Monte Carlo execution time estimation for Privacy-preserving Distributed Function Evaluation protocols

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Abstract—Recent developments in Machine Learning and Deep Learning depend heavily on cloud computing and specialized hardware, such as GPUs and TPUs. This forces those using those models to trust private data to cloud servers. Such scenario has prompted a large interest on Homomorphic Cryptography and Secure Multi-party Computation protocols that allow the use of cloud computing power in a privacy-preserving manner.

When comparing the efficiency of such protocols, most works in literature resort to complexity analysis that gives asymptotic higher-bounding limits of computational cost when input size tends to infinite. These limits may be very different from the actual cost or execution time, when performing such computations over small, or average-sized datasets.

We argue that Monte Carlo methods can render better computational cost and time estimates, fostering better design and implementation decisions for complex systems, such as Privacy-Preserving Machine Learning Frameworks.

Keywords—Monte Carlo Methods, Cost Analysis, Homomorphic Cryptography, Secret Sharing

I. Introduction

MACHINE LEARNING (ML) applications are revolutionizing industry, education, and many other fields. Recent developments of ML, especially Deep Learning (DL) methods and algorithms, have shown remarkable results in a wide range of applications: from computational vision to text generation [1].

As new ML algorithms increase in complexity and computing cost, developments in the area extend their dependency on cloud computing and hardware accelerated functions found on specialized chipsets, such as Graphical Processing Unities (GPUs) and Google’s Tensor Processing Units (TPUs) [2].

This move towards the cloud forces individuals and organizations to trust their private data to external servers in order to harness the predictive power of such algorithms. Electronic Health Records and tax information are examples of sensitive data that are extremely relevant for predictive modeling but are also legally bound to strong privacy-preserving guarantees. Many information-theoretical and cryptographic protocols were developed in order to allow secure and privacy-preserving delegation of computation. Most are based on homomorphic encryption systems (HE) or secret sharing Secure Multi-Party Computation (MPC) protocols.

In order to compare the efficiency of these protocols, researchers usually resort to theoretical complexity analysis, that provides for asymptotic higher-bounding limits of computational cost when the input size tends to infinite [3]. These limits, drafted from the the underlying mathematical primitives, often drive design and implementation decisions on large and complex systems. Ultimately, they may determine important investment in research and development of such protocols. Nonetheless, theoretical limits may be very different from the actual average computational cost and execution times observed when executing the protocols over small, or medium-sized datasets.

Probabilistic and ML models are commonly used to estimate cost, execution time and other statistics over complex systems and algorithms, especially in control or real-time systems engineering [4], [5].

We propose the use of Monte Carlo methods in order to estimate execution times for privacy-preserving computations, considering different protocols and input sizes. Section II presents a short review on privacy-preserving computation and its cost. Section III has a brief description of the Monte Carlo methods used. Section IV discusses implementation details and results of the various Monte Carlo experiments we performed. Finally, Section V presents key conclusions and points out relevant questions open for further investigation.

II. Privacy-Preserving Computation

As privacy-preserving computation grew in importance and attention, many Privacy-Preserving Machine Learning (PPML) and Privacy-Preserving Function Evaluation (PPFE) frameworks have been devel-
Asymmetric cryptography: it is possible to perform homomorphism between the fields \( \mathbb{Z} \) and \( \mathbb{Z}_{N^2} \) to render the following features:

Additive homomorphism: the multiplication of two ciphertexts equals the ciphertext of the sum of their respective messages. That is:

\[
Enc(m_1)Enc(m_2) \mod N^2 = Enc(m_1 + m_2 \mod N)
\]

Multiplicative homomorphism: a ciphertext to the power of an integer equals the ciphertext of the multiplication of the original message by that integer. That is:

\[
Enc(m_1)^{m_2} \mod N^2 = Enc(m_1m_2 \mod N)
\]

B. Secret Sharing

Introduced by Yao [17], Secure Multi-Party Computation refers to a set of protocols and algorithms that allow a group of computing parties \( \mathcal{P} \) to evaluate a function \( F(X) \) over a set \( X = (x_1, x_2, ..., x_n) \) of private inputs, in a way that guarantees participants gain knowledge only on the global function result, but not on each others inputs.

| Protocol: \( \pi_{ADD} \) |
|---|
| **Input:** Secret shares \([x_1], ..., [x_n]\) |
| **Output:** \([z] = \sum_{i=1}^{n} [x_i]\) |
| **Execution:** |
| 1) Each party \( P_i \in \mathcal{P} \) computes \( z_i = x_i + y_i \) |
| 2) Each party \( P_i \) broadcasts \( z_i \) |

Protocol 1: Secure Distributed Addition Protocol \( \pi_{ADD} \)

Additive secret sharing is one way to implement MPC. Protocol parties have additive shares of their secret values and perform joint computations over those shares. For example, to create \( n \) additive shares of a secret value \( x \in \mathbb{Z}_q \), a participant can draw \( (x_1, ..., x_n) \) uniformly from \( \{0, ..., q - 1\} \) such that \( x = \sum_{i=1}^{n} x_i \mod q \). We denote this set of shares by \([x]\)ₙ.

Notice that access to any proper subset of \([x]\)ₙ gives no information about \( x \). A shared secret can only be revealed after gathering all shares. Likewise, the result of a protocol executing linear transformations over such shares can only be known if all the local results at each computing party are combined.

Given two sets of shares \([x]\)ₙ, \([y]\)ₙ and a constant \( \alpha \), it is trivial to implement a protocol like \( \pi_{ADD} \) or \( \pi_{MUL} \) in order to locally compute linear functions over the sum of their respective shares and broadcast local results to securely compute values such as \([z]\)ₙ = \( \alpha ([x]\)ₙ, \([y]\)ₙ), \([z] = \alpha (x_1 + y_1)\), and \([z]\)ₙ = \( \alpha_1(x_1 + y_1)\). In all those operations, \([z]\)ₙ is the shared secret result of the protocol. The real value of \( z \) can only be obtained if one has knowledge of the local \( z_i \) values held by all computing parties, and performs a last step of computation to obtain \( z = \sum_{i=1}^{n} z_i \mod q \).

A. Homomorphic Cryptography

A cryptosystem is said to be homomorphic if there is an homomorphism between the domain (the message space \( \mathcal{M} \)) and the image (the cipher space \( \mathcal{C} \)) of its encryption function \( Enc(m) \). An homomorphism is a map from one algebraic structure to another, that maintains its internal properties. So, if there is an internally well defined relation, or function, in \( \mathcal{M} \), \( f_M : \mathcal{M} \rightarrow \mathcal{M} \), there will be a corresponding function defined in \( \mathcal{C} \), \( f_C : \mathcal{C} \rightarrow \mathcal{C} \), such that:

\[
\forall m \in \mathcal{M}, \quad f_C(Enc(m)) = Enc(f_M(m))
\]

Fully Homomorphic Encryption (FHE) refers to a class of cryptosystems for which the homomorphism is valid for every function defined in \( \mathcal{M} \). That is:

\[
\forall f_M : \mathcal{M} \rightarrow \mathcal{M}, \quad \exists f_C : \mathcal{C} \rightarrow \mathcal{C} \mid f_C(Enc(m)) = Enc(f_M(m))
\]

The most commonly used homomorphic cryptography systems, however, are only partially homomorphic. There are additive homomorphic systems, multiplicative homomorphic systems and systems that combine a few homomorphic features. For example, Paillier’s cryptosystem has additive and multiplicative homomorphic features that can be used to delegate a limited set of computations over a dataset, without compromising its confidentiality [15], [16].

The underlying primitive in Paillier’s system is the quadratic residuosity problem. Its construction harnesses the homomorphism between the fields \( \mathbb{Z}_N \) and \( \mathbb{Z}_{N^2} \) to render the following features:

Asymmetric cryptography: it is possible to perform homomorphic computations over the encrypted data using the public key. Knowing the results of the computation, nevertheless, requires access to the private key;
than large enough value of \( n \) given algorithm over its input size. So, if \( \text{der} \) is present, it is usually the complexity or- the Iris dataset). When any general estimate mea-
stimated computational cost or execution times. Solutions, authors usually only discuss very briefly the computational cost. Expected execution time and power consumption may drive decisions that have impact on millions of users and on relevant fields of application. In spite of the importance of the efficiency of their solutions, authors usually only discuss very briefly the estimated computational cost or execution times.

Very few works on PPML publish their results with computing times observed against benchmark datasets/tasks (e.g. classification on the ImageNet or the Iris dataset). When any general estimate mea- sure is present, it is usually the complexity or-der \( O(g(n)) \), which defines an asymptotically lower-bound on the number of operations to be performed by the algorithm. However, it does not inform an accurate estimate for execution time. And, more importantly, the order function will only bound the actual cost function for extremely large input sizes. Recall that \( t(Kn) \in O(n) \), regardless of how arbitrarily large the constant \( K \) may be.

Thus, for small input sizes, the actual cost may be many orders of magnitude higher than the asymptotic bound. The addition protocol in [18] is also of order \( O(n) \), but one would never assume that a protocol with many matrix multiplications and inversions can run as fast as the one with a few simple additions.

III. Monte Carlo methods for integration

There is another way to estimate execution times. All examples found in literature of privacy-preserving computation have one thing in common: their protocols depend heavily on pseudo-randomly generated numbers, used to mask or encrypt private data. Those numbers are assumed to be drawn independently according to a specific probability density function. That is, the algorithms use at least one random variable as input. Although the observed execution time does not depend directly on the random inputs, it is directly affected by their magnitude, or more specifically, their average bit-size.

Also, the size of the dataset has direct impact on execution time. If we consider the size of the dataset as a random variable, then the interaction between the magnitude of the random numbers and the numerical representation of the dataset are, unequivocally, random variables. So, it is safe to assume that protocol runtimes, that are a function of the previous two variables, are also random variables.

Monte Carlo methods are a class of algorithms based on repeated random sampling that render numerical
approximations, or estimations, to a wide range of statistics, as well as the associated standard error for the empirical average of any function of the parameters of interest. We know, for example, that if \( X \) is a random variable with density \( f(x) \), then the mathematical expectation of the random variable \( T = t(X) \) is:

\[
E[t(X)] = \int_{-\infty}^{\infty} t(x)f(x)dx.
\]

And, if \( t(X) \) is unknown, or the analytic solution for the integral is hard or impossible, then we can use a Monte Carlo estimation for the expected value. It can be obtained with:

\[
\hat{\theta} = \frac{1}{M} \sum_{i=1}^{M} t(x_i)f(x_i)
\]

(2)

In other words, if the probability density function \( f(x) \) has support on a set \( \mathcal{X} \), (that is, \( f(x) \geq 0 \) \( \forall x \in \mathcal{X} \) and \( \int_{\mathcal{X}} f(x) = 1 \)), we can estimate the integral

\[
\theta = \int_{\mathcal{X}} t(x)f(x)dx
\]

by sampling \( M \) instances from \( f(x) \) and computing

\[
\hat{\theta} = \frac{1}{M} \sum_{i=1}^{M} t(x_i)
\]

(4)

The intuition is that, as \( M \) grows, \( X = \{x_1, \ldots, x_m\} \) sampled from \( \mathcal{X} \), the support interval of \( f(x) \), becomes closer to \( \mathcal{X} \) itself. Therefore, the estimation \( \hat{\theta} \) will converge to the expected value \( \theta \). This comes from the fact that the sample mean is an unbiased estimator for the expected value.

We know that, by the Law of Large Numbers, the sample mean \( \bar{\theta} \) converges to \( E[\bar{\theta}] = \theta \) as \( M \to \infty \). Therefore, we are assured that for a sufficiently large \( M \), the error \( \varepsilon = E[\bar{\theta}] - \theta \) becomes negligible.

The associated variance for \( \hat{\theta} \) is \( \text{Var}(\hat{\theta}) = \sigma^2/M \), where \( \sigma^2 \) is the variance of \( t(x) \). Since we may not know the exact form of \( t(x) \), or the corresponding mean and variance, we can use the following approximation:

\[
\text{Var}(\hat{\theta}) = \frac{1}{M^2} \sum_{i=1}^{M} \left(t(x_i) - \bar{\theta}\right)^2
\]

(5)

In order to improve the accuracy of our estimation, we can always increase \( M \), the divisor in the variance expression. That comes, however, with increased computational cost. We explore this trade-off in our experiments by performing the simulations with different values of \( M \) and then examining the impact of \( M \) on the observed sample variance and on the execution time of the experiment.

IV. Simulating a simple “Mean Protocol”

In order to simulate the scenario where the data owner wants to delegate the computation of some statistic over a private dataset, we implemented two simple protocols that compute the floor of the mean of a list of numbers. Let \( X = x_0, \ldots, x_k \) be the input of the protocols, then the output is \( \hat{\mu} = \lfloor \frac{1}{k} \sum_{i=1}^{k} x_i \rfloor \).

Both protocols have a client delegating a distributed computation to a fixed number of servers. The \( \pi_{\text{HE}} \) protocol uses homomorphic encryption. The client encrypts the instances in the dataset and sends the ciphertexts to the servers. The servers perform a series of homomorphic additions and one final homomorphic multiplication to multiply the sum by \( \ell^{-1} \mod N \) (the modular multiplicative inverse of the size of the dataset).

The \( \pi_{\text{MPC}} \) protocol is a composition of the Distributed Addition Protocol \( \pi_{\text{ADD}} \), to sum the instances, with the Distributed Multiplication Protocol \( \pi_{\text{MUL}} \), used to multiply that sum to \( \ell^{-1} \). The server part is performed by a fixed number \( k \) of computing parties. The client generates \( k \) shares for each instance on the dataset and sends a set of \( k \) shares to each computing party. The parties will respond with \( [\hat{\mu}]_{\sigma} \). The client then computes \( \hat{\mu} = \frac{1}{k} \sum_{i=1}^{k} \hat{\mu}_i \mod q \). In our implementation, the client also performs the protocol steps designed to be executed by the Trusted Initializer (as expressed in \( \pi_{\text{ADD}} \) and \( \pi_{\text{MUL}} \)).

A. Experiment Type I

Using \( \pi_{\text{HE}} \) and \( \pi_{\text{MPC}} \), we perform two types of experiment. The first type consists in running the protocols for \( M \in \{1000, 5000\} \) iterations with fixed datasets. We use the Dow Jones Index dataset from [19], with 750 instances, to compute the mean of the ‘balance’
feature. We also use the short Bank Marketing dataset from [20], with 4521 instances, to compute the mean of the ‘volume’ feature.

We know that each $\pi_{\mu\text{HE}}$ protocol run will sample at least $\ell$ (the size of the dataset) instances from the uniform distribution $\text{Uniform}(1,n)$ (for the encryption under Paillier’s system). We are running the MPC protocols with 3 computing parties. Thus, each $\pi_{\mu\text{MPC}}$ run will sample at least $3\ell$ instances from $\text{Uniform}(0,q)$, as defined in $\pi_{\text{ADD}}$.

For each protocol run, we record the execution times for client and server: $t_{cli}$, $t_{srv}$. We consider that these values are observations from $t_{cli}(h(U))$ and $t_{srv}(h(U))$, functions that give the runtimes for client and server, respectively, given $U = \{u_1, \ldots, u_\ell\}$ - a sample from the uniform distributions used internally by the protocols.

Recall that we do not regard runtime as a direct function of $U$, but rather of a measure of magnitude of $u \in U$. So let $h(U)$ be, for example, a function with image on $\mathbb{R}$, that gives the average position of the most significant bit in the unsigned integer representation of each $u_i \in U$. It is clear that the runtime function $t(h(U))$ has its domain on a Real interval. For readability, we will suppress the notation of function composition ($t(h(U))$) and write $t_{cli}(u)$ and $t_{srv}(u)$ from now on.

Now, we want to estimate:

$$\hat{\theta}_{cli} = \int t_{cli}(u) f(u) \, du$$  \hspace{1cm} (6)

$$\hat{\theta}_{srv} = \int t_{srv}(u) f(u) \, du$$  \hspace{1cm} (7)

So we use the following Monte Carlo approximations:

$$\hat{\theta}_{cli} = \frac{1}{M} \sum_{i=1}^{M} t_{cli}^{(i)}$$  \hspace{1cm} (8)

$$\hat{\theta}_{srv} = \frac{1}{M} \sum_{i=1}^{M} t_{srv}^{(i)}$$  \hspace{1cm} (9)

We present the results in Table II for $M \in \{1000, 5000\}$, along with the associated variances.

| Table II: Experiment II - Runtime in Milliseconds |
|-----------------------------------------------|
| Distribution | Protocol | M | $\hat{\theta}_{cli}$ | $\hat{\theta}_{srv}$ | $\hat{\theta}_{cli}$ | $\hat{\theta}_{srv}$ |
|---------------|----------|---|-----------------|-----------------|-----------------|-----------------|
| Uniform       | $\pi_{\mu\text{HE}}$ | 1000 | 184.73 0.88 12.51 0.010 | 1727.79 0.34 11.66 1.41e-4 | 2555.45 12.77 13.43 9.99e-4 |
|               |          | 5000 | 167.58 0.06 11.57 7.19e-4 | 1249.13 0.89 11.50 1.57e-4 | 2510.23 5.49 13.24 1.05e-4 |
| Normal        | $\pi_{\mu\text{HE}}$ | 1000 | 118.11 8.73 0.990 1.81e-4 | 122.28 7.39 0.195 5.65e-5 | 142.88 6.63 0.273 1.09e-4 |
|               |          | 5000 | 109.36 1.44 0.062 1.27e-4 | 118.69 1.29 0.171 6.25e-4 | 139.51 1.33 0.256 2.47e-4 |
| Gamma         | $\pi_{\mu\text{HE}}$ | 1000 | 182.10 0.79 12.53 0.009 | 1273.84 0.38 11.67 6.86e-4 | 2551.78 11.26 13.44 0.001 |
|               |          | 5000 | 167.26 0.06 11.55 4.67e-4 | 1248.96 0.85 11.05 3.10e-5 | 2508.26 1.49 13.22 1.02e-4 |
| Beta          | $\pi_{\mu\text{HE}}$ | 1000 | 119.31 9.52 0.073 4.36e-6 | 118.09 5.92 0.195 3.62e-6 | 142.40 6.68 0.279 1.26e-6 |
|               |          | 5000 | 108.58 1.47 0.065 4.12e-6 | 118.65 1.22 0.169 5.56e-7 | 139.28 1.28 0.253 1.75e-6 |

B. Experiment Type II

In the second batch of experiments, we wanted to examine the influence of the probability distribution of the values in the dataset on runtimes. We modeled an experiment where datasets of sizes $\ell \in \{50, 100, 1000\}$ are sampled from $U(80,120)$, $N(120,30)$ and the r.v.’s $G’ = 120 \times G$, where $G \sim \text{Gamma}(2,2)$, and $B’ = 120 \times B$, where $B \sim \text{Beta}(30,2)$.

As we did in the previous series of experiments, we record $t_{cli}$, $t_{srv}$. This time, we consider that these values are observations from $t_{cli}(X)$ and $t_{srv}(X)$, the functions that render the runtimes for client and server, respectively, given the random dataset $X$. So, let $f(x)$ be the density of $X$, we want to estimate

$$\theta_{cli} = \int t_{cli}(x) f(x) \, dx$$  \hspace{1cm} (10)

$$\theta_{srv} = \int t_{srv}(x) f(x) \, dx$$  \hspace{1cm} (11)

Notice that these have the same form of the integrals estimated in the first experiment. Hence, we use the
the same form for the Monte Carlo approximations:

\[ \hat{\theta}_{\text{cl}} = \frac{1}{M} \sum_{i=1}^{M} t_{\text{cl}}^{(i)} \]  

(12)

\[ \hat{\theta}_{\text{srv}} = \frac{1}{M} \sum_{i=1}^{M} t_{\text{srv}}^{(i)} \]  

(13)

The estimations produced in the second group of experiments are listed on Table II along with the associated variances.

C. Implementation details

Our experiments were written in Go. For the modular arithmetic, we used the native arbitrary-precision arithmetic library "math/big". To simulate the distributed computation and communication, we used goroutines, a lightweight form of thread managed by the Go runtime, and Go channels (typed sockets used for communication between goroutines).

All experiments were compiled with Go 1.12.3, on a Linux kernel 4.9.0-9-amd64, and ran on an Intel® Core™ i7-6500U CPU, with 4 cores at 2.50GHz clock. The code for the experiments is open-sourced at the public git repository https://github.com/stefanomozart/montecarlo-protocol-runtime.

D. Results

Table I shows the approximated values for \( t_{\text{cl}} \) and \( t_{\text{srv}} \) for \( \pi_{\text{HE}} \) and \( \pi_{\text{MPC}} \) running with two datasets with different sizes and different magnitudes, as detailed in the previous section. It also brings the associated variance for those estimates for simulations with 1000 and 5000 iterations.

Table II shows the values for \( t_{\text{cl}} \) and \( t_{\text{srv}} \), and the respective variances, when the datasets vary in size and in density distribution.

The results of both experiments, type I and type II, confirm that increasing the number of simulation iterations reduces significantly the variance of our estimator. In Table II, we can see that this reduction of variance is more noticeable for the larger datasets. We can affirm that, for the given scenario, \( M = 5000 \) iterations produce an acceptable estimation.

The results in Table II also indicate that, for both protocols, the runtime may be a linear function of the size of the dataset. Fitting a simple model \( t_{\text{cl}} \sim \beta_0 + \beta_1 \ell \) (with R’s implementation of the QR regression method), we get \( \beta_0 = 18.479 \), and \( \beta_1 = 2.849 \) for the \( \pi_{\text{HE}} \) protocol, and \( \beta_0 = 107.317 \), and \( \beta_1 = 0.0414 \) for \( \pi_{\text{MPC}} \). The fitted \( p \)-values are all smaller then \( 2.2\times10^{-16} \) for both models. This suggests that the runtime for the \( \pi_{\text{HE}} \) protocol is more sensitive to variation in input size.

V. Conclusions and Future Work

We demonstrated how Monte Carlo methods can be used to estimate runtimes of cryptographic and secure multi-party computation protocols. We presented runtimes estimates, along with the respective variances, for different dataset sizes. The simulation results were also used to fit regression models with statistically significant coefficients showing the effect of input size on protocol runtime.

We want to note that our implementations are very simple, with no optimizations of any kind. We are only interested in validating the use of Monte Carlo integration for runtime estimation. Although the observed values and estimations show a consistent advantage for the MPC protocol, it is important to clarify that our experiments do not represent a very realistic scenario for MPC. As discussed in the implementation details, the recorded runtimes do not include communication complexity and cost introduced by distributing computation parties on multiple cloud providers or networks, since all processes ran in threads on the same machine.

The impact of communication complexity on runtimes, as the number of computing parties grows, or as other network variables (throughput, latency, etc.) vary, is a question open for further investigation.

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