Chiron: Privacy-preserving Machine Learning as a Service

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Abstract
Major cloud operators offer machine learning (ML) as a service, enabling customers who have the data but not ML expertise or infrastructure to train predictive models on this data. Existing ML-as-a-service platforms require users to reveal all training data to the service operator.

We design, implement, and evaluate Chiron, a system for privacy-preserving machine learning as a service. First, Chiron conceals the training data from the service operator. Second, in keeping with how many existing ML-as-a-service platforms work, Chiron reveals neither the training algorithm nor the model structure to the user, providing only black-box access to the trained model.

Chiron is implemented using SGX enclaves, but SGX alone does not achieve the dual goals of data privacy and model confidentiality. Chiron runs the standard ML training toolchain (including the popular Theano framework and C compiler) in an enclave, but the untrusted model-creation code from the service operator is further confined in a Ryoan sandbox to prevent it from leaking the training data outside the enclave. To support distributed training, Chiron executes multiple concurrent enclaves that exchange model parameters via a parameter server.

We evaluate Chiron on popular deep learning models, focusing on benchmark image classification tasks such as CIFAR and ImageNet, and show that its training performance and accuracy of the resulting models are practical for common uses of ML-as-a-service.

1. Introduction
The impressive accuracy achieved by modern machine learning (ML) in business [12], medicine [6], and communication [5, 17] motivates many data holders to apply ML to their own datasets. Existing ML frameworks, however, are not easy to deploy by non-expert users due to a large number of configuration parameters and general lack of understanding of why and how modern ML works. Furthermore, ML expertise is scarce and often unrelated to data holders’ primary competency (e.g., customer relationship management or biomedical research).

This mismatch has created a growing business in machine learning as a service, with offerings from Google [4], Amazon [2], and Microsoft [13], and several startups [3, 7, 14, 15]. ML-as-a-service promises to bring high-quality ML techniques to non-expert users, but privacy and confidentiality are obstacles to its adoption. Machine learning is useful insofar as it enables accurate quantitative predictions. When using conventional ML services, users are revealing precisely the data that (they hope) can give them a competitive advantage. If the training data is sensitive—commercial transactions, confidential documents, medical images, etc.—owners will not want to expose it to ML service providers and thus will not be able to take advantage of their services.

On the service provider side, many commercial ML services, including Google’s Prediction API and Amazon ML, do not reveal their training algorithms or resulting models to the customers. In part, this helps support their business: they give customers API access to the trained models and charge per API use. They may also be concerned about the intellectual property contained in their proprietary models and the configuration parameters they use for particular ML tasks. We assume that ML services are not actually interested in stealing their customers’ data and would be willing to forego their access to this data in exchange for the increased adoption of their services by privacy-sensitive customers.

Our contributions. We present Chiron, a system that enables data holders to train ML models on an outsourced service without revealing their training data.

The service provider is free to choose the type of the model to train, how to configure and train it, and what transformations, if any, to apply to the inputs into the model. These choices can adaptively depend on the user’s data and ML task. The user obtains API access to the trained model but no other information about it. This matches how ML-as-a-service operates today.

To enforce data confidentiality while allowing the provider to select, configure, and train a model any way they want, Chiron employs a Ryoan [41] sandbox, which in turn is based

1 In Greek mythology, Chiron is a centaur entrusted with training demigods and heroes.
on a hardware-protected enclave such as Intel’s SGX [18]. An enclave alone is insufficient because it only protects trusted code executing on an untrusted platform. Code can only be trusted if it is public and thus can be checked by users. In Chiron, however, the ML service provider’s code is untrusted, thus users must be assured that this code is not stealing their data even though they cannot inspect it.

Chiron leverages the confinement provided by Ryoan to enable the service provider’s code to access users’ data, then define and train a model, while preventing it from exfiltrating the data. Users can verify that the the enclave is executing a Ryoan sandbox extended with standard ML toolchain code, but without seeing the specifics of the model being trained. Ryoan inherits SGX limitations, such as vulnerability to cache-timing and memory-access channels (discussed in §6).

For performance, Chiron places a generic, model-independent ML toolchain—in particular, the standard Theano framework and C compiler—inside the hardware-protected sandbox outside the sandbox. The untrusted code inside sandbox can only interact with this framework via an interface controlled by the sandbox and cannot use it to leak information. The integrity of the toolchain and sandbox is attested to the user. Therefore, the user only needs to trust the sandbox and ML toolchain, both of which are public and standard. There are no checks specific to the ML model.

Modern ML models, especially deep learning models, benefit from concurrent training of multiple models on different batches of the training data. Chiron provides support for concurrent training via a parameter server and data-oblivious channels between enclaves that enable them to exchange model parameters during training.

To evaluate Chiron, we focus on the popular deep learning approach that demonstrated exceptional accuracy for many classification tasks. We measure the convergence times, scalability, and performance of Chiron when training ML models on standard benchmarks such as CIFAR [44] and ImageNet [38]. We also explore the effects of training multiple models and of varying the parameter exchange rate for several levels of parallelism.

2. Background

2.1 Machine learning

A machine learning model (ML model) is a function with a set of parameters that maps an input to a target output. For example, the inputs to a facial recognition model are images; the target is the identity of the person in the image. The model parameters are usually floating point numbers. For example, a linear regression model is a function \( f(x) = W^T x \) where \( W \) is the parameters (aka the weight vector) and \( x \) is the input. In artificial neural networks, the parameters are the weights on the connections between the nodes of the network.

We focus on supervised learning. The training data in this case is a set of input points, each labeled with its correct target. The goal of training is to find a set of parameters that maximizes the model’s accuracy on the training data. This is usually done by optimizing the objective (or loss) function, which penalizes the model when it outputs a wrong target on a data point. A regularization term can be added to the objective function to penalize model complexity. This helps prevent overfitting, when the model exhibits high accuracy on the training data but poor accuracy on the test data.

After training has finished, the model is evaluated using test data which was not used during training. A standard metric is test accuracy, which is the percentage of test data points that are classified correctly.

For many ML tasks and models, the objective function cannot be optimized in one step. Instead, the learning algorithm initializes the model parameters, then iteratively feeds batches of training data to the model, calculates the loss, and updates the parameters to reduce the loss. Training typically finishes when the loss value stops decreasing or when parameter updates become smaller than a certain threshold, i.e., when the model converges, or else after a fixed number of iterations, or when the model achieves acceptable accuracy on a validation dataset (distinct from the training dataset).

Most modern ML algorithms have a set of tunable hyper-parameters, distinct from the model parameters. Hyper-parameters control the configuration of the algorithm such as the number of training iterations, the ratio of regularization term in the loss function, the size of each training batch, etc.

Deep learning. Deep learning has become very popular for many ML tasks, especially related to computer vision and image recognition (e.g., [44, 45]). Deep learning models are composed of layers of nonlinear mappings from input to intermediate hidden states and finally to output. Each connection between layers has a floating point weight matrix as parameters. These weights are updated during training. The topology of the connections between layers is task-dependent and important to the ultimate accuracy of the model.

Training a deep neural network on a large dataset can take a long time. A common way to scale deep learning is through data and model parallelism, with multiple models training concurrently and exchanging parameters via a parameter server [34, 37, 56]. The training dataset is partitioned into subsets and a separate model is trained on each subset. The parameter server stores the global set of all model parameters. During training, each local model pulls the parameters from this server, calculates the updates based on its current batch of training data, then pushes these updates back to the server, which updates the global parameters.

Model design vs. model training. In the architecture of Chiron, we distinguish model design from model training (see §4.2). Model design code specifies the type and topology of the model, the loss function, the optimization algorithm, the values of the hyper-parameters, and the transformations, if any, to apply to the model inputs (e.g., scaling, rotating, or resampling images).
Model training is the generic process of repeatedly applying the model to a batch of data, calculating the loss, and updating the parameters according to the specifications provided by the model design code.

### 2.2 Symbolic computation

Most ML algorithms are essentially series of mathematical operations, e.g., matrix multiplication that maps input to output or the loss calculation given the model’s output and the corresponding target values. These operations can be defined symbolically and thus training algorithms can be constructed independently of the data.

Modern ML libraries including Theano [61], TensorFlow [20], Chainer [62], and MXNET [33] support symbolic computation. A model is defined as a computational graph with input and output nodes. Inner nodes are mathematical operations, such as element-wise addition and dot product, that connect the computation in order from input to output. Data is fed into the input node and flows through the series of operations defined by the graph.

Figure 1 shows a simple example that defines a logistic regression model in Theano. It first initializes parameters \( W \), then defines the input and target nodes of the computational graph, then defines the loss and the parameter update functions. Finally, it calls theano.function to build the computational graph with the input data nodes, output loss node, and parameter updates. Internally, Theano will optimize the graph and generate and compile C code for each operation in the graph.

Figure 2 shows another Theano example, defining a two-layer neural network for a binary classification task. The model is defined as \( y = \sigma(W_2^\top \sigma(W_1^\top x)) \) where \( W_1 \) and \( W_2 \) are the parameters we want to learn and \( \sigma(z) = \max(z, 0) \) is the activation function. The loss function and parameter updates are the same as in the logistic regression example.

### 2.3 Machine learning as a service

ML-as-a-service platforms provide convenient APIs for users to upload their data and train an ML model. The trained model can be returned directly to the user or made available for querying through a special API. Many major cloud providers now offer this service, including Google’s Prediction API [4] (soon to be replaced by Cloud Machine Learning Engine), Amazon ML [2], and Microsoft’s Azure ML [13].

ML-as-a-service APIs are usually provided as black boxes. In many services, the user does not know the type of the
model selected by the provider (which could depend on the user’s data and task) or the details of the training. Google’s Prediction API hides all details; users have no information about how the model is designed and trained. Amazon ML lets users choose a few hyper-parameters such as model size, regularization, and the number of training iterations. The choice of the model depends on these hyper-parameters but is invisible to the user. Model training involves stochastic gradient descent but the implementation details are hidden. Microsoft’s Azure ML provides a wide range of built-in models. Users can choose a model but have no information about the implementation details of the learning algorithm.

Our design of Chiron preserves this separation between model design, which is proprietary to the service operator and not available to the user, and model training, which is a generic procedure of repeatedly applying the training function to batches of training data.

2.4 Hardware-protected enclaves

Software Guard Extensions (SGX [18]), available on Intel processors starting with Skylake, provide enclaves that protect code and data from all other software on the platform, including privileged software such as the operating system and hypervisor. Code in an enclave can safely operate on secret data without fear of unintentional disclosure to the platform. The privacy and integrity of the enclave is enforced by hardware [18]. Enclaves are sometimes called trusted execution environments (TEEs), but we will use “enclave” as a generic term.

SGX supports remote attestation of the code and data that make up the initial state of the enclave. This enables a remote user to verify that the initial code and data matching a given cryptographic hash are loaded into a genuine enclave. Remote attestation is always the first step in bootstrapping a secure channel to an enclave.

Attacks on SGX. The design of SGX leaves untrusted privileged software in control of system resources, enabling it to mount subtle attacks (see §6) which are beyond the scope of this paper.

Rollback. A platform can rollback persistent state. While SGX allows enclaves to hash and encrypt data for storage using a hardware-generated secret key, it provides no guarantees about freshness. This drawback forces enclave designers to rely on hardware counters [60], which have limitations and performance issues, or software-based strategies that leverage other machines [49].

Enclave indistinguishably. While SGX enables enclaves to attest their integrity to outside parties, nothing prevents the platform from instantiating multiple copies of enclaves. Without a mechanism to uniquely identify different instances of the same enclave, a malicious platform could confuse remote users about the state of a particular enclave by maliciously redirecting communication between a set of enclaves that remote users perceive as a single enclave.

2.5 Ryoan

Ryoan [41] enables service providers to keep proprietary code secret while simultaneously ensuring users that the confined code cannot leak their data. Instead of asking users to trust the provider’s code, Ryoan asks them to trust the sandbox that confines this code. Users can audit Ryoan to gain confidence in its correctness.

Ryoan is based on Native Client [53, 66], which uses compiler techniques to confine code. Binaries are checked at load time to ensure they are properly restricted. Confined code relies on the sandbox for all interactions with the outside world. Ryoan runs inside an SGX enclave, which removes the need to trust the privileged software of the computational platform.

3. Threat Model

The primary goal of Chiron is to protect users’ data from malicious providers of ML-as-a-service. We assume that training a model and deploying it afterwards both take place on the provider’s computational platform. Training data should remain confidential while the model is being trained, even if the model architecture, loss and optimization functions, and the hyper-parameters of the training algorithm are defined by the service provider. Queries to the model and its outputs should remain confidential when a trained model is being used.

We assume that the entire platform is untrusted, including the privileged code such as the operating system and hypervisor. The attacker could be the machine’s owner and operator, a curious or even malicious administrator, or an invader who has taken control of the OS and/or hypervisor. The attacker may own a virtual machine (VM) physically co-located with the VM being attacked or she could even be a malicious OS developer and add functionality that directly records user input. Therefore, Chiron aims to prevent the untrusted code used during training from exfiltrating secrets about the training data to the underlying platform.

By default, Chiron does not reveal any information about the model architecture or training to the user. This matches the current practice of many commercial ML-as-a-service operators (see § 2.3).

Trusted computing base. Both the user and the service operator must trust Ryoan’s sandboxing code, which we assume will be distributed by a disinterested third party. Ryoan is a generic sandbox that is not tailored to machine learning. Our prototype makes several modifications to Ryoan to accommodate Chiron, such as the logic for distributed enclaves to coordinate model setup (see § 4 for a summary of these modifications).

Ryoan requires both parties to trust the hardware and its implementation of SGX and SGX is more complicated than most hardware features [23]. Remote attestation for enclaves requires trusting a remote attestation service [8]. In §6, we discuss the limitations of Chiron with respect to the covert and side channels affecting SGX.
Cloud Provider Platform

| Training Enclave |
|------------------|
| Service Provider Code |
|                 |
|                 |
| Admin Code      |
| ML Toolchain    |
| ML Model        |
|                 |
|                 |
|                 |
|                 |
| Key: Trusted Untrusted Confined |
| Hardware (SGX) |

Figure 3. Chiron architecture.

We assume a standard, generic ML toolchain for defining and training models. In our prototype, we use the popular Theano framework for this purpose. Because the code of ML toolchains such as Theano is public and well-understood, we assume that it has been scrutinized and that it does not deliberately steal information about the training data and exfiltrate it from the enclave where it executes. The enclave attests to the identity of Ryoan, and Ryoan attests to the identity of the ML toolchain (further details about the chain of trust are available in [41]).

Denial of service. Denial of service is outside the scope of our threat model. The service provider’s model design code can simply refuse to run or the underlying untrusted operating system can refuse to schedule our trusted code. The provider can skip the training or train an inaccurate model. We assume that the user will test any generated model with data held back from the training dataset to see if the model is sufficiently accurate for their purposes. This is identical to the current usage of ML-as-a-service.

Adversarial access to the model. A trained model accessed by an adversary, even via black-box queries, may leak its training data either accidentally [57], or because the model was maliciously designed [59] to reveal its training data in response to certain queries. This appears to be a generic feature of ML models, such as deep neural networks, that have very high memorization capacity. This threat is still poorly understood and no generic mitigations are currently available (see discussion in §8).

Chiron loads trained models into special query enclaves protected with a key that the provider does not know (see §4.5). A model can be queried only by the user whose data was used to train it. Adversaries, including the provider itself, can neither observe the user’s queries, nor query the model themselves. This scenario corresponds to many common uses of ML-as-a-service.

4. Design

The main component of Chiron is the training enclave (seen in Figure 3), which consists of a Ryoan sandbox (which is part of “Admin code” in the figure) extended with a standard ML toolchain (Theano, in our implementation). The cloud provider platform encompasses all system software including the operating system and hypervisor. The code in the training enclave is public, so its integrity can be remotely attested using standard remote attestation for enclaves [18]. The service provider loads its own untrusted code into the Ryoan sandbox and makes one or more training enclaves available to the user. The user connects to training enclaves and submits data. Service provider code then performs two tasks.

First, service provider code sets up the model architecture, loss function, optimization function, and training hyper-parameters. These choices may depend on the user’s data, but Chiron confinement prevents service provider code from leaking information about that data outside the sandbox.

Some existing ML services allow users to specify certain hyper-parameters. For example, Amazon ML lets users set the number of training iterations. In principle, Chiron could support this by adding trusted enforcement code to the ML toolchain that checks the service provider’s compliance with the user-specified hyper-parameters. In our current prototype, we assume that the service provider controls all hyper-parameters (this matches how Google’s Prediction API operates today).

Service provider code must use Chiron’s ML toolchain to define the model; all other forms of output are disallowed by Chiron’s confinement. The ML toolchain compiles the model description into executable, model-specific training code inside the enclave.

Second, service provider code drives the training of the model by feeding user data to the ML toolchain and invoking the training code that updates the model parameters. If necessary, service provider code may apply data transformations (e.g., scaling or rotating images) before passing the data to the training code. The ML toolchain executes this code as usual, but the service provider cannot observe the state of the model due to SGX and Ryoan sandbox protections.

When the training is distributed over multiple training enclaves, each working on its own shard of the user’s training data, Chiron coordinates them using a dedicated parameter server enclave. Each training enclave periodically pulls model parameters from the parameter server, updates them, and sends them back to the parameter server. This helps all training enclaves collectively converge to the same model. Training enclaves exchange parameter updates with the parameter server via secure channels that only send fixed-sized messages at a fixed rate. Updates thus do not leak information about the training data or the current state of the model.

Figure 3 shows the architecture of Chiron. Service provider code is confined in several training enclaves, where it may interact through a controlled interface with a trusted ML toolchain. All enclaves contain trusted admin code, which includes the code for establishing secure channels, managing...
access to other outside resources, and loading and sandboxing service provider code.

After training has finished, Chiron outputs a model encrypted with a key known only to the user. The service provider may send the model to the user or keep it, in which case the model is instantiated in a dedicated query enclave and the user must use Chiron to submit encrypted queries and receive the model’s outputs.

**Ryoan modifications.** First, Chiron replaces Ryoan’s communication model. Ryoan is designed for request-oriented services, allowing untrusted code to send one message for every request. Chiron is optimized for the iterative nature of ML training: it allows many messages for a single input, but sends them at a fixed rate.

Second, Ryoan supports labeled data to help multiple service providers who do not trust each other to avoid disclosing their secrets to the user. This functionality is not useful for Chiron, which assumes that all untrusted code is written by a single service provider.

Finally, Ryoan mitigates the cost of constructing enclaves by providing a mechanism to reuse initialized enclaves without mixing data from different users. This is important to applications that run on the order of seconds per request. Chiron, however, is designed to support ML model training, which runs on the order of hours or even days, and initialization time is a tiny fraction of the total execution time. Therefore, Chiron does not reuse enclaves because the time and space overheads for reuse outweigh the benefits.

### 4.1 Initialization

To initialize Chiron, the service provider starts up the parameter server and a set of training enclaves. The parameter server and training enclaves attest each other and construct secure communication channels (see §4.4 for details). Having established a secure channel with each training enclave, the parameter server generates a nonce using randomness from the processor and sends it to the training enclaves over the secure channels. This nonce uniquely identifies the parameter server instance.

After receiving the nonce, training enclaves load untrusted service provider code and wait to be contacted by the user. The user verifies the integrity of each training enclave via attestation and establishes a pairwise secure channel with each one (see §4.4 for details).

Through secure channel establishment, each training enclave learns the user’s public key. This public key is forwarded to the parameter server and the parameter server’s nonce is forwarded to the user. To ensure that all training enclaves have been contacted by the same user, the server checks whether it received the same public key from every training enclave; otherwise, it does not allow training to begin. The user ensures that all training enclaves are using the same parameter server by comparing the nonces received from the training enclaves; otherwise, he does not send the data. These checks are necessary since SGX does not prevent the platform from instantiating multiple, unexpected copies of Chiron enclaves and directing network traffic to them.

The user then shards training data into \( n \) pieces for \( n \) training enclaves (randomly or according to any other criterion) and sends each shard to a distinct training enclave along with the learning task (e.g., if the task is classification, the specification includes the output classes of the model). Each training enclave exposes the data shard and the learning task to service provider code so that it can define the model and begin training.

### 4.2 Training enclave

Each training enclave is a Ryoan [41] sandbox augmented with an ML toolchain, as depicted in Figure 4. The sandbox confines service provider code and supports the following interfaces: `get_data` allows confined code to read user data, `build_model` allows it to construct a model, `train_model` allows it to train the model for a single iteration. The following interfaces are not depicted in the figure to avoid clutter: `examine_model` allows untrusted code to examine the model as it is being trained, `test_model` allows it to test the model on validation data, and `finish` notifies the trusted code that training is complete (unless the user gets to set the number of iterations).

Each training enclave has a life cycle consisting of four stages: initialize, model design, model training, and dead. Transitions between the stages are determined by the confined code’s use of the interfaces described above.

**Initialize stage.** Each new training enclave starts in this stage. It initializes trusted code before loading the untrusted service provider code. In this stage, service provider code can interact with the network and persistent storage, which it may use to initialize itself (e.g., load the latest model configurations). After this process has finished, the untrusted code calls `get_...
In the model design stage (shown in Figure 5), the trusted service provider code has access to the user’s data and learning task. Service provider code is now confined and its access to the network and persistent storage is cut off by the admin code in the training enclave. Confined code may call `get_data` at any time to read some or all of the data. The specification of the learning task is always prepended to the data and service provider code can access it through `get_data`. This allows service provider code to adaptively choose the architecture and hyper-parameters of the model depending on the nature of the data or the user-specified task. For example, for an image classification task, it may adaptively choose a support vector machine (SVM) or an artificial neural network.

Service provider code defines the model, including its computational graph, loss function, and the hyper-parameters. These are standard Theano operations, illustrated in Figures 1 and 2 in Section 2.2.

In Chiron, model design is separated from model training. After defining the model, service provider code must call `build_model` with a description of the model, as shown in Figure 5. This invokes generic, data- and model-independent Theano code, which is trusted and runs outside the sandbox. It generates the model-training function. The model is now ready for training and the training enclave transitions to the model training stage.

Code generation. Modern ML libraries such as Theano optimize the training process by generating, compiling, and executing model-specific native code. While it is technically possible to build and train an ML model without code generation, this dramatically decreases training performance. Therefore, in Chiron we opted to keep code generation intact.

Our sandboxing mechanism [41] relies on examining all code before it is loaded. Therefore, we cannot let service provider code directly generate executable code lest it use this code to escape the sandbox. Instead, we use a trusted Theano toolchain to generate the code (the same way as it does in conventional usage), based on the specification from the sandboxed service provider code.

An alternative solution would be to include the ML toolchain in service provider code and provide a sandbox interface that (1) checks that the generated code does not violate the sandbox and (2) safely loads it. This would result in a smaller trusted computing base because Chiron would no longer trust the code generation component of the ML toolchain. On the negative side, this approach would incur a non-trivial performance penalty. For example, the authors of Native Client report execution time overheads for sandboxed code as high as 43% on SPECC2000 benchmarks [53]. We leave a thorough exploration of this approach to future work.

Coordination between training enclaves. Because each training enclave receives a different shard of the data, Chiron allows confined code to broadcast one message of a pre-defined size to all other training enclaves. The purpose of this message is for all training enclaves running confined model design code to agree on the same model. For example, the service provider can designate one training enclave as a leader who defines the model based on its sample of the user’s data (or, alternatively, based on the reports from other training enclaves) and broadcasts its decision to all training enclaves. The timing of this message creates a timing channel (see §6 for details), thus this added flexibility comes at the cost of leaking a few more bits.

If this additional leakage is unacceptable, users could randomly select a data sample and send it to all training enclaves along with the data shards. This enables the service provider to coordinate model choice without exchanging messages if this choice is deterministic.

Model training stage. The model training stage is shown in the right half of Figure 4. Before returning control to service provider code, the training enclave contacts the parameter server, initializing copies of the newly created model parameters. If they already exist, the training enclave instead updates local parameters with the current values obtained from parameter server. Throughout the training stage, a separate thread exchanges periodic updates with the parameter server. After exchanging data with the parameter server, Chiron returns control to service provider code. Service provider code updates the local parameters by calling `train_model` on a batch of training data. The `train_model` function may be called as many times as necessary.

Each invocation of `train_model` applies `train_func`. This is a callable object, generated from the model definition, which takes a batch of data as input, computes the loss for that data, and updates the parameters accordingly. The `train_func` object is generated by the trusted ML toolchain and is therefore trusted not to leak.

Service provider code signals to trusted code that training has finished by calling `finish`. Service provider code may call `examine_model` and `test_model` at any time during model training to help decide that the model is ready. The `examine_model` interface allows service provider code to examine properties of the model (e.g., the values of the loss

def untrusted_design_model(dim1, dim2, lr):
    # same design code as in Figure 2
    ...
    # serialize the python objects
    model_str = serialize(x, t, loss, sgd_step)
    # make a call to trusted build_model and
    # let Chiron take over
    build_model(model_str)

Figure 5. Building a model in Chiron.
function or parameter gradients in the most recent round of training). The test_model interface allows untrusted code to evaluate the model on validation data. This approach gives service providers the most flexibility. Chiron could easily adopt other policies, e.g., letting the user specify the total number of train_model invocations.

Dead stage. After transitioning to the dead stage, service provider code is no longer executed. Chiron encrypts the final model with a symmetric key provided by the user. It then returns a hash of the model to the user, before storing the encrypted model in the platform. See §4.5 for an explanation of how the user can access the model.

4.3 Parameter exchange

Parameter server. The parameter server is a trusted, in-memory key-value store which runs in a dedicated enclave. Training enclaves initialize a particular set of keys that represent model parameters. During training, the parameter server exchanges parameters with each training enclave. This design is standard in distributed machine learning, e.g., it is similar to the parameter store in Project Adam [34].

Updates from each training enclave contain the differences between its current parameters and those it received in the last communication with the parameter server. The parameter server applies these differences to its own copies of the parameters and replies with the updated values. The training enclave replaces its parameters with the updated values from the parameter server.

Fixed-rate exchange. Exchanges between each training enclave and the parameter server are network operations and therefore visible to the platform. The content of the messages is always encrypted but Chiron does not hide the fact that communication is taking place.

Chiron prevents service provider code from turning these exchanges into a covert channel by ensuring that their timing is data-independent. Instead of tying the frequency of exchanges to the frequency of updates (e.g., exchange after every call to train_model), Chiron adopts a fixed-rate update policy. The parameter-exchange thread never synchronizes with the data-processing thread. Instead, it sleeps for a configurable amount of time, performs an exchange, then sleeps again.

Chiron relies on the platform to schedule the parameter-exchange thread according to this policy. Relying on the platform as a source of time is safe in this case because the platform cannot see the training data, thus any scheduling policy it chooses must be data-oblivious.

4.4 Secure communication channels

Communication channels between the enclaves and between the user and the enclaves are secured using AES-GCM [40], and an authenticated key agreement protocol, which together provide end-to-end application-level encryption, message integrity, and endpoint authentication. Keys are derived sepa-
into the query enclave. Untrusted provider code within the query enclave can examine and query the model. The result of the query is returned to the untrusted code, which then passes it to the user over the secure channel. Since the untrusted code is confined, it cannot leak this result to the service provider. Chiron pads or truncates the message to a fixed size to ensure that message sizes are data-oblivious.

5. Implementation Issues

SGX compatibility. All Chiron components are designed to run in SGX enclaves. We use an SGX compatibility layer implemented in libc. Our modified libc marshals system call arguments and passes them to the training enclave; it also unmarshals results. Finally, it protects against all currently known Iago attacks [30].

C compiler. Chiron must replace Theano’s C compiler, which is gcc. To avoid a side channel from the compilation process, the compiler running in the training enclave cannot write files, because that would leak model-building activities to the untrusted platform. We could not get gcc to stop writing files, thus Chiron uses libclang and llvm’s execution engine to compile the model training code (following the “clang-interpreter” example from the llvm repository [11]). We measure the performance cost of this decision in Section 7.3.

Parameter server. The Chiron parameter server is based on Redis version 3.2.8 [16], modified to support Chiron’s application-level encryption and to apply received updates to the in-memory parameters. Training enclaves initialize a key for each model parameter. In each parameter exchange, the parameter server adds any value received from the training enclaves to the value of the associated key and returns the updated value.

The parameter server uses time from the platform to calculate the epoch (e.g., nanosleep). The platform can deny service by providing inconsistent time but cannot leak the data via a timing channel (see §4.3).

Managing data within enclave. Chiron requires that users shard their data before uploading it to the set of training enclaves. Our Chiron prototype assumes that each shard will fit in enclave memory because this simplifies the design. In our experiments, the shards are always small enough to fit. That said, enclave memory is a limited resource, with current SGX hardware restricted to 128MB of enclave memory. Furthermore, physical memory for enclaves must be statically partitioned at boot time, and the memory dedicated to enclave use is not usable by non-enclave code. This static partitioning will likely lead to conservative partition sizes.

When data does not fit into memory, Chiron streams data in. Trusted code in each training enclave reads a chunk of data of configurable size at a configurable fixed rate (similar to our fixed-rate parameter exchange), overwriting the old chunk. It is the service provider’s job to ensure that the fixed rates are adequate given the time it takes to train on each chunk. We leave exploration of efficient policies for managing insufficient enclave memory for future work.

6. Limitations

Covert and side channels. Chiron is based on Ryoan, which blocks untrusted code from exfiltrating information about the training data to the platform using software interfaces such as syscall sequences and arguments. Chiron inherits Ryoan’s limitations regarding covert and side channels, which in turn result from the limitations of the underlying hardware—in particular, the internal monitoring that an untrusted platform can perform using the processor monitoring unit (PMU). Intel explicitly places certain timing channels outside the scope of SGX [42]. Untrusted code can leak bits by modulating cache accesses, page accesses, execution time, etc. These limitations are discussed at length by Hunt et al. [41].

The current specification for SGX allows privileged software to manipulate the page tables of an enclave to observe its code and data trace at page-level granularity. This can lead to devastating attacks that use application-specific information to reconstruct fine-grained secrets from these coarse addresses, e.g., words in a document and images [65]. While these channels pose a serious risk for SGX as it exists today, we hope that hardware vendors will mitigate them in the future. Even assuming the current SGX architecture, there is active ongoing research on how to use other processor features, e.g., transactional memory support, to detect and prevent privileged software from attacking enclaves [32, 55].

In a machine learning context, one software technique for mitigating page-based side channel attacks is to transform the learning algorithm so that it is data-oblivious, i.e., its access pattern is independent of the training data [50]. Chiron, however, is designed to support ML-as-a-service where service providers do not reveal their models to users. In this setting, the provider’s code that sets up the model is both untrusted and hidden from the user. There is no way for the user to verify that it is indeed data-oblivious.

Chiron also has Chiron-specific timing channels. For example, an adversarial service provider can encode some secret about the training data in the number of training iterations (if that hyper-parameter is under the provider’s control), time until the model coordination message is broadcast or the training time. Similarly, refusing to terminate or outputting a deliberately inaccurate model is another channel. Our current prototype does not mitigate these channels which can leak dozens of bits given the current design of Chiron. Standard defenses include quantizing or padding execution time.

Lack of GPU support. State-of-the-art deep learning models rely on GPUs to achieve high performance during training [45]. Chiron cannot use GPUs because Chiron fundamentally relies on hardware-supported trusted execution environments, such as those enabled by SGX. These environments do not exist on today’s GPUs. If users’ data is processed on a
GPU, we are not aware of any techniques that can protect it from the GPU operator.

Some frameworks for distributed deep learning [34, 37] do not use GPUs because GPUs’ memory limitations inherently restrict the size of the models that can be trained. More recent work showed how to take advantage of model parallelism [54] and specialized parameter servers [36] to support distributed learning with GPUs.

7. Evaluation

Our evaluation of Chiron is conducted on two machines (A and B). Machine A has an 8-core Intel Xeon 3.20GHz processor with 16 GB RAM and machine B has a 4-core Intel Core i7-6700 3.40GHz processor with 32 GB RAM. We use Theano version 0.8.2. The Ryoan sandbox used is based on NaCl commit 2d5bba1. All enclaves use Ryoan’s modified eglibc version 2.19.

CIFAR is an object classification dataset with 50,000 training images (ten categories, 5,000 images per category) and 10,000 test images [44]. Each image is 32x32 pixels, each pixel has three 8-bit values corresponding to RGB intensities.

To benchmark the CIFAR dataset, we use a 9-layer VGG-style network [58] with batch normalization [43]. The trained model has 2.3 million parameters. We use L2 regularization with the ratio of 0.0005 and stochastic gradient descent with the learning rate of 0.1, batch size of 128 and 60 training epochs (each epoch sweeps through the whole dataset).

ImageNet is a large-scale visual object recognition dataset [38]. The original dataset has over 1.2 millions images in 1,000 categories. We picked a subset with 250,000 images in 200 categories (ImageNetLite), which is a reasonably large dataset for current ML-as-a-service applications. We held out 25,000 images for test evaluation. It takes about 38 hours to train a model on this dataset, which is large enough to represent real workloads while making experimentation tractable.

We use AlexNet for ImageNetLite training, with the same preprocessing and configuration as [45]. We scale each image to 128x128 pixels with three color channels (RGB) and train the network on a randomly cropped 112x112 image. During evaluation, we deterministically crop the image to 112x112, following the same procedure as the AlexNet authors. The model has 6 million parameters. We also use L2 regularization with the ratio of 0.0005, stochastic gradient descent with the learning rate of 0.05, batch size of 64, and 60 training epochs.

7.1 Performance modeling

The Chiron prototype requires features only supported by SGX V2. At the time of writing there is no publicly available processor which supports SGX V2. SGX V2 introduces additional instructions which can change memory mappings of running enclaves. In accordance with Ryoan [41] (and other related work [24, 52]), we evaluate performance using an SGX performance model that mixes measurements from an SGX V1 processor with reasonable guesses for latencies of V2 instructions.

Our SGX performance model includes penalties for enclave exit events, the major source of overhead introduced by SGX. Events that cause enclave exits are page faults, system calls, and interrupts, which all flush the TLB. Exiting and reentering the enclave also comes with additional overhead from executing SGX instructions. System calls require an explicit enclave exit then reenter (EEXIT, EENTER); page faults and interrupts trigger an involuntary (asynchronous in the literature [18]) exit and require a resume operation (ERESUME).

We measure SGX instruction overheads on real SGX hardware (a Dell Inspiron 7359 laptop with Intel Core i5-6200U 2.3 GHz processor). Measurements were collected using Intels SGX Linux Driver [10] and SDK [9]. Explicit exits incur a 3.9 microsecond penalty, involuntary exits incur a 3.14 microsecond penalty. We use a modified Linux kernel that counts each exit event and flushes the TLB for designated enclave threads. We multiply the exit counts by the overheads measured on hardware and add the result to the enclave execution time.

As explained in §5, Chiron marshals and copies system call arguments and return values across the enclave boundary, which also adds execution time overhead.

7.2 Parameter server throughput

Machine learning is computationally intensive and benefits from being split across multiple enclaves, which exchange parameter updates via a parameter server. The parameter server receives updates (usually 4-byte floating point numbers) and performs a single floating point addition for each received delta (applying it to the corresponding parameter). The Chiron prototype parameter server is based on Redis version 3.2.8 [16]. All operations are done in memory; all persistence mechanisms provided by Redis are disabled. When using dummy clients that flood the parameter server with updates, it saturates at 22.6 million floats per second (about 86MB/s), confirming that the network hardware and stack is not a bottleneck for our experiments. While this performance is sufficient for our experiments, parameter server implementation could be improved. Redis is single-threaded, which is limiting when it must also perform floating point operations.

7.3 CIFAR experiments

We compare Chiron to the conventional baseline training time and accuracy while varying the number of training enclaves from two to four to eight (n). Table 1 shows the training time, including latencies from the SGX performance model (¶7.1), for different parameter exchange policies (Ex Rate). The table also shows the test accuracy of the resulting models, as measured by the percentage of successfully classified test data.

The table shows a drop in test accuracy for the resulting model as the number of enclaves increases. This is a common
Table 1. Performance and accuracy with different parameter exchange policies and number of training enclaves ($n$). Baseline is unmodified Theano, exchanging parameters after each training epoch. Ideal is Chiron without fixed-rating the exchange. Avg is Chiron with the fixed rate set to the average duration of one training iteration. Half and one-third Avg exchange at twice and three times the rate of Avg. For 8 enclaves, the 8(1) configuration runs all 8 enclaves on machine A (8 cores), 8(2) runs five enclaves and the parameter server on machine A and the remaining three enclaves on machine B (4 cores).

| n   | Ex Rate | Test Acc(%) | Time (hr) |
|-----|---------|-------------|-----------|
| 2   | Baseline | 89.56       | 9.70      |
|     | Ideal   | 89.38       | 10.07     |
|     | 1/3 avg | 89.17       | 9.92      |
|     | 1/2 avg | 88.50       | 9.79      |
|     | Avg     | 88.98       | 9.69      |
| 4   | Baseline | 88.89       | 6.09      |
|     | Ideal   | 88.97       | 6.86      |
|     | 1/3 avg | 88.38       | 6.59      |
|     | 1/2 avg | 87.66       | 6.70      |
|     | Avg     | 88.07       | 6.74      |
| 8(1)| Baseline | 88.52       | 3.14      |
|     | Ideal   | 88.28       | 3.79      |
|     | 1/3 avg | 86.66       | 3.91      |
|     | 1/2 avg | 86.24       | 3.81      |
|     | Avg     | 81.09       | 3.73      |
| 8(2)| Baseline | 88.41       | 3.18      |
|     | Ideal   | 88.05       | 3.68      |
|     | 1/3 avg | 86.90       | 3.57      |
|     | 1/2 avg | 86.46       | 3.67      |
|     | Avg     | 84.63       | 3.66      |

Table 2. Model accuracy, training time, and query time for ImageNetLite. Top 1 is the accuracy for the most likely prediction. Top 5 is the accuracy of the five most likely predictions. Query shows time for querying 100,000 images in batches of 1,000.

|       | Top1(%) | Top5(%) | Train(hr) | Query(sec) |
|-------|---------|---------|-----------|------------|
| Baseline | 55.12   | 78.51   | 39.83     | 3825.30    |
| Chiron  | 52.41   | 76.42   | 38.85     | 3843.53    |

7.4 ImageNetLite experiments

We demonstrate Chiron’s ability to scale to more substantial ML tasks by training ImageNetLite using 16 training enclaves. We use the one-third Avg parameter exchange policy in this experiment, which does not leak training time and as shown by the CIFAR experiments, provides best model accuracy. Table 2 shows that Chiron slows down ImageNetLite training by 16%, while preserving the accuracy of the trained model. For comparison, a random guess with five chances would have a top-5 accuracy of 0.025.

Chiron must be invoked in order to perform queries on the model. Table 2 shows the performance impact Chiron imposes on model queries, which is less than 1%.

Cost of outsourced training. While Chiron supports training on machines owned by the service provider, this is not a requirement. At the time of this writing, Amazon EC2 charges $0.0665 per core per hour for computation and $0.02 per GB for network communication (between data centers) [11]. Training ImageNetLite on the baseline would cost $36.19 for compute and $7.67 for network IO. Chiron increases the compute cost to $43.12. Chiron’s network cost depends on the parameter exchange policy, ranging from $7.67 if parameters are exchanged using the average-iteration-length policy to $23.00 for the 1/3-average policy. Note, however, network bandwidth within a single data center is free, and model training would likely occur within a single data center. Our experiments with CIFAR show that more frequent updates consume network bandwidth but provide better models.

8. Related Work

Secure ML environments. Ohrimenko et al. describe an SGX-based system for multi-party machine learning on an untrusted platform [50]. They focus on collaborative
learning, as opposed to Chiron, which focuses on outsourced learning and, in particular, machine learning provided as a service by a cloud operator.

The critical distinction between the two scenarios is that in collaborative learning, the model architecture and learning algorithms are public, whereas in ML-as-a-service, they are secret and proprietary to the service provider. A significant advantage of [50] is that their learning algorithms are data-oblivious and thus secure against page-fault side channels. Obliviousness, however, must be verified by the clients, thus the entire codebase inside the SGX enclave must be public, including any data-dependent model design choices. Therefore, [50] is unsuitable for ML-as-a-service, where the model is chosen adaptively based on the client’s data and task, but (in most existing ML services) remains hidden from the client. By contrast, Chiron (1) lets training SGX enclaves execute untrusted service provider code to adaptively define the model, but (2) sandboxes this code to prevent it from leaking the data outside the enclave.

CQSTR [67] lets a trusted platform operator confine untrusted machine learning code so that it can be securely applied to user data. By contrast, Chiron protects user data from an untrusted platform operator.

**Cryptographically protected ML.** Many papers describe how to use cryptographic techniques, including secure multiparty computation, to learn and apply relatively simple classifiers without decrypting the data [25, 27, 28, 47, 63]. It is not clear whether and how these techniques can be applied to modern ML problems, such as training deep neural networks on ImageNet-scale datasets, without a prohibitive performance penalty.

More recent work [39, 48] demonstrated how to efficiently apply neural networks to encrypted data. As far as we know, today there are no practical techniques for training deep neural networks on encrypted data.

**Leakage of training data from ML models.** Overfitted machine learning models can be vulnerable to “membership inference”: an adversary can infer, with black-box access to the model, whether a given input was used to train the model [57]. A malicious training algorithm can construct a model that leaks significant parts of the training dataset in response to certain queries [59].

Information leakage from the model’s training dataset can be mitigated by differentially private learning algorithms [21, 51]. These algorithms produce the same model with approximately the same probability if a particular input was included in the training dataset or not.

In this paper, we assume that the owner of the training dataset and the user of the resulting model are the same, and that the model is not exposed to other parties (including the operator of the service that trained the model). This assumption holds for many common uses of ML-as-a-service. In this scenario, there are no adversaries who have query access to the trained model.

**SGX-protected execution environments.** Several recently proposed systems aim to protect applications from an untrusted platform. Haven [24], SCONE [22], and Graphene-SGX [29] provide an environment to support unmodified legacy applications. VC3 [52] and Opaque [68] provide SGX-protected data processing platforms. All of these systems assume that all of the code inside the enclave is trusted. Chiron protects user data from untrusted code.

**Side-channel attacks on SGX.** As discussed in §6, side channels can subvert the protections provided by SGX. Side channels based on page faults [64, 65] enable the platform to extract private data by observing page-granularity memory accesses. Physical monitoring of the bus gives an attacker access to word-granularity memory accesses. Existing side channels on modern processors (e.g., cache [26], power, and time) apply to enclave-protected code as well [42].

Processor monitoring units (PMUs) record information about execution and can leak information about enclave code if they are not cleared. Lee et al. demonstrate an attack using the branch history [46]. The processor’s uncore counters (e.g., L3 events) are enabled during enclave execution [35] and could possibly be used to construct a side channel.

**9. Conclusion**

We presented Chiron, a new system for privacy-preserving outsourced machine learning (ML). Chiron enables data holders to use ML-as-a-service without disclosing their data to the service providers, yet—in keeping with the current practice of these services—does not require that the providers make their models, configuration parameters, and training algorithms public.
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