Secure Multiparty Computation Protocol used for Privacy Preserving Data Mining-Zero Data Leakage Approach

Prof. Anand R.Padwalkar
Department Of Computer Application
Shri Ramdeobaba Of Engg & Management,
Nagpur,India

Prof.M. Aehtesham Malik
Department Of Computer Application
ITM's Institute of Management & Research,
Nagpur,India

Prof. Sandeep Samrit
Department Of Computer Application
Priyadarshini Institute of Engg & Tech,
Nagpur,India

Abstract - In a modern information-driven society, the everyday life of individuals and companies is full of cases where various kinds of private information is an important resource. While a cryptographer might think of PIN-codes and keys in this context, this type of secrets is not our main concern here. Secure Multiparty Computation (SMC) allows parties to compute the combine result of their individual data without revealing their data to others. SMC also allows parties with similar background to compute results upon their private data, minimizing the threat of disclosure. On SMC many eminent researchers give their protocols especially in secure sum computation, researchers show their interest. The process involves encrypting data in a manner that it does not affect the result of the computation. Virtual parties are created by all organizations and encrypted data is distributed among them. Modifier tokens are generated along encryption which are assigned to virtual parties, and finally used in the computation. The computation function uses the acquired data and modifier tokens to compute result. As the data involved in computation was encrypted, without revealing the data right result can be computed and privacy of the parties is maintained. In this paper, we survey the basic paradigms and notions of secure multiparty computation and discuss their relevance to the field of privacy-preserving data mining. In addition to reviewing definitions and constructions for secure multiparty computation, we discuss the issue of efficiency and demonstrate the difficulties involved in constructing highly efficient protocols. Finally, we discuss the relationship between secure multiparty computation and privacy-preserving data mining, and show which problems it solves and which problems it does not.

Keywords - Secure Multiparty Computation (SMC); zero data leakage, Third Party (TP); Secure Sum Protocol; Hybrid, Pool of function.

I. INTRODUCTION

Privacy-preserving data mining considers the problem of running data mining algorithms on confidential data that is not supposed to be revealed even to the party running the algorithm. There are two classic settings for privacy-preserving data mining (although these are by no means the only ones). In the rest, the data is divided among two or more different parties; the aim being to run a data mining algorithm on the union of the parties' databases without allowing any party to view another individual's private data. In the second, some statistical data that is to be released (so that it can be used for research using statistics and/or data mining) may contain confidential data; hence, it is first modified so that (a) the data does not compromise anyone's privacy, and (b) it is still possible to obtain meaningful results by running data mining algorithms on the modified data set. In this paper, we will mainly refer to scenarios of the first type.

Secure Multiparty computation problem is not a problem of single party as the name itself says it is the problem of multiple parties' i.e. n parties. In SMC problem, n parties want to compute their private data or function as input in secure mode means data of individual party cannot be disclose or reveal to other and correct result is computed.

The aim of secure multiparty computation is to enable parties to carry out such distributed computing tasks in a secure manner. Whereas distributed computing classically deals with questions of computing under the threat of machine crashes and other faults. Two important requirements on any secure computation protocol are privacy and correctness. The privacy requirement states that nothing should be learned beyond what is absolutely necessary; the correctness requirement states that each party should receive its correct output. The setting of secure multiparty computation encompasses tasks as simple as coin-tossing and broadcast, and as complex as electronic voting, electronic auctions, electronic cash schemes, contract signing, anonymous transactions, and private information retrieval schemes. Due to its generality, the setting of secure multiparty computation can model almost every cryptographic problem.

II. LITERATURE SURVEY

Secure multi-party computation (also known as secure computation or multi-party computation (MPC)) is a subfield of cryptography. The goal of methods for secure multi-party computation is to enable parties to jointly compute a function over their inputs, while at the same time keeping these inputs private. For example, two millionaires can compute which one is richer, but without revealing their net worth. In fact, this very example was initially suggested by Andrew C. Yao in a 1982 paper [1] and was later named the millionaire problem.

In this problem two millionaires wanted to know who is richer among them without disclosing their wealth to each other. The solution provided by Yao was for semi honest. Semi honest parties' means they want to know other information also. Then Clifton et al introduce tools for privacy preserving distributed data mining. He gave four efficient methods for privacy preserving computation that can be used to support data mining. They used circuit evaluation protocols for secure computation. All these are the theoretical aspects of SMC. Privacy preserving data mining using SMC has great importance and many applications have been developed. Du et al. reviewed the various industrial problems and listed.

A new concept was put forward by D.K.Mishra through his multi-layer protocols. Initially a two-layer protocol along with a tentative architecture for its implementation was proposed. This two-layer protocol was improvised by a three layer protocol in which an anonymizer layer was added in between the parties and the third party. This new layer hides the information of the parties from the third party, who computes the data and provides the result. After theoretical studies few practical problems of SMC was introduced i.e. Privacy information retrieval problem (PIR), Privacy preserving Statistical analysis, Privacy Preserving Scientific Computation, Privacy preserving Data Mining, Privacy Preserving Geometric Computation etc. In PIR problem there is a client and a server, client want to hack the information from the server without letting know I to server and server do not want that client ever know the binary sequence. Beside this, Lindall et al [2] and Agrawal et al [3] respectively provide cryptographic technique and solutions for SMC and for mining association rule, provide fast and secure algorithm. Through PORTIA project of Rebecca Wright some of the problems of SMC and privacy preserving data mining got the solution. Many eminent researchers provided their views and solutions of problems for SMC. After this Sheikh et al worked on the real model of SMC. In which they proposed many protocols for secure sum computation. In these protocols they used random numbers for privacy of input data of individual parties.

III. HYBRID TECHNIQUE OF SECURE MULTIPARTY PROTOCOL

In this protocol Hybrid model of secure multi-parties computation is proposed as shown in figure 1. In Hybrid model third party and individual parties both do computation partially at their end. In this protocol each party divides its data in three segments and with each segment parties adds different random number.

Steps:

1. Each party send its sum of first segment D11, D21, D13,….Dn1 and random no. r11, r21, r31…..rn1 to third party.
2.(i) Third party do sum of all the first segments received from all the parties P1, P2, P3….Pn i.e. S.
(ii) Third party send sum S to party P1.
3. Party Pi subtracts its random no. ri1 and add its second segment Di2 and its random no. ri2 and then send sum to next party Pi+1. This step repeat till i=n.
4. Party Pn send sum S to Pn-1.
5. Party Pn-1 subtracts its random no. ri2 and add its third segment Di3 and its random no. ri3 and send sum to previous party Pi-1. This step repeat till i=1
6. Party P1 send sum S to TP and TP send this sum to Pn.

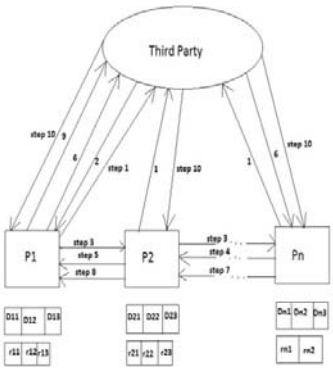


Fig 1: Hybrid Secure Sum Architecture

7. Party Pn subtracts its random no. rn2 and add its third segment Dn3 and send sum to Pn-1.
8. Party Pi-1 subtracts its random no. ri3 and send sum to Pi-2. Repeat this step till i=1.
9. Party P1 sends sum S to TP.
10. Third party TP broadcast the sum S to P1, P2, P3,….Pn.

IV. FORMULATION OF ARCHITECTURE

Secure Multiparty Computation Protocol Algorithm
1. Assume P1, P2, P3,….Pn are n parties involved in Hybrid secure computation.

2. Each party divides its data Di in three segments Di1, Di2 & Di3 and division of data in segments will be decided by parties itself, where i= 1,2,3…n.

3. Each party decide three random no. ri1,ri2,ri3 for each segment except nth party. Nth party has only two random nos. rn1& rn2 for first two segments.

4. For i=1 to n
n
$S= \Sigma(Di1+ri1)$
i=1

5. TP send sum S to party P1.

6. for i= 1 to n
S= [(S-ri1)+(Di2+ri2)]

7. nth party send Sum S to (n-1)th party.
8. for i= n-1 to 1
S= [(S-ri2)+(Di3+ri3)]

9. Party P1 send sum S to third Party TP.

10. TP send sum S to nth party.

11. for i= n to 1
Begin
If i= n
Then
S= [(S-ri2) + (Di3)]
// S is a global variable
Else
S= [(S-ri3)]

12. Party P1 send final Sum S to TP.

13. TP broadcast sum S to all the parties.

V. ANALYSIS AND BEHAVIORAL STUDY OF SYSTEM

Case I: If any party and third party become malicious.
If any one party and third party collude party can know only data of itself and third party knows the segment of party by whom it colludes. There is no other way of knowing the input data of other parties.

Case II: If any two parties collude:
If any two parties collude they can't get the data of other parties because data is divided into segments and each segment is secure with random number added in each round.

Case III: When all the parties are honest including third party.

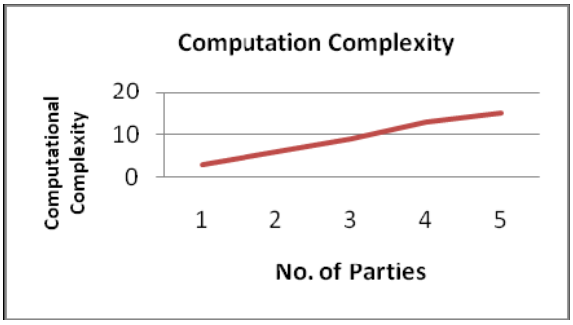
In first round computation at TP= 1

In second round computation on all the parties clockwise i.e. P1 to Pn= n

In third round computation on all the parties anticlockwise i.e. P(n-1) to P1= (n-1)

In fourth round computation on all the parties anticlockwise Pn to P1= n

On adding all the values obtain in each round we get:
1+n+(n-1)+n= 3n
3n is the computation complexity of our protocol.
Communication complexity is (4n+1).
The communication and computation complexity of our protocol is O (n).



Our protocol is completely secure which give zero data leakage. In case any party becomes malicious or two parties collude then too the secure computation is possible without data leakage. Malicious parties cannot identify or calculate the actual data or segment in any round of algorithm; they only get some computed part of data by which no relevant information is retrieved.

VI. FUTURE SCOPE AND CONCLUSION

Secure Multi-Party Computation is a well researched. Quite a few protocols already exist, and work is going-on on another handful. These protocols for secure computation achieve remarkable results: it has been shown that generic constructions can be used to compute any function securely, and it has also been demonstrated that some functions can be computed even more efficiently using specialized constructions. Still, a secure protocol for computing a certain function will always be more costly than a naive protocol that does not provide any security.
Our protocol also reduces the complexities that are encountered in three and four layer protocols. Subsequent enhancement of the protocol is expected the function domain is being further developed and the transforming functions that leverage the proposed architecture in different areas are being fine-tuned.
We believe that further research in this area is crucial for the development of secure and efficient protocols in this field. Of course, this must go hand in hand with research on privacy in general and the question of what information leakage is acceptable and what is not.

REFERENCES

[1] Yao Andrew C., "Protocols for secure computations," *Proc. of 23rd Annual Symposium Foundations of omputer Science*, pp. 160-164.
[2] Y. Lindell and B. Pinkas. (2000), Privacy preserving data mining, in advances in cryptography-Crypto2000, lecture notes in computer science, vol. 1880,2000.

[3] G. Aggarwal, N. Mishra and B. Pinkas. Secure Computation of the k-th Ranked Ele-ment. In *EUROCRYPT 2004*, Springer-Verlag (LNCS 3027), pages 40{55, 2004.
[4] W. Aiello, Y. Ishai and O. Reingold. Priced Oblivious Transfer: How to Sell Digital Goods. In *EUROCRYPT 2001*, Springer-Verlag (LNCS 2045), pages 119-135, 2001.
[5] Y. Aumann and Y. Lindell. Security Against Covert Adversaries: E±cient Protocols for Realistic Adversaries. In 4*th TCC*, Springer-Verlag (LNCS 4392), pages 137-156,2007.
[6] D. Beaver. Foundations of Secure Interactive Computing. In *CRYPTO'91*, Springer-Verlag (LNCS 576), pages 377{391, 1991.
[7] D. Beaver, S. Micali and P. Rogaway. The Round Complexity of Secure Protocols. In 22*nd STOC*, pages 503{513, 1990.
[8] M. Bellare and S. Micali. Non-Interactive Oblivious Transfer and Applications. In *CRYPTO'89*, Springer-Verlag (LNCS 435), pages 547{557, 1989.
[9] W. Du, and M. J. Attalah, "Secure Multi – Party Computation Problems and Their Applications: A Review
[10] Open Problems." *Tech Report CERIAS Tech Report 2001-51*, Centre for Education and Research in Information Assurance and Security and Department of Computer Sciences, Purdue University, West Lafayette,IN 47906, 2001.
[11] J. Vaidya, and C. Clifton, "Leveraging the Multi in Secure Multi-Party Computation." *WPES'03 October 30, 2003*, Washington DC, USA, ACM Transaction 2003, pp 120- 128.
[12] M. J. Atallah and W. Du., "Secure Multi-Party Computation Geometry." *Seventh International Workshop on Algorithms and Data Structures (WADS 2001)*, 116 Providence, Phode Island, USA, Aug 8- 10, 2001, pp 136-152.
[13] Jean-Sebastien Coron and_Ecole Normale Superieure, "Resistance Against Di_erential Power Analysis for Elliptic Curve Cryptosystems", [Published in C_ .K. Ko_c and C. Paar, Eds., Cryptographic Hardware and Embedded Systems, vol. 1717 of Lecture Notes in Computer Science, pp. 292 Springer-Verlag, 1999.]
[14] Whitfield Diffie and Martin E. Hellman. New directions in cryptography. *IEEE Transactions on Information Theory*, IT-22(6):644–654, 1976.
[15] S. Goldwasser and S. Micali. Probabilistic encryptionand how to play mental poker keeping secret all partial information. In *Proceedings of the 14th ACM Symposium on Theory of Computing (STOC'82)*,pages 365–377, San Francisco, CA, USA, May 1982.
[16] M. O. Rabin. Digitalized signatures and public-keyfunctions as intractable as factorization. Technical Report LCS/TR-212, Massachusetts Institute of Technology, 1979.
[17] R. L. Rivest, Adi Shamir, and Leonard M. Adleman. A method for obtaining digital signatures and publickey cryptosystems. *Communications of the ACM*, 21(2):120–126, February 1978.