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Secure Improvement Computation Outsourcing In Cloud Computing : A Case Study of Linear Programming

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ABSTRACT

Cloud computing has terrific ability of imparting robust computational electricity to the society at reduced cost. it allows clients with confined computational assets to outsource their huge computation workloads to the cloud, and economically enjoy the big computational energy, bandwidth, garage, or even suitable software program that may be shared in a pay-per-use manner. despite the first-rate blessings, safety is the number one impediment that prevents the wide adoption of this promising computing version, specially for customers while their personal data are ate up and produced at some point of the computation. treating the cloud as an intrinsically insecure computing platform from the viewpoint of the cloud customers, we must layout mechanisms that not best guard sensitive records by means of enabling computations with encrypted statistics, however additionally shield customers from malicious behaviors by means of enabling the validation of the computation result. one of these mechanism of trendy relaxed computation outsourcing was these days proven to be viable in principle, however to design mechanisms that are practically efficient remains a very challenging trouble. This paper investigates comfy outsourcing of widely applicable linear programming (lp) computations. in an effort to acquire sensible efficiency, our mechanism layout explicitly decomposes the lp computation outsourcing into public lp solvers running at the cloud and private lp parameters owned by way of the client. the resulting flexibility permits us to discover appropriate secu rity/performance tradeoff thru higher-level abstraction of lp computations than the general circuit representation.

Keywords: Confidential Data, Secure Outsourcing Algorithms, Problem Optimization, Cloud Computing

I. INTRODUCTION

Outsourcing is a general procedure employed in the business world when the customer chooses to farm out a certain task to an agent. The reasons for the customer to outsource the task to the agent can be many, ranging from a lack of resources to perform the task locally to a deliberate choice made for financial or response time reasons. Cloud Computing provides convenient on-demand network access to a shared pool of configurable computing resources that can be rapidly deployed with great efficiency and minimal management overhead. One fundamental advantage of the cloud paradigm is computation outsourcing, where the computational power of cloud customers is no longer limited by their resource-constraint devices. By outsourcing the workloads into the cloud, customers could enjoy the literally unlimited computing resources in a pay-per-use manner without committing.

In spite of the tremendous benefits, there are many security concerns and challenges because the customers and cloud are not in the same trusted domain [1]. The data that are processed and generated during the computation in cloud are often confidential data. Moreover, since the operational details inside the cloud are not transparent enough to customers, so no guarantee is provided on the quality of the computed results from the cloud. For example, for computations which demand a large amount of resources, it is very likely that the cloud server (CS) can become "lazy" and might not evaluate the customer cannot tell the correctness of the answer. Therefore, the cloud is assumed to be not secure from the viewpoint of customers. Without providing a mechanism for secure

computation outsourcing, i.e., to protect the sensitive input and output data and to validate the computation result integrity, it would be hard to expect customers to turn over control of their computing needs from local machines to cloud solely based on its economic savings.

This paper deals with secure outsourcing of large-scale systems of linear equations (LE), which are among the most popular algorithmic and computational tools in various engineering disciplines that analyze and optimize real-world systems. The storage requirements of the system coefficient matrix may easily exceed the available memory of the customer's computing device [2]. There are many real-world problems that would lead to very large-scale systems of linear equations with up to hundreds of thousands [3]. A typical double-precision 50,000×50,000 system matrix that can result from an electromagnetic application would easily occupy up to 20 GB storage space which challenges the computational power of low-end computing devices. Also, the execution time of a computer program depends not only on the number of operations it must execute, but also on the location of the data in the memory hierarchy [2].Therefore, solving large-scale problems on customer's devices can be impossible, due to huge Input/Output(IO) cost that is involved. Thus, resorting to cloud for such computation intensive tasks can be the only choice for customers with weak computing power, especially when the solution is demanded in a timely fashion.

Existing approaches do not address the asymmetry among the computational power possessed by cloud and the customer. Moreover, all these solutions are based on direct method for solving the LE, like the Gaussian elimination method [4] or the secure matrix inversion method in [5]. These approaches work well for small size problems, however it do not derive acceptable solution time for large-scale LE, due to the expensive cubic time computational burden for matrix-matrix operations and the huge IO cost on customer's weak devices. The proposed mechanism designs a secure mechanism of outsourcing LE via the Jacobi iterative method, where the solution is extracted via finding successive approximations to the solution until the required accuracy is obtained. Compared to direct method, an iterative method only demands relatively simpler matrix-vector operations with $O(n^2)$ computational cost, which is much easier to implement in practice and widely adopted for large-scale LE [3], [7]. This proposed mechanism also utilizes the additive homomorphic encryption scheme, e.g., the Paillier cryptosystem [8]. Paillier cryptosystem is a probabilistic asymmetric algorithm for public key cryptography. It is used due to its flexibility for fitting larger plaintexts with a constant expansion ratio. For a linear system with $n \times n$ coefficient matrix, the proposed mechanism is based on a one-time amortizable setup with $O(n^2)$ cost. In each iterative algorithm execution, the proposed mechanism only incurs $O(n)$ local computational burden to the customer and asymptotically eliminates the expensive IO cost. To ensure computation result integrity, a very efficient cheating detection mechanism is also proposed to effectively verify the computation results by the cloud server from previous algorithm iterations with high probability.

II. LITERATURE REVIEW

Secure Computation Outsourcing

The theory based on Yao's garbled circuits [11] and Gentry's fully homomorphic encryption (FHE) scheme [12] would be impractical due to the extremely high complexity of FHE operation and the pessimistic circuit sizes that can hardly be handled. In [13], Atallah et al. give the first investigation of secure outsourcing of scientific computation. Their work explicitly allows private information leakage. Besides, the important case of result verification is not considered. In [9], Atallah et al. give a protocol design for secure matrix multiplication outsourcing. The design is built upon the assumption of two non-colluding servers and thus vulnerable to colluding attacks. Later on in [10], Atallah et al. give an improved protocol for secure outsourcing matrix multiplications based on secret sharing, which outperforms their previous work in terms of single server assumption and computation efficiency. But due to secret sharing technique, all scalar operations in original matrix multiplication are expanded to polynomials, introducing significant communication overhead. Very recently, Wang et al. [14] give the first study of secure outsourcing of linear programming in cloud computing. Their solution is based on problem transformation, and has the advantage of bringing customer savings without introducing substantial overhead on cloud. However, those techniques involve cubic-time computational

burden matrix-matrix operations, which the weak customer is not necessarily able to handle for large-scale problems.

B. Secure Two-party Computation

Securely solving LE has also been studied under the framework of SMC [11]. The work under SMC may not be well-suited for the computation outsourcing model, primarily because they generally do not address the computation asymmetry among different parties. Besides, in SMC no single involved party knows the entire problem input information, making result verification usually a difficult task. But in the proposed model, the fact that the customer knows all input information can be explicitly exploited and thus design efficient batch result verification mechanism. The most communication efficient work such as [4], [5] focus only on the direct method based solution, and thus are not necessarily able to tackle the large-scale problem. Troncoso-Pastoriza et al. [6] give the first study on iterative methods for collaboratively solving systems of linear equations under the SMC framework, which is the closest related work. However, their work can only support very limited number of iterative algorithm execution and cannot support reasonably large-scale systems of linear equations due to the continuing growth of the ciphertext in each of the iteration, which is not the case in the proposed design. In addition to the computation asymmetry issue mentioned previously, they only consider honest-but-curious model and thus do not guarantee that the final solution is correct under the possible presence of truly malicious adversary.

C. Computation Delegating and Cheating Detection

Detecting the unfaithful behaviors for computation outsourcing is not an easy task, even without consideration of input/output privacy. Verifiable computation delegation, where a computationally weak customer can verify the correctness of the delegated computation results from a powerful but untrusted server without investing too much resource, has found great interests in theoretical computer science community. Szajda et al. [15] propose methods to deal with cheating detection of other classes of computation outsourcing, including

$$x(k+1)=T.x(k)+c \quad (2)$$

optimization tasks and Monte Carlo simulations. In [16], Du. et al. propose a method of cheating detection for general computation outsourcing in grid computing. The server is required to provide a commitment via a Merkle tree based on the results it computed. The customer can then use the commitment combined with a sampling approach to carry out the result verification, without re-doing much of the outsourced work. However, all above schemes allow server actually see the data and result it is computing with, which is strictly prohibited in secure computation outsourcing model for data privacy. Thus, the problem of result verification essentially becomes more difficult, when both the input/output privacy is demanded.

III. PROBLEM STATEMENT

System Model

Suppose the cloud customer has a large-scale LE problem Ax=b which is required to be solved and is denoted by $\Phi=(A,b)$. Due to lack of computing resources, he cannot carry out the expensive $(O(n^{\rho})(2<\rho\leq 3))$ computation locally. Therefore the customer outsources the linear equation problem to the cloud server. For the protection of the data, the customer uses a secret key K to map Φ into an encrypted version Φ_K. Then, based on Φ_K, the customer starts the computation outsourcing protocol with CS, and harnesses the cloud resources in a privacy-preserving manner. The CS finds the answer of Φ_K, and after receiving the solution of encrypted problem Φ_K, the customer should be able to first verify the answer. If the answer is correct, he then uses the secret K to map the output into the desired answer for the original problem Φ. The computation outsourcing architecture involving cloud customer and CS is considered as illustrated in Fig.1.

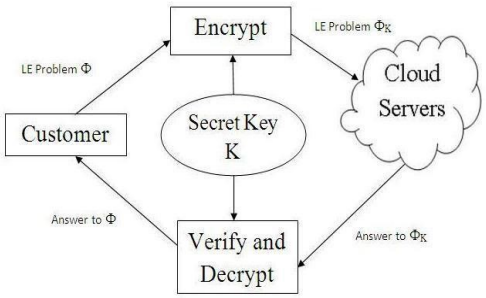

Figure 1. Architecture of secure outsourcing of linear computations into the cloud.

Here, the customer needs to perform a one-time setup phase of encrypting the coefficient matrix with relatively costly $O(n^2)$ computation. But it is important to stress that this process can be performed under a trusted environment where the weak customer with no sufficient computational power outsources it to a trusted party. The motivating example can be a military application where the customer has a one-time encryption process executed inside the military base by a trusted server, and then goes off into the field access only to untrusted CS.

So, it is assumed that CS is already in possession of the encrypted coefficient matrix, and the customer who knows the decryption key hopes to securely harness the cloud for on-demand computing outsourcing needs.

1. *Methodologies*
2. *Jacobi Iterative Method:*

In computational mathematics, an iterative method is a mathematical procedure that generates a sequence of improving approximate solutions for a class of problems. An iterative method is called convergent if the corresponding sequence converges for given initial approximations. In contrast, direct methods attempt to solve the problem by a finite sequence of operations. In the absence of rounding errors, direct methods would deliver an exact solution. Iterative methods are often the only choice for nonlinear equations. However, iterative methods are often useful even for linear problems involving a large number of variables where direct methods would be prohibitively expensive even with the best available computing power.

A system of linear equations is written as

$$Ax=b \quad (1)$$

where x is the $n\times1$ vector of unknowns, A is an $n\times n$(nonsingular) coefficient matrix, and b is an $n\times1$ right-hand side vector (so called constant terms).

Examples of iterative methods are Jacobi method, Gauss-Seidel method and the successive over-relaxation method. Without loss of generality, Jacobi iteration [7] is focused here for its simplicity. The method starts with the decomposition: A=D+R, where D is the diagonal component and R is the remaining matrix. The Equation (1) can be written as Ax=(D+R)x=b, and finally reorganized as: $x=-D^{-1}.R.x+D^{-1}.b$. According to the Jacobi method, an iterative technique can be used to solve the left hand side of this expression for $x^{(k+1)}$, using previous value for $x^{(k)}$ on the right hand side. If the iteration matrix is denoted by $T=-D^{-1}.R$ and $c=D^{-1}.b$, the above iterative equations can be represented as

2) Homomorphic Encryption:

Additive homomorphic property is used for a secure encryption scheme. Let x_1 and x_2 be two integers where $Enc(x_1+x_2)=Enc(x_1)*Enc(x_2)$ and $Enc(x_1*x_2)=Enc(x_1)^{x_2}$. In this implementation, the Paillier cryptosystem [8] is adopted. It is a probabilistic asymmetric algorithm for public key cryptography. For a vector $x=(x_1,x_2,....,x_n)^T \in (\mathbb{Z}_N)^n$, Enc(x) can be used to denote the coordinate-wise encryption of x: $Enc(x)=(Enc(x_1), Enc(x_2),\ldots, Enc(x_n))^T$. For some $n\times n$ matrix T, where each of the component $T[i,j]$ in T is from $\mathbb{Z}_N$, the component-wise encryption of T is denoted as Enc(T), and $Enc(T)[i,j]=Enc(T[i,j])$.

IV. THE FRAMEWORK AND BASIC MECHANISM

The framework for the proposed mechanism design is shown in this section and a basic mechanism is provided based on direct method. The basic mechanism fulfills the input/output privacy, but does not meet the efficiency requirement. The analysis of this basic solution gives insights and motivations on the main mechanism design based on iterative methods.

A. The General Framework

There are three phases: TransfProb, SolvProb, ResultVerify.

1. ***TransfProb****:* In this phase, cloud customer initializes a randomized key generation algorithm and transforms the LE problem into an encrypted form Φ_K via key K for phase SolvProb.
2. ***SolvProb****:* In this phase, cloud customer uses the encrypted form Φ_K of LE to start the computation outsourcing process. The protocol ends when the solution within the required accuracy is found.
3. ***ResultVerify****:* In this phase, the cloud customer verifies the encrypted result produced from cloud server, using the randomized secret key K. A correct output x to the problem is produced by decrypting the encrypted output. When the

validation fails, then it means that the cloud server is cheating.

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Basic Mechanism

The analysis of this basic solution gives motivations on the proposed mechanism design based on iterative methods. In the TransfProb phase, a random vector $r \in \mathbb{R}^n$ is taken as a secret keying material by the customer. Then, Equation (1) is rewritten as A(x+r)=b+Ar. Now, let y=x+r and b′=b+Ar, and Ay=b′. To hide the coefficient matrix A, a random invertible matrix Q is selected which has the same size as A. Left multiplying Q to both sides of Ay=b′ give us

$$A'y=b \quad (3)$$

where A′=QA and b′′=Q(b+Ar). The customer can then start the SolvProb phase by outsourcing Φ_K=(A′,b′′) to the cloud, who solves Φ_K and sends back y. After verifying the correctness of y, the customer can derive the original x via x=y-r.

While achieving the input/output protection, this approach is not attractive for the following reasons:

1) The local problem transformation cost for matrix multiplication QA is $O(n^3)$, which is comparable to the cost of solving Ax=b[11]. Considering the extra cost of ResultVerify, there is no guaranteed computational saving for the customer.
2) The local cubic time cost can become prohibitively expensive when n goes large to the orders of hundreds of thousands. Besides, it violates the assumption that the customer cannot carry out expensive $O(n^{\rho})(2<\rho\leq 3)$ computation locally.

V. RESEARCH DIRECTIONS

Linear programming(LP) is a kind of computational mechanism which takes the first order effects of various system parameters that has to be optimized, and is necessary to the engineering optimiza-tion. Based on the advancement in this area, which has been done in past years, we have identified the main problems and drawbacks in the present system. The problem identification and further future research directions are presented as follows:-

5.1 Problem Identification

Today, data privacy and security becomes an essential part of var-ious cloud based applications, multiparty computation scenarios etc. Due to lack of computational resources, clients need to direct their computational problem parameters to cloud. But, security, privacy and confidentiality of client's private data in this whole outsourcing process is a big challenge. The core problems, which we have identified in the present existing system are as below -

To resist against unauthorized information leakage, sensitive data has to be encrypted before outsourcing. Ordinary data encryption techniques, in essence, prevent the cloud from per-forming any meaningful operation of the underlying plaintext data, making the computation over encrypted data, a very harsh problem.

Also, customers are not aware of the computation which is run-ning inside the cloud. So, from customer side, it is also some problem to verify and ensure the correctness of computational results.

5.2 Future Research Directions

Security and privacy of data, specially in clouds, has become most essential part for various applications in present scenario. Research directions are presented as points below -

1. To come up with a new Fully Homomorphic encryption(FHE) scheme and apply it to secure computation outsourcing in cloud. Fully Homomorphic Encryption is an special form of encryption that allows computations to be carried out on ci-phertext, thus generating an encrypted result which, when de-crypted, matches the result of operations performed on the plaintext.
2. Fully Homomorphic encryption(FHE) is a tremendous way to perform processing and computations on the en-crypted data in cloud environment, which is being used by any third parties without the knowledge of private secret key.
3. Lets the FHE scheme, where - the encryptions on the plain text M_1 and M_2 can be Encr(M_1) and Encr(M_2). Now, since FHE acheives both additive and multiplicative properties, so both Encr(M_1 + M_2) and Encr(M_1 M_2) can be computed in a secure and efficient manner. Thus Fully Homomorphic encryption ful-fills the purpose of secure outsourcing of customer's prob-lematic data in a great extent.
4. Since, customers are not aware of the computation which is running inside the cloud. So, from customer side, it is also some problem to verify and

ensure the correctness of compu-tational results. So, we will come up with a scheme, which will be having the proof of correctness for the particular outsourced computational problem in the cloud environment.

VI. CONCLUSION

This paper formulates the problem of securely outsourcing linear equations via the Jacobi iterative method and provides mechanism designs fulfilling input/output privacy, cheating resilience and efficiency. The proposed mechanism brings computational savings. Within each iteration, it incurs $O(n)$ computation burden for the customer and demands no unrealistic IO cost, while solving the linear equations locally incurs $O(n^2)$ per iteration cost in terms of both time and memory requirements. It also allows the customers to verify all results of previous iterations from cloud in one batch. It ensures both the efficiency advantage and robustness of the design.

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