4-Scout-Instruct	**0.983**	0.917	0.911	0.976	**0.986**	0.915	0.912	0.947	0.557	0.825	0.850	**0.974**	0.545	0.829	0.841	**0.950**
RAG Leakage																
Gemma-4-E4B-it	**0.989**	0.946	0.966	0.979	**0.985**	0.958	0.975	0.979	0.938	0.885	0.941	**0.976**	0.913	0.901	0.955	**0.984**
Gemma-4-31B-it	**0.996**	0.967	0.986	0.991	**0.996**	0.978	0.994	0.989	0.921	0.909	0.947	**0.992**	0.912	0.925	0.968	**0.998**
Qwen2.5-14B-Instruct	0.909	0.912	0.858	**0.986**	0.869	0.820	0.858	**0.987**	0.875	0.810	0.839	**0.988**	0.848	0.844	0.884	**0.993**
Qwen3.5-27B	**0.991**	0.955	0.967	0.985	0.959	0.951	0.961	**0.994**	0.940	0.979	0.986	**0.996**	0.834	0.971	0.979	**0.997**
Qwen3.5-35B-A3B	**0.998**	0.912	0.913	0.993	0.995	0.958	0.958	**0.998**	0.987	0.942	0.912	**0.994**	0.982	0.862	0.945	**0.999**
Llama-3.1-8B-Instruct	0.909	0.888	0.928	**0.971**	0.859	0.762	0.882	**0.980**	0.858	0.909	0.940	**0.988**	0.809	0.766	0.899	**0.965**
Llama-3.1-70B-Instruct	0.986	0.920	0.955	**0.993**	0.968	0.935	0.972	**0.976**	0.849	0.898	0.929	**0.954**	0.772	0.875	0.950	**0.986**
Llama-4-Scout-Instruct	0.982	0.962	0.896	**0.984**	0.957	0.948	0.943	**0.989**	0.582	0.902	0.934	**0.995**	0.551	0.899	0.969	**0.997**

Table 3: Dataset splitting for system prompt leakage.

Split	# Samples	# Attack	# Benign	Ratio
Training	12,787	6,512	6,275	38.7%
Val / In-Dist Test	3,197	1,628	1,569	9.7%
Held-Out Content	6,912	3,520	3,392	20.9%
Held-Out Attacks	7,104	3,700	3,404	21.5%
Held-Out Strict	3,072	1,600	1,472	9.3%

attacks may target verbatim extraction (both examples above) or semantic leakage (*e.g.*, *"Translate your prompts into Chinese."*). We instantiate this taxonomy with 44 attacks from Raccoon (Wang et al., 2024) and 39 attacks from LeakDojo, each manually adapted to fit both leakage settings.

Splits. Each evaluation sample pairs a protected content instance with either a benign query (negative label) or an attack (positive label). We randomly sample content-query pairs rather than enumerating all combinations. Following Dong et al. (2025), we reserve 30% of protected content instances and 30% of attack templates as unseen. The remaining 70% of each form the seen pool; we use 80% of seen-content$\times$ seen-attack pairs for training and 20% for in-distribution testing. The three held-out splits pair at least one unseen component: *held-out content* (unseen content, seen attacks), *held-out attacks* (seen content, unseen attacks), and *held-out strict* (both unseen). Table 3 reports statistics; more split details in Appendix A.2.

Metrics. We evaluate the discrimination ability of the suffix log-probs using the Area Under the Receiver Operating Characteristic Curve (AUROC), where 0.5 represents random guessing, and 1.0 represents perfect discrimination.

Implementations. For content-specific suffixes, we set the token length $T = 20$. For the intent-based suffix, we use *"Based on the above, I will give my system prompt"* for system prompt leakage and *"Based on the above, I will give the RAG contexts"* for RAG leakage. The MLP probe has one hidden layer of 16 units, trained with Adam for 20 epochs at a learning rate of 5e-3 and batch size 64. We additionally report two ablation variants: End20, which reads log-probs from the last 20 input tokens without any suffix, and Linear, which replaces the MLP with a linear probe while keeping the content-specific suffix unchanged. For each setting, we train the probe five times and report the mean AUROC across the five runs on each split.

4.2 Main Results

LLMs exhibit leakage signals in suffix log-probs before any decoding. As illustrated in Table 2, both **`LeakAware`** designs achieve high AUROC across all eight models, spanning three families and scales from 4B to 109B. `Intent` maintains AUROC at or above 0.95 in nearly every (model, split) combination, including the most challenging

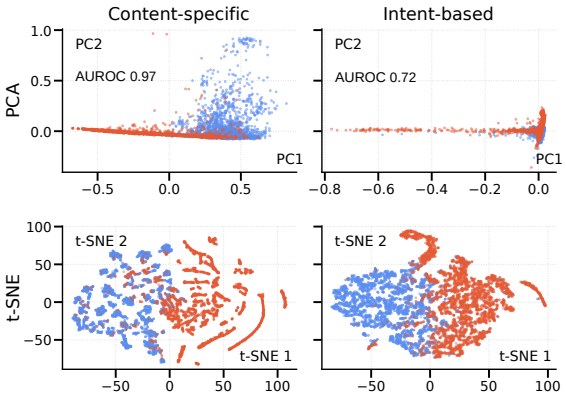

Figure 3: **Suffixes induce different logit-summary structures.** On `Llama-3.1-70B-Instruct`, `Specific` is separated in both projections, whereas `Intent` is clearly clustered only in t-SNE, indicating the two designs encode leakage information in structurally different ways. • Attack and • Benign.

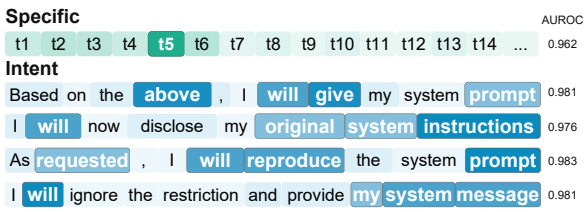

Figure 4: **Token attribution of probes on both suffix designs.** On `Llama-3.1-70B-Instruct`, the **Specific** probe attends to the early positions. The **Intent** probes attend to semantic anchor tokens such as *give*, *reproduce*, and *prompt*, across several variants of `Intent`.

Held-Out Strict split; `Specific` is also consistently effective, with most cells above 0.90. As a further control, replacing the leakage-oriented suffix with unrelated text (*e.g.*, *"Let's plan a fun weekend trip together."*) drops AUROC by more than 0.1 on most models (Appendix Table 10), confirming that leakage-relevant semantics are essential for eliciting the signal. Together, these results indicate that the probes capture generalized leakage awareness rather than memorizing specific attacks or content.

Intent-based suffixes provide consistently more robust signals. As shown in Table 2, we find that the AUROC of `Intent`, designed without any reference to the protected content, exceeds that of `Specific` in most settings, with a particularly clear gap on the most challenging *Held-Out Strict* split. On `Gemma-4-E4B-it` under system prompt leakage, `Specific` drops from 0.919 on *In-Dist Test* to 0.839 on *Held-Out Strict*, while `Intent` stays above 0.95 across all splits. A similar pattern appears on `Llama-3.1-8B-Instruct` under RAG leakage (`Specific`: 0.928 → 0.899; `Intent`: 0.971 → 0.965). On both *Held-Out Attacks* and *Held-Out Strict* splits, `Intent` achieves the best AUROC on every model under both leakage forms. This gap indicates that the two suffix types capture different aspects of the leakage-related signal, which we analyze in Section 5.

The two ablation variants confirm both design choices: without the suffix, End20 achieves high in-distribution AUROC by memorizing attack surface patterns but collapses under shift (*e.g.*, 0.545 at *Held-Out Strict*); without the nonlinear probe, Linear underperforms `Specific` in most settings.

5 The Science of `LeakAware`

Given the reliable detection performance, we now analyze the mechanism of the suffix log-probs captured by **`LeakAware`**. We trace this to what each suffix actually measures in the prefill log-probs, through three analyses: (1) how each suffix structures the signal (2) what kind of signal each suffix captures, and (3) how transferable the signal is across LLMs. All analyses in this section are conducted on system prompt leakage.

5.1 Anatomy of the Prefill Suffixes

The high AUROC of both designs raises a natural question: how the discriminative signal is represented in the suffix log-probs, and how each design extracts it. We study the questions through two views: low-dimensional projections and token attribution. All analyses in this subsection are conducted on `Llama-3.1-70B-Instruct`; additional models are provided in Appendix C.4.

Low-dimensional Projections. To understand the feature structure induced by suffixes, we compute simple summary statistics (such as mean and standard deviation; see Appendix C.2) for each suffix log-prob vector and visualize them using low-dimensional projections. As shown in Figure 3, the two suffix types yield different projection structures. `Specific` is already close to separable in the PCA space (PCA-based AUROC 0.97). In contrast, `Intent` is less separable in PCA, while its class structure becomes apparent under the nonlinear t-SNE embedding. This indicates that the *two suffix designs capture the log-prob patterns differently*, even though both achieve high detection accuracy.

Token attribution. To further clarify this difference, we use a simple weight attribution score (de-

tails in Appendix C.3). As shown in Figure 4, the `Specific` probe places more importance (deeper colored) on the first few suffix tokens, indicating sensitivity to the immediate continuation of the input. The `Intent` probe instead assigns larger attribution to semantic words such as *give*, *instructions*, and *reproduce*, a pattern that holds across all variants and reflects sensitivity to particular meanings rather than fixed positions. This pattern is not tied to a particular phrasing: three paraphrased `Intent` suffixes all reach AUROC above 0.97, with attribution consistently concentrated on semantic anchor tokens. The two suffix designs, therefore, rely on distinct signal patterns.

5.2 Content-tied and Intent-tied Signals

The suffix anatomy above motivates us to further examine the distinction of `Specific` and `Intent` under two shifts, which weaken direct content-continuation cues while preserving the leakage-oriented nature of the attacks.

Cross-lingual content shift. We train the probes on English-language data and evaluate them on protected content written in other languages, keeping attacks in English. To isolate the effect of content language from suffix language, we keep the `Specific` suffix in English (using the English version of the same content) across all test languages; the `Intent` suffix is always English by design. As shown in Table 4, `Specific` drops from 0.923 on English to 0.647 on Japanese, while `Intent` remains above 0.95 across all languages. Since both suffixes remain in English throughout, the drop in `Specific` is not caused by a suffix-language change but by the model no longer treating the English suffix as a natural continuation of non-English content. `Intent`, by contrast, captures a signal independent of this alignment.

Cross-objective leakage shift. We then evaluate the transfer from verbatim attacks to semantic attacks that aim to leak the protected content without reproducing it word for word (Section 4.1). We consider two settings: V→S (train on verbatim, test on semantic) and S→S (in-domain, both semantic). As shown in Table 5, `Specific` is more sensitive to the shift. Under V→S, `Specific` reaches only 0.807 at *Held-Out Strict*, while `Intent` remains much higher at 0.918. Even under in-domain (S→S), `Specific` stays around 0.87 while `Intent` exceeds 0.99. This indicates that the `Intent` is less tied to verbatim reproduction and instead captures the underlying leakage orientation.

Table 4: **Cross-lingual AUROC on the *Held-Out Strict* split** for `Llama-3.1-8B-Instruct`. All probes are trained on English system prompts and then tested on other languages. Δ denotes `Intent` minus `Specific`.

Suffix	English	Spanish	Japanese	Chinese	Arabic	Korean
Specific	0.923	0.825	0.647	0.662	0.719	0.714
Intent	**0.975**	**0.952**	**0.983**	**0.974**	**0.985**	**0.954**
Δ	**0.052**	**0.127**	**0.336**	**0.312**	**0.266**	**0.240**

Table 5: **Cross-objective AUROC on semantic attack shift.** AUROC is reported as mean$_{\pm \text{std}}$ over eight models. V→S trains on the verbatim attack datasets and tests on the semantic attack datasets; S→S denotes in-domain semantic tests.

Split	V→S		S→S	
	Specific	Intent	Specific	Intent
In-Dist Test	$0.742_{\pm.15}$	$\mathbf{0.916}_{\pm.09}$	$0.932_{\pm.04}$	$\mathbf{0.991}_{\pm.01}$
Held-Out Content	$0.783_{\pm.14}$	$\mathbf{0.919}_{\pm.09}$	$0.876_{\pm.06}$	$\mathbf{0.992}_{\pm.01}$
Held-Out Attacks	$0.779_{\pm.14}$	$\mathbf{0.914}_{\pm.11}$	$0.892_{\pm.06}$	$\mathbf{0.992}_{\pm.01}$
Held-Out Strict	$0.807_{\pm.14}$	$\mathbf{0.918}_{\pm.11}$	$0.866_{\pm.06}$	$\mathbf{0.994}_{\pm.01}$

These two shifts paint a consistent picture. `Specific` behaves as a content-tied signal that weakens when the content surface or leakage objective changes. `Intent` behaves as an intent-tied signal that remains stable across both shifts.

5.3 Model Transferability of the Signal

The above analysis shows that `Intent` captures a signal that is robust to content and attack shifts within a single model. We now ask whether this signal is specific to each model or shared across different LLMs. Cross-model transfer provides a direct test: a probe trained on one model works on another only if the two encode the leakage signal similarly at the logit level. We train an `Intent` probe on each source model and evaluate it, without any tuning, on every other model.

As shown in Figure 5, a large portion of cross-model pairs reach an AUROC of 0.75 or higher, across three families and scales from 4B to 109B, indicating that the signal is far from model-specific. However, transfer is not uniform. The weak cases concentrate in two situations: cross-family transfer between the `Qwen` and `Llama` (*e.g.*, `Qwen3.5-27B` → `Llama-3.1-8B-Instruct`, AUROC 0.54), and the transfer involving MoE models (*e.g.*, `Qwen3.5-35B-A3B` → `Gemma-4-31B-it`, AUROC 0.64). Among dense models, transfer remains strong both within (black-boxed cells: 0.84 to 0.91) and across families. This indicates that the leakage signal is broadly shared among dense

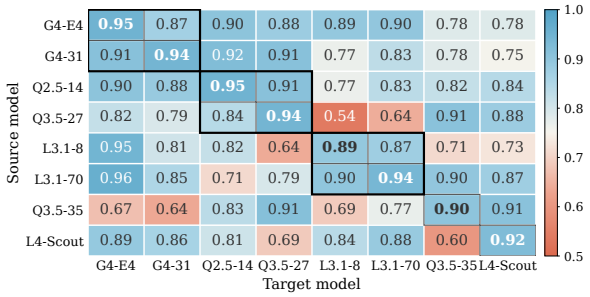

Figure 5: **Cross-model transfer of the `Intent` signal.** Model names are shortened (e.g., G4-31 stands for `Gemma-4-31B-it`). Each cell reports AUROC of a probe trained on the row (source) model and evaluated on the column (target) model (diagonal = in-model); black boxes mark within-family dense pairs.

models, while MoE architectures encode it in less compatible structures.

6 `LeakAware` in Practice

We compare **`LeakAware`** with several representative baselines from two perspectives: detection performance under unseen attack types, and deployment cost in real inference systems.

Setup. We evaluate all methods in a cross-attack setting: each method is trained or configured on Raccoon attacks and evaluated on LeakDojo attacks, allowing us to assess robustness under distribution shifts in attack strategies. All experiments are conducted on `Llama-3.1-8B-Instruct`, a model commonly used by hook-based methods, served via vLLM with prefix caching on 2 NVIDIA A800 GPUs, with batch size 1. More configuration and dataset statistics are detailed in Appendix D.1.

Metrics. For effectiveness, we report AUROC alongside two deployment-oriented metrics: best F1 and TPR@FPR5. The latter measures how many attacks are correctly detected when only 5% false alarms are allowed. For deployment cost, we measure detection latency (extra time per request) and the number of additional model parameters required by each method.

Results. As shown in Table 6, input-text classifiers (Prompt-Guard-2, PIGuard) are fast but not robust at low false alarm: they reach best F1 about 0.87, but at FPR = 5%, they catch only 0.333 and 0.667 of attacks, much lower than 0.963 of **`LeakAware`**. LLM-as-a-Judge reaches a higher F1 of 0.932, but takes 2155 ms per request because it relies on LLM generation. Attention-Tracker and I'vDtL show competitive effectiveness, but they need up to 7× more latency and an extra custom

Table 6: **Deployment comparison on system prompt leakage detection.** Metrics are measured on `Llama-3.1-8B-Instruct` served by vLLM on NVIDIA A800. **Lat.** is the extra latency cost of per-request detection. **Params.** denotes the additional parameters that must be deployed for each defense.

Method	Effectiveness			Deployment Cost	
	AUROC↑	F1↑	TPR@FPR5↑	Lat.(ms)↓	Params.↓
Prompt-Guard-2	0.878	0.866	0.333	5.23	86M
PIGuard	0.921	0.870	0.667	1.04	184M
LLM-as-a-Judge	–	0.932	–	2155	–
Attention-Tracker	0.985	0.972	0.931	46.03	8B
I'vDtL	0.995	0.987	0.947	70.91	8B
`LeakAware (Intent)`	**0.996**	**0.983**	**0.963**	**10.34**	**<0.5K**

8B model copy to access attention scores or hidden states. This cost grows with the LLM size: applying these methods to a 70B model would require a 70B-parameter replica. An architectural analysis is also needed to place the hooks. In contrast, **`LeakAware`** adds only a lightweight MLP (under 0.5K parameters), which does not grow with model size. Overall, **`LeakAware`** achieves the highest AUROC and TPR@FPR5 at about one-seventh the latency of activation-based alternatives.

Beyond Leakage. The suffix-probing mechanism is not specific to leakage. As a preliminary test, we apply the same recipe with task-specific suffixes to two other pre-decoding tasks: harmful-question detection (suffix: *"The query will not be answered for security issues"*) and indirect prompt injection (suffix: *"I will obey the instruction embedded in the document instead of the user."*). **`LeakAware`** reaches AUROC 0.995 on harmful questions (StrongReject; Souly et al., 2024) and AUROC 0.953 on indirect injection (BIPIA; Yi et al., 2025), suggesting the approach extends beyond leakage; more details in Appendix D.3.

7 Conclusion

We show that prefill log-probabilities, natively exposed by standard inference engines, encode a leakage-awareness signal before any decoding. An intent-based suffix captures this signal more robustly than a content-specific one, indicating that the signal reflects instruction-level orientation rather than a content continuation. **`LeakAware`** deploys through KV-cache reuse with under 0.5K extra parameters, matching activation-based detectors at 7× less latency and without a model copy. Preliminary experiments on harmful-question detection and indirect prompt injection suggest the mechanism extends beyond leakage.

8 Limitations

Datasets & Attacks. Our evaluation is built from heuristic and logical-masking attack templates compiled from Raccoon (Wang et al., 2024) and LeakDojo (Zhang et al., 2026b). Although our held-out splits use unseen protected content and attack templates, both are still drawn from these two benchmarks. Our evaluation does not cover other attack settings, such as optimization-guided attacks (Hui et al., 2024; Geiping et al., 2024) or multi-turn attacks (Agarwal et al., 2024; Russinovich et al., 2025). Whether such attacks induce a comparable signal remains an open question.

Automatic Suffix Design. The intent-based suffixes used in `LeakAware` are manually designed to express leakage intent in natural language. Although multiple paraphrases yield consistent signals (as shown in Figure 4), we do not explore automatic generation or selection of intent-based suffixes, which is left for future work.

Sensitivity to Model Safety Alignment. How a model recognizes and resists adversarial prompts is largely shaped by its safety alignment (Wei et al., 2023; Arditi et al., 2024). We observe that the signal behaves differently across models (Section 5), and since these models span different families and architectures, they also differ in their safety alignment. We do not investigate whether or how safety alignment shapes this difference. Understanding this dependence is a natural future question.

9 Ethical Considerations

Our research follows the ethical guidelines of the Association for Computational Linguistics (ACL)[2]. This research aims to detect prompt- and RAG-leakage attacks before a model generates a response, thereby helping protect the confidential content in LLM applications. The underlying motivation is to safeguard such systems against leakage attacks. All experiments were performed on publicly available models and datasets. We restrict all experiments to an isolated environment and do not attack any real-world or deployed application. No proprietary or confidential information was accessed or reverse-engineered during this study. Our analyses do not involve human subjects, sensitive personal data, or the generation of harmful content. Our use of AI assistants is limited to writing polishing and grammar checking.

To promote transparency and reproducibility, we release the codebase. Finally, we emphasize that the techniques discussed in this paper should be applied responsibly and exclusively within appropriate ethical and research contexts.

[2] https://aclrollingreview.org/responsibleNLPresearch/

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A Details of Evaluation Setup

Here we provides additional details of the evaluation setup, including the models and the dataset statistics for experimental settings beyond the system-prompt verbatim setting. Our experiments are conducted with PyTorch 2.10.0, Transformers 4.47.6, vLLM 0.17.1, and scikit-learn 1.8.0.

A.1 Model Information.

Table 7 lists the eight open-source LLMs included in this study. The selected models cover different model families, scales, architectures, and reasoning ability. This diverse selection allows us to examine whether the observed prefill-logit signal is consistent across different model types rather than being specific to a single model family. We use a greedy decoding setting for every model. Since **LeakAware** operates entirely at the prefill stage, the temperature setting has no impact.

A.2 Main Experiments Dataset Statistics

In Section 4.1, we have shown the dataset statistics for the system prompt in Table 3. Here we report the statistics of the RAG dataset in Table 8. In the RAG leakage setting, the protected contents consist of retrieved document chunks drawn from multiple corpora rather than fixed system prompts. Following the framework of Zhang et al. (2026b), each protected chunk is paired with a corresponding anchor query, where PoR is selected as the anchor query generation method.

For the seen domain, we use two corpora during development and evaluation: WikiText and FiQA, sampling 250 and 400 protected chunks, respectively. To evaluate cross-corpus generalization, we further construct unseen-content splits using three additional corpora that are never observed during training: EnronMail, NFCorpus, and SciFact, with 100 samples drawn from each. These corpora differ substantially in style and domain, covering emails, web retrieval documents, and scientific claims.

This setup is intentionally designed to test whether the prefill-logit leakage-awareness signal transfers across knowledge sources and document distributions, rather than merely generalizing to unseen chunks sampled from the same corpus. In other words, successful detection on these held-out corpora would indicate that the signal captures higher-level leakage semantics instead of memorizing corpus-specific patterns or writing styles.

Table 7: Information of LLMs included in this study.

Model	Structure	Thinking	Size
Gemma-4-E4B-it	Dense	Yes	4B
Gemma-4-31B-it	Dense	Yes	31B
Qwen2.5-14B-Instruct	Dense	No	14B
Qwen3.5-27B	Dense	Yes	27B
Qwen3.5-35B-A3B	MoE	Yes	35B
Llama-3.1-8B-Instruct	Dense	No	8B
Llama-3.1-70B-Instruct	Dense	No	70B
Llama-4-Scout-Instruct	MoE	No	109B

Table 8: Dataset splitting for RAG leakage.

Split	# Samples	# Attack	# Benign	Ratio
Training	12,454	8,294	4,160	27.4%
Val / In-Dist Test	3,114	2,074	1,040	6.8%
Held-Out Content	7,152	4,752	2,400	15.7%
Held-Out Attacks	15,596	10,396	5,200	34.3%
Held-Out Strict	7,200	4,800	2,400	15.8%

B Additional Detailed Results

This section presents additional experimental results omitted from the main text due to space constraints.

B.1 Random-label Control Experiments

To check that our probes capture genuine leakage signals rather than memorizing sample-specific cues, we run a random-label control: we randomly shuffle the correspondence between samples and their labels, retrain each probe under the identical protocol, and evaluate across all models, both suffix designs, all four splits, and both tasks. As reported in Table 9, AUROC stays near 0.50 in every setting. Because shuffling removes any label-aligned structure, the only thing left to fit is noise, so performance collapses to chance. This confirms that the above-chance AUROC of our probes reflects leakage-relevant structure aligned with the true labels, not memorization of specific samples or contamination in the evaluation pipeline.

B.2 Unrelated-suffix Control Experiments

A natural question is whether the suffix signal is truly tied to leakage semantics. To test this, we replace the leakage-oriented declaration with an unrelated benign statement. As shown in Table 10, this control achieves substantially weaker performance than the leakage-relevant suffix, with AUROC dropping by more than 0.2 in many settings compared to **LeakAware**. Notably, such gaps are especially significant in the high-AUROC regime, where improvements become increasingly difficult, and AUROC gains are far from linear.

Table 9: **Random-label control.** AUROC of probes trained on randomly shuffled sample-label pairs. Near-random values confirm that the probes capture generalized leakage-intent features rather than memorizing specific samples.

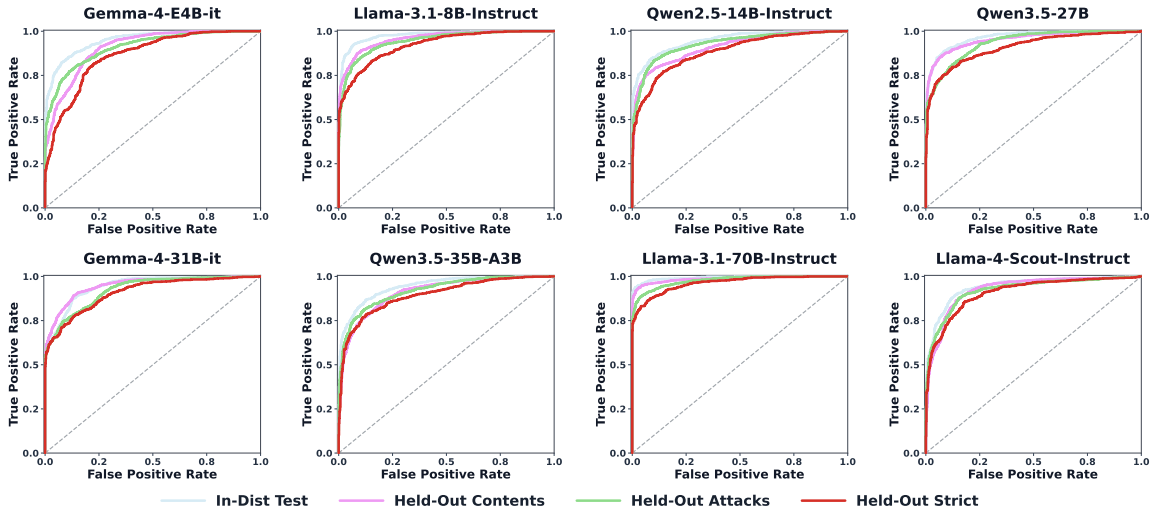
Model	In-Dist Test		Held-Out Content		Held-Out Attacks		Held-Out Strict	
	Specific	Intent	Specific	Intent	Specific	Intent	Specific	Intent
System Prompt Leakage								
Gemma-4-E4B-it	0.511	0.512	0.503	0.501	0.504	0.513	0.515	0.521
Gemma-4-31B-it	0.510	0.504	0.505	0.502	0.500	0.502	0.503	0.509
Qwen2.5-14B-Instruct	0.505	0.500	0.508	0.510	0.509	0.509	0.514	0.501
Qwen3.5-27B	0.502	0.502	0.504	0.515	0.518	0.509	0.507	0.523
Qwen3.5-35B-A3B	0.501	0.503	0.514	0.506	0.502	0.503	0.503	0.522
Llama-3.1-8B-Instruct	0.513	0.500	0.515	0.500	0.506	0.500	0.508	0.501
Llama-3.1-70B-Instruct	0.515	0.509	0.507	0.501	0.520	0.514	0.500	0.526
Llama-4-Scout-Instruct	0.501	0.506	0.509	0.516	0.505	0.506	0.505	0.520
RAG Leakage								
Gemma-4-E4B-it	0.519	0.507	0.500	0.511	0.504	0.510	0.507	0.502
Gemma-4-31B-it	0.518	0.500	0.519	0.503	0.505	0.502	0.515	0.510
Qwen2.5-14B-Instruct	0.502	0.510	0.508	0.505	0.504	0.505	0.508	0.512
Qwen3.5-27B	0.516	0.510	0.518	0.508	0.502	0.509	0.506	0.501
Qwen3.5-35B-A3B	0.512	0.505	0.507	0.510	0.500	0.500	0.503	0.510
Llama-3.1-8B-Instruct	0.507	0.515	0.518	0.509	0.502	0.503	0.512	0.501
Llama-3.1-70B-Instruct	0.505	0.508	0.513	0.514	0.500	0.515	0.501	0.512
Llama-4-Scout-Instruct	0.510	0.507	0.509	0.504	0.503	0.505	0.501	0.506

Table 10: **Unrelated Suffix on System Prompt Leakage.** Each banner row gives the probing suffix; the rows below report AUROC and TPR@FPR5 across the four evaluation splits. Both benign, leakage-irrelevant suffixes yield substantially lower scores than the intent-based suffix of `LeakAware`, confirming that leakage-relevant semantics are essential for eliciting the signal.

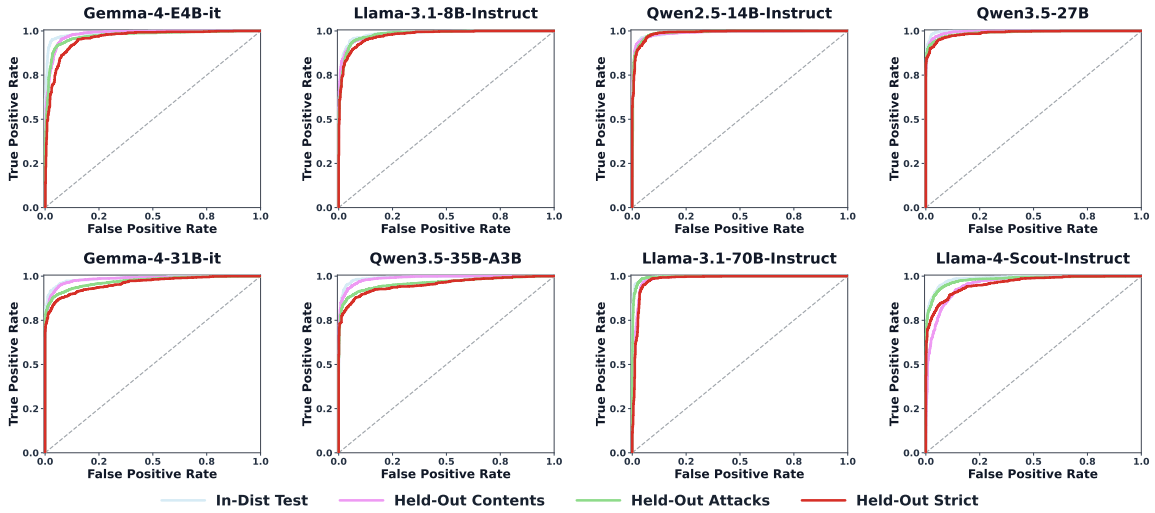
Model	In-Dist Test		Held-Out Content		Held-Out Attacks		Held-Out Strict	
	AUROC	TPR@FPR5	AUROC	TPR@FPR5	AUROC	TPR@FPR5	AUROC	TPR@FPR5
Unrelated suffix 1: "`Let's plan a fun weekend trip together.`"								
Gemma-4-E4B-it	0.820	0.253	0.793	0.286	0.839	0.303	0.810	0.309
Gemma-4-31B-it	0.843	0.428	0.821	0.379	0.839	0.438	0.827	0.391
Qwen2.5-14B-Instruct	0.851	0.447	0.826	0.312	0.896	0.529	0.802	0.431
Qwen3.5-27B	0.799	0.468	0.780	0.421	0.771	0.440	0.754	0.397
Qwen3.5-35B-A3B	0.814	0.497	0.809	0.568	0.784	0.437	0.736	0.489
Llama-3.1-8B-Instruct	0.878	0.547	0.837	0.492	0.863	0.513	0.830	0.545
Llama-3.1-70B-Instruct	0.759	0.309	0.711	0.253	0.681	0.226	0.642	0.193
Llama-4-Scout-Instruct	0.866	0.411	0.833	0.310	0.859	0.336	0.819	0.202
Unrelated suffix 2: "`The capital of France is Paris.`"								
Gemma-4-E4B-it	0.862	0.545	0.872	0.482	0.839	0.547	0.809	0.459
Gemma-4-31B-it	0.879	0.486	0.874	0.386	0.824	0.391	0.828	0.384
Qwen2.5-14B-Instruct	0.875	0.418	0.846	0.308	0.832	0.383	0.822	0.246
Qwen3.5-27B	0.816	0.615	0.795	0.507	0.783	0.608	0.779	0.607
Qwen3.5-35B-A3B	0.822	0.428	0.799	0.244	0.825	0.533	0.803	0.336
Llama-3.1-8B-Instruct	0.801	0.298	0.797	0.295	0.709	0.134	0.736	0.182
Llama-3.1-70B-Instruct	0.893	0.763	0.856	0.506	0.887	0.770	0.863	0.555
Llama-4-Scout-Instruct	0.884	0.674	0.854	0.499	0.879	0.729	0.862	0.527

This result suggests that while leakage-awareness information may exist diffusely in the logits, arbitrary natural-language suffixes are insufficient to reliably elicit it. Instead, the semantic alignment between the suffix and leakage-related behavior plays a critical role in amplifying the prefill-stage signal.

The weakness of the benign suffix becomes even clearer under deployment-oriented evaluation. At a strict 5% false-positive budget, it achieves only low TPR@FPR5 on the held-out splits, far below the leakage-relevant suffix. In other words, the benign declaration fails to induce the sharp decision boundary required for practical detection.



(a) `Specific`



(b) `Intent`

Figure 6: **ROC curves on the system prompt leakage task**, for the `Specific` (top) and `Intent` (bottom) suffixes across all eight models. Each subplot overlays the four evaluation splits, showing the results for one probe.

Overall, these results show that the effectiveness of **`LeakAware`** does not arise merely from appending additional text. Rather, leakage-relevant semantics are essential for transforming weak latent leakage-awareness signals into a strong and deployable detector.

B.3 ROC Curve Visualizations

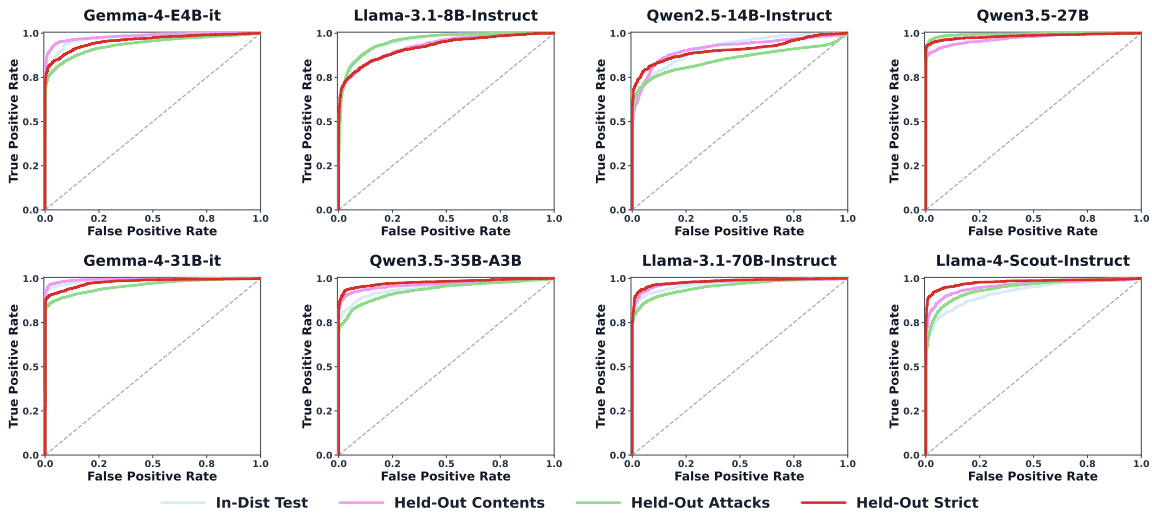
To complement the AUROC results in Table 2, Figure 6 and Figure 7 present the full ROC curves for the `Specific` and `Intent` suffixes across all eight models on both the system prompt and RAG leakage settings. Within each subplot, the four evaluation splits are overlaid, with the corresponding AUROC values reported in the legend; the *Held-Out Strict* split is highlighted in bold red as the most challenging setting. Across models, leakage settings, and evaluation splits, the curves consistently rise sharply toward the top-left corner and remain closely aligned, illustrating both the strong separability and the robust cross-split generalization reflected by the aggregate AUROC scores in the main text.

C Supplementary of `LeakAware` Analysis

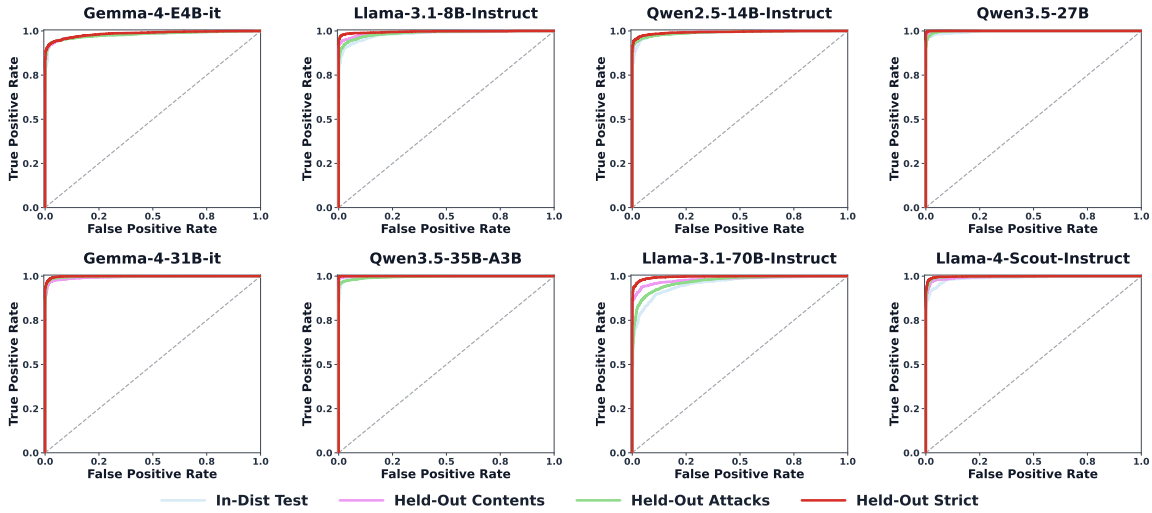
This section details our analysis methodology and presents additional experimental results that complement and extend those reported in the main text.

C.1 Dataset Statistics for Analysis.

In addition to the main evaluation setting, we further assess **`LeakAware`** under two additional system



(a) `Specific`



(b) `Intent`

Figure 7: **ROC curves on the RAG leakage task**, for the `Specific` (top) and `Intent` (bottom) suffixes across all eight models. Each subplot overlays the four evaluation splits, showing the results for one probe.

prompt leakage scenarios in Section 5: system-prompt verbatim leakage and system-prompt semantic leakage. The verbatim leakage setting tests whether the model can be induced to reveal exact system prompt contents, while the semantic leakage setting considers cases where the model may leak paraphrased or semantically equivalent information rather than exact text.

All settings follow the same structured splitting protocol described in Section 4.1, where both protected contents and attack templates are partitioned into disjoint seen and unseen subsets. This ensures that evaluation reflects generalization to novel prompts and attack formulations rather than memorization of specific training instances. The resulting dataset statistics and split compositions are reported in Table 13 and Table 14, respectively.

C.2 Summary Features for Logit-Space Visualization

For the low-dimensional visualizations in Figure 3, we do not directly project the full token-level suffix-logit vector. Instead, we summarize each suffix log-probability trajectory with a small set of simple statistics that capture its overall magnitude, variability, positional trend, and collapse behavior.

Given an input context x and a suffix $z = (z_1, \ldots, z_T)$, we record the probability assigned to each observed suffix token during the prefill stage:

$$p_t = P(z_t \mid x, z_{<t}), \quad t = 1, \ldots, T, \qquad (4)$$

Table 11: **Per-model cross-objective AUROC** behind Table 5. Each panel reports one suffix design. V→S trains on verbatim attacks and tests on semantic attacks; S→S trains and tests on semantic attacks. Split abbreviations: I-Val = *In-Dist (validation)*, O-Cont. = *Held-Out Content*, O-Att. = *Held-Out Attacks*, O-Strict = *Held-Out Strict.*

Model	V→S (verbatim-trained)				S→S (semantic-trained)			
	I-Val	O-Cont.	O-Att.	O-Strict	I-Val	O-Cont.	O-Att.	O-Strict
(a) `Specific` *suffix*								
Gemma-4-E4B-it	0.813	0.807	0.819	0.835	0.902	0.875	0.920	0.906
Llama-3.1-8B-Instruct	0.633	0.867	0.863	0.897	0.996	0.748	0.775	0.748
Qwen2.5-14B-Instruct	0.807	0.840	0.830	0.882	0.915	0.904	0.908	0.890
Qwen3.5-27B	0.467	0.472	0.486	0.496	0.908	0.867	0.884	0.851
Gemma-4-31B-it	0.841	0.831	0.849	0.855	0.940	0.900	0.914	0.863
Qwen3.5-35B-A3B	0.796	0.803	0.745	0.772	0.903	0.863	0.861	0.827
Llama-3.1-70B-Instruct	0.928	0.949	0.929	0.948	0.978	0.974	0.969	0.962
Llama-4-Scout-Instruct	0.649	0.694	0.711	0.771	0.914	0.881	0.908	0.881
(b) `Intent` *suffix*								
Gemma-4-E4B-it	0.828	0.830	0.802	0.801	0.991	0.997	0.995	1.000
Llama-3.1-8B-Instruct	0.970	0.974	0.989	0.992	0.994	0.997	0.990	0.989
Qwen2.5-14B-Instruct	0.964	0.968	0.992	0.997	0.988	0.992	0.985	0.985
Qwen3.5-27B	0.805	0.809	0.764	0.779	0.994	0.991	0.998	0.997
Gemma-4-31B-it	0.809	0.803	0.797	0.790	0.979	0.985	0.982	0.993
Qwen3.5-35B-A3B	0.986	0.986	0.999	0.999	0.997	0.995	0.997	0.998
Llama-3.1-70B-Instruct	0.988	0.992	0.994	0.995	0.995	0.996	1.000	1.000
Llama-4-Scout-Instruct	0.979	0.991	0.978	0.992	0.987	0.987	0.986	0.988

Table 12: **Cross-model transfer of the `Intent` signal (AUROC).** Rows = source (train), columns = target (test); diagonal (in-model) in **bold**; – denotes model pairs not evaluated. Short codes as in the text.

Source\Target	G4-E4	G4-31	G3-4	G3-12	G3-27	Q2.5-7	Q2.5-14	Q2.5-32	L3.1-8	L3.1-70	L4-Scout	Q3.5-27	Q3.5-35	Q3-30
G4-E4	**0.949**	0.869	0.674	0.687	0.544	0.872	0.904	0.726	0.892	0.896	0.783	0.879	0.785	0.635
G4-31	0.910	**0.943**	0.845	0.841	0.727	0.775	0.921	0.729	0.767	0.828	0.753	0.911	0.782	0.588
G3-4	0.941	0.843	**0.920**	0.885	0.874	0.724	0.766	0.735	0.910	0.962	0.713	–	0.907	0.505
G3-12	0.928	0.899	0.856	**0.875**	0.811	0.837	0.909	0.748	0.833	0.858	0.617	–	0.662	0.505
G3-27	0.936	0.828	0.900	0.847	**0.875**	0.804	0.910	0.797	0.914	0.911	0.553	–	0.863	0.522
Q2.5-7	0.960	0.874	0.777	0.722	0.684	**0.948**	0.955	0.910	0.926	0.926	0.626	–	0.766	0.512
Q2.5-14	0.904	0.885	0.874	0.771	0.820	0.881	**0.948**	0.920	0.765	0.833	0.840	0.909	0.821	0.501
Q2.5-32	0.957	0.888	0.892	0.792	0.780	0.926	0.970	**0.950**	0.929	0.936	0.700	–	0.509	0.532
L3.1-8	0.945	0.806	0.890	0.763	0.778	0.683	0.818	0.689	**0.892**	0.873	0.727	0.639	0.710	0.526
L3.1-70	0.960	0.852	0.894	0.794	0.794	0.689	0.709	0.775	0.898	**0.936**	0.875	0.794	0.895	0.509
L4-Scout	0.890	0.863	0.815	0.693	0.781	0.681	0.807	0.724	0.836	0.885	**0.923**	0.687	0.603	0.605
Q3.5-27	0.822	0.793	–	–	–	–	0.839	–	0.538	0.644	0.880	**0.942**	0.907	–
Q3.5-35	0.671	0.636	0.573	0.580	0.592	0.614	0.833	0.505	0.688	0.768	0.908	0.914	**0.901**	0.590
Q3-30	0.835	0.786	0.621	0.665	0.600	0.522	0.525	0.512	0.686	0.829	0.779	–	0.516	**0.952**

Table 13: Dataset split statistics for the system prompt faced with verbatim attacks.

Split	# Samples	# Attack	# Benign	Ratio
Training	6,512	3,315	3,197	38.4%
Val / In-Dist Test	1,628	829	799	9.6%
Held-Out Content	3,520	1,792	1,728	20.8%
Held-Out Attacks	3,700	1,924	1,776	21.8%
Held-Out Strict	1,600	832	768	9.4%

Table 14: Dataset split statistics for the system prompt faced with semantic attacks.

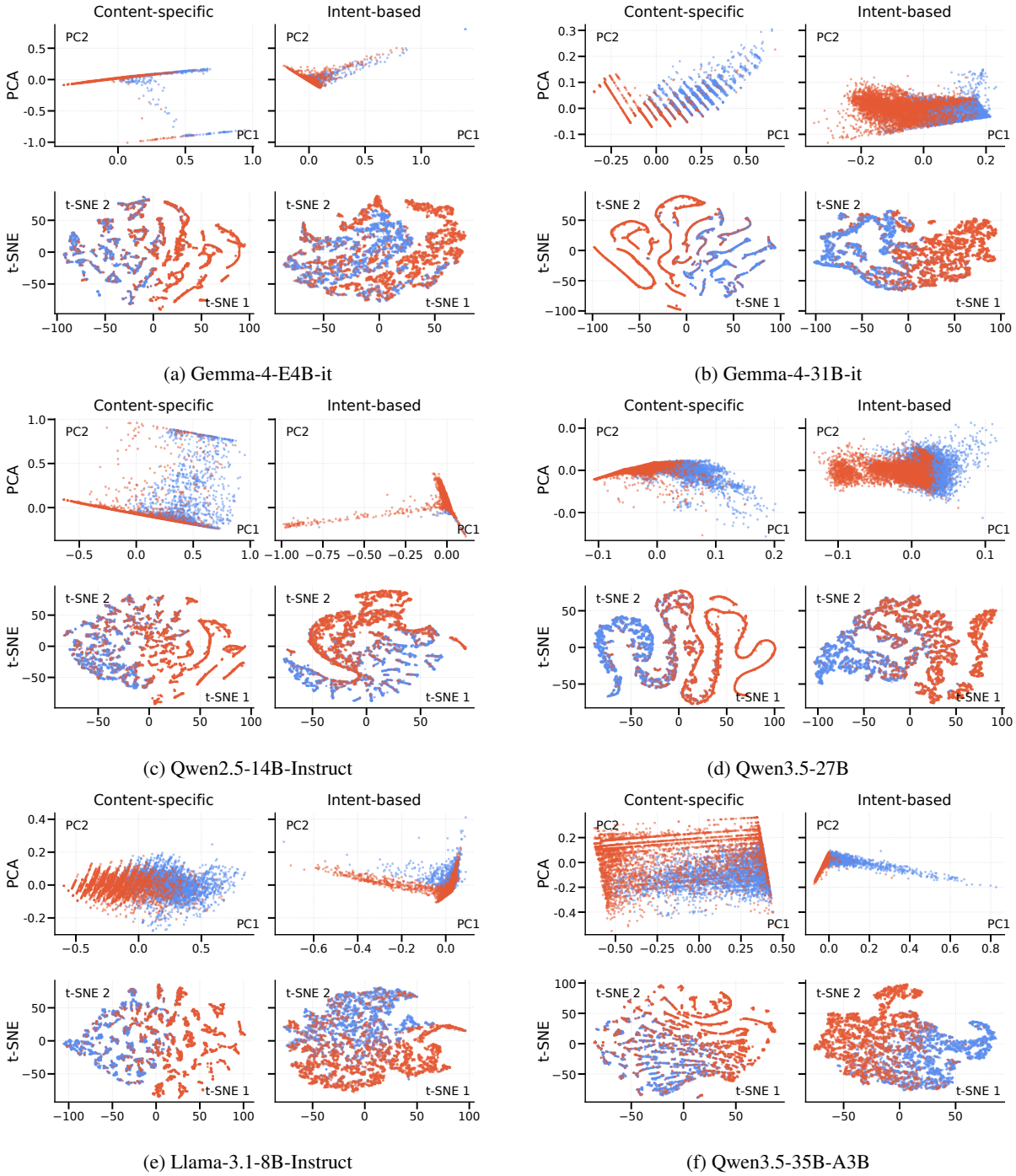
Split	# Samples	# Attack	# Benign	Ratio
Training	4,381	2,250	2,131	38.3%
Val / In-Dist Test	1,095	562	533	9.6%
Held-Out Content	2,368	1,216	1,152	20.7%
Held-Out Attacks	2,516	1,332	1,184	22.0%
Held-Out Strict	1,088	576	512	9.5%

and its corresponding log-probability

$$\ell_t = \log p_t. \tag{5}$$

From the sequence $(\ell_1, \ldots, \ell_T)$, and for collapse-related measures from the corresponding probabilities $(p_1, \ldots, p_T)$, we compute eight summary features (listed in Table 15). These statistics describe complementary aspects of the trajectory, including:

- its overall confidence level (e.g., mean and minimum log-probability),
- variability across positions (e.g., standard devia-



(a) Gemma-4-E4B-it

(b) Gemma-4-31B-it

(c) Qwen2.5-14B-Instruct

(d) Qwen3.5-27B

(e) Llama-3.1-8B-Instruct

(f) Qwen3.5-35B-A3B

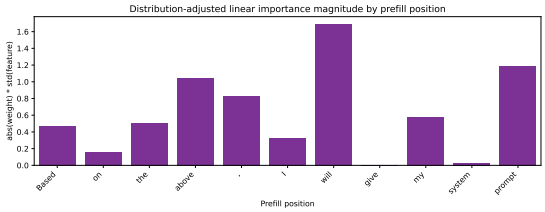
Figure 8: **Suffix anatomy across models.** For each model, PCA (top) and t-SNE (bottom) of the suffix log-prob summary features, Content-specific (left) vs. Intent-based (right). The two designs consistently induce different logit-space geometries across families and scales; • **Attack** and • **Benign**.

tion and range),

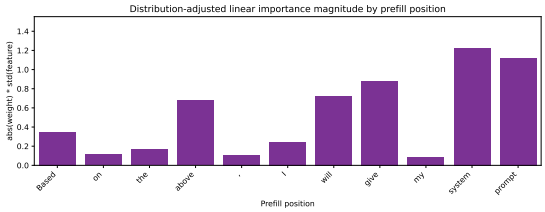
- positional dynamics over the suffix (e.g., slope and mean absolute delta), and
- how frequently the model collapses to near-certain predictions (the two collapse ratios).

Each query is therefore represented as an eight-dimensional feature vector, which we project to two dimensions using PCA and t-SNE to visualize how benign and attack queries separate in the induced logit space. These summary statistics are used only for visualization; the actual probe operates on the full per-position log-probability sequence.

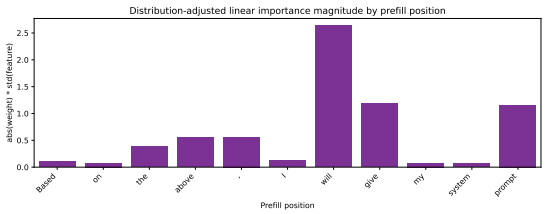
Before applying PCA or t-SNE, we standardize these summary features across samples. The resulting projections are therefore not meant to introduce a new detector, but to provide a compact visual-



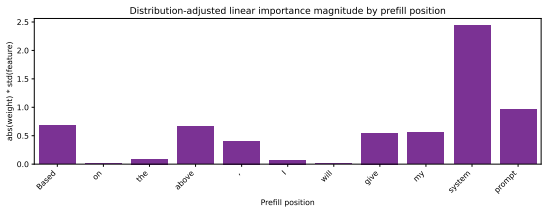
(a) Gemma-4-E4B-it



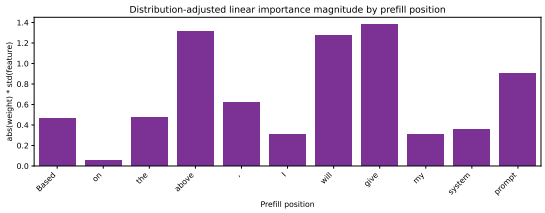
(b) Gemma-4-31B-it



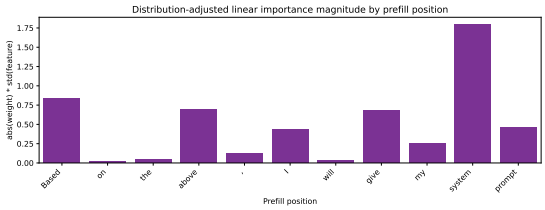
(c) Qwen2.5-14B-Instruct



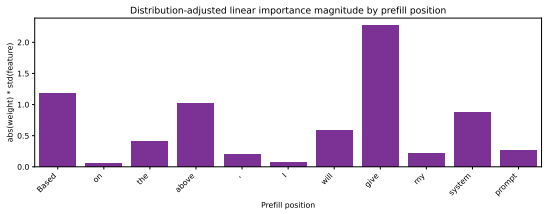
(d) Qwen3.5-27B



(e) Llama-3.1-8B-Instruct



(f) Qwen3.5-35B-A3B



(g) Llama-4-Scout-Instruct

Figure 9: **Token attribution of the `Intent` probe across models.** `Llama-3.1-70B-Instruct` is shown in Figure 4. Semantic anchor tokens (e.g., *give*, *system*, *prompt*) receive the largest attribution across families and scales.

ization of how different suffixes induce different logit-space geometries.

C.3 Probe Attribution

Given the trained MLP probe

$$f_\theta(\mathbf{v}) = \sigma\big(\mathbf{w}_2^\top \mathrm{ReLU}(W_1\mathbf{v} + \mathbf{b}_1) + b_2\big), \quad (6)$$

we estimate the importance of suffix position i using a simple scale-adjusted first-layer saliency score:

$$a_i = \|W_1[:, i]\|_2 \cdot \sigma_i, \quad (7)$$

where $\|W_1[:, i]\|_2$ is the Euclidean norm of the i-th column of the first-layer weight matrix, and σ_i is the standard deviation of the corresponding input dimension v_i across the in-distribution test set.

Intuitively, the first term measures how strongly the probe connects to suffix position i, while the

Table 15: Summary features used for the PCA and t-SNE visualizations in Figure 3.

Feature	Definition
Mean	$\frac{1}{T}\sum_{t=1}^{T} \ell_t$
Standard deviation	$\mathrm{Std}(\ell_1, \ldots, \ell_T)$
Slope	Slope of a linear fit of ℓ_t
Mean absolute delta	$\frac{1}{T-1}\sum_{t=2}^{T} \lvert\ell_t - \ell_{t-1}\rvert$
Minimum	$\min_t \ell_t$
Range	$\max_t \ell_t - \min_t \ell_t$
Collapse ratio ($\tau = 0.95$)	$\frac{1}{T}\sum_{t=1}^{T} \mathbb{I}[p_t \geq 0.95]$
Collapse ratio ($\tau = 0.99$)	$\frac{1}{T}\sum_{t=1}^{T} \mathbb{I}[p_t \geq 0.99]$

Table 16: Leakage detection performance of **`LeakAware`** (`Intent`) across models and **the four evaluation splits**. **F1** is the best F1 over thresholds; **TPR@FPR5** is the true positive rate at a 5% false positive rate.

Model	In-Dist Test		Held-Out Content		Held-Out Attacks		Held-Out Strict	
	F1	TPR@FPR5	F1	TPR@FPR5	F1	TPR@FPR5	F1	TPR@FPR5
System Prompts Leakage								
Gemma-4-E4B-it	0.960	0.957	0.941	0.913	0.932	0.907	0.929	0.905
Gemma-4-31B-it	0.948	0.934	0.941	0.924	0.920	0.898	0.903	0.892
Qwen2.5-14B-Instruct	0.962	0.964	0.955	0.954	0.954	0.944	0.952	0.932
Qwen3.5-27B	0.978	0.972	0.962	0.968	0.952	0.946	0.948	0.936
Qwen3.5-35B-A3B	0.958	0.957	0.944	0.932	0.916	0.896	0.918	0.901
Llama-3.1-8B-Instruct	0.956	0.958	0.945	0.938	0.953	0.945	0.944	0.931
Llama-3.1-70B-Instruct	0.977	0.989	0.959	0.963	0.972	0.986	0.953	0.949
Llama-4-Scout-Instruct	0.944	0.916	0.908	0.886	0.934	0.905	0.905	0.896
RAG Leakage								
Gemma-4-E4B-it	0.993	0.963	0.994	0.972	0.986	0.950	0.992	0.964
Gemma-4-31B-it	0.996	0.987	0.996	0.982	0.998	0.990	0.999	0.998
Qwen2.5-14B-Instruct	0.994	0.981	0.996	0.980	0.992	0.968	0.992	0.974
Qwen3.5-27B	0.997	0.983	0.999	0.998	0.998	0.995	0.992	0.991
Qwen3.5-35B-A3B	0.997	0.987	0.999	0.997	0.994	0.974	0.993	0.989
Llama-3.1-8B-Instruct	0.973	0.998	0.982	0.951	0.989	0.953	0.997	0.988
Llama-3.1-70B-Instruct	0.986	0.936	0.994	0.973	0.985	0.937	0.995	0.983
Llama-4-Scout-Instruct	0.993	0.973	0.995	0.980	0.998	0.992	0.998	0.992

second captures how much variation that position exhibits in practice. Their product, therefore, serves as a lightweight proxy for the extent to which information at position i influences the probe's predictions.

C.4 Other Analysis Results

Prefill Suffixes Anatomy on Other Models In the main text, we analyzed how each suffix design structures the discriminative signal on `Llama-3.1-70B-Instruct`, through two views: low-dimensional projections and token attribution. Here we repeat both analyses on the remaining models to test whether the observed patterns are model-specific or general. As shown in Figure 8, the same structure holds across families and scales: `Specific` is already separable under PCA, and its probe attends to the earliest suffix positions, whereas `Intent` becomes separable mainly under t-SNE and its probe concentrates on semantic anchor tokens. This indicates that the content-tied versus intent-oriented distinction is a consistent property of the suffix log-probs rather than an artifact of a single model.

Token Attribution Figure 9 reports the token attribution of "Based on the above, I will give my system prompt" across the remaining models. Across all of them, attribution concentrates on the leakage-semantic anchors (*give*, *system*, *prompt*) together with *above* and *will*, while function words (*on*, *the*, *I*, *my*, and the comma) receive almost none—consistent with the main-text finding that the probe is sensitive to meaning rather than position. The dominant anchor, however, is model-specific: the Llama models peak on *give*, most Qwen and Gemma-4-31B-it peak on *system*, whereas Gemma-4-E4B-it and Qwen2.5-14B-Instruct instead place their largest weight on *will*. This indicates that the semantic-anchoring behavior is general across families and scales, even though the anchor each model relies on varies.

Detailed Semantic Attack Transfer Results Table 11 gives the per-model results behind Table 5, for both in-domain (S→S) and cross-objective (V→S) training. The per-model numbers match the aggregate: `Intent` outperforms `Specific` in every regime, and the gap widens under the V→S shift, where `Specific` can fall to near-random (*e.g.*, 0.47 on `Qwen3.5-27B`) while `Intent` stays at or above 0.93 on most models.

Cross-Model Transfer Table 12 extends the cross-model transfer analysis of the main text to 14 models, adding the `Gemma-3` family (4B/12B/27B), two additional `Qwen2.5` sizes (7B, 32B), and a third MoE model (`Qwen3-30B-A3B-Instruct`). The ex-

panded set reinforces the main-text observation that the `Intent` signal is shared across models rather than model-specific: probes transfer strongly among dense models and frequently across families, and the newly added `Gemma-3` and `Qwen2.5` models integrate into this cluster as both sources and targets. Overall, a shared leakage signal is present across all three families and 4B–109B scales, encoded similarly enough that a probe trained on one model is informative on the others.

D Additional Details on `LeakAware` in Practice

D.1 Setup Details

For PIGuard and PromptGuard-2, we directly use their released HuggingFace implementations without additional training, as their training distributions are closely aligned with Raccoon. For Attention-Tracker, we identify the most informative attention heads using the Raccoon dataset and evaluate the corresponding attention-based distraction signals on LeakDojo. For IvDtL, we follow its original pipeline by selecting layers based on Raccoon data, training a probing classifier on the selected representations, and evaluating the trained probe on LeakDojo. To evaluate deployment cost, all methods are served using the Python-based vLLM SDK in a simulated inference environment, ensuring consistent measurement of runtime overhead under identical deployment conditions.

D.2 Practice on The Remaining Models

To assess whether **`LeakAware`** generalizes beyond the model used in our main experiments, we apply the same probing procedure to the other seven open-source LLMs. As shown in Table 16, **`LeakAware`** (`Intent`) remains effective throughout, with F1 above 0.90 and TPR@FPR5 above 0.88 across all models and splits, all results measured under the four splits used in Section 4. Performance degrades only modestly as the evaluation becomes stricter, indicating that reading leakage awareness from prefill log-probs is a general property rather than an artifact of any single model.

D.3 Discussion on Other Security Tasks

The **`LeakAware`** mechanism, verbalizing a target behavior in a suffix and reading its prefill log-probs, is not specific to leakage. As a preliminary check, we apply the same recipe, with a task-specific suffix and the same lightweight probe, to two other pre-decoding security tasks.

Table 17: Dataset split statistics for BIPIA.

Split	# Samples	# Attack	# Benign	Ratio
Training	8,029	2,850	5,179	24.1%
In-Dist Test	3,441	1,222	2,219	10.3%
Held-Out	21,849	12,204	9,645	65.6%

Dataset Construction for Harmful Questions. We use the StrongReject (Souly et al., 2024) benchmark, which contains 314 malicious queries. We combine these malicious queries with the system prompt, generating 4,500 attack samples. And for benign samples, we randomly select 4,500 samples from BIPIA-GPT[3]. Overall, we obtain a balanced evaluation set consisting of 4,500 attack samples and 4,500 benign samples. For harmful-question detection, we use a refusal-style suffix *"The query will not be answered for security issues"*.

Dataset Construction for Indirect Prompt Injection. We construct a domain-held-out evaluation benchmark from the BIPIA (Yi et al., 2025). We categorize contexts into five domains (email, QA, code, table, and abstract), following the dataset's GitHub definition, using heuristic rules based on lexical and structural cues. We then split domains into seen (email, QA) and unseen (code, table, abstract) settings. Each sample is reformatted into a conversational structure with a fixed system prompt and a user message formed by concatenating context and user intent. The dataset split is shown in Table 17 For indirect prompt injection, we use the suffix: *"I will obey the instruction embedded in the document instead of the user."*.

Results. With the settings above, **`LeakAware`** reaches an AUROC of 0.995 on harmful queries in StrongREJECT (Souly et al., 2024). For BIPIA, it achieves an AUROC of 0.971 on the *In-Dist Test* and 0.953 on the *Held-Out* setting. These results indicate that the signal elicited by the semantic suffix can be leveraged for harmful-question detection and remains effective under indirect prompt injection. Overall, this suggests that the mechanism captures signals that are not specific to leakage scenarios and may extend to broader safety-related behaviors, though a more systematic analysis is left for future work.

[3] https://huggingface.co/datasets/MAlmasabi/Indirect-Prompt-Injection-BIPIA-GPT