PRIVACY-PRESERVING MECHANISMS ENABLE CHEAP VERIFIABLE INFERENCE OF LLMS

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ABSTRACT

As large language models (LLMs) continue to grow in size, fewer users are able to host and run models locally. This has led to increased use of third-party hosting services. However, in this setting, there is a lack of guarantees on the computation performed by the inference provider. For example, a dishonest provider may replace an expensive large model with a cheaper-to-run weaker model and return the results from the weaker model to the user. Existing tools to verify inference typically rely on methods from cryptography such as zero-knowledge proofs (ZKPs), but these add significant computational overhead, and remain infeasible for use for large models. In this work, we develop a new insight – that given a method for performing *private* LLM inference, one can obtain forms of *verified* inference at marginal extra cost. Specifically, we propose three new protocols, each of which leverage privacy-preserving LLM inference in order to provide different guarantees over the inference that was carried out. Our approaches are cheap, requiring the addition of a few extra tokens of computation, and have little to no downstream impact. As the fastest privacy-preserving inference methods are typically faster than ZK methods, the proposed protocols also improve verification runtime. Our work provides novel insights into the connections between privacy and verifiability in LLM inference.

1 INTRODUCTION

Large language models (LLMs) have increased significantly in size over the last few years. Recent models achieving cutting-edge performance (DeepSeek-AI et al., 2025; Qwen et al., 2025; Team et al., 2025), for example, now often contain hundreds of billions of parameters. The hardware requirements to run these models are often too high for individuals, or even organizations, to run on their own, leading to a significant growth in demand for third-party LLM inference providers. However, this trend raises critical concerns about the integrity and trustworthiness of the services provided, particularly in the growing decentralized inference space. In this setting, any entity with surplus computational resources can offer to complete computational tasks, such as LLM inference, for another user. As the providers in this setting are often not subject to strict vetting, it is imperative to ensure that the service paid for is actually one that is performed by the provider.

Traditionally, the verification of outsourced computation has been addressed through cryptographic methods, such as zero-knowledge proofs (ZKPs). Although offering strong theoretical guarantees, these methods often introduce substantial computational overhead for either the prover (the inference provider) or the verifier (the user), or both. Despite significant progress in recent years, the state-of-the-art for ZK verification of LLM inference remains thousands of times slower than vanilla inference (Sun et al., 2024), rendering it infeasible for large models, which are particularly likely to be in demand for third-party inference provision.

A related concern for third-party compute provision is that of *privacy-preservation*. Performing LLM inference for another party requires the user to share their prompts, resulting in a loss of privacy. Therefore, a seemingly orthogonal line of work in recent years has focused on privacy-preserving computation. These include methods such as secure multi-party computation (SMPC) and fully homomorphic encryption (FHE).

Our work examines the question: **if a privacy mechanism is already in use, can this be leveraged to provide verification of the LLM inference computation as well?** We answer this question

in the affirmative; specifically, we propose three simple but novel protocols, 'logit fingerprinting', 'logit fingerprinting with noise', and 'key appending', that use privacy to obtain differing levels of verification guarantees. We examine the costs and security properties of each of these protocols. Although our protocols have limitations and do not offer identical guarantees to those of ZK, we show that they are robust to many varieties of attacks. Moreover, we demonstrate that our 'logit fingerprinting with noise' protocol run with an SMPC method, SIGMA (Gupta et al., 2023), is $\sim 15\times$ faster than the state-of-the-art ZK method for proof of LLM inference on a single forward pass of Llama-2-7B (Touvron et al., 2023). We further hope that connecting privacy and verification for LLM inference will spur the creation of improved protocols and further research in this area.

2 Background & Related Work

Privacy-preserving inference. There are four main families of privacy-preserving LLM inference methods that have been proposed in the literature: SMPC (Secure Multi-Party Computation), FHE (Fully Homomorphic Encryption), TEEs (Trusted Execution Environments), and statistical methods. SMPC and FHE are general privacy-preserving computation methods which provide strong guarantees on computational indistinguishability of the inputs. Both methods add significant overhead to plaintext computation; for SMPC, a large component of this is communication between the multiple parties involved. Recently, both SMPC (Huang et al., 2022; Hao et al., 2022; Pang et al., 2023; Akimoto et al., 2023; Dong et al., 2023; Li et al., 2023) and FHE (Moon et al., 2024; Zhang et al., 2024) have been applied to LLM inference. Our protocols are agnostic to the exact method used, though differing attacks are possible with each choice of privacy mechanism. For a more detailed account of these methods, see Section A.1.

Verifiable inference. Zero-knowledge proofs (ZKPs) are a class of methods that allows one party, the prover, to prove to another party, the verifier, that a staement is true, without revealing any additional information beyond the proof itself. ZK methods have recently been applied to proving LLM inference, such as in Sun et al. (2024); Qu et al. (2025). However, these approaches have significant overhead, and remain thousands of times slower than vanilla inference. By contrast, recent work has introduced 'statistical' methods for verifiable LLM inference, where the guarantees are relaxed in order to reduce the overhead added. For a more detailed account of these methods, see Section A.2.

Connections between privacy and verification. The connection between privacy and verification has not been extensively studied previously. Perhaps the closest work is MPC-in-the-Head (Ishai et al., 2007), which introduced a zero-knowledge verification protocol by utilizing any SMPC protocol. The protocol comes with steep costs for both the prover and verifier. For example, the prover must not only locally simulate every party in the underlying MPC execution but also repeat the computation multiple times. On the verifier's end, the party must perform several confirmation tasks, including recomputing opened views, consistency checks, and typically engage in multiple rounds of checking to achieve acceptable soundness. The crucial distinction of our suggested protocols to MPC-in-the-Head is that we use the privacy scheme *directly* to encode inexpensive secrets that are easily verifiable. To the best of our knowledge, there has not previously been any work that specifically examines the relationship between privacy-preserving LLM inference and verifiable inference of LLMs in this way.

3 Threat Model

We consider a setting with two primary roles: the **user**, who also acts as the verifier, and an **inference provider**, who also acts as the prover. The user wishes to run inference with a model M on their prompts x, but cannot do so themselves due to e.g. lack of computational resources. They therefore request the inference provider to perform inference on x with M. The inference provider is untrusted and may act as an adversary without behavorial constraints; other external adversaries are out of scope. We assume the use of a privacy-preserving mechanism providing computational indistinguishability of the inputs to ensure that the inference provider cannot view x. The model weights are assumed to be public. Our security goal is verifiability – that is, ensuring that the output the inference provider returns to the user can be verified as being the correct forward pass on the requested model on the given privatized prompt.

4 PROTOCOL 1: LOGIT FINGERPRINTING

Our first proposal for obtaining verification cheaply given access to a privacy-preserving method of LLM inference is **logit fingerprinting**. We hypothesize that the logit vector returned by performing a forward pass on any set of tokens on modern LLMs is a highly unique 'fingerprint' of the model. Our proposed protocol leverages this property to provide inference verification as follows:

1. First, the user inserts K *sentinel tokens* into the tokenized prompt, at random positions within the prompt. Call these positions $p_1, p_2, ..., p_K$. These K tokens are taken randomly from a public cache C, consisting of many such length K sequences.
2. Next, the user creates the 2D attention mask to be used by the LLM by taking their desired attention mask (e.g., lower triangular for decoder-only LLMs) and inserting rows and columns as follows.
   - Add a row at p_i that is 0 everywhere except positions $p_j \, \forall \, j \leq i$, where it is set to 1.
   - Add a column at p_i that is 0 everywhere except positions $p_j \, \forall \, j \geq i$, where it is set to 1.
3. The attention mask and augmented tokenized prompt are given to the inference provider under a privacy-preserving scheme, and the inference provider carries out a forward pass, and returns the output logit vector at all token positions to the user.
4. The user verifies that the sentinel token logits match against the precomputed cached logits for that specific model.

The construction of the attention mask is such that the sentinel tokens do not attend to, and are not attended by, any of the original prompt tokens, but they do attend to each other in standard autoregressive fashion. This also ensures that sentinel tokens have no downstream impact on the original prompt when inference is performed. A formal description of this procedure is given in Section B.

4.1 COST ANALYSIS

Inference provider (prover). Excluding the overhead of the private inference scheme, the total number of extra operations is a factor of $\frac{K}{N}$, where N is the length of the original prompt. As we discuss in Section 4.2, K can be set to be as small as 3 and retain strong security properties, so this is very small for reasonably sized N. Furthermore, if the privacy scheme supports parallelized inference, this can result in almost no extra runtime.

User (verifier). The verifier is required to pick a sequence from a public cache and perform a matching on the returned logits against the same cache. The cost of this is minimal and does not require specialized hardware.

Construction of the cache. Constructing the cache entails an initial computational cost and also must be performed by a trusted party, since it underpins the correctness of the protocol. Ideally, this responsibility is delegated to an entity with sufficient computational resources to produce a verifiable proof of correctness, for example, in the form of a zero-knowledge proof. Although the computational expense of this might be significant, the cost is incurred only once and is then amortized across all subsequent inference calls, including potentially all prover-verifier pairs.

4.2 SECURITY ANALYSIS

In this section, we assume that logits are indeed unique fingerprints of models. We perform analysis across a range of models in Section 4.3 to verify this is the case.

In order for the inference provider to not be able to guess the logits to return for the sentinel tokens, the set of sentinel tokens must be randomly chosen from a large set of possibilities. The crux of this protocol is that the inference provider cannot determine which of the possibilities is specifically being asked for in any particular instance due to the privacy mechanism.

Probabilistic attacks. This protocol utilizes two elements of randomization: the choice of the sentinel tokens, and their positions. For the former, if the user selects the sequence uniformly at random from a cache of size $|C|$, then a dishonest inference provider can guess it with probability $1/|C|$. $|C|$ can

therefore be set to desired tolerances. For the latter, under a privacy-preserving mechanism that also preserves tensor structure (such as SMPC), correctly guessing the sentinel tokens' exact positions is sufficient for a successful attack: the inference provider can perform the forward pass on only those components, and return arbitrary values for the other token positions. However, this occurs with probability $\binom{N+K}{K}^{-1}$, where N is the length of the original prompt. When $K = 3$, for example, with $N = 14$, this is less than $1\mathrm{e}{-3}$, and it drops further with increasing $N = 100$ to circa $1\mathrm{e}{-6}$.

A related attack is to perform computation only on a random subset of the token indices. In the most extreme case, a dishonest provider takes $N + K - 1$ tokens, i.e. excludes exactly one token. The probability that all sentinel tokens are still selected (hence successfully passing verification) is $\frac{N}{N+K}$, requiring an infeasibly large K to make secure – although it should be noted that in this case the dishonest provider is saving very little computation over honest behavior.

Approximation attacks. Another line of possible attacks are attempts by the inference provider to use a different model – especially, cheaper-to-run replacements – that still succeed in passing verification. Such alternatives could include smaller models from the same model family or approximations to the models by using e.g. low-rank projections of the weights. We perform experiments to test the robustness of the protocol to each of the above in Section 4.3 and find that verification fails immediately when any of the above are attempted.

4.3 Experiments

Setup. We test the claim from Section 4.2 that pre–softmax logits can serve as model fingerprints. For each model m, we sample $N = 50{,}000$ token sequences of fixed length $K = 3$ from the model's token vocabulary (excluding special tokens). Given a sequence $\mathbf{t} = (t_1, t_2, t_3)$, we run a forward pass and record the next-token *logit vectors* at each position, $\ell_m^{(k)}(\mathbf{t}) \in \mathbb{R}^{V_m}$ for $k \in \{1, 2, 3\}$, where V_m is the vocabulary size of model m. We define the *logit fingerprint*

$$\phi_m(\mathbf{t}) \;=\; \mathrm{concat}\big(\ell_m^{(1)}(\mathbf{t}),\, \ell_m^{(2)}(\mathbf{t}),\, \ell_m^{(3)}(\mathbf{t})\big) \in \mathbb{R}^{3V_m},$$

and compare fingerprints using L1 distance. We test on Llama 3.2 Instruct 1B, 3B, and 8B (Grattafiori et al., 2024), and on Qwen 2.5 Instruct 0.5B, 1.5B, 3B and 7B (Qwen et al., 2025). Comparisons are performed on FP32 logits; dropout is disabled.

4.3.1 Honest Behaviors

Floating point non-determinism. We first provide context on the expected L1 distance due to non-determinism of floating-point operations (Shanmugavelu et al., 2024). This can be constituted as honest behavior; although, it is possible to also require an exact match, which would entail detecting hardware and batched-inference deviations. We run the *same* sequence multiple times with different batch sizes on GPU to measure this. We observe a maximum L1 deviation in doing so across all models tested of 10.90.

4.3.2 Dishonest Behaviors

We now test a wide range of dishonest behaviors and strategies.

Intra-model. Within each model, we compute the nearest-neighbor similarity among fingerprints from *distinct* sequences (i.e. $\mathbf{t} \neq \mathbf{s}$). Across $N = 50$k samples per model, there are no exact matches; the closest pair has an L1 distance of 2909.

Within-family. For the Llama family, the smallest L1 distance of logits we obtain is 329096. For the Qwen family, the minimum cross-model distance is 643719. These results indicate that even with a family of models, the logits are significantly different and suitable as fingerprints.

Cross-family. To enable comparisons across families with different vocabularies, we align dimensions by truncating the larger logit vectors to the smaller vocabulary size (i.e. comparing the first $\min(V_m, V_{m'})$ coordinates). Under this conservative alignment, Llama–Qwen comparisons exhibit substantially higher distances than the within-family maxima reported above (qualitatively, well above 800000).

Low-rank factorization. We approximate the linear layers of Llama 3.2 1B Instruct by replacing each weight matrix $W \in \mathbb{R}^{d_{\text{in}} \times d_{\text{out}}}$ with a rank-r factorization $W \approx UV^\top$, where $U \in \mathbb{R}^{d_{\text{in}} \times r}$ and $V \in$

Model Approximation	Llama	Qwen
Same model, GPU non-determinism	4.08	10.91
Same model, different sequence	2909	68326
Cross-Model, same sequence	329096	643719
Low-rank factorization ($r = 2047$)	833	7223
Low-rank factorization ($r = 2040$)	8029	124195
Low-rank factorization ($r = 2000$)	31194	216765
8-bit Quantization	3499	8746
Single step of finetuning	471	1090

Table 1: L1 distances of logit fingerprints across different experimental settings for the Llama and Qwen families of models. **Honest behavior (GPU non-determinism) is clearly separated from dishonest behavior (all other rows).**

$\mathbb{R}^{d_{\text{out}} \times r}$. The default hidden dimension of this model is 2048, so we test with $r \in \{2047, 2040, 2000\}$. Comparing fingerprints of 50k sequences between the full-rank and the low-rank variants, the minimum L1 distances observed are:

$$r = 2047 : 833.97, \quad r = 2040 : 8029.45, \quad r = 2000 : 31194.02.$$

Similarly, we obtained the following results for Qwen 2.5 3B Instruct:

$$r = 2047 : 7223, \quad r = 2040 : 124195, \quad r = 2000 : 216765.$$

Quantization. We next load Llama 3.2 1B Instruct and Qwen 2.5 3B Instruct in 8-bit precision using `bitsandbytes` and compare fingerprints to the full-precision (bfloat16) baseline. The minimum L1 distance is 3499 for Llama and 8746 for Qwen, again easily separated from the original model.

Fine-tuning. Finally, we evaluate robustness against model fine-tuning by comparing each of Llama 3.2 1B Instruct and Qwen 2.5 3B Instruct with a finetuned variant of each corresponding model on a single sample from FineWeb dataset for a single step. The minimum observed distance is 471 for Llama and 1090 for Qwen, consistent with the previous cases and again easily separable from the original model.

Our results are summarized in Table 1. The minimum L1 distance observed under dishonest behavior is 471, as seen in Llama's finetuning setting, while the maximum deviation with honest behavior due to floating point non-determinism is only 10.90 for Qwen. The significant difference allows for clear identification of honest vs. dishonest behavior; based on these results, we recommend using a matching threshold in the range of 15–20. Sequences whose logits differ by less than this threshold can be confidently regarded as originating from the same model; and even a single step of fine-tuning is easily detectable with this threshold.

4.4 Limitations

The main limitation of this protocol is that it can only be used to verify a single forward pass at a time, i.e. only generate a single new token, before requiring the user to repeat the protocol above with a fresh set of sentinel tokens and positions; otherwise, a dishonest provider could honestly perform the first forward pass (to pass verification) and provide spurious outputs for all subsequent forward passes. Thus, this protocol inherently requires user interaction for every step of token decoding. Another limitation is the vulnerability to the subsetting attack mentioned in Section 4.2. As such, we recommend that this protocol not be used in isolation with privacy mechanisms that retain tensor structure, such as SMPC methods.

5 Protocol 2: Logit Fingerprinting With Noise

The vulnerability of Protocol 1 to a subsetting attack reduces the space of privacy gadgets that it can be used with. Our second proposed protocol is designed to resist this attack. Our modification consists of adding randomly sampled noise to the token embeddings before they are passed into the LLM for the forward pass, and then using a lightweight predictor on the returned final hidden states to predict the noise that was used. Our proposed protocol is as follows:

1. First the user samples noise $b \in \mathbb{R}_e^d$, where d_e is the embedding dimension of the model being used for inference, from a discrete set of possibilities B.
2. The user concatenates the noise to the embedding of the original prompt $e \in \mathbb{R}^{N \times d_e}$ in the d_e dimension, to obtain a tensor $b_e \in \mathbb{R}^{N \times 2d_e}$.
3. The user applies the previously trained *NoiseEmbedder* module on b_e to obtain $e' \in \mathbb{R}^{N \times d_e}$.
4. The user sends privatized e', augmented with K randomly-positioned sentinel tokens as in Protocol 1, to the inference provider.
5. The inference provider performs the forward pass and returns the final hidden states $h \in \mathbb{R}^{(N+K) \times d_h}$, where d_h is the hidden dimension.
6. The user applies the logit-projection to the hidden states at the sentinel token positions, and checks the validity of these logits against the cache, as in Protocol 1.
7. The user applies the previously trained prediction module, the *NoisePredictor*, on h at the non-sentinel positions to obtain estimated $\hat{b}$ at each such position. If each obtained $\hat{b}$ matches the sampled b at that position, *and* the sentinel token logit check passes above, then the user can consider the inference to be verified.

In the above procedure, the sentinel tokens are not modified by the sampled noise, and so can be compared against the cache as in Protocol 1. For the remainder of the tokens, the predicted noise is compared to the sampled noise to verify that the forward pass was indeed carried out on each token position. The complete procedure is formally described in Section C.

5.1 Cost Analysis

Inference provider (prover). The cost to the inference provider is the same in this protocol as in Protocol 1.

User (verifier). In addition to the cost associated with the sentinel tokens, the user must now generate the sampled noise – which requires little computational cost – as well as run the NoiseEmbedder and NoisePredictor.

Construction of the cache. This cost remains the same as in Protocol 1.

Training of NoiseEmbedder and NoisePredictor. The NoiseEmbedder and NoisePredictor modules need to be trained for each different LLM in use. This entails an initial computational cost and also must be performed by a trusted party; however, similarly to the cache construction, this is a one-time cost that is then amortized over all subsequent inference calls on that model.

In Section 5.3, we show that the NoiseEmbedder and NoisePredictor can be simple linear projections, so that the additional cost to the user and the training cost can be made low in practice.

5.2 Security Analysis

We inherit the security analysis of Protocol 1 as it pertains to sentinel tokens – that is, sentinel tokens remain effective markers of the model that was used for the forward pass and are able to detect even very close replacements. For the non-sentinel tokens, the crux of the protocol's security now rests on the predictability of the injected noise.

Let the sample space size be given by $|B|$, and denote the accuracy of the prediction at token position n under honest inference by $\text{acc}_n := P(\hat{b}_n = b_n \mid \text{honest})$.

Honest provider (completeness). If the inference provider is honest, the probability that the user incorrectly rejects the returned computation is given by the probability that there is at least one mismatch in the predicted noise: $P(\text{incorrect rejection}) = 1 - \Pi_{n=1}^{N} \text{acc}_n$.

Dishonest provider (soundness). If the inference provider is dishonest, the probability that the user incorrectly accepts the returned computation is given by the probability that $\hat{b}_n = b_n$ at all token positions n. Due to the privacy-preserving mechanism, the provider cannot know which b_n was used, so the probability that $\hat{b}_n = b_n$ for any particular n is upper bounded by $\frac{1}{|B|}$. In particular, the above

implies that in a leave-one-out subsetting attack as described in Section 4.2, the probability of success is at most $\frac{1}{|B|}$.

5.3 EXPERIMENTS

In this section, we describe a performant and lightweight architecture of the NoiseEmbedder and NoisePredictor; and we demonstrate their performance on Llama-3.2-1B, evaluating on the FineWeb-Edu dataset (Lozhkov et al., 2024).

NoiseEmbedder architecture. This module consists of a learned embedding $E \in \mathbb{R}^{|B| \times d_e}$, and a linear layer that is applied to the concatenation of the learned noise embeddings and the original embedding, and produces a single combined embedding as an output. Therefore the linear layer has a weight matrix: $W \in \mathbb{R}^{2d_e \times d_e}$.

NoisePredictor architecture. This module consists of a linear layer that takes the final hidden layer representations from the forward pass of the LLM and outputs unnormalized logits over the sample space B. Therefore the linear layer has a weight matrix: $W \in \mathbb{R}^{d_h \times |B|}$.

We fine-tune the NoiseEmbedder and NoisePredictor modules **whilst keeping the original model weights frozen**. As we are adding noise to the model embeddings, we train to optimize for both the log-likelihood on the dataset, as well as the classification accuracy of the NoisePredictor, using the cross-entropy loss. Our training objective is therefore given by:

$$\begin{aligned}\mathcal{L}_{\theta,\phi} \;=\; \mathbb{E}_{x,y\sim\mathcal{D}}\, \mathbb{E}_{b\sim B}\Big[-\log f\big(y \mid \text{NoiseEmbedder}_\theta(x,b)\big) \;+ \\ \lambda\, \mathrm{CE}\big(\text{NoisePredictor}_\phi(f(\text{NoiseEmbedder}_\theta(x,b))),\, b\big)\Big]\end{aligned} \tag{1}$$

where x, y are the training data, f is the base model, θ and ϕ are the parameters of the NoiseEmbedder and NoisePredictor respectively, and λ is a hyperparameter to be tuned. In practice, we find best results applying the same sampled noise to every token in the sequence. This does not impact the security analysis of Section 5.2. For further training and hyperparameter details, see Section D.

Results. Despite using a very lightweight NoiseEmbedder and NoisePredictor, and not modifying the original model weights at all, we find that we are able to achieve $\sim 99\%$ classification accuracy with $|B| = 100$ without *any* worsening of the log-loss on the given dataset. In particular, the base model's log-prob is ~ 3.45, and we achieve a held-out evaluation set log-prob of ~ 3.43 after training the modules, with noise injected.

5.4 LIMITATIONS

In comparison with Protocol 1, this protocol is resistant to subset attacks, due to the introduction of noise at each token position. However, this protocol adds extra computational burden to the user – they must now perform additional NoiseEmbedder and NoisePredictor forward passes. Although we have shown that these can be effective even if comprising just a single linear layer each, there may be some cases where even this extra computational requirement cannot be met. Moreover, the user must now also perform projection of the final hidden states to the logits themselves, necessitating another matrix multiplication. There is also now the additional computational requirement of training the modules prior to deployment, in a trust-secured manner. Finally, although we are able to achieve good accuracy rates of 99% with $|B| = 100$, we have neither perfect soundness nor completeness; we hope that future work is capable of improving on the results we present here.

6 PROTOCOL 3: KEY APPENDING

A conceptually distinct proposal for obtaining verification cheaply under privacy assumptions is **key appending**. The high-level idea of this protocol is to ask the LLM to emit a randomly generated key at the end of its normal response – for example, 'strawberry reticent gestalt' – wrapped in a specific tag structure, and to verify at the end of inference that the key was correctly replicated.

User prompt augmentation. Given a user's original prompt p and a randomly sampled key $w_1, w_2, \ldots, w_K$ of K words, p is augmented by appending the following instruction to the end:

> `At the end of your response, repeat this key: <key>` w_1 w_2 $\cdots$ w_K `</key>\nDO NOT print anything else after it.`

Verification. The encrypted response is returned to the user, who decrypts it and parses the contents of the `<key>...</key>` span. Verification succeeds if and only if the extracted string matches the originally sampled key. Using HTML-/XML-like tags facilitates robust parsing and prevents ambiguity in locating the verification key within the model's output.

Further details on system prompt modification and the stopping criterion are given in Section E.

The main benefit of this protocol as compared to Protocols 1 and 2 is that it does not require continual user interaction at every decoding step; it is an entirely non-interactive protocol.

6.1 Cost Analysis

Inference provider (Prover). Adding an extra t tokens to the prompt adds an overhead of a factor of $\frac{t}{N}$ operations (in addition to the system prompt and remaining augmentations, which are of constant length). Given that, for most tokenizers and English words, words are approximately 1–2 tokens in length, and that the protocol offers good security with just $K = 3$ words (see Section E.2), this therefore introduces little extra overhead.

User (Verifier). Similar to the logit fingerprinting protocol, the verifier is required to perform minimal work. They must select a sequence of K words $w_1 w_2 \cdots w_K$ and append them together with the augmentation template to the prompt, as well as prepend the system prompt. When the inference is complete, the verifier checks the words between the `key` tags of the decoded output against the original words $w_1 w_2 \cdots w_K$. Again, no specialized hardware is necessary.

6.2 Security Analysis

Probabilistic Attacks. Suppose that tokenizing the K words results in a total of t tokens. An adversarial party must correctly guess each token exactly out of the total vocabulary, resulting in a success probability of $\frac{1}{|V|^t}$, where $|V|$ is the vocabulary size. As modern LLMs typically have $|V| \geq 1\text{e}5$, with a key length of only 3 tokens, this is already on the order of $1\text{e}{-15}$ or lower.

Approximation Attacks. This protocol is potentially vulnerable to the model approximation attacks as described in Section 4.2, especially if they largely retain the instruction following capabilities of the original model. We perform an in-depth examination of the viability of such in the specific case of use of SMPC for privacy preservation, with one honest party, in Section G. We find that in this setting, any such approximation does fail.

6.3 Experiments

We conduct two tests in this section. First, we test the ability of LLMs to perform the protocol successfully under honest behavior; this is analogous to the cryptographic property of *completeness*. Second, we test the performance impact of running the appending protocol on other downstream tasks. We find that models of large enough size $\geq$ 3B parameters in scale, have nearly perfect key transcription rates. Further, we find minimal performance impact for models of size 8B or larger on downstream tasks. Further details of our results are given in Section E.

6.4 Limitations

The main limitation of this protocol is that it cannot specify exactly the model that is being used; it only guarantees that the model is capable of performing the verification task. In the SMPC setting, if there is at least one honest participant, then we show in Section G that any approximations result in the verification failing. However, in the FHE or TEE setting, this remains a limitation. Furthermore, this protocol does not offer 100% completeness, although we see figures close to this (see Table 3).

7 OUTPERFORMING STATE-OF-THE-ART ZK INFERENCE

We have shown that privacy-preserving mechanisms can enable verified inference. In this section, we describe the performance of privacy-preserving inference and our protocols, compared to the standard approach of zero-knowledge (ZK) proofs of inference. In particular, we focus on secure multi-party computation (SMPC) and fully homomorphic encryption (FHE) schemes for the latter. For a detailed background on these methods, see Section A.1 and Section A.2.

The protocols we proposed in Section 4 and Section 5 are both compatible with FHE privacy schemes. However, state-of-the-art FHE schemes typically have greater overhead than ZK; for example, THOR (Moon et al., 2024) reports approximately 10 minutes for a single forward pass on an input of 128 tokens with BERT-Base (a model with 110M params), with GPU acceleration. By contrast, zkLLM reports just 74s of prover overhead for a forward pass with an input of 2048 tokens on OPT-125M. However, Protocol 2 (Section 5) is designed to resist tensor subset attacks, and is therefore also compatible for use with SMPC schemes. State-of-the-art SMPC schemes operate much faster than FHE.

We perform a direct comparison of our protocol with SMPC to zkLLM. We run zkLLM on Llama-2-7B (Touvron et al., 2023) on sequences of length 125, and measure the total prover time for a single complete forward pass and associated proof generation on a machine with an A6000 GPU. We compare this to the results described in SIGMA (Gupta et al., 2023). SIGMA is a 2-party SMPC scheme that is optimized for GPU acceleration. The authors of that paper report performance on a machine also accelerated with an A6000 GPU. We take the result from Table 5 of that paper indicating a total runtime of Llama-2-7B on SIGMA of 23s for a single forward pass, on sequence lengths of 128 tokens. The extra 3 tokens in the SIGMA setting correspond to the sentinel tokens used in our protocol.

Our results are shown in Table 2. We see that Protocol 2 under SIGMA is approximately $\sim 15\times$ faster than zkLLM.

Method	Time (s)
zkLLM	352
Protocol 2 w/ SIGMA (ours)	23

Table 2: Inference provider runtime for a single forward pass of Llama-2-7B on a prompt with length 125 tokens with state-of-the-art ZK method zkLLM, and with our Protocol 2 with SMPC protocol SIGMA as the privacy-preserving mechanism. SIGMA numbers are taken from Gupta et al. (2023).

Discussion. Our protocol as tested in a like-for-like setting is nearly $15\times$ faster than the state-of-the-art ZK method for proof of LLM inference. However, there are two key differences. First, ZK has fewer security assumptions. Although SMPC guarantees strong computational indistinguishability of its inputs in the non-colluding setting, it is vulnerable when all parties involved are dishonest and collude to pool their secret shares. By contrast, ZK is provably secure regardless of prover behavior assumptions. Second, our protocol still relies on statistical results, such as the accuracy of the NoisePredictor module. Therefore, our inference guarantees are not directly comparable to those produced by ZK methods.

Nevertheless, in settings where non-collusion can be ensured or encouraged, and where statistical guarantees are sufficient, our protocol offers a significant speedup over the state-of-the-art for proof of LLM inference.

8 CONCLUSION

We have introduced three protocols for verifying LLM inference, given the use of privacy-preserving mechanisms. These protocols are cheap for both the prover and the verifier and have little to no downstream impact. Future work may focus on mitigating the limitations of our protocols, for example by (1) boosting efficiency during many-token generation, (2) improving the statistical guarantees, or (3) guaranteeing resistance to attacks. We believe that connecting privacy and verifiability, particularly in LLM inference, will inspire future work on new and improved protocols.

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A Background and Related Work

In this section, we provide a brief background on general methods of privacy-preserving function computation, general methods of verification, and their application to LLM inference in particular.

A.1 Privacy-Preservation

There are four main families of privacy-preserving inference of LLMs that have been proposed in the literature: **SMPC** (Secure Multi-Party Computation), **FHE** (Fully Homomorphic Encryption), **TEEs** (Trusted Execution Environments), and **statistical methods**. Here we provide brief background on each of these.

SMPC SMPC protocols split the required computation among multiple parties. The key ideas were originally developed in the 1980s (Yao, 1982; Goldreich et al., 1987) and provide mathematical guarantees that no single party can reconstruct the data on their own. Recently, the methodologies of SMPC have been applied to LLMs (Huang et al., 2022; Hao et al., 2022; Pang et al., 2023; Akimoto et al., 2023; Dong et al., 2023; Li et al., 2024). A difficulty uniformly faced by these protocols is efficient computation of the many non-linearities present in transformer-based LLMs; most of the works attempt to ameliorate this by using piecewise polynomial approximations which are more well-suited for MPC algorithms. However, this approximation leads to degraded inference results, and remains more expensive than direct computation of the non-linearities. The requirement of multiple parties also engenders significant communication overheads, and the further non-collusion requirement among the parties may be difficult to guarantee.

FHE FHE protocols require only a single party and make use of cryptographic methods to ensure that the result of the computation on the ciphertext is the same as that performed on the plaintext. The adjective 'fully' indicates the capability of performing arbitrary computations, not limited to a particular type or complexity. The first plausible construction of an FHE scheme was described in Gentry (2009); a more modern and widely used incarnation is CKKS (Cheon et al., 2017). Recently, CKKS has been further optimized and applied to LLM inference (Moon et al., 2024; Zhang et al., 2024), but similar issues arise with the non-linearities as SMPC methods. The overheads both for linear and non-linear operations are typically even larger than those in the SMPC setting.

TEEs Trusted Execution Environments (TEEs) (Sabt et al., 2015; Narra et al., 2019) create secure and isolated enclaves at the hardware level. This ensures confidentiality via memory encryption – allowing only the process running in the enclave to read the data. Furthermore, TEEs support integrity via attestation mechanisms. However, a significant concern is the vulnerability to side-channel attacks (Jauernig et al., 2020). Furthermore, attestation is only provided at boot-time and is not equivalent to an ongoing verification process. This process typically involves the TEE measuring the code and its environment, signing these measurements cryptographically, and sending a report for external verification. However, this is often a one-time check at the start and does not guarantee the integrity of the TEE throughout its execution. Finally, in cloud environments, attestation can rely on the cloud provider's services, which means users must trust the provider's proprietary attestation process without full transparency. This introduces a level of trust in the cloud provider's integrity, as these attestation services can be opaque "black boxes" that are not open to external audit. Moreover, there may be no independent way to verify the boot measurements provided by the cloud provider's infrastructure.

Statistical Methods A more broad and diverse grouping than the above is what we term 'statistical methods'. These are protocols without the mathematical guarantees of FHE or SMPC approaches, or the hardware-based guarantees of TEEs, but that instead employ statistical or empirical arguments to support the difficult of reversing ciphertext. Some ideas in this domain include the use of permutation-based security (Zheng et al., 2024; Yuan et al., 2024; Luo et al., 2024) or token-sharding based security (Thomas et al., 2025). These methods typically trade off the stronger guarantees of the above methods for greatly reduced overheads, sometimes approaching similar speeds to vanilla inference.

A.2 Verification

Zero-Knowledge Proofs (ZKP) ZKPs are a class of methods that allows one party (the prover) to prove to another party (the verifier) that a statement is true, without revealing any additional

information beyond the proof itself. The main properties that ZKPs satisfy are completeness (an honest prover can convince a verifier that they performed the work as stated), soundness (a dishonest prover cannot convince a verifier that they performed the work), and the zero-knowledge property of not revealing any further information than the fact the work was done as stated. The first ZK protocol was introduced in 1985 in Goldwasser et al. (1985). Recently, ZK methods have been applied as proofs of inference for machine learning models, and specifically LLMs, in works such as Sun et al. (2024); Qu et al. (2025). However, these approaches remain thousands of times slower than vanilla inference – for example, zkLLM takes 15 minutes for generating a proof of a single forward pass for Llama-2-13B, compared to milliseconds for vanilla inference.

Statistical Methods Analogously to statistical methods of privacy-preservation, very recent work has investigated methods of relaxing the standard of proof of work provided in order to reduce computational overhead. Ong et al. (2025) encodes and validates the most salient features of the last hidden state tensor of an LLM using a compact, verifiable proof, which is then recomputed in parallel by the verifier. Although the authors demonstrate how to set up a commitment scheme that has relatively little overhead to the prover, and verification is faster than full recomputation thanks to parallelization, there is still a requirement for the verifier to perform a full LLM forward pass, potentially necessitating specialized hardware. Sun et al. (2025) proposes the use of a 'proxy task' based on the last hidden layer features of an LLM that can then be utilized by the user to compare to a label that they would expect based on their original input. The method proposed requires trust assumptions from the platform for generation of the proxy-task feature extractor and labeller networks, as well as secret generation/embedding, and adds the overhead of computation to perform all of the above.

B Formal Algorithm for Protocol 1

The procedure is comprised of three components: cache generation through Algorithm 1, inference request through Algorithm 2, and the verification stage through Algorithm 3.

Algorithm 1 Cache Generation

Input: model, cache size $|C| \in \mathbb{N}$, sentinel token count $K \in \mathbb{N}$
Output: cache: mapping $s \mapsto \ell_{1:K} \in \mathbb{R}^{K \times V}$

cache $\leftarrow \emptyset$
while $|cache| < |C|$ **do**
  $s_{1:K} \leftarrow$ sample with replacement K tokens from V
  $m_{1:K,1:K} \leftarrow 0$ ▷ initialize $K \times K$ attention mask
  for $i = 1..K$ **do**
    for $j = 1..i$ **do**
      $m_{i,j} \leftarrow 1$
    end for
  end for
  $\ell \leftarrow$ model.forward(s, m) ▷ $\ell \in \mathbb{R}^{K \times V}$
  cache$[s] \leftarrow \ell$
end while
return cache

Algorithm 2 Inference Request

Input: prompt token embeddings $x_{1:N}$, attention mask $a_{1:N}$, sentinel token sequence $s_{1:K}$
Output: logits $\ell_{1:N+K} \in \mathbb{R}^{(N+K)\times V}$

positions $p_{1:K} \leftarrow$ sample without replacement K times from Uniform$[1, N+K]$
augmented embeddings $x'_{1:N+K} \leftarrow$ insert sentinel tokens $s_{1:K}$ at positions $p_{1:K}$
augmented mask $a'_{1:N+K} \leftarrow$ expand $a_{1:N}$ at positions $p_{1:K}$ with 0-filled rows and columns
for i = 1..K **do**
    for j = 1..i **do**
        $a'[p_i, p_j] \leftarrow 1$
    end for
    for j=i..K **do**
        $a'[p_j, p_i] \leftarrow 1$
    end for
end for
$x' \leftarrow$ encrypt(x')
$a' \leftarrow$ encrypt(a')
encrypted $\ell_{1:N+K} \leftarrow$ inference provider forward pass on encrypted x', a'
return decrypt($\ell_{1:N+K}$)

Algorithm 3 Verification

Input: logits $\ell_{1:N+K} \in \mathbb{R}^{(N+K)\times V}$, sentinel positions $p_{1:K} \subset \{1, 2, ..N+K\}$, sentinel sequence $s_{1:K}$, cache $\in \mathbb{R}^{C\times K\times V}$, tolerance $tol > 0$
Output: verified: bool

verified $\leftarrow$ true
for $i = 1..K$ **do**
    $p' \leftarrow p[i]$
    $err \leftarrow \|\ell[p'] - \text{cache}[s][i]\|_1$
    if $err > tol$ **then**
        verified $\leftarrow$ false
    end if
end for
return verified

C Formal Algorithm for Protocol 2

The procedure is also comprised of three algorithms similar to those in Section B: noised embedding generation Algorithm 4, noisy inference request Algorithm 5, and verification with noisy prediction Algorithm 6.

Algorithm 4 Noised Embedding Generation

Input: discrete noise set B, trained NoiseEmbedder E, embedding dim d_e, token embedding $e \in R^{d_e}$
Output: sampled noise $b \in R^{d_e}$, noised embedding $e_b \in \mathbb{R}^{d_e}$

$b \leftarrow$ sample one value uniformly from B
$b_e \leftarrow \text{concat}(e, b)$ ▷ $b_e \in \mathbb{R}^{2d_e}$
$e' \leftarrow E.\text{forward}(b_e)$ ▷ $e' \in \mathbb{R}^{d_e}$
return (b, e')

Algorithm 5 Noisy Inference Request

Input: prompt token embeddings $x_{1:N}$, attention mask $a_{1:N}$, sentinel token sequence $s_{1:K}$
Output: hidden states $h \in \mathbb{R}^{(N+K)\times d_h}$, noise_cache $\in B^N$

positions $p_{1:K} \leftarrow$ sample without replacement K times from Uniform$[1, N+K]$
augmented embeddings $x'_{1:N+K} \leftarrow$ insert sentinel tokens $s_{1:K}$ at positions $p_{1:K}$
augmented mask $a'_{1:N+K} \leftarrow$ expand $a_{1:N}$ at positions $p_{1:K}$ with 0-filled rows and columns
for i = 1..K **do**
    for j = 1..i **do**
        $a'[p_i, p_j] \leftarrow 1$
    end for
    for j=i..K **do**
        $a'[p_j, p_i] \leftarrow 1$
    end for
end for
for each non-sentinel token t in x' **do**
    $b, e' \leftarrow$ call Algorithm 4 on $x'[t]$
    $x'[t] \leftarrow e'$
    noise_cache[t] $\leftarrow$ b
end for
$x' \leftarrow \text{encrypt}(x')$
$a' \leftarrow \text{encrypt}(a')$
encrypted $h_{1:N+K} \leftarrow$ inference provider forward pass on encrypted x', a'
$h \leftarrow decrypt(h_{1:N+K})$
return h, noise_cache

Algorithm 6 Verification With Noise Prediction

Input: decrypted hidden states $h_{1:N+K} \in \mathbb{R}^{(N+K)\times d_h}$, sentinel positions $p_{1:K}$, sentinel sequence $s_{1:K}$, logit_cache $\in R^{C\times K\times V}$, noise_cache $\in B^N$, NoisePredictor NP, logit projection $L : \mathbb{R}^{d_h} \to \mathbb{R}^V$, sentinel tolerance tol_s
Output: verified: bool

for $i = 1..K$ **do**
  $p' \leftarrow p_i$
  $\ell \leftarrow L(h[p'])$
  $err \leftarrow \|\ell - \text{logit\_cache}[s][i]\|_1$
  if $err > tol_s$ **then**
    verified $\leftarrow$ false
  end if
end for
for $j = 1..N + K$ **do**
  if $j \in P$ **then**
    continue
  end if
  $\hat{b} \leftarrow NP.\text{forward}(h[j])$
  if $\hat{b} \neq \text{noise\_cache}[j]$ **then**
    verified $\leftarrow$ false
  end if
end for
return verified

D Training Details for Protocol 2

In this section we provide further details for the experiments conducted in Section 5.3.

We train on the FineWeb-Edu dataset (Lozhkov et al., 2024). This is a large-scale dataset of 1.3T total tokens consisting of high-quality educational web pages filtered from the larger FineWeb dataset. This dataset has been used for pretraining, and is suitable for general testing of language modeling capabilities of LLMs. We take 40000 samples from this dataset and divide these into an 80/20 train-validation split. We perform training for 500 steps with a batch size of 64 on sequences of length 256. We use the optimizer AdamW (Loshchilov & Hutter, 2019) with a learning rate of $5e-4$, with no warmup steps. The base model is Llama-3.2-1B, and the weights of this model are frozen; gradients are backpropagated through this model in order to reach the NoiseEmbedder module.

We utilize the same sampled noise at every token position, but a different noise is sampled for each batch element. Our results are reported using a λ hyperparameter value of 3.5. We train using an A100 GPU.

E Protocol 3: Key Appending – Further Details

In this section, we give further details on the Key Appending protocol introduced in Section 6.

We also tested the same protocol but instead of appending the key repeating prompt to the end of the user's prompt, we insert it in any whitespace randomly. This approach performs less well – we report results for this in Section F.

E.1 Further Protocol Details

In addition to the augmented prompt, we also modify the system prompt to encourage model compliance to the protocol.

System prompt. The user adds a system-level instruction that enforces the verification protocol and prevents premature conversation termination:

Table 3: Transcription success rate on 1000 prompts of our 'key appending' verification protocol, with keys of length $K = 3$ words. We see that models with parameter sizes of 3B and above obtain very high transcription rates of $> 98\%$.

Model	Transcription rate
Llama 3.2 1B	56.6%
Gemma 3 1B	73.1%
Llama 3.2 3B	98.1%
Gemma 3 4B	99.7%
Mistral 7B	99.6%
Llama 3.1 8B	98.7%
Gemma 3 12B	98.0%
Mistral 24B	100.0%
Qwen 2.5 32B	99.9%
Llama 3.1 70B	99.6%

Table 4: LiveBench scores for models under the 'key appending' protocol. Higher is better. There is a relatively large degradation in performance for smaller models, but models of size 8B and larger exhibit much smaller relative degradation.

Model	Vanilla	Append	Δ
Llama 3.2 1B	10.7	6.7	−4.0
Gemma 3 1B	14.7	9.9	−4.8
Llama 3.2 3B	20.5	16.9	−3.6
Qwen 2.5 3B	24.2	18.3	−5.9
Gemma 3 4B	30.2	26.4	−3.8
Mistral 7B	20.4	14.5	−5.9
Llama 3.1 8B	25.4	25.6	+0.2
Gemma 3 12B	41.0	36.8	−4.2
Mistral 24B	30.5	32.1	+1.6
Qwen 2.5 32B	42.7	41.7	−1.0
Llama 3.1 70B	42.3	39.8	−2.5

```
You are a helpful assistant who should never speak in
two consecutive turns.  At the end of your response,
repeat the key mentioned at the end of the prompt.
You must print the key between tags like the following
structure:  <key> *insert key here* </key>.
```

This system prompt explicitly conditions the model to always conclude with the verification key enclosed in `<key>...</key>` tags, and discourages it from generating the turn-termination token prior to key emission.

Stopping criterion. Unlike standard decoding, where inference continues until the model produces an end-of-sequence token, the user adopts a custom stopping rule: decoding halts once the closing tag `</key>` is generated. This ensures that inference completes exactly after the verification key is produced, with no trailing tokens.

E.2 Experiments

Key Transcription Capability. We first examine the capability of LLMs to perform our protocol successfully; this is analogous to the cryptographic property of *completeness*. We evaluate multiple open-source models on a random sample of 1000 prompts from the Databricks dolly-15k dataset (Argilla, 2023). The key is sampled uniformly at random from the standard Ubuntu `words` file provided by the `wordlist` package (any similar list of English words suffices) and appended via the protocol; success is recorded if the words enclosed in the `key` tags match the key exactly.

Table 3 reports the transcription success rate. We observe near-perfect adherence for models at or above the 3–4B scale. Therefore, a simple capacity criterion suffices in practice: models with $\geq$3B parameters reliably satisfy the protocol's instruction, making them suitable drop-in choices for verified inference with key appending.

Downstream Performance Impact. We now test the impact of the additional key-transcription instruction on model downstream performance. To quantify this, we evaluate all models on LiveBench (White et al., 2025) (30–05–2025 release), a benchmark testing model performance on a range of tasks including data analysis, instruction following, language, math, and reasoning. Table 4 compares overall performance of the models in vanilla inference against our protocol. Extended tables showing complete results for all LiveBench categories are presented in Section H and Section F.

We find that there there is a relatively large performance impact for smaller models. However, for larger models, the performance impact is reduced. Indeed, for Mistral 24B, the performance is actually slightly higher – which we attribute to the natural variability inherent in the benchmark. In

practice, using a model of size 8B or larger seems sufficient to ensure minimal relative downstream performance impact from applying this protocol.

Approximation Attack Experiments As described in Section 6.2, this protocol is potentially vulnerable to model approximation attacks. We perform an in-depth examination of the viability of such in the specific case of use of SMPC for privacy preservation, with one honest party, in Section G. We find that in this setting, any such approximation does fail.

F Random Whitespace Protocol

As an alternative to the key appending protocol of Section E, we also tested requiring the model to repeat the key in a random whitespace. **Protocol description.** This protocol adopts the same stopping criterion and verification method as the key–appending protocol, but modifies both the system prompt and the user prompt transformation.

System prompt. We prepend the following system instruction:

```
You are a helpful assistant who should never speak in
two consecutive turns.  Somewhere in the prompt, you
will find a secret key of {K} words in curly braces
right after the marker <{marker}>.  Print that key at
the very end of your response.  Ignore what is inside
the <verify> </verify> tags when answering the main
prompt.\nYou must print the key between tags like the
following structure:  <key> *insert key here* </key>.
```

This system prompt enforces the placement of the key at the end of the model's response and ensures that the verification tags are ignored during the main task, preventing interference with downstream output.

User prompt transformation. Given an original user prompt p, the user selects a random whitespace location and inserts the following structure:

```
<verify> <{marker}> {key} </{marker}> </verify>.
```

Here, the marker is a randomly generated four-character ASCII string, and the key consists of three English words sampled uniformly at random, as in the key–appending protocol.

Design rationale. The system prompt explicitly instructs the model to ignore the inserted tags when answering the main query, which tries to minimize the impact of the injected verification key on downstream task performance. Moreover, we deliberately employ HTML-like tags for three reasons:

1. Large language models are extensively exposed during pretraining to HTML/XML patterns, which aids reliable parsing and generation.
2. Wrapping the marker–key pair inside `<verify>` tags avoids accidental collisions with ordinary prompts (e.g., programming queries that might already include custom markers).
3. Randomly generating the marker string reduces the probability of unintentional matches with existing content, while including the outer `<verify>` tags improves transcription accuracy compared to using only `<marker>` ... `</marker>`.

The transcription rates and downstream performance impact of the protocol are shown in Table 5 and Table 6 respectively. Although the transcription rates match that of key appending for models of size 8B and above, the downstream performance impact is significantly larger than that of key appending.

Table 6: LiveBench scores for models under the 'random whitespace' protocol. Higher is better. There is generally a larger degradation in performance than for the key appending protocol.

Model	Vanilla	Random Whitespace	Δ
Llama 3.2 1B	10.7	5.4	−5.3
Gemma 3 1B	14.7	9.2	−5.5
Llama 3.2 3B	20.5	14.2	−6.3
Qwen 2.5 3B	24.2	17.2	−7.0
Gemma 3 4B	30.2	21.3	−8.9
Mistral 7B	20.4	12.2	−8.2
Llama 3.1 8B	25.4	20.7	−4.7
Gemma 3 12B	41.0	29.1	−11.9
Mistral 24B	30.5	25.3	−5.2
Qwen 2.5 32B	42.7	39.3	−3.4
Llama 3.1 70B	42.3	32.1	−10.2

Table 5: Transcription success rate on 1000 prompts of our 'Random Whitespace' verification protocol, with keys of length $K = 3$ words. We see that models with parameter sizes of 8B and above obtain very high transcription rates of $> 98\%$.

Model	Transcription rate
Llama 3.2 1B	6.7%
Gemma 3 1B	2.2%
Llama 3.2 3B	88.8%
Gemma 3 4B	79.0%
Mistral 7B	86.6%
Llama 3.1 8B	98.5%
Gemma 3 12B	99.0%
Mistral 24B	99.6%
Qwen 2.5 32B	99.2%
Llama 3.1 70B	99.3%

G Approximation Attack Experiments – Key Appending

We perform approximation attack tests in the SMPC setting. We assume the existence of at least one honest party; in the case where all parties are dishonest (i.e. performing the same, matching approximation), the approximated model still can potentially accurately produce the key and evade detection. We use the CrypTen Python library (Knott et al., 2021).

For the dishonest party, we uniformly reduce the rank of all weight matrices in the models to various proportions of the original rank, and test the protocol to see whether the approximated model is still capable of correctly outputting the key. We select the following for our parameters:

1. Models: Llama 3.2 3B Instruct, Qwen 2.5 3B. We select two models with very high key transcription rates in the non-attack setting from different model classes.
2. We test the reduction of original ranks of very weight matrix M to the following percentage reductions: 1%, 5%, 10%, 25%, 50%, 75%, 90%, 99%, using SVD. We desire to test a wide variety of different ranks, ranging from an extremely significant reduction in rank to a slight decrease in rank, and we hence select the previously listed percentages for significant coverage of all of these possibilities.

For each combination of model and rank, we run the framework as described at the beginning of this section, selecting $n = 20$ prompts and $K = 3$ words.

The results of such experiments revealed that regardless of the model used or rank approximated to, the model was *always unable to output the key* (i.e. 0 of the 20 tests succeeded). Notably, even in the

99% test, both models were unable to produce anything legible, and tokens outputted were entirely random: an example decoded result from one prompt was "deesestiftigiongh" with random unicode characters inserted inside.

Quantizer Attacks A malicious actor can also potentially quantize the model's weights to a different precision, which is straightforward to test: given a model, we quantize all its weights to a different precision and perform the common tests to determine performance.

We again perform tests in an SMPC setting encrypted with CrypTen with two parties, one honest and one dishonest. We again note the potential weakness of this strategy when both parties are dishonest or a different encryption scheme is used.

1. Models: Llama 3.2 3B Instruct, Qwen 2.5 3B. We select the same models as for the low-rank approximations, due to their ordinarily high transcription rates.
2. Precisions: 8-bit and 4-bit floats. The weights in the Llama model tested are 16-bit floats at full precision, and in the Qwen model are 32-bit floats. Therefore, to reduce precision, we test quantization to 8- and 4-bit precision.

Once again, we run the common testing framework with $n = 20$ prompts and $K = 3$ words. Similar to the low-rank tests, in all cases, the models were *never able to output* the key, or in fact anything legible, revealing the effectiveness of the key appending protocol in defending against quantization attacks.

H KEY APPENDING – EXTENDED LIVEBENCH RESULTS

Table 7: LiveBench category scores for vanilla inference.

Model	Average	Data Analysis	Instr. Follow.	Language	Math	Reasoning
Llama 3.2 1B	10.7	12.9	25.1	0.0	9.5	5.8
Gemma 3 1B	14.7	12.0	42.1	3.7	13.1	2.9
Llama 3.2 3B	20.5	23.3	48.4	3.5	15.5	11.9
Qwen 2.5 3B	24.2	29.0	43.2	10.7	23.5	14.6
Gemma 3 4B	30.2	38.3	61.5	6.3	33.0	11.8
Mistral 7B	20.4	26.4	46.2	1.5	13.4	14.4
Llama 3.1 8B	25.4	36.0	48.0	13.8	15.9	13.1
Gemma 3 12B	41.0	46.4	71.2	19.3	39.5	28.8
Mistral 24B	30.5	42.1	50.4	17.3	19.0	23.4
Qwen 2.5 32B	42.7	50.7	61.2	27.3	43.9	30.4
Llama 3.1 70B	42.3	52.6	65.9	30.3	31.4	31.4

Table 8: LiveBench category scores under the 'key appending' protocol. Higher is better.

Model	Average	Data Analysis	Instr. Follow.	Language	Math	Reasoning
Llama 3.2 1B	6.7	0.9	24.9	0.0	2.3	5.5
Gemma 3 1B	9.9	3.3	32.1	2.3	4.8	6.6
Llama 3.2 3B	16.9	8.0	43.4	7.8	11.7	13.5
Qwen 2.5 3B	18.3	18.2	30.4	5.8	21.4	15.9
Gemma 3 4B	26.4	38.6	41.3	8.0	24.5	19.8
Mistral 7B	14.5	21.7	31.8	6.7	6.6	5.5
Llama 3.1 8B	25.6	35.3	51.7	9.3	15.2	16.6
Gemma 3 12B	36.8	46.1	60.5	16.5	37.0	24.0
Mistral 24B	32.1	41.1	47.2	24.0	21.0	26.9
Qwen 2.5 32B	41.7	47.2	58.2	24.0	44.2	35.0
Llama 3.1 70B	39.8	50.4	69.2	22.0	29.1	28.5