

CHEX-MIX: Combining Homomorphic Encryption with Trusted Execution Environments for Oblivious Inference in the Cloud

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Abstract—Data, when coupled with state-of-the-art machine learning models, can enable remarkable applications. But, there exists an underlying tension: users wish to keep their data private, and model providers wish to protect their intellectual property. Homomorphic encryption (HE) and multi-party computation (MPC) techniques have been proposed as solutions to this problem; however, both techniques require model providers to fully trust the server performing the machine learning computation. This limits the scale of inference applications, since it prevents model providers from leveraging shared public cloud infrastructures.

In this work, we present CHEX-MIX, a solution to the problem of privacy-preserving machine learning between two mutually distrustful parties in an untrusted cloud setting. CHEX-MIX relies on a combination of HE and trusted execution environments (TEEs), using HE to provide clients with confidentiality guarantees, and TEEs to provide model providers with confidentiality guarantees and protect the integrity of computation from malicious cloud adversaries. Unlike prior solutions to this problem, such as multi-key HE, single-key HE, MPC, or TEE-only techniques, our solution assumes that both the client and the cloud can be malicious, makes no collusion assumptions, and frees model providers from needing to maintain private online infrastructures. Our results show that CHEX-MIX can execute at high efficiency, with low communication cost, while providing security guarantees unaddressed by prior work. Compared to a recent multi-key HE work that allows partial cloud offload, for example, CHEX-MIX achieves a $3\times$ lower communication cost and a $3\times$ faster computation time.

1. Introduction

The rise of machine learning (ML) has enabled a host of improvements in nearly all aspects of life, from medical diagnoses [85], [99], to finance [39], personal assistants [80], and more [34], [104]. Alongside the rise of cloud computing, these technologies can reach users across the globe at increasingly large scales. However, users often incur a high privacy cost when using inference services since users must reveal their personal data (e.g., heart rate, sleep patterns, or speech data) to model providers to obtain inference results. This threat is further exacerbated by attacks on cloud data centers, allowing cloud attackers direct access to user data.

A simple solution to this problem is to require model providers to deploy their models close to users, such as directly on client devices. However, training robust and useful models is difficult and monetarily expensive.

Models are thus often considered key intellectual property, which model owners are reluctant to share [81]. Moreover, sharing the details of a model can increase the ability of attackers to perform re-identification or membership inference attacks [9], [115] that violate the privacy of user data in the model training set.

This problem of providing privacy to both clients and model providers during machine learning inference, known generally as *oblivious inference* [27], [97], is often addressed with cryptographic techniques such as multi-party computation (MPC) [66], [75], [97], homomorphic encryption (HE) [24], [48], or hybrid HE-MPC techniques [61], [70], [82]. These techniques provide cryptographic guarantees that user data is completely hidden from model providers. But, these techniques only provide privacy to model providers when model providers host their inference services on *private* servers. This burdens model providers with the drawbacks of hosting and maintaining private cloud infrastructures, such as requiring the model providers to know in advance the maximum number of instances they would need for their service, purchasing enough hardware and software support infrastructure (e.g., space, physical security) for the full server set, and paying the full cost of maintaining and upgrading the hardware and infrastructure.

Instead, model providers could host their service in the *public* cloud, freeing the providers from needing to maintain, scale, and update their own infrastructure, and allowing them to pay only for the resources in use at any time. However, as even recent reports have shown [7], [25], [92], [116], the complexity of cloud computing stacks often leads to vulnerabilities in infrastructures that malicious cloud attackers can exploit. Thus, hosting their services in the public cloud would require model providers to risk the secrecy of their trained model as well as the integrity of the computation against cloud attackers.

Prior works have proposed hardware isolation using trusted execution environments (TEEs) as a solution for secure machine learning [87], [96], [112], [113] in the cloud. TEEs allow model providers to host their models on public clouds with privacy and integrity guarantees against cloud attackers. But, TEEs provide only marginal benefits to end users since users must still fully trust the model provider’s code running inside of the TEE. Even the attestation property of TEEs, whereby a client can precisely verify the code running inside of the TEE, is of little use, as providers are still unwilling to share their intellectual property (IP) for independent auditing and inspection [15], [53], [62], [101], [110]. Further, independent and trustworthy auditing of model provider

code becomes infeasible as the number of model providers continues to scale.

What is lacking is a solution that provides scalability, flexibility, and security to model providers and privacy to users. We hypothesize that a careful integration of cryptographic *and* hardware isolation techniques can enable this desired protection for both users and model providers at scale. In particular, we propose the CHEX-MIX protocol for oblivious inference in the cloud, based on a combination of homomorphic encryption and trusted execution environments. In general, HE and TEEs are often posed as *competing* solutions to the problem of privacy-preserving computation. Thus, our work disrupts conventional wisdom by underscoring how these techniques need not be competing, and can actually work *together* to solve limitations of the other.

The general idea of our solution, illustrated in Figure 1, is to have model providers run their models inside TEEs on the servers of their cloud provider of choice, and clients use HE when sending their data to the cloud for inference. The privacy of the client’s data is protected by HE, while the privacy of the model provider’s model is protected by the TEE. By modeling the model provider as a rational actor, the combination of HE and TEEs together can additionally ensure the correctness of computation, including the integrity of the input and intermediate and final results.

Despite its simplicity, however, a naive implementation of a hybrid HE-TEE solution would be self-contradictory. In particular, requiring clients to attest the enclave would assume that clients are able to fully trust the security of the enclave code, eliminating the need for HE. However, verification of the enclave code is unrealistic for clients to achieve in practice, since enclave code can be difficult for clients to fully validate. Yet, simply skipping attestation would limit the client’s trust in the correctness of the results.

In this work, we show how the attestation requirement can be removed through the use of a trust framework that leverages the privacy properties of HE. This trust framework, which treats the model provider as a rational party, is stronger and more realistic than the passive adversary models of prior solutions in this setting. Under this framework, we show how our solution provides privacy guarantees to clients and model providers under a strong adversary model, tolerating malicious clients, malicious cloud adversaries, and malicious model providers, and correctness guarantees to clients tolerating malicious cloud adversaries and rational, actively adversarial ML model providers, while making no assumptions about collusion between the parties.

Further, we show how the properties of CHEX-MIX can be leveraged to additionally offer model providers confidentiality of their inference *code*, which can in turn allow model providers more control over their intellectual property and even limit certain vulnerabilities [68]. Importantly, we note that this feature is only possible through our combined solution that removes the client attestation requirement altogether. We show how this variant of our solution is fully compatible with the baseline setup and discuss how CHEX-MIX can offer this protection essentially *for free*, with no added performance or privacy cost over the baseline solution.

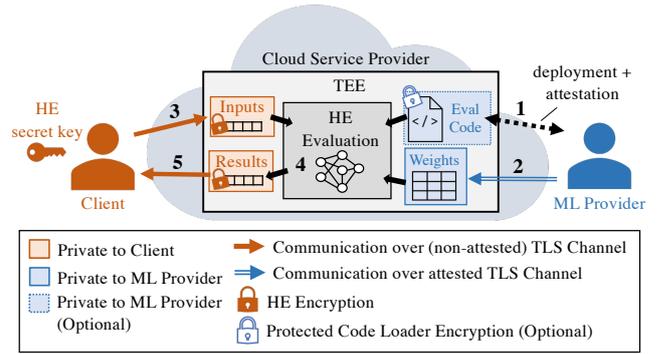


Figure 1: Overview of CHEX-MIX. The ML model provider attests and sends the model parameters to the cloud TEE. The client homomorphically encrypts and sends their inputs to the TEE, which homomorphically computes and returns the inference results.

Finally, we evaluate the feasibility of an HE-TEE hybrid approach for oblivious inference in modern cloud infrastructures. Modern TEEs are resource-constrained and difficult to program, while state-of-the-art HE libraries are (relatively) large and complex. These conflicting characteristics suggest that an implementation of an HE-TEE hybrid solution would be impractically slow compared to an HE-only solution. However, we show through our implementation of CHEX-MIX on a commodity cloud server that not only is an HE-TEE hybrid solution possible, but it can also significantly *improve* computation and communication costs compared to prior solutions for oblivious inference. Compared to a recent multi-key HE work [27], for example, that allows (partial) offload to an untrusted cloud, CHEX-MIX achieves a 3× lower communication cost and a 3× faster computation time.

To summarize, we make the following contributions:

- Propose CHEX-MIX, a new protocol for two-party oblivious inference based on a combination of HE and TEEs.
- Adapt the baseline protocol to further provide the model provider with confidentiality of their inference *code*.
- Present a security analysis of our protocols for a strong adversary model, tolerating malicious clients, malicious cloud adversaries, and malicious or rational actively adversarial model providers, with no collusion assumptions.
- Evaluate the CHEX-MIX protocol for a five-layer convolutional neural network (CNN) for inference over the MNIST dataset. Our results show that CHEX-MIX is more efficient than prior solutions for two-party oblivious inference over the target workload, and provides security guarantees not addressed by prior works.
- Demonstrate the scalability of our protocol by evaluating CHEX-MIX for a SqueezeNet CNN (the largest homomorphically evaluated CNN to date, to the best of our knowledge).

2. Background

In this section, we provide the background necessary to understand CHEX-MIX and its security arguments.

2.1. Trusted Execution Environments

The shared nature of cloud environments often results in cloud computing stacks that are large and difficult to verify. Hidden vulnerabilities in complex stacks [7], [25], [92], [116] provide malicious actors more opportunities to access user data. TEEs help solve this problem through *enclaves*, or private regions of memory in which users can store and operate on sensitive data with added protection. Several types of TEEs exist to date, including AMD SEV [1], ARM TrustZone [51], and Intel SGX [79]. We focus on SGX in this paper, but the principles discussed can be extended to any TEE of a similar nature.

To utilize an enclave, a user first partitions their application code into host and enclave processes and verifies that the enclave process is trustworthy and free of vulnerabilities. The user then loads the trusted enclave component of the code into the enclave through a series of enclave setup procedures [36]. The user confirms that the enclave was created securely and loaded with the expected trusted code using (*remote*) *attestation*, which provides protection against all attacks assumed by the SGX threat model [2], [79]. TLS channel establishment can be integrated with the attestation procedure for protection of data transferred between a user and an enclave [36], [65].

Principally, SGX is limited in what it can guarantee; it does not guarantee protection of enclaves containing code written in an insecure manner (e.g., containing buffer overflow vulnerabilities or side-channel-producing computation). Prior works have demonstrated how deploying software with realistic memory safety vulnerabilities to an enclave can lead to full attacker workload compromise [67], and have even shown how attackers can take advantage of vulnerabilities in enclave code to completely bypass detection through attestation [68].

2.2. Homomorphic Encryption

HE schemes enable computation directly on encrypted data. This property enables users to outsource computation to untrusted entities without requiring the users to reveal their personal data. To use HE, users choose encryption parameters (i.e., the ring degree and coefficient moduli of certain polynomial quotient rings) to be within the bounds of the HE Security Standard [26] consistent with the desired security level and the maximum multiplicative depth of the target computation circuit. Users generate a secret key (**SK**) for encryption/decryption using these parameters, as well as certain encryptions of the secret key called *evaluation keys* (**EK**) that assist with outsourced computation evaluation by an untrusted party.

Homomorphic Inference. Prior works [24], [27], [33], [48], [58] have shown how to use HE for private neural network inference by interpreting linear network layers as a series of (homomorphic) additions, multiplications, and rotations between fixed-length vectors, and modeling nonlinear network layers, such as ReLU, by low-degree polynomials. Efficient HE schemes such as BGV [21],

BFV [20], [43], and CKKS [30] represent plaintexts and ciphertexts as elements in polynomial quotient rings, and can operate on vectors of input values in a single-instruction-multiple-data (SIMD) fashion by using special encoding techniques [107]. Using these methods, prior works achieved an accuracy of $\geq 98.4\%$ for inference over the MNIST dataset for HE evaluation of a 5-layer convolutional neural network [24].

The CKKS scheme allows users to efficiently discard unwanted precision in the results of HE computation, essentially preserving an *approximate* computation on the input vector. Since machine learning computations are also approximate in nature, CKKS is widely considered the scheme of choice for machine learning tasks [27], [58], [63], [71]. Given our target application of oblivious inference, we focus on the CKKS scheme in this work. However, our solution is not limited to the CKKS scheme and is applicable to other efficient HE schemes such as BFV and BGV as well.

Security of HE and CKKS. The CKKS scheme is based on the Ring Learning with Errors (RLWE) assumption and is IND-CPA secure. Though a recent work [71] demonstrated a passive key-recovery attack on the CKKS scheme, this attack requires access to a decryption oracle. A known simple mitigation for this attack, which we apply in this work, is to have the decryptor (user) not share the raw decryption results with any untrusted entity [29].¹

Importantly, HE schemes are *malleable* by nature; they offer no guarantee that an untrusted party computes a function $f()$ instead of a different function $f'()$ over an input during evaluation. Thus, HE alone cannot provide computational integrity. We note that a lack of computational integrity in ML inference can be severe. For example, a manipulation of the result of a medical inference could lead to an incorrect diagnosis, while incorrect interpretations of voice commands can lead to attacker control of voice-controlled infrastructure.

2.3. Adversary Modeling

Next, we motivate the need for a model that more accurately captures real world adversarial behavior in the ML-as-a-service paradigm.

Traditionally in the field of multi-party computation and related works, adversaries are classified into one of two categories: *semi-honest* (or *honest-but-curious*) and *malicious*. A *semi-honest* adversary refers to an adversary that, given a prescribed protocol, will passively follow the protocol as described; thus, this adversary may only infer information about other parties from the protocol messages it receives. A *malicious* adversary, by contrast, may actively and arbitrarily deviate from the protocol specification.

We argue that these two models do not adequately reflect the behavior of real-world adversaries in the ML-as-a-service use case. The semi-honest model assumes that adversaries can only act passively, though many real-world adversaries actually possess the means to act actively [11], [73]. Active deviation includes the ability to inject, alter, or omit messages, with the intent to break privacy or

1. Note that the general outcome of a decryption, such as the predicted class in a classification network, is not considered raw decryption.

correctness. An example of how semi-honest assumptions can lead to privacy breaches when active deviation is allowed is shown in the attack of the MUSE work [70].

On the other hand, the malicious adversary model makes the overly cautious assumption that the adversary may deviate randomly and arbitrarily from the protocol, even when the adversary has no incentive to do so.

We need a model that considers the active capabilities of the adversary but can benefit from realistic assumptions on the adversarial party. To this end, we consider a third type of adversary known as a *rational* adversary that has capabilities nearly equivalent to that of a malicious adversary (i.e., is actively adversarial), but is bounded by their incentive to maximize their utility over a set of utility-providing actions. This adversary is described in several works at the intersection of multi-party computation and game theory as a realistic yet powerful assumption [6], [50], [78], [121]. In later sections, we show how we can utilize this rational assumption to provide clients with correctness of results during oblivious inference (without requiring the rational assumption for privacy of data).

3. Problem Statement

Here we define our problem statement. Table 1 gives a summary of terms used in this and the remaining sections.

We consider the scenario of two-party oblivious neural network inference in the cloud. Specifically, we assume that there exists an ML model provider \mathcal{M} with a pre-trained neural network model with weights and bias values, and a client \mathcal{C} with inputs \mathbf{X} . We refer to \mathcal{M} 's weights and bias values collectively as \mathbf{W} and \mathcal{M} 's model architecture (i.e., the number, ordering, types, and sizes of layers) as \mathbf{F} . We refer to inputs \mathbf{X} and results $\mathbf{Y}=\mathbf{F}(\mathbf{X}, \mathbf{W})$ collectively as *client data*.

Importantly, we wish to enable model providers to take advantage of the benefits of using the public cloud. These include, for example, the ability to scale a service to a large number of clients across the globe, as well as the flexibility and cost-effectiveness of dynamically scaling a service's resources as needed based on demand. Thus, we introduce an additional entity \mathcal{S} as the cloud service provider (e.g., Amazon AWS or Microsoft Azure). We aim to allow \mathcal{M} to host their inference service on a server (or collection of servers) hosted by \mathcal{S} .

Given this setting, our goal is to allow the client \mathcal{C} to submit their inputs to provider \mathcal{M} , who may be hosting their service on \mathcal{S} 's servers, to obtain the result of inference $\mathbf{Y}=\mathbf{F}(\mathbf{X}, \mathbf{W})$ in a manner that preserves the privacy of \mathcal{C} 's data and \mathcal{M} 's weights and the correctness of inference result \mathbf{Y} . This satisfies the requirements for oblivious inference in the cloud.

3.1. Adversary Model

We consider three main types of adversaries in this setting: a cloud server adversary \mathcal{A}_S , a client adversary \mathcal{A}_C , and an ML model provider adversary \mathcal{A}_M . The cloud server adversary \mathcal{A}_S is an untrusted cloud provider or a third-party attacker that uses vulnerabilities in the public cloud infrastructure to access \mathcal{M} 's or \mathcal{C} 's private data or tamper with computation execution. We assume \mathcal{A}_S

TABLE 1: Summary of Terms / Symbols.

\mathcal{C}	Client / Feature Provider
\mathcal{M}	ML model provider
\mathcal{S}	Cloud server / Cloud service provider
\mathcal{E}_S	Enclave established on \mathcal{S}
\mathcal{A}_C	Adversary \mathcal{C}
\mathcal{A}_M	Adversary \mathcal{M}
\mathcal{A}_S	Adversary \mathcal{S}
π	HE parameters
\mathbf{X}, \mathbf{Y}	\mathcal{C} 's neural network feature inputs, outputs
\mathbf{W}	\mathcal{M} 's neural network weights and biases
\mathbf{N}	Intermediate inference results
$\bar{\mathbf{X}}, \bar{\mathbf{Y}}, \bar{\mathbf{N}}$	HE-encrypted $\mathbf{X}, \mathbf{Y}, \mathbf{N}$
\mathbf{F}	Neural network inference circuit
\mathbf{I}_F	An implementation / code of \mathbf{F}
$\bar{\mathbf{I}}_F$	\mathbf{I}_F encrypted with Intel PCL [55]
σ	Communication channel

may have full control of the OS or hypervisor layer of any public cloud-based servers. Meanwhile, the client adversary's goal is to try and learn as much about the model provider's weights and bias values as possible. We assume both \mathcal{A}_S and \mathcal{A}_C may be fully malicious.

We employ two separate adversary models for the model provider adversary \mathcal{A}_M . First, we assume a malicious \mathcal{A}_M , representing either a model provider themselves or a third-party adversary who is able to take control of \mathcal{M} 's servers.

Then, we consider an adversary model for \mathcal{A}_M to match the realistic use case of ML-as-a-service. For this case, we relax the malicious assumption slightly and treat \mathcal{A}_M as a rational adversary that seeks to maximize their utility under the following objectives: 1) learning the values of \mathbf{X} or \mathbf{Y} (i.e., \mathcal{C} 's private data) and 2) providing \mathcal{C} with a useful inference service. Here we define "useful" as a service that will allow \mathcal{M} to maintain enough users by some performance metric (see "best performing", Section 3.2). This means we can assume that \mathcal{M} would like to provide \mathcal{C} with a useful inference service and will in general not act in a way that counteracts this purpose *unless doing so might help reveal \mathcal{C} 's private data*.² This constraint closely models real-world service provider adversaries who are unlikely to compromise the utility of their service, as this would deter users, but who may still seek to learn private user data given the high value of such data today [94], [128].

We make no assumptions about collusion between the adversaries in any of the above cases (i.e., we assume \mathcal{A}_M may collude with \mathcal{A}_S , and \mathcal{A}_C may collude with \mathcal{A}_S).

2. There may be other model provider adversaries who have different objective functions, such as targeting the correctness of a service for users without any goal of disrupting users' privacy. We do not aim to provide *correctness* protection against such model provider adversaries for our setting, though the technique discussed in Appendix C can also be used to detect even this behavior, if desired. Our model provider adversary is still much more powerful and realistic for our setting than the standard semi-honest adversary used in prior oblivious inference works (see Section 6).

3.2. Privacy and Security Goals

Given the aforementioned setting, we target a solution that provides the following guarantees:

- 1) Privacy of \mathcal{C} 's data \mathbf{X} and \mathbf{Y} against a malicious $\mathcal{A}_{\mathcal{S}}$ and a malicious or rational $\mathcal{A}_{\mathcal{M}}$
- 2) Privacy of \mathcal{M} 's data \mathbf{W} against a malicious $\mathcal{A}_{\mathcal{S}}$ and a malicious $\mathcal{A}_{\mathcal{C}}$
- 3) Correctness of \mathbf{Y} (for \mathcal{C}) against a malicious $\mathcal{A}_{\mathcal{S}}$ and a rational $\mathcal{A}_{\mathcal{M}}$

To better reason about Guarantee 3, we introduce some additional notation:

- Let P represent the service clients are expecting to interact with (e.g., a handwriting recognition service).
- Let T represent the set of all possible inference applications \mathcal{M} may offer for service P .
- Let $\theta \in T$ be an inference application with some specific weights \mathbf{W} and code $\mathbf{I}_{\mathbf{F}}$ implementing a neural network circuit \mathbf{F} . For some input x from a client, $\theta(x) := \mathbf{I}_{\mathbf{F}}(x, \mathbf{W}) = y_{\theta}$ is the result this application provides to the user.
- Denote as $\theta^* \in T$ the inference application that is considered “best-performing”, where best-performing is determined by what ensures \mathcal{M} maintains enough users (i.e., would provide enough utility to users that they would want to use the application³). A correct result should return $y_{\theta^*} = \theta^*(x)$ to the user upon receiving input x .

3.2.1. Scope. Recent works have demonstrated how clients can infer information about models by analyzing the plaintext results of input queries (e.g., through *model-inversion* [114] or *membership inference* attacks [105], [115]). Protection against this class of attacks is not the focus of our work, and several other works detail mitigations that model providers can take against such attacks in practice [47], [60], [75], [105]. We discuss how these techniques can be implemented on top of our solution in more detail in Appendix D.

Consistent with the threat model of SGX [59], we do not consider side-channel attacks as part of our threat model. However, we give a more detailed consideration of side channels in Section 8. We also consider denial-of-service attacks out of scope.

3.2.2. Assumptions. We assume that all parties have access to standard network protection mechanisms for transferring private data over an untrusted network. In this work, we use the TLS protocol for secure channel establishment.

Additionally, and to the best of our knowledge, all prior HE works for inference [24], [27], [33], [48] implement any final softmax layers directly on the client device as part of the client decryption and decoding process since this layer is expensive to approximate for HE evaluation [31]. We employ the same approach in our

3. Examples of a “best performing” implementation may be the fastest implementation of P known by \mathcal{M} above a certain accuracy threshold, or the most accurate implementation of P known by \mathcal{M} above a certain runtime threshold. In reality, there may be several such best-performing applications for any service P . In this case, θ^* may be any one of these applications.

evaluation, and we often refer to the “machine learning model” as the model without this final layer.

To securely share evaluation keys \mathbf{EK} with untrusted parties, we make the usual circular security assumption used by prior HE works [21], [27].

Finally, we assume that \mathcal{C} and \mathcal{M} trust Intel attestation services to correctly identify when an enclave is malformed. (Though we do not require this assumption to ensure the privacy of \mathcal{C} 's data, we require it to ensure the privacy of \mathcal{M} 's data and the correctness of protocol execution.)

4. Limitations of a TEE-only Approach

Before we describe our solution, we discuss why a TEE-only solution would not fulfill our problem statement. In a TEE-only solution, a model provider creates an implementation of an inference service $\mathbf{I}_{\mathbf{F}}$ to offer to clients through the public cloud. The model provider deploys $\mathbf{I}_{\mathbf{F}}$ to an enclave in the cloud and releases the code for $\mathbf{I}_{\mathbf{F}}$ somewhere accessible to the client. The client verifies the trustworthiness of $\mathbf{I}_{\mathbf{F}}$, verifies that the enclave is a secure enclave running $\mathbf{I}_{\mathbf{F}}$, and sends its private data to the enclave. When the enclave is done computing the results, it sends the results to the client.

The above solution seems secure at first. However, recall that *enclaves do not provide protection against vulnerabilities—including any purposely inserted backdoors—contained in the enclave code itself*. Thus, for this solution to be secure, both parties must ensure $\mathbf{I}_{\mathbf{F}}$ does not contain any vulnerabilities exploitable by $\mathcal{A}_{\mathcal{S}}$, and the client must additionally ensure $\mathbf{I}_{\mathbf{F}}$ does not contain any opportunities for $\mathcal{A}_{\mathcal{M}}$ to access the enclave. It is plausible that the model provider could possess the ability to do this verification to a reasonable extent, since software service providers often employ dedicated security teams to analyze code for vulnerabilities.

It is less plausible, however, that a client (who may just be an individual user) could achieve this verification in practice. Clients could rely on some trusted third-party service (e.g., the open-source community) to independently audit the code. However, this would require model providers to give up all secrecy of their inference code for independent auditing, and providers are often unwilling to give up secrecy of their code for IP protection [15], [53], [62], [110] or even security reasons [101]. Moreover, as the number of application settings and model providers continues to grow at a fast pace⁴, so too will the number of ML services, the complexity of inference backends, and the frequency of algorithmic updates. At this scale, it becomes infeasible for independent trusted third parties to fully verify the security of all inference services, even if their implementations were made publicly available.

Alternatively, providers could use a TEE to secure a minimal OS acting as a sandbox (e.g., by using a secure VM technology such as Intel TDX [4] or AMD SEV-SNP [3]) to try to remove the $\mathbf{I}_{\mathbf{F}}$ attestation requirement. If clients could fully trust this OS to maintain the confidentiality of their data in the enclave, then they would not need to verify the details of $\mathbf{I}_{\mathbf{F}}$.

4. By one estimate, the machine learning market is expected to grow from USD 21 billion in 2022 to USD 210 billion by 2029 (a $10\times$ increase in less than a decade) [5].

However, designing and implementing a performant, sandboxing OS for this purpose is difficult; even a bare-bones implementation would at a minimum need to support network communication with potentially malicious actors, as well as somehow prohibit applications from storing meaningful data from one client to later share with another client. This complexity makes it difficult for the client (or client-trusted third party) to adequately verify all possible vulnerabilities and code paths in the OS for all potential confidentiality breaches. Indeed, there are several examples of recent vulnerabilities in commonly used sandboxing implementations in practice [14], [22], [46], [64], [90], [91], [103], [108].

Additionally, limiting the OS functionality in this way dramatically limits design space flexibility. For emerging workloads like machine learning, providers desire as much flexibility in the design space as possible. Thus, inevitably, the single secure OS would grow to include a multitude more optional features and appear in many different flavors. This again increases the potential verification space for the client to an unmanageable point, thus leading back to the original problem of a vulnerable cloud.

We need a solution that removes the verification requirement from the client altogether. In the next section, we show how we can achieve this using our solution, CHEX-MIX.

5. Our Solution: CHEX-MIX

An overview of our solution is as follows: the model provider deploys their inference service in an enclave in the public cloud. A client wishing to use the service homomorphically encrypts their inputs and sends them to the enclave. The enclave then computes the inference result and sends the (still HE-encrypted) result to the client. Finally, the client decrypts the HE-encrypted result to obtain the result of inference.

5.1. Baseline Protocol

We describe our baseline protocol for two-party oblivious inference below, detailed further in Figure 2.

\mathcal{M} begins the setup phase of the protocol by verifying that \mathbf{I}_F securely implements F (where \mathbf{I}_F , along with weights \mathbf{W} , implements service P). Next, \mathcal{M} establishes an enclave \mathcal{E}_S with code \mathbf{I}_F . Before provisioning \mathcal{E}_S with \mathbf{W} , \mathcal{M} establishes an attested TLS channel with \mathcal{E}_S to ensure \mathcal{E}_S is correctly initialized and that the communication endpoint is the expected enclave. To later allow clients to connect to \mathcal{E}_S without attestation, \mathcal{M} establishes a key pair for the TLS channel establishment, obtains a certificate from a certificate authority (CA) trusted by both \mathcal{M} and \mathcal{C} , and provisions \mathcal{E}_S with this certificate. \mathcal{M} establishes a certificate chain by further issuing and provisioning \mathcal{E}_S with a certificate for \mathcal{E}_S 's public key. At the end of this process, which is only required once across all clients, \mathcal{M} exits the protocol and goes offline.

After \mathcal{M} 's setup, \mathcal{C} connects to \mathcal{E}_S to receive the aforementioned certificates and the HE encryption parameters π to use. After verifying the parameters and certificates, \mathcal{C} establishes a (*non-attested*) TLS channel with \mathcal{E}_S . \mathcal{C} generates HE keys \mathbf{SK} and \mathbf{EK} based on π and sends

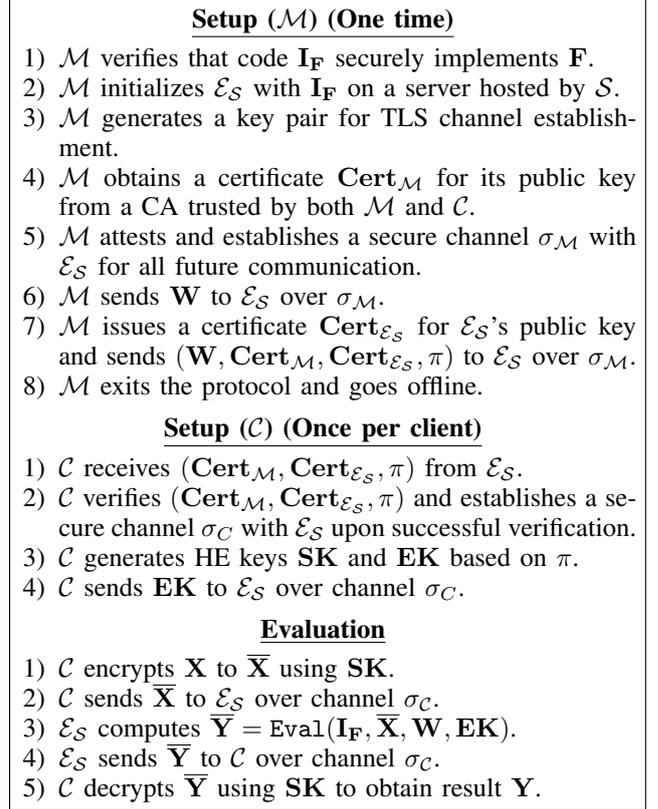


Figure 2: CHEX-MIX baseline protocol.

\mathbf{EK} to \mathcal{E}_S over the secure channel. The setup phase for \mathcal{C} is executed once per client.

Following the setup phases, \mathcal{C} requests an inference result from \mathcal{E}_S based on its inputs \mathbf{X} . \mathcal{C} encrypts \mathbf{X} to $\overline{\mathbf{X}}$ using \mathbf{SK} , sends $\overline{\mathbf{X}}$ to \mathcal{E}_S over the established network channel, and waits for \mathcal{E}_S to compute the neural network evaluation. \mathcal{C} then receives the (still HE encrypted) result $\overline{\mathbf{Y}}$ from \mathcal{E}_S and decrypts and decodes $\overline{\mathbf{Y}}$ to \mathbf{Y} using \mathbf{SK} to obtain the result.

5.1.1. Protocol Details. All communication between clients and the enclave and between the model provider and the enclave must be secured by the TLS protocol. Once two entities establish a secure communication channel in the protocol, all further communication between them occurs over that channel. This is essential to protect the integrity of all data, keys, and certificates and the confidentiality and integrity of sensitive metadata/headers associated with the network packets themselves.

Since evaluation keys \mathbf{EK} are types of HE ciphertexts, they also require integrity protection during and after use. During evaluation, the enclave \mathcal{E}_S provides this integrity protection of \mathbf{EK} . After evaluation, \mathcal{E}_S can store each client's \mathbf{EK} in an integrity-protected database and retrieve the client's \mathbf{EK} from the database upon subsequent connections. \mathcal{M} may implement this service within the evaluation enclave itself, by establishing a separate enclave or set of enclaves for this purpose (for example, using an SGX-based database design such as those detailed in prior works [95], [118]), or by using some other integrity-protected database scheme.

Finally, unlike inference backends, the client-side HE

code can be open-sourced, reviewed by trusted experts, and standardized, while also remaining relatively stable. It is thus possible for users to trust client-side HE code.

5.1.2. Security Analysis. In claims 1 and 2 below, we show how CHEX-MIX provides Guarantees (1) and (2) from Section 3.2 in the presence of malicious adversaries \mathcal{A}_S , \mathcal{A}_C , and \mathcal{A}_M . Since a malicious adversary can exhibit any behavior (including acting rationally), this analysis also holds for a rational \mathcal{A}_M . Note that these guarantees also imply that the underlying values \mathbf{N} of any intermediate ciphertexts of an HE-inference network should not be revealed to any entity, since doing so could allow recovery of private data \mathbf{X} , \mathbf{Y} , or \mathbf{W} through simple calculations [19] (we omit consideration for the trivial case of all-zero \mathbf{W}). Guarantee (2) also implies that $\bar{\mathbf{N}}$ should not be revealed to any entity other than \mathcal{M} , since knowledge of this and $\bar{\mathbf{X}}$ or $\bar{\mathbf{Y}}$ could allow an adversary to compute the values of \mathbf{W} .

In claim 3, we show how CHEX-MIX provides Guarantee (3) from Section 3.2 in the presence of a malicious adversary \mathcal{A}_S and a rational adversary \mathcal{A}_M . If \mathbf{I}_F is an HE inference application, then $x = (\bar{\mathbf{X}}, \mathbf{EK})$ and $y = \theta(x) = \mathbf{I}_F(\bar{\mathbf{X}}, \mathbf{EK}, \mathbf{W}) = \bar{\mathbf{Y}}$. For y to be considered correct in this case, $\text{Decrypt}_{\mathbf{SK}}(y)$ should return some final result \mathbf{Y} to the client to ensure θ satisfies the “best-performing” property (implying $\theta = \theta^*$). We say \mathbf{Y} is correct if $\bar{\mathbf{Y}} = \theta^*(x)$ and $\mathbf{Y} = \text{Decrypt}_{\mathbf{SK}}(\bar{\mathbf{Y}})$.

CLAIM 1. CHEX-MIX ensures privacy of \mathcal{C} ’s inputs \mathbf{X} and results \mathbf{Y} from a malicious \mathcal{A}_S and a malicious \mathcal{A}_M .

Security Analysis. \mathcal{C} uses HE to encrypt \mathbf{X} to $\bar{\mathbf{X}}$. \mathcal{C} only sends the encrypted result $\bar{\mathbf{X}}$ to \mathcal{E}_S . By the IND-CPA property of HE, $\bar{\mathbf{X}}$ does not reveal \mathbf{X} , \mathbf{Y} , or \mathbf{N} to passive or active adversaries. \mathcal{C} performs key generation and encryption locally in a trusted environment and never shares \mathbf{SK} , \mathbf{X} , or \mathbf{Y} with untrusted parties. Since $\bar{\mathbf{X}}$ does not reveal \mathbf{X} , \mathbf{Y} , or \mathbf{N} , and since no party but \mathcal{C} has the secret key \mathbf{SK} or direct access to $\bar{\mathbf{X}}$ or $\bar{\mathbf{Y}}$, CHEX-MIX guarantees the privacy of \mathbf{X} and \mathbf{Y} for \mathcal{C} against all malicious adversaries. \square

CLAIM 2. CHEX-MIX ensures privacy of \mathcal{M} ’s weights and biases \mathbf{W} from a malicious \mathcal{A}_S and a malicious \mathcal{A}_C .

Security Analysis. \mathcal{M} verifies that \mathbf{I}_F contains no vulnerabilities exploitable by \mathcal{A}_C or \mathcal{A}_S to access (view or tamper with) enclave data. \mathcal{M} uses remote attestation to guarantee that \mathcal{E}_S is a valid SGX enclave containing code \mathbf{I}_F . Since \mathcal{E}_S contains \mathbf{I}_F , and since \mathbf{I}_F is not exploitable by \mathcal{A}_C or \mathcal{A}_S , \mathcal{A}_C and \mathcal{A}_S cannot access \mathbf{W} or $\bar{\mathbf{N}}$ through \mathcal{E}_S . \mathcal{M} securely transfers \mathbf{W} to \mathcal{E}_S via an attested TLS channel and does not share \mathbf{W} or $\bar{\mathbf{N}}$ with any untrusted parties. Since the TLS channel protects the privacy of data against active attacks, \mathcal{A}_C and \mathcal{A}_S cannot access \mathbf{W} during data transfer. Since \mathcal{A}_C and \mathcal{A}_S cannot access \mathbf{W} or $\bar{\mathbf{N}}$ during data transfer or at either endpoint, they cannot access \mathbf{W} or $\bar{\mathbf{N}}$ at any point in the protocol and the privacy of \mathbf{W} for \mathcal{M} is guaranteed. \square

CLAIM 3. CHEX-MIX guarantees the correctness of results \mathbf{Y} for \mathcal{C} against a malicious \mathcal{A}_S and a rational \mathcal{A}_M .

Security Analysis. To ensure computation correctness, it is necessary to ensure that \mathcal{M} deploys some $\theta = \theta^*$ as the inference service (Requirement 1) and that the result $\bar{\mathbf{Y}}$ provided to \mathcal{C} is the result y of applying this θ^* to \mathcal{C} ’s inputs x (i.e., $y = \theta^*(x) = \bar{\mathbf{Y}}$) (Requirement 2). There are three possible scenarios for \mathcal{M} ’s deployments (described below). Let U_i denote the utility of Scenario i to \mathcal{A}_M .

First, assume \mathcal{M} deploys some $\theta \neq \theta^*$ (Scenario 1). This directly contradicts objective 2 of a rational \mathcal{A}_M as defined in Section 3.1 to provide \mathcal{C} with a useful inference service. Thus, \mathcal{M} would only deploy $\theta \neq \theta^*$ to learn the values of \mathbf{X} or \mathbf{Y} (objective 1). By claim 1, \mathcal{A}_M cannot learn the values of \mathbf{X} or \mathbf{Y} and thus cannot achieve objective 1. Since $\theta \neq \theta^*$ would not be considered a useful service, it would not allow \mathcal{M} to achieve objective 2. Since \mathcal{A}_M cannot achieve objectives 1 or 2 in Scenario 1, $U_1 = 0$.

Next, assume \mathcal{M} deploys no service at all (Scenario 2). Like in Scenario 1, claim 1 ensures \mathcal{A}_M cannot learn \mathbf{X} or \mathbf{Y} (objective 1). Additionally, failing to deploy any service is not useful to \mathcal{C} (objective 2). Therefore, $U_2 = 0$.

Finally, assume \mathcal{M} deploys some $\theta = \theta^*$ (Scenario 3). Since θ allows \mathcal{M} to maintain enough users, it is considered a useful service and allows \mathcal{A}_M to achieve objective 2. Since \mathcal{A}_M achieves at least objective 2 in Scenario 3, $U_3 > 0$. Since $U_3 > U_1$ and $U_3 > U_2$, \mathcal{A}_M enacts Scenario 3 and attempts to deploy some $\theta = \theta^*$, satisfying Requirement 1.

In order for \mathcal{M} to ensure the deployed θ is the intended θ^* , \mathcal{M} must ensure that the \mathbf{I}_F constituting θ implements \mathbf{F} using \mathbf{W} for the service P , where $\theta(x) = \bar{\mathbf{Y}} = \mathbf{I}_F(\bar{\mathbf{X}}, \mathbf{EK}, \mathbf{W})$ is a useful enough result for service P to satisfy the “best performing” requirement for $\theta = \theta^*$. Any vulnerability in \mathbf{I}_F that could lead to \mathcal{A}_S tampering with results such that $\bar{\mathbf{Y}}$ is no longer a useful result would lead to $\theta \neq \theta^*$. Thus, to ensure $\theta = \theta^*$, \mathcal{M} will verify that \mathbf{I}_F is free of vulnerabilities exploitable by \mathcal{A}_S to corrupt $\bar{\mathbf{Y}}$.

Standard certificate verification with attestation ensures \mathcal{M} securely communicates with \mathcal{E}_S to deploy the verified \mathbf{I}_F and corresponding \mathbf{W} and ensures \mathcal{A}_S cannot tamper with \mathbf{I}_F or \mathbf{W} . Standard certificate verification ensures \mathcal{C} communicates with an entity set up by \mathcal{M} . \mathcal{M} verifies this entity is \mathcal{E}_S to ensure protection against \mathcal{A}_S and satisfy $\theta = \theta^*$. \mathcal{C} securely sends its inputs $x = (\bar{\mathbf{X}}, \mathbf{EK})$ to \mathcal{E}_S and receives results y from \mathcal{E}_S using the TLS channel. The TEE protects all data and code execution from \mathcal{A}_S once in the enclave. Since a rational \mathcal{A}_M deploys a useful service, and since the deployed service computation and execution are protected at all points from tampering by \mathcal{A}_S , the deployed service θ is equal to θ^* . Since $\theta = \theta^*$, the result y returned to \mathcal{C} is $\bar{\mathbf{Y}} = \theta^*(x)$, satisfying Requirement 2. Since CHEX-MIX satisfies Requirements 1 and 2, it provides \mathcal{C} with correct results $y = \bar{\mathbf{Y}}$, which \mathcal{C} decrypts to obtain the final correct result \mathbf{Y} . \square

5.1.3. Takeaways. CHEX-MIX is beneficial to \mathcal{C} and \mathcal{M} in several ways. First, it relieves \mathcal{C} of the burden of needing to thoroughly analyze code \mathbf{I}_F for security vulnerabilities by removing the client attestation requirement.⁵

⁵ Appendix A provides a discussion of the minimal additional protection that including client attestation in the protocol would provide, if desired.

Second, it guarantees privacy of provider data \mathbf{W} , privacy of client data \mathbf{X} and \mathbf{Y} , and correctness of inference execution \mathbf{F} even while deployed in the public cloud. Third, it allows \mathcal{M} to remain offline after the setup phase of the protocol and offload all subsequent computation. Altogether, CHEX-MIX allows ML model providers to securely utilize the scale made possible by the cloud.

5.2. Achieving Confidentiality of \mathbf{I}_F

While the baseline protocol protects the implementation \mathbf{I}_F from integrity attacks during computation, it does not natively protect the privacy of the \mathbf{I}_F binary itself. In particular, the baseline protocol requires \mathcal{M} to send the \mathbf{I}_F binary to the cloud server *in-the-clear* to instantiate the enclave \mathcal{E}_S , allowing attackers in the cloud to view the contents of the \mathbf{I}_F binary. Several prior works have shown that it is possible to reverse-engineer binaries to learn the details of their original application code [13], [23], [69], [122]. Thus, this setup leaves \mathbf{I}_F vulnerable to confidentiality attacks.

However, confidentiality of \mathbf{I}_F code could be significantly beneficial to service providers. Software implementations of services contain decisions based on a provider’s expertise, such as algorithm choice or robust coding practices, and are thus often considered valuable IP [15], [53], [62], [110]. Therefore, protecting the details of the software implementation could protect the valuable IP that allows the provider to maintain a competitive advantage in the market. Furthermore, prior work has shown that encrypting binaries in this way can make certain classes of attacks (e.g., return-oriented programming attacks) more difficult to mount [68].

To attempt to solve the problem of maintaining software IP privacy in the public cloud, Intel released a Protected Code Loader (PCL) library [55] for SGX to allow users to treat an enclave binary as private enclave data. PCL encrypts several sections of the generated shared object binary of the enclave code (see: Appendix F for an example of a PCL-encrypted elf file). Intel describes PCL as a tool that can protect a developer’s private code IP [57], as long as the provider ensures that the segments of code which PCL does not encrypt (e.g., the code loader itself, the BSS segment, and any debugging info, with the full list given in the PCL documentation [57]) do not contain sensitive information.

However, a naive TEE-only solution for two-party computation cannot adequately make use of the PCL tool. In particular, in a TEE-only solution, the client would need access to \mathbf{I}_F code to 1) be able to verify the security of \mathbf{I}_F code, and 2) attest that \mathbf{I}_F is loaded in the enclave. This precludes \mathcal{M} from treating \mathbf{I}_F as private data.

CHEX-MIX, on the other hand, removes the attestation requirement from the client altogether, ensuring client trust in enclave code through its trust framework instead. Since CHEX-MIX does not require \mathcal{C} to have access to \mathbf{I}_F code, it allows \mathcal{M} to make use of PCL protection. Thus, CHEX-MIX establishes the prerequisites for achieving \mathbf{I}_F code confidentiality.

To utilize Intel PCL as part of our solution, we only need to make minor modifications to part of \mathcal{M} ’s setup phase in the CHEX-MIX baseline protocol. After analyzing the code for vulnerabilities as before, \mathcal{M} uses PCL

Setup (\mathcal{M}) (One time)

- 1) \mathcal{M} verifies that code \mathbf{I}_F securely implements \mathbf{F} .
- 2) \mathcal{M} generates a symmetric (e.g., AES-GCM) encryption key k for use with Intel PCL.
- 3) \mathcal{M} uses Intel’s PCL to encrypt the shared binary object of \mathbf{I}_F into $\overline{\mathbf{I}_F}$ using k .
- 4) \mathcal{M} establishes an enclave \mathcal{E}_{S_1} on a server hosted by \mathcal{S} .
- 5) \mathcal{M} generates a key pair for TLS channel establishment.
- 6) \mathcal{M} obtains a certificate $\text{Cert}_{\mathcal{M}}$ for its public key from a CA trusted by both \mathcal{M} and \mathcal{C} .
- 7) \mathcal{M} attests and establishes a secure channel $\sigma_{\mathcal{M}}$ with \mathcal{E}_{S_1} for all future communication.
- 8) \mathcal{M} sends k to \mathcal{E}_{S_1} over $\sigma_{\mathcal{M}}$.
- 9) \mathcal{E}_{S_1} seals k to server storage and terminates.
- 10) \mathcal{M} repeats steps 4-7 with enclave \mathcal{E}_{S_2} , where \mathcal{E}_{S_2} ’s binary consists of $\overline{\mathbf{I}_F}$ and Intel PCL components.
- 11) \mathcal{E}_{S_2} unseals k , decrypts $\overline{\mathbf{I}_F}$ to \mathbf{I}_F using k , and executes \mathbf{I}_F .
- 12) \mathcal{M} sends \mathbf{W} to \mathcal{E}_{S_2} over $\sigma_{\mathcal{M}}$.
- 13) \mathcal{M} issues a certificate $\text{Cert}_{\mathcal{E}_{S_2}}$ for \mathcal{E}_{S_2} ’s public key and sends $(\mathbf{W}, \text{Cert}_{\mathcal{M}}, \text{Cert}_{\mathcal{E}_{S_2}}, \pi)$ to \mathcal{E}_{S_2} over $\sigma_{\mathcal{M}}$.
- 14) \mathcal{M} exits the protocol and goes offline.

Figure 3: CHEX-MIX-PCL protocol for \mathbf{I}_F IP privacy for \mathcal{M}

to encrypt the shared object file for the code \mathbf{I}_F ⁶. \mathcal{M} shares this encrypted file with the enclave \mathcal{E}_S , which then decrypts and runs the \mathbf{I}_F binary from inside the enclave. We give a revised setup protocol for \mathcal{M} incorporating these modifications in Figure 3 (CHEX-MIX-PCL). Note that the logical enclave \mathcal{E}_S is actually split into two enclaves \mathcal{E}_{S_1} and \mathcal{E}_{S_2} in the protocol description, consistent with the actual implementation of the PCL library. \mathcal{E}_{S_1} shares data with \mathcal{E}_{S_2} by encrypting the desired shared data using a *sealing* key that \mathcal{E}_{S_1} derives from the identity of the enclave developer (and that can be obtained only by enclaves signed by the same developer). Since both \mathcal{E}_{S_1} and \mathcal{E}_{S_2} are developed and signed by developer \mathcal{M} , \mathcal{E}_{S_2} can then decrypt the file containing the secret data after deriving the sealing key in a similar manner. In the above procedure using PCL, this “secret data” is the key k used to encrypt \mathbf{I}_F .

This version of our solution provides the following guarantee in addition to the baseline protocol guarantees:

CLAIM 4. CHEX-MIX-PCL ensures confidentiality of \mathbf{I}_F for \mathcal{M} against a malicious \mathcal{A}_C and a malicious \mathcal{A}_S .

Security Analysis. \mathcal{M} verifies via remote attestation that \mathcal{E}_{S_1} is a secure enclave containing code to receive and seal a key k from \mathcal{M} , and that \mathcal{E}_{S_1} contains no vulnerabilities exploitable by \mathcal{A}_C or \mathcal{A}_S to access enclave code or data. \mathcal{M} securely transfers key k to \mathcal{E}_S via an attested TLS channel. \mathcal{M} verifies that $\overline{\mathbf{I}_F}$ fully encrypts the components

6. Since we assume \mathcal{M} , with its dedicated security team, can adequately vet the security of their own enclave code, we also assume \mathcal{M} can verify that the sensitive components of its private IP are not contained in the unencrypted segments.

of its code that it considers private IP. \mathcal{M} verifies via remote attestation that \mathcal{E}_{S_2} is a secure enclave containing code $\overline{\mathbf{I}}_{\mathbf{F}}$, code to unseal a key k , and PCL code to decrypt $\overline{\mathbf{I}}_{\mathbf{F}}$ into $\mathbf{I}_{\mathbf{F}}$. The TEEs ensure $\mathcal{A}_{\mathcal{C}}$ and $\mathcal{A}_{\mathcal{S}}$ cannot access key k . Since \mathcal{M} 's private code IP is only decrypted in enclave \mathcal{E}_{S_2} , and since only \mathcal{M} and the TEEs possess the key to decrypt code $\overline{\mathbf{I}}_{\mathbf{F}}$ into $\mathbf{I}_{\mathbf{F}}$, the confidentiality of \mathcal{M} 's private code IP is guaranteed. \square

5.2.1. Takeaways. CHEX-MIX provides the baseline protocol and framework that allows model providers to take advantage of private code protection. Adding PCL protection requires only minor modifications to the CHEX-MIX baseline protocol and requires no changes to the security model of the solution. Thus, CHEX-MIX provides model providers with a unique opportunity for greater IP protection in cloud deployments.

6. Related Work

In this section, we describe alternate approaches proposed by prior works for privacy-preserving inference. We intentionally leave this section detailed to provide more context for our evaluation and provide a summary of the main points discussed in this section in Table 2.

TEE-Only. TEE-only solutions for privacy-preserving inference [87], [96], [112], [113] heavily rely on remote attestation to guarantee privacy of client data. Since client data in these solutions is processed in-the-clear within the enclaves, *any security vulnerabilities in the enclave code, including any back doors purposely inserted by the model provider, could expose direct access to enclave data.* Malicious security in TEE-only solutions thus requires the impractical assumption that clients can thoroughly verify or blindly trust the security of enclave code, and thus cannot solve the problem of oblivious inference.

HE-Only. In CryptoNets [48] and LoLa [24], clients encrypt their private inputs and send the resulting ciphertexts to an untrusted server for homomorphic inference. These solutions require the model provider to maintain a private online infrastructure to perform the homomorphic evaluation since the model must be in-the-clear, preventing the model provider from making use of the public cloud. Alternatively, E2DM [58] encrypts both client and model provider data under the client's key. This allows an untrusted cloud to perform the HE evaluation, but requires a *semi-honest* cloud and an *honest* client.

MKHE / Hybrid-MKHE. A multi-key HE (MKHE) construction [27], [28], [72] enables a client and model provider to encrypt their private values using separate secret keys and outsource HE evaluation to an untrusted cloud server. The result ciphertext is encrypted under the keys of both parties and must be partially decrypted by the model provider before the client device decryption. Thus, this technique still requires the model provider to maintain a private online infrastructure for partial decryption. More importantly, this technique is only secure against even just semi-honest adversaries if the partial decryption is performed with a secure method such as noise flooding.

To the best of our knowledge, an MKHE-TEE hybrid solution has not been proposed or evaluated in any prior work, but our results in Tables 3 and 4 indicate that this

solution would be less efficient than CHEX-MIX since Eff.-MKHE is already less efficient when not inside a TEE.

2PC / Hybrid-2PC. We use the terms 2PC or MPC to refer to protocols built with secret sharing, oblivious transfer, and/or garbled circuits, and the terms hybrid-2PC or hybrid-MPC to refer to works that use MPC in conjunction with additional techniques such as HE.

Prior 2PC and hybrid-2PC protocols proposed for the problem of oblivious inference [16], [52], [54], [61], [70], [75], [82], [84], [86], [93], [97] assume the model provider maintains a private infrastructure for protocol execution and thus do not utilize the public cloud. With the exception of MUSE [70], these works also make a much weaker semi-honest adversary assumption for both model provider and client adversaries, which MUSE demonstrates can lead to devastating results in the client-malicious setting. While some works claim that the benefit of 2PC techniques over HE is their ability to evaluate "unmodified" non-polynomial activation functions, we note that prior works nevertheless choose to implement truncated versions of these activation functions [70], [82] or prefer using square activations for some or all of the activation layers anyway [82] to reduce computation and communication costs.

CryptFlow [66] proposed an interesting MPC-TEE hybrid solution, though unfortunately, without any experimental results for inference in the 2PC setting. Their protocol also requires the *client* to possess a TEE for the model provider to attest, which may not be feasible in practice, in addition to still requiring the client to attest the TEE of the model provider.

To the best of our knowledge, no other works have proposed or evaluated a 2PC-TEE or hybrid 2PC-TEE solution. Our evaluation suggests that comparable 2PC solutions and 2PC-HE solutions have a larger communication cost and runtime than CHEX-MIX, and the runtimes of these works will further increase if moved to a TEE. Additionally, naive placement of a semi-honest 2PC solution inside a TEE would not necessarily guarantee more than semi-honest security, and it is not clear what such a solution would provide over a TEE-only solution. Still, this may be an interesting direction for future work.

3PC. Known 3PC solutions for oblivious inference [66], [83], [98], [119], [120] require two of the three parties to act honestly. This requirement is difficult to set up in practice since it requires either an honest third-party server or a non-collusion assumption between public cloud servers. These solutions also include a large communication cost to share the model with all parties.

Zero-knowledge proofs. Known zero-knowledge proof solutions for secure machine learning [44], [76], [126] can only either provide privacy to \mathcal{M} or \mathcal{C} , but not both. Therefore, they do not address the problem of oblivious inference.

Other HE-TEE. Most prior HE-TEE works [35], [45], [124] propose using TEEs to perform sensitive (e.g., requiring access to the client's secret key) stages of the HE flow. Thus, they share the drawback of TEE-only solutions that the enclave code must be thoroughly verified by a client, who must possess an unrealistic level of expertise to guarantee that enclave code is free from vulnerabilities that could lead to compromised data privacy. Further, since HE evaluation still occurs outside the enclave, they offer no integrity protections against a malicious server. These

TABLE 2: Threat and deployment model comparison of prior approaches for privacy-preserving inference. A combined HE+TEE solution for oblivious inference provides security guarantees unaddressed by prior approaches, while allowing \mathcal{M} to offload computation to the public cloud. (R) refers to a rational adversary type as defined in Section 3.1, and (M) refers to a malicious adversary type. Dashes (–) indicate that a feature does not apply (e.g., the technique does not allow offload to an untrusted cloud).

Technique	Oblivious Inference?	\mathcal{M} can fully offload	Privacy of \mathbf{X}, \mathbf{Y} (for \mathcal{C})		Correctness of \mathbf{Y} (for \mathcal{C})		Privacy of \mathbf{W} (for \mathcal{M})	
			$\mathcal{A}_{\mathcal{M}}$ (M)	$\mathcal{A}_{\mathcal{S}}$ (M)	$\mathcal{A}_{\mathcal{M}}$ (R)	$\mathcal{A}_{\mathcal{S}}$ (M)	$\mathcal{A}_{\mathcal{C}}$ (M)	$\mathcal{A}_{\mathcal{S}}$ (M)
TEE	✗	✓	✗	✓	✗	✗	✓	✓
HE-Only	✓	✗	✓	–	✓	–	✓	–
MKHE	✓	✗	✓	✓	✓	✗	✗	✗
2PC	✓	✗	✗ ¹	–	✗ ¹	–	✗ ²	–
HE+2PC	✓	✗	✗ ¹	–	✗ ¹	–	✗/✓ ²	–
HE+TEE	✓	✓	✓	✓	✓	✓	✓	✓

¹ Most prior 2PC or HE-2PC solutions such as [61], [82] assume only a semi-honest/passive model provider.

² Most prior 2PC and HE-2PC solutions, with the exception of MUSE [70], assume a semi-honest client.

works also target single-party outsourced computation rather than two-party oblivious inference.

Drucker and Gueron [41], [42] suggest combining HE and TEEs for outsourced computation. Their evaluation over a database query uses the significantly less computationally powerful Pallier HE scheme. Thus, their demonstration is only applicable to a small range of problems and cannot be applied to neural network inference. Singh evaluates a version of the TFHE HE library [32], [111] for a “fused” millionaire problem inside an enclave for a single party [106]. The author does not address protecting the privacy of two separate parties, nor present an evaluation of an ML benchmark. Since this work requires bootstrapping after each Boolean arithmetic operation and does not use SIMD packing, it is also less communication and computation efficient for our problem setting. In both of the above sets of works, the authors do not specify when TEEs can be trusted to provide integrity but not confidentiality to justify their need for HE. Unlike our solution, their solutions do not remove the attestation requirement from TEEs, nor enable provider code encryption.

7. Evaluation

7.1. Experiments Overview

To evaluate the feasibility of our solution, we implement CHEX-MIX across three experiments on a commodity cloud server. In all experiments, we use the Microsoft SEAL library (v3.7.1) [102] to implement the HE-component of our solution.

Experiment 1: Baseline Protocol. We first demonstrate a proof of concept of CHEX-MIX for inference over a convolutional neural network (CNN). We target the same CNN as used in the Eff.-MKHE [27] work, which consists of 1 convolutional, 2 fully connected, and 2 square activation layers (see Table 7 for further details).

For this experiment, we use the Open Enclave SDK (v0.17.6)⁷ [89] to develop the enclave code. We base our implementation on the `attested_tls` sample code mbedTLS networking library [8], and we disable any

7. We prefer the Open Enclave SDK to other enclave SDKs since Open Enclave provides extensive documentation on integrating secure channel establishment (i.e., TLS) with attestation.

optional performance optimization flags in the enclave-side instance of Microsoft SEAL that are incompatible with Open Enclave.

We do not integrate an integrity-protected database for **EK** into our experiments since it is not the focus of our work. Any effort required to retrieve the **EK** for a client can be done between an initial “client hello” and subsequent client communication. Furthermore, consecutive requests from the same client would not require additional database access. Thus, we assume this cost can be hidden from the effective runtime.

Experiment 2: \mathbf{I}_F Privacy Protocol We also implement the version of our solution to provide \mathcal{M} with privacy of code \mathbf{I}_F using Intel PCL [55]. We use a similar setup in this experiment as in Experiment 1 and target the same CNN. However, since Open Enclave does not yet support Intel PCL integration, we instead use the Intel SGX SDK (v2.15) [56] for this implementation. For simplicity, and since we already implement the baseline protocol using full attestation and secure channel establishment procedures, we do not replicate these components in this proof of concept and instead fill the HE plaintext and ciphertext objects with random values. We run this proof of concept both with and without PCL to understand the overhead of adding PCL-provided protection.

Experiment 3: Evaluating Scalability Given the relatively recent introduction of efficient HE schemes such as CKKS, a benchmark suite (or even another efficient stand-alone network implementation) is not yet available for homomorphic inference. While some compilers exist for auto-generating HE evaluation code [17], [18], [37], [38], the efficiency of their compiled outputs is still much lower than that of hand-optimized implementations by HE experts. The state-of-the-art HE compiler EVA [37] (which subsumes prior work CHET [38]), for example, does not implement known essential optimizations such as merging of adjacent linear network layers [48], or using the baby-step-giant-step algorithm for fully connected layers [49]. Even using *56 threads*, EVA incurs a latency of 0.6 seconds—over *triple* the latency of the *single*-threaded hand-optimized HE neural network implementation we use in this work—to evaluate a similarly sized network.

Given the currently limited ability of modern HE compilers to produce efficient inference code, it would be unfair to use the output of these compilers to analyze the efficiency of our solution against other (non-HE-only)

approaches for oblivious inference. However, we still wish to evaluate the ability of our solution to scale to larger efficient HE networks as they are developed. To this end, we evaluate CHEX-MIX over a version of the SqueezeNet CNN used to evaluate the CHET homomorphic compiler [38] over the CIFAR-10 dataset. To the best of our knowledge, *this is the largest neural network evaluated using HE to date* and contains a total of 10 convolutional layers. For this experiment, we follow a similar strategy to Experiment 2 and randomize the values for all inputs inside the enclave prior to evaluation.

7.2. Experimental Setup

We run Experiments 1 and 2 on a Microsoft Azure Standard DC8ds_v3 VM with 64 GB of RAM with a maximum of 32 GB of Enclave Page Cache and Experiment 3 on an Azure Standard DC48ds_v3 VM with 384 GB of RAM with a maximum of 256 GB of Enclave Page Cache. All our experiments are compiled with GNU CC (version 7) on Ubuntu 20.04 and executed with a single thread at 2.8 GHz.

HE Parameters. Eff.-MKHE uses a degree of 16384 to obtain an optimal SIMD packing strategy for the CNN in Experiments 1 and 2. We use this as well for a fair comparison with their work. Since we do not need to perform as many ciphertext-ciphertext operations as Eff.-MKHE (as we do not require weights in ciphertext form), we can use only 5 modulus primes of bit lengths $\{60, 57, 57, 57, 60\}$ rather than the 8 primes used in Eff.-MKHE without any change to the underlying HE algorithm, SIMD packing strategy, or accuracy. We use encoding scales of 2^{53} , 2^{34} , 2^{27} , 2^{30} , and 2^{20} for the input, layers 1-3 weights, and the masking plaintext in the final fully connected layer, respectively. Both our work and Eff.-MKHE achieve an accuracy of 97.95% over the MNIST test dataset, which is the same as the accuracy the model achieves for evaluation in-the-clear.

The authors of CHET instantiated SqueezeNet with parameters with < 128 -bits of security. We analyzed the computation and discovered that we could reduce parameter selection from a total modulus bit length of 940 to a bit length of 840 for a degree of 32768, which *does* provide 128-bit security. We use these improved parameters and scales of 2^{10} , 2^{20} , and 2^{53} for the weights, masking plaintexts, and initial input, respectively. We evaluate this version of SqueezeNet over 100 random inputs in the CIFAR-10 test set and observe an accuracy of 77%, which is close to the 81.5% accuracy that the initial CHET work obtained over all test examples for less secure parameters. We emphasize that the purpose of Experiment 3 is to demonstrate scalability rather than efficiency or accuracy of HE, and recent work [77] has already demonstrated methods to significantly improve both the performance and accuracy of HE evaluation of this network using even smaller parameters.

Measurement Methodology. Open Enclave and the Intel SGX SDK do not provide access to runtime counters (e.g., via the C++ `chrono` library) that developers typically use to measure code performance. Instead, we opt to call custom functions in the untrusted host through enclave OCALLs (a term used for function calls that call the untrusted host process from the enclave), and we

use these host functions to implement the measurement checkpoints. Since our measurements include the runtime of executing these OCALL switches, our results may slightly overestimate the enclave code runtime.

Since communication latencies can vary widely between network infrastructures, user devices, and application types (e.g., high-performance use cases vs. IoT, cellular vs. ethernet, etc.), we do not include these in our overall runtime results.

SGX Memory Specification. Two versions of SGX have been released to date, which differ in their handling of memory allocation. The first, SGXv1, requires the user to specify the maximum enclave memory size required for the workload prior to enclave initialization, while SGXv2 allows the enclave to dynamically allocate memory as needed. For our experiments, we target the more widely available SGXv1. We configured Experiments 1 and 2 to use up to 128 KB of stack and up to 512 MB of heap enclave memory, and Experiment 3 to use up to 2 GB of stack and up to 310 GB of heap enclave memory.

We measured the total memory consumption of our modified SqueezeNet CNN benchmark and found that it consumes more than 300 GB. This is larger than the largest Enclave Page Cache offered by Azure VMs, and additionally causes the OS to terminate the enclave process. However, our solution can easily scale to larger network sizes by dividing the evaluation across multiple enclaves. We therefore evaluate this benchmark by splitting the computation in half and evaluating each half separately. We report the results for this experiment as the sum of these halves. We omit the communication cost between the enclaves since this cost can be hidden in parallel with the main evaluation.

7.3. Results

Table 3 shows the results of Experiment 1 for evaluating the baseline CHEX-MIX protocol over the Eff.-MKHE CNN benchmark, along with the performance costs of prior solutions for oblivious inference. Below, we compare this version of our solution to prior works in more detail. Appendix B provides additional performance metrics.

For Experiment 2, we found that both the PCL and non-PCL versions of the benchmarks had the same runtime⁸ of 0.38 seconds. Thus, CHEX-MIX can offer this protection for *no added performance cost*.

Finally, Table 5 shows the results of Experiment 3 for evaluating CHEX-MIX over our modified SqueezeNet benchmark. Compared to an HE-only execution of the same network, CHEX-MIX is only $2.28\times$ slower. Since this is approximately the same slowdown we observed compared to HE-only for Experiment 1, these results suggest that CHEX-MIX maintains its scalability across a range of network sizes.

7.3.1. Comparison with Prior Work. We emphasize that it would be misleading to compare solely the performance of our solution with prior works since prior solutions do not address the same problem statement and/or assume a weaker threat model than ours. Nevertheless, we compare our baseline Experiment 1 proof of concept to prior

⁸ We verified with the developers of the Intel SGX library that this is the expected behavior.

TABLE 3: Experiment 1 computation runtime and communication cost of CHEX-MIX compared to prior works for two-party oblivious inference. CHEX-MIX achieves a competitive runtime and communication cost to prior approaches, while providing security guarantees not provided by prior work. Measurements below the middle line are from this work. Dashes (–) indicate that a feature does not apply (e.g., the technique does not allow offload to an untrusted cloud).

Work	Technique	\mathcal{M} can fully offload	Privacy ($X, Y / \mathcal{A}_M$)	Privacy (W / \mathcal{A}_C)	Correctness (Y / \mathcal{A}_S)	Runtime (s)	Comm. (MB)
XONN ³ [97]	2PC	✗	✗	✗	–	0.16	38.28
GAZELLE ^{1,2,3} [61]	2PC+HE	✗	✗	✗	–	0.15 + 0.05	5.9 + 2.1
MUSE ^{1,3,4} [70]	2PC+HE	✗	✗	✓	–	22.67 (1-6) + 0.80 (8)	4270.08 + 10.24
DELPHI ^{1,3,4} [82]	2PC+HE	✗	✗	✗	–	7.41 (1-8) + 0.48 (8)	235.52 + 10.24
DELPHI ¹ [82]	2PC+HE	✗	✗	✗	–	1.20 + 0.14	43.65 + 0.15
Eff.-MKHE [27]	MKHE	✗	✓	✗	✗	1.23	2.125
-	HE	✗	✓	✓	–	0.19	0.75
CHEX-MIX	HE+TEE	✓	✓	✓	✓	0.46	0.75

¹ Costs separated into “offline” and “online” components (though both must be repeated per inference). Separation indicated by the (+) symbol.

² Work did not explicitly mention evaluation thread count.

³ Runtime includes computation and LAN communication latency. Authors did not provide separate runtimes for computation only.

⁴ Runtime is the sum of multiple parts, each with a different thread count. Thread count listed in parenthesis.

TABLE 4: Experiment 1 computation runtime and communication size breakdown. HE-only and CHEX-MIX solutions enable lower client runtime and communication costs than DELPHI or Eff.-MKHE.

Work	Runtime (s)		Comm. (MB)	
	Client	Server	C→S	S→C
DELPHI [82]	0.20	1.20	41.7	2.06
Eff.-MKHE [27]	0.017	1.22	1.75	0.375
HE-only	0.007	0.20	0.5	0.25
CHEX-MIX		0.45		

TABLE 5: Experiment 3 computation runtime and communication size breakdown for HE-Only and CHEX-MIX evaluation of the modified CHET-SqueezeNet CNN.

Work	Runtime (s)		Comm. (MB)	
	Client	Server	C→S	S→C
HE-only	0.21	891	14.25	10
CHEX-MIX		2028		

approaches for oblivious inference for inference over the MNIST dataset for similarly-sized CNNs (see Appendix E for details of the CNNs) to provide some perspective of our results. We list a subset of the problem statement differences between works alongside these results, with more information below.

XONN. Like other 2PC solutions, XONN does not allow \mathcal{M} to offload computation to the public cloud. Additionally, XONN assumes a much weaker passive threat model and therefore does not provide privacy guarantees in the presence of a malicious \mathcal{A}_C or malicious or rational \mathcal{A}_M . In spite of this, CHEX-MIX has a $51\times$ smaller communication cost and is only $3\times$ slower than XONN.

GAZELLE, DELPHI, and MUSE. Similar to XONN, these solutions do not allow \mathcal{M} to offload computation to the cloud and only assume a semi-honest threat model (with the exception of MUSE client-malicious protection).

Compared to GAZELLE, CHEX-MIX is only slightly more than twice as slow but achieves a nearly $11\times$ smaller communication cost. Compared to DELPHI [82] and MUSE [70] with *multiple* threads evaluated over a CNN that achieves similar accuracy as our network, our solution with a *single* thread is $17\times$ and $51\times$ faster

and has a $328\times$ and $5707\times$ smaller communication cost, respectively. We count the reported so-called “offline” and “online” costs for this comparison together since both of these phases need to be repeated for *every* inference.

For an additional comparison point, we implement our target CNN benchmark (with square activations) using the open-source DELPHI code and measure its performance using a single thread on the same platform used to benchmark our first two experiments. We measure the runtime for computation only (omitting time spent on communication) and report this runtime along with the total communication size in Table 3 below the middle line. Even in this case, our solution is nearly $3\times$ faster and has a more than $58\times$ smaller communication cost per inference. Table 4 further shows that DELPHI requires a $29\times$ larger computation time and an $83\times$ larger client upload communication cost than CHEX-MIX, implying it would be more burdensome for constrained client devices.

Eff.-MKHE. To ensure as fair a comparison with Eff.-MKHE [27] as possible, we upgrade the original Eff.-MKHE implementation to use the latest version of Microsoft SEAL. Compared to Eff.-MKHE, CHEX-MIX is nearly $3\times$ faster and achieves a nearly $3\times$ smaller communication cost. Further, Table 4 shows that Eff.-MKHE has a $2\times$ larger computation cost and a $3\times$ larger upload communication cost for the client compared to CHEX-MIX, making it less ideal for scenarios in which a client device is constrained.

Eff.-MKHE allows the offload of some computation to an untrusted cloud; however, it still requires \mathcal{M} to maintain a private online infrastructure to perform partial decryption of results. Eff.-MKHE is also not secure against active adversaries, and it is only secure against even a semi-honest server if the model provider performs the partial decryption with a secure method such as noise flooding. The implementation in [27] did not include such a secure method and is therefore vulnerable to a passive key-recovery attack on CKKS [71].

HE-only. We measured the runtimes of “HE” and “HE+TEE” in Table 3 with the same code, executed outside and inside an enclave, respectively. The HE-only solution provides no privacy guarantees to \mathcal{M} when \mathcal{M} wants to offload computation to the public cloud. To achieve a comparable threat model to our solution, \mathcal{M}

would need to host a private online infrastructure for HE evaluation, losing the scalability and flexibility offered by the public cloud. Thus, while a combined HE+TEE solution is slightly slower than an HE-only solution, the technique can scale to many more clients than an HE-only solution, allowing providers to more than make up for the slight performance loss.

TEE-only For experiment 1, a TEE-only solution takes 0.0002 seconds and 0.00076 MB of communication. However, recall that a TEE-only solution does not provide privacy to clients (see Sections 4 and 6), and thus does not solve the problem of oblivious inference.

8. Discussion

Performance. Compared to in-the-clear evaluation of a neural network, HE-based neural network evaluation is still slow. However, evidence suggests that, given enough attention, the runtime of HE-based solutions will continue to improve rapidly with time. The original CryptoNets work that proposed using HE for machine learning in 2016 [48], for example, reported a runtime of almost 300 seconds for a similarly-structured CNN used in Experiments 1 and 2 of our work. This demonstrates a performance improvement of at least $1579\times$ in six years using algorithmic and software improvements alone. With the recent DARPA DPRIVE program that invested over 53 million USD into HE accelerator development [10], [125], we might see this type of rapid orders-of-magnitude performance improvement of HE-based techniques again in the near future. We believe our work can enable HE to be applied to more scenarios, further motivating research into more efficient HE algorithms, benchmarks, and schemes to bring this comparison even closer.

Circuit Privacy. At a high level, a circuit-private protocol should ensure that clients learn no more about the computation than the outputs of their input queries. HE ciphertexts contain error terms that change during evaluation, potentially leaking information about the plaintext values applied to an encrypted input. XONN [97] noted that the implementation in GAZELLE [61] does not satisfy the circuit privacy property. Indeed, as a hybrid 2PC-HE protocol, GAZELLE requires client decryption of HE ciphertexts after *every* linear layer, making it conceivable that a client adversary could, in theory, derive model weights from the decrypted values.

By contrast, our protocol only involves client decryption after *all* network layers are evaluated. It is not known whether, after several layer computations, especially when including multiple nonlinear layers, an attacker could still use the final ciphertext error to learn the weights used in intermediate layers. No prior work has sufficiently demonstrated how an adversary could extract plaintext input from noise in the resulting ciphertexts of a nonlinear circuit in practice. Nonetheless, a simple mitigation for this problem is to use an HE scheme like BFV or BGV with increased parameter sizes rather than CKKS [82], [97]. The defenses listed in Appendix D may also be helpful to defend against circuit privacy attacks.

Side channels. Although we do not consider side channels as part of our threat model (consistent with Intel’s official threat model for SGX [59]), we neverthe-

less wish to devote some discussion to them given their attention in the literature.

Side-channel attacks on TEEs fall into two main categories: those that the software (enclave) developer can mitigate, and those that they cannot. Intel contends that it is the responsibility of enclave developers to write their enclave code in a secret-data-independent manner for protection against the first type of attack [59].

The second type of side-channel attacks appears much more complicated to defend against, and prior works detail side channel attacks that are difficult for developers to properly prevent (e.g., [74], [117], [123], to name just a few). Intel purports to take these attacks seriously and continues to actively issue patches to SGX for numerous side channels as mitigations are developed [59], [109]. It is therefore critical that SGX users use proper enclave attestation to ensure they are using the most up-to-date version of the technology. Additionally, several works [12], [40], [88] propose techniques to mitigate the ability of attackers to perform side-channel attacks on TEEs, which providers can add on top of our solution for added protection.

A significant advantage of our solution is that it natively offers *clients* privacy protection from malicious side-channel adversaries. In particular, since client data is always in encrypted form inside the enclave, any attack on the enclave cannot view the underlying data of the HE ciphertexts. Clients can also use the strategy discussed in Appendix C for added assurance of computational correctness even against side channel attacks.

Additionally, we ensure that our implementation does not leak any information about \mathcal{M} ’s private values \mathbf{W} through timing side channels by verifying that our inference code and the implementation of operations in Microsoft SEAL do not contain any data-dependent computation, branching, or memory accesses based on \mathcal{M} ’s private data. While this is possible for any HE inference solution (since HE-inference does not *require* any non-constant-time operations on \mathcal{M} ’s private data), we note that this is not a default property of an HE-TEE hybrid solution, but rather results from a secure implementation of both enclave code and SGX technology.

9. Conclusion

In this work, we propose a novel approach for oblivious inference in the public cloud setting. Our solution, CHEX-MIX, features a hybrid HE-TEE protocol that provides both clients and model providers with confidentiality and integrity guarantees under a strong adversary model, tolerating malicious clients, malicious cloud providers, and rational, actively adversarial model providers. We investigate the feasibility of performing homomorphic evaluation inside TEEs by deploying CHEX-MIX on a Microsoft Azure confidential computing virtual machine. Our experiments demonstrate that CHEX-MIX is able to achieve runtime and communication costs comparable to or more efficient than prior approaches, while providing powerful security guarantees not addressed by prior works. We hope that this work will enable more scenarios for HE deployments and that this will in turn encourage the development of more openly available, hand-optimized HE benchmarks as well as more research into HE performance improvements in the future.

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A. Client Attestation

In CHEX-MIX, the rational behavior of the ML model provider \mathcal{M} ensures the correctness of computation against \mathcal{M} when the client \mathcal{C} encrypts their data with HE. However, if \mathcal{M} were malicious instead of rational, \mathcal{C} could not assume \mathcal{M} would provide a correct implementation of service P , nor could \mathcal{C} be sure that \mathcal{M} would not insert backdoors into \mathbf{I}_F for exploitation by \mathcal{A}_M . At first, it may seem that this problem can be solved by having \mathcal{M} release \mathbf{I}_F and \mathcal{C} attest enclave \mathcal{E}_S . Indeed, assuming \mathcal{C} knew the underlying \mathbf{F} that would provide service P , \mathcal{C} could, in theory, verify for themselves that \mathbf{I}_F implements \mathbf{F} . However, in practice, this places a high burden on \mathcal{C} , and \mathcal{C} would still need to verify that \mathbf{I}_F is free from all vulnerabilities that could affect computational correctness, including any hidden backdoors inserted by a malicious \mathcal{M} (see Sections 4 and 6).

Instead, \mathcal{C} could again apply the rational assumption to guarantee that \mathcal{M} would not insert any backdoors into \mathbf{I}_F (still assuming \mathcal{C} uses HE to encrypt their data) that would affect computational correctness. Then, \mathcal{C} could attest \mathcal{E}_S to verify that the enclave is loaded with the expected \mathbf{I}_F . While this method does not allow for a fully malicious \mathcal{M} , it reduces the functionality dependent on the rational behavior of \mathcal{M} and allows \mathcal{C} more control over verifying correct enclave execution. However, it limits \mathcal{M} from being able to encrypt \mathbf{I}_F (e.g., using Intel PCL [55]). Figures 4 and 5 give the modifications required to the CHEX-MIX protocol to provide these additional properties.

B. Additional Performance Metrics

If ML service providers are adept at resource scaling, they would be able to scale their service as needed to

Setup (\mathcal{M}) (One time)

- 1) \mathcal{M} verifies that code \mathbf{I}_F securely implements F .
- 2) \mathcal{M} uploads \mathbf{I}_F to some public domain accessible by \mathcal{C} .
- 3) \mathcal{M} establishes an enclave \mathcal{E}_S with code \mathbf{I}_F on a server hosted by \mathcal{S} .
- 4) \mathcal{M} generates a key pair for TLS channel establishment.
- 5) \mathcal{M} obtains a certificate $\text{Cert}_{\mathcal{M}}$ for its public key from a CA trusted by both \mathcal{M} and \mathcal{C} .
- 6) \mathcal{M} attests and establishes a secure channel $\sigma_{\mathcal{M}}$ with \mathcal{E}_S for all future communication.
- 7) \mathcal{M} sends \mathbf{W} to \mathcal{E}_S over $\sigma_{\mathcal{M}}$.
- 8) \mathcal{M} issues a certificate $\text{Cert}_{\mathcal{E}_S}$ for \mathcal{E}_S 's public key and sends $(\mathbf{I}_F, \mathbf{W}, \text{Cert}_{\mathcal{M}}, \text{Cert}_{\mathcal{E}_S}, \pi)$ to \mathcal{E}_S over $\sigma_{\mathcal{M}}$.
- 9) \mathcal{M} exits the protocol and goes offline.

Figure 4: CHEX-MIX enhanced correctness verification setup protocol for \mathcal{M}

Setup (\mathcal{C}) (Once per client)

- 1) \mathcal{C} verifies that \mathbf{I}_F implements the expected functionality.
- 2) \mathcal{C} receives $(\text{Cert}_{\mathcal{M}}, \text{Cert}_{\mathcal{E}_S}, \pi)$ from \mathcal{E}_S .
- 3) \mathcal{C} verifies $(\text{Cert}_{\mathcal{M}}, \text{Cert}_{\mathcal{E}_S}, \pi)$, attests \mathcal{E}_S , and establishes a secure channel $\sigma_{\mathcal{C}}$ with \mathcal{E}_S upon successful verification.
- 4) \mathcal{C} generates HE keys \mathbf{SK} and \mathbf{EK} based on π .
- 5) \mathcal{C} sends \mathbf{EK} to \mathcal{E}_S over channel $\sigma_{\mathcal{C}}$.

Figure 5: CHEX-MIX enhanced correctness verification setup protocol for \mathcal{C}

accommodate changes in demand. Proper resource scaling will ensure there are slightly more resources readily available than are being used by clients at any given moment. Since the setup process would be performed before clients would be ready to connect, any setup time would not contribute to the effective workload runtime. Furthermore, any setup time must only be incurred on enclave initialization, and does not need to be incurred again for each connecting client for the lifetime of the enclave. Nevertheless, for completeness, we provide a few extra performance measurements for enclave setup time, including components relevant to attestation. We measure the time to create the enclave in Experiment 1 using the Open Enclave framework and generate attestation evidence, the runtime of the `verify_callback` function of the Open Enclave `attested_tls` sample code for the non-enclave client, and the response time of receiving a token from the Microsoft Azure Attestation service upon submitting it a quote for verification as 0.39, 0.018, and 0.0077 seconds, respectively.

Additionally, we can calculate a rough estimate for the energy consumption of our workload for Experiment 1 as follows: we run our experiments on an Intel Xeon Scalable Processor 8370C, which has a thermal design power of 270 Watts for its 32 cores. Since the experiment uses a single core, we calculate $\frac{1}{32} \times 270 \text{ Watts} \times 0.46 \text{ sec} \approx 0.001078 \text{ Wh} \approx 3.88 \text{ J}$ as a rough upper bound for the

timed server portion of the workload.

C. Sensitive Samples

A client may want additional guarantees of computational integrity from adversaries outside the scope of our threat model (e.g., side-channel adversaries). In such cases, the following integrity-checking mechanism may be helpful and can be used with our solution: the client \mathcal{C} chooses a value \mathbf{X} to encrypt for which \mathcal{C} knows the expected output \mathbf{Y} . (In the case where \mathcal{C} is not able to know the value of \mathbf{Y} ahead of time for even a single \mathbf{X} , this pair can be shared directly by \mathcal{M} if \mathcal{M} is trusted to be rational). \mathcal{C} encrypts this value \mathbf{X} and sends it to \mathcal{E}_S for evaluation. If the decryption of \mathbf{Y} matches what \mathcal{C} expects, \mathcal{C} can be more confident that the data path is free of the types of integrity violations that would cause the result to be incorrect.

The above method was proposed by Xu et al. [127] for providing users with integrity assurance for outsourced HE computation. The authors further discuss how a set of “sensitive samples”—input-output pairs that would detect integrity violations of concern with high probability—could be used to make this technique more robust. We note that this integrity-checking property is unique to techniques such as HE that maintain the encrypted form of client inputs throughout the computation, preventing adversaries from simply identifying when inputs are part of the sample set and changing their behavior (e.g., malicious to honest) to evade detection.

D. Additional Defenses for \mathcal{M}

Recent works have demonstrated how a client adversary can extract the private weights of a model provider through *model-stealing* attacks [114], or learn information about the initial model training data set through *model-inversion* or *re-identification/membership inference* attacks [105], [115] by analyzing the results of several queries made to the inference server. We note that these attacks are possible against all prior works in oblivious inference, and thus are not uniquely applicable to our work. Nevertheless, we follow the approach taken by XONN [97] and discuss how providers can apply defense mechanisms for these attacks on top of our work.

A simple mitigation, suggested in prior work [60], [75] involves having the server rate-limit the prediction requests from any given \mathcal{C} . We note that this approach requires the server to keep track of the identity of each client, or at least be able to differentiate one client from another. However, it may still be possible for a client to masquerade as or collude with another client to collect additional query responses.

A related but more difficult approach is to use statistical properties of the network to guarantee that results do not leak information. Here, a model provider can analyze a stand-alone network to ensure that the required number of queries to reverse engineer the model parameters is larger than is computationally feasible for clients to analyze.

Additionally, since the aforementioned attacks rely on having the server reveal to the client the confidence scores of the result, another mitigation suggested by prior

TABLE 6: Description of the CNN used to benchmark DELPHI [82] and MUSE [70] (based on the description given in MiniONN [75]) in the MUSE work. Adjacent linear layers are listed together since they are typically combined for homomorphic inference. Measurements reported in MUSE for this network were measured on an AWS c5.9xlarge instance with 72 GB of RAM on an Intel Xeon 8000 series CPU at 3.6 GHz.

Layer	Description
Conv-1	28x28-pixel images, 5x5 windows, (2,2) strides, 16 output channels
Act-1	Applies a truncated ReLU activation to each of the 9216 inputs
Pool-1, Conv-2	Average Pooling, 2x2 windows, 2304 outputs; 5x5 windows, (1,1) strides, 16 output channels
Act-2	Applies a truncated ReLU activation to each of the 1024 inputs
Pool-2, FC-1	Average Pooling, 2x2 windows, 256 outputs; Fully connects 256 inputs to 100 outputs
Act-3	Applies a truncated ReLU activation to each of the 100 inputs
FC-3	Fully connects 100 inputs to 10 outputs

TABLE 7: Description of the CNN used for Experiments 1 and 2 for our solution and Eff.-MKHE based on the description given in Eff.-MKHE [27].

Layer	Description
Convolution	28x28-pixel images, 4x4 windows, (2,2) strides, 5 output channels
Square-1	Squares each of the 845 inputs
FC-1	Fully connects 845 inputs to 64 outputs
Square-2	Squares each of the 64 inputs
FC-2	Fully connects 64 inputs to 10 outputs

works [47], [105] involves having the model provider apply a rounding filter layer to the result before sharing the result with the client. This technique ensures that, while the maximum predicted class remains the same, the result does not leak additional information about the weights through the precise confidence score values. We note that, unlike BFV or BGV, CKKS is particularly adept at removing the least significant bits of a result. Thus, it is easy to add a rounding filter layer to our CKKS-based approach.

E. Neural Network Descriptions

We provide a description of the CNNs used in our work and prior works to implement the MNIST inference network from Experiment 1 in Tables 6, 7, 8, and 9.

F. PCL-encrypted ELF File Output

As an example of the protection provided by the Intel PCL library, Figures 6a and 6b show the difference in the output of the `readelf` command on the enclave binaries, with and without using the Intel PCL library to encrypt the binaries, respectively.

TABLE 8: Description of the CNN used to benchmark GAZELLE [61] in the original work, as described in DeepSecure [100]. Measurements reported in GAZELLE for this network were measured on an AWS c4.xlarge instance with 7.5 GB of RAM at 2.90 GHz.

Layer	Description
Convolution	28x28-pixel images, 5x5 windows, (2,2) strides, 5 output channels
ReLU-1	Applies a ReLU activation to each of the 845 inputs
FC-1	Fully connects 845 inputs to 100 outputs
ReLU-2	Applies a ReLU activation to each of the 100 inputs
FC-2	Fully connects 100 inputs to 10 outputs

TABLE 9: Description of CNN used to benchmark XONN [97] in the original work. Measurements reported in XONN for this network were measured on an Intel Core i7-7700k at 4.20 GHz with 32 GB of RAM and achieved an accuracy of 98.4%.

Layer	Description
Convolution	28x28-pixel images, 5x5 windows, (2,2) strides, 5 output channels
BN-BA-1	Applies a binary normalization and binary activation to each of the 845 inputs
FC-1	Fully connects 845 inputs to 100 outputs
BN-BA-2	Applies a binary normalization and binary activation to each of the 100 inputs
FC-2	Fully connects 100 inputs to 10 outputs

```

33: 0000000000005d80 54 FUNC LOCAL DEFAULT 12 sgx_ecall_type_int
34: 0000000000005dc0 70 FUNC LOCAL DEFAULT 12 sgx_ecall_type_char
35: 0000000000005e18 54 FUNC LOCAL DEFAULT 12 sgx_start_nm_app
36: 0000000000000000 0 FILE LOCAL DEFAULT ABS rms.cpp
37: 0000000000003a20 140 FUNC LOCAL DEFAULT 12 _ZN4seal4util7PointerIN5
38: 00000000000030c0 140 FUNC LOCAL DEFAULT 12 _ZN4seal4util7PointerIN5
39: 0000000000003138 140 FUNC LOCAL DEFAULT 12 _ZN4seal4util7PointerIN5
40: 0000000000007508 11 OBJECT LOCAL DEFAULT 14 _ZNKSt3_10vectorIN5seal
41: 00000000000031c4 77 FUNC LOCAL DEFAULT 12 _ZN4seal4util7PointerIN5
42: 0000000000003212 77 FUNC LOCAL DEFAULT 12 _ZN4seal4util7PointerIN5
43: 0000000000000000 0 FILE LOCAL DEFAULT ABS context.cpp
44: 0000000000003260 140 FUNC LOCAL DEFAULT 12 _ZN4seal4util7PointerIN5
45: 0000000000007628 11 OBJECT LOCAL DEFAULT 14 _ZNKSt3_10vectorIN5seal
46: 0000000000007678 9 OBJECT LOCAL DEFAULT 14 _ZNKSt3_10vectorIN5seal7
47: 0000000000000000 0 FILE LOCAL DEFAULT ABS evaluator.cpp
48: 00000000000032ec 58 FUNC LOCAL DEFAULT 12 _ZN4seal12_GLOBAL__N_122i
49: 0000000000003326 78 FUNC LOCAL DEFAULT 12 _ZN4seal4util8mul_safeInJ
50: 0000000000003326 78 FUNC LOCAL DEFAULT 12 _ZN4seal4util8mul_safeInJ
51: 0000000000003374 106 FUNC LOCAL DEFAULT 12 _ZN4seal4util110GaloisToo
52: 00000000000033de 124 FUNC LOCAL DEFAULT 12 _ZN4seal4util115seal_for_e
53: 000000000000345a 75 FUNC LOCAL DEFAULT 12 _ZN4seal4util134inverse_n
54: 00000000000034a5 183 FUNC LOCAL DEFAULT 12 _ZN4seal4util120negate_pol
55: 000000000000355c 133 FUNC LOCAL DEFAULT 12 _ZN4seal4util117odd_poly_c
56: 00000000000035e1 133 FUNC LOCAL DEFAULT 12 _ZN4seal4util123yadic_pro
57: 0000000000003666 211 FUNC LOCAL DEFAULT 12 _ZN4seal9evaluator10bfv

```

(a)

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54: 0000000000000000 0 NOTYPE LOCAL DEFAULT UND
55: 0000000000000000 0 NOTYPE LOCAL DEFAULT UND
56: 0000000000000000 0 NOTYPE LOCAL DEFAULT UND
57: 0000000000000000 0 NOTYPE LOCAL DEFAULT UND

```

(b)

Figure 6: Excerpt from symbol table output of running the `readelf` command on unencrypted (a) and PCL-encrypted (b) enclave binaries. The unencrypted symbol table reveals function calls and file names, while the PCL-encrypted symbol table does not.