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Cryptography-Based Privacy-Preserving Data Analysis and Empowering Data Privacy through Secure Multi-Party Computation: Challenges and Solutions

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***Abstract*— The conflict between the necessity of data analysis and the preservation of personal privacy is greater than ever in today's data-driven society. This conference paper offers a comprehensive examination of privacy-preserving data analysis, illuminating the methods, difficulties, and solutions related to this crucial nexus. The article begins with a "Introduction," which highlights the rising worries about data privacy and breaches and establishes the value of data analysis in numerous sectors, including healthcare, finance, and social sciences. It emphasises how important privacy protection is, particularly in situations involving collaborative data analysis when several parties contribute data without jeopardising individual privacy.The study concludes with a discussion of "Practical Challenges in Secure MPC Implementation," which emphasises the practicalities of using privacy-preserving data analysis methods in everyday situations. It emphasises how crucial safe setup, knowledge of cryptography, and data pretreatment are. In summary, this conference paper provides readers with a clearer grasp of the difficulties and approaches involved in striking a balance between the demands of data analysis and data privacy by providing a thorough review of privacy-preserving data analysis. It is meant to be an important tool for academics, professionals, and organisations that want to use data to its full potential while protecting people's right to privacy.**

Keywords—Analysis of Data, Preserving Privacy 3. Data Privacy, Cooperative Analysis of Data, Techniques for Preserving Privacy, Multi-Party Computation That Is Secure (MPC), Security Issues, Operations on Matrix, Integration of Data, Protocols for Cryptography

I. Introduction

In a time when data is frequently heralded as the new oil, privacy protection is becoming a more important issue. Sensitive data is persistently becoming more and more prevalent in our digital environment, which brings both benefits and concerns. One the one hand, this data may be used to gain insightful knowledge, enhance science, and develop technology. However, it also highlights the urgent necessity to protect personal data and privacy of individuals. The topic of secure multi-party computing (MPC) protocols was born out of the juxtaposition of data usefulness and privacy protection, and it is essential to the privacy-preserving data analysis that it enables.

The technological foundation for this idea is provided by secure multi-party computing protocols, which enable parties to collaboratively calculate functions over their private inputs without disclosing those inputs to one another. Fundamentally, MPC aims to resolve the tension that arises from preserving individual privacy while exchanging data for joint analysis. Through the use of cryptography, parties are able to process their data and maintain its confidentiality.

There are several reasons for using secure MPC protocols. It primarily tackles the problem of doing group analysis on sensitive material while guaranteeing that each member's

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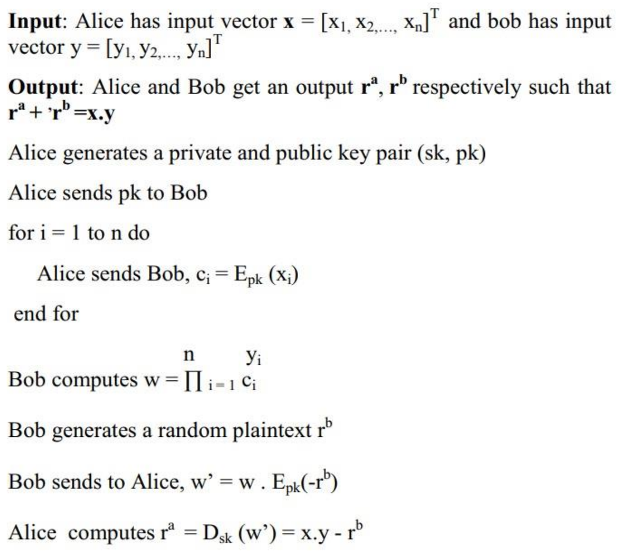
contribution is kept secret from the others. These kinds of situations are common and have applicability in many different fields. In order to maintain people' privacy rights while facilitating government access to cross-sectional data for policy formation, public health evaluations, and infrastructure planning, Secure MPC also expands its impact into e-government activities. These protocols also aid the fields of artificial intelligence and machine learning, since they allow different organisations to pool their datasets for the purpose of training more accurate models without disclosing the raw data. The purpose of this study is to investigate the role and uses of secure multi-party computing protocols in data analysis that protects privacy. We will examine the underlying ideas of secure MPC and analyse the methods and cryptographic building blocks that make it work. The study will offer a thorough examination of many secure MPC protocols, assessing their advantages, disadvantages, and applicability for diverse use cases.

II. Privacy-Preserving Data Mining

We present a handful of our study's safe privacy-preserving procedures in this part. Goethals et al.'s Secure Scalar Product Protocol is one of them. We examine three more safe, privacy-preserving methods that were dependent upon the Safe Scalar Product Interface. Secure Matrix is available. Safe Matrix Multiplication (SMM), Quick and Easy (FSSM), Matrix Sum Secure Matrix Inverse (SIMS). The Secure Scalar Product Protocol has been shown to be accurate and secure . Thus, our analysis is limited to the computational complexity and cost of the aforementioned methods' communication. These four methods employ a homomorphic additive encryption system ring-shaped message space in their system. As an example, +pk is a The result of their public key with two ciphertexts is Epk (m1) × M2 Epk = M1 Epk.

A. Secure Data Mining

Finding the number of records that contain a set of attribute values is the Secure Scalar Product's task while building decision trees for vertically partitioned data. Different Secure Scalar Product protocols with varying degrees of security and complexity It is suggested to use to safely calculate support level and confidence level to assess the frequency of an association rule. They facilitate a range of data mining methods, such as K-means Naïve Bayes classifier , clustering . To sum up, this protocol is an essential component of security. for several data mining methods that protect privacy in in tandem with the partially truthful model. The secret to the the usage of a homomorphic encryption method, like The Pallier cryptosystem, the Naccahe-Stern cryptosystem , and the cryptosystem that Okamoto-Uchiyama developed.



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Input: Alice has input vector $\mathbf{x} = [x_1, x_2, ..., x_n]^T$ and bob has input vector $y = [y_1, y_2, ..., y_n]^T$
Output: Alice and Bob get an output $\mathbf{r^a}$, $\mathbf{r^b}$ respectively such that $\mathbf{r^a} + \text{'}\mathbf{r^b} = \mathbf{x.y}$
Alice generates a private and public key pair (sk, pk)
Alice sends pk to Bob
for i = 1 to n do
    Alice sends Bob, $c_i = E_{pk}(x_i)$
end for
Bob computes $w = \prod_{i=1}^{n} c_i^{y_i}$
Bob generates a random plaintext $r^b$
Bob sends to Alice, $w' = w \,.\, E_{pk}(-r^b)$
Alice computes $r^a = D_{sk}(w') = x.y - r^b$
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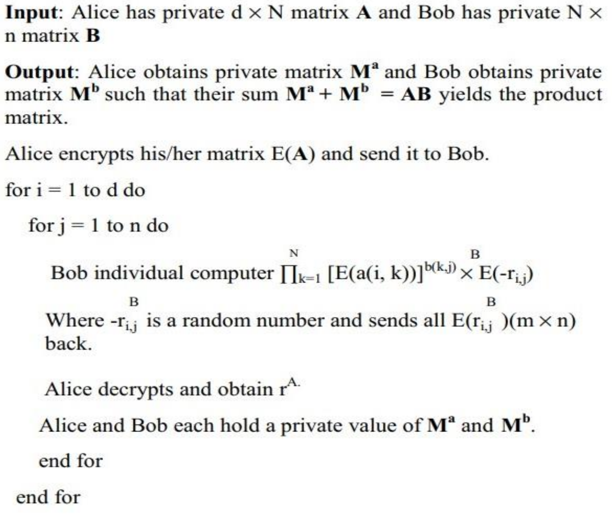
Fig. 1. E PROTOCOL FOR SECURE SCALAR PRODUCT

B. Singular Matrix Perturbation

If the sum matrix A + B is singular, then the sum matrix can be perturbed simply to become non-singular. As an example, the disturbance suggested by Hong and Yong can be applied to apply a little perturbation matrix A to stabilise A + B alternatively B.



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Input: Alice has private d × N matrix $\mathbf{A}$ and Bob has private N × n matrix $\mathbf{B}$
Output: Alice obtains private matrix $\mathbf{M^a}$ and Bob obtains private matrix $\mathbf{M^b}$ such that their sum $\mathbf{M^a} + \mathbf{M^b} = \mathbf{AB}$ yields the product matrix.
Alice encrypts his/her matrix E(A) and send it to Bob.
for i = 1 to d do
    for j = 1 to n do
        Bob individual computer $\prod_{k=1}^{N} [E(a(i, k))]^{b(k,j)} \times E(-\overset{B}{r}_{i,j})$
        Where $-\overset{B}{r}_{i,j}$ is a random number and sends all $E(\overset{B}{r}_{i,j})(m \times n)$ back.
        Alice decrypts and obtain $r^{A.}$
        Alice and Bob each hold a private value of $\mathbf{M^a}$ and $\mathbf{M^b}$.
    end for
end for
```

Fig. 2. E PROTOCOL FOR RAPID AND SECURE MATRIX MULTIPLICATION (RSMM)

III. Efficient Secure Matrix Operations

Provably valid and safe is the safe Scalar Product Protocol [2] put out by Goethals et al. The protocol's communication cost and computational complexity are O(N) and O(N), where N is the vector length, in that order. Calculating the Secure Matrix Multiplication Product Protocol When d × N matrix A and N × n matrix B are multiplied, the Protocol for Secure Scalar Product [2] d × n times. Thus, The cost of communication and computing complexity are d × nO(n) and d × nO(n) in that order. This approach is simpler and more simple in contrast to Du et al. [11] Locked Matrix Interruption.

We are able to compute each matrix element's product. simultaneously to boost productivity. An enhanced variant of the Fast Secure Matrix Multiplication is Safe Multiplication of Matrix.

Bob exposes SB + BP to Alice via the Secure Inverse of Matrix Sum Protocol. This information is concealed by random matrices P and SB that are only known to Bob. Bob creates random m × m on his own O(m2) computational complexity matrix P Nevertheless, Bob the Fast Secure Matrix Multiplication protocol may be started by P is being encrypted. Matrix P encryption once, then forward to Alice too, once. Thus, the intricacy of the computation and Communication cost for computing two m × m multiplication A 2 m2 matrix O(m3) = m with m2 = O(m2) in that order. We are able to boost the effectiveness of performance by using concurrent processing on Quick Safe Multiplication of Matrix.

TABLE I. PROTOCOL COMPLEXITY AND COMMUNICATION COSTS

Secure Building Block	Input Alice & Bob	Computational Complexity	Communication Cost
Secure Scalar Product	x & y	O(n)	O(n)
Secure Matrix Multiplication	m x N & N x n	O(mnN)	O(mnN)
Fast Secure Matrix Multiplication	m x N & N x n	O(mn)	O(τN) where τ = min(m,n)
Secure Sum of Scalar Product	m x 1 & m x 1	O(m + n)	O(m + n)
Secure Inverse of Matrix Sum	m x m & m x m	O(m^3)	O(m^2)

IV. PRIVACY-PRESERVING DATA AGGREGATION

In Singapore, security and privacy issues have been brought up , and a number of protocols have already been suggested .These procedures often need two steps to secure users' privacy methods: aggregation or anonymization. The Efthymiou and It was suggested by Kalogridis that every SM have an anonymous ID for submitting operational metering data alone. But still, According to Cleemput et al, de-anonymization is feasible. Homomorphic encryption was suggested by Li et al as a means of achieving privacy-friendly aggregation. But their procedure neither aids current attacks nor provides defence against active attackers marketplaces for electricity. Mustafa and associates, tackled these restrictions by employing chosen data and digital signatures method of distribution and aggregation. A privacy-preserving demand response management and billing aggregation technique called EDAS was suggested by Gope and Sikdar [19]. It masks the individual measurements of SMs using random values. The service provider is completely trusted, so it has all of the consumers' metering data, and the aggregator also obtains the aggregate data of users in the same area. As a result, their approach only partially protects the privacy of users. A data aggregation system called 3PDA was presented by Liu et al. [20]; it used a virtual aggregation area to conceal the metering data of specific users.

Masking is used by Knirsch et al to accomplish error-resilient data aggregation. Their technique adds more communication even if it allows aggregation over numerous sets of SMs expenses when SMs converse with one another to trade their occulting qualities. Shen and Abdallah suggested a homomorphic data aggregation approach based on lattices, in contrast to Using a cube-data aggregation approach, Shen et al permits the summation of multidimensional data using aggregation of each dimension without disclosing personal information to consumers. But these programmes don't allow for the aggregation of Several sets of SMs were proposed by Borges and Muhlh ¨ auser . protocol based on homomorphic encryption, in which every SM possesses An permitted data receiver is aware of the two secret keys.

MPC is another method for efficiently and effectively aggregating data while maintaining anonymity. Danezis et al. [16] suggested procedures that use MPC based on secret-sharing to identify fraud and to obtain sophisticated grid data. According to Rottondi et al. [17], a unique security framework for collecting and combining metering information. Nevertheless, their construction necessitates more nodes in the system, such as gates positioned in the homes of the users. In contrast to the previous research, our suggested MPC-based A true smart metering architecture serves as the foundation for the privacy-preserving protocol for operational metering data collecting (i). (ii) is easily adaptable to a market for liberalised electricity.

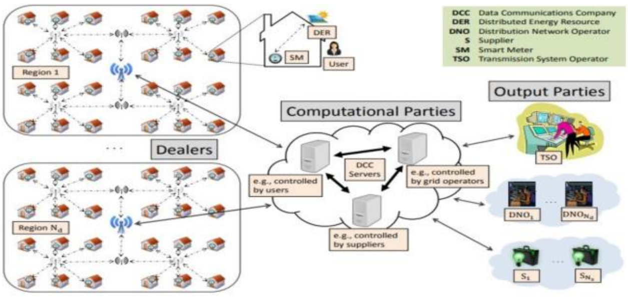
DCC Data Communications Company
DER Distributed Energy Resource
DNO Distribution Network Operator
S Supplier
SM Smart Meter
TSO Transmission System Operator
Region 1
DER
SM
User
Output Parties
Computational Parties
Dealers
DCC Servers
e.g., controlled by users
e.g., controlled by grid operators
e.g., controlled by suppliers
TSO
Region N_d
DNO_1
DNO_{N_d}
S_1
S_{N_s}

Fig. 3. System Model

V. BALANCING DATA ANALYSIS AND PRIVACY

“Data Analysis Protecting Privacy: Finding a Balance Between Confidentiality and Insight” The search for insights through data and the protection of individual privacy are two pressing issues in our digital age that are intersected by privacy-preserving data analysis. We examine the foundations of privacy-preserving data analysis in this review, as well as its requirements, methods, and difficulties. Informed decision-making has become more dependent on data analysis in a variety of fields, including social sciences, marketing, healthcare, and finance. But as data collecting grows, so do worries about data breaches, abuse, and even loss of personal privacy. People are understandably concerned that their private information could be compromised in the course of data analysis.

A. Data Analysis and Privacy Concerns

Informed decision-making has become more dependent on data analysis in a variety of fields, including social sciences, marketing, healthcare, and finance. But as data collecting grows, so do worries about data breaches, abuse, and even loss of personal privacy. People are understandably concerned that their private information could be compromised in the course of data analysis. This issue becomes especially urgent when data from several parties or sources needs to be examined collaboratively. In the healthcare industry, for instance, research may need to combine patient information from several facilities while maintaining the privacy of each patient's medical history. In these kinds of situations, privacy protection becomes critical. Analysing data while protecting privacy guarantees that important information is gathered without jeopardising privacy.

B. Data Analysis and Privacy Concerns

Numerous privacy-preserving methods have been developed to meet this demand. By using these methods, data analysts can obtain valuable insights without having to access or reveal the original data itself. Some well-known techniques are: Differential privacy: In order to make it more difficult to identify specific individuals' data inside the dataset, this method adds controlled noise to query results. Homomorphic Encryption: This cryptographic method enables analysis that protects privacy by permitting calculations on encrypted data without disclosing the content of the data. Safe Multi-Party Computation (MPC): In MPC, a number of participants work together to jointly calculate a function over their private inputs while maintaining the privacy of those inputs. Federated Learning: This method guarantees that data stays on users' devices and is not centralised by training machine learning models on decentralised data sources.

C. Challenges in Privacy-Preserving Methods

Although privacy-preserving methods provide encouraging alternatives, they also present a unique set of difficulties: Privacy vs Accuracy Trade-off: The accuracy of the analysis may be impacted by privacy precautions like increasing noise or restricting access to data. Finding the ideal balance between accuracy and privacy is a constant struggle. Costs of compute and Communication: The additional compute and communication resources needed for privacy-preserving techniques might make them impractical in practise. Data Integration: It might be difficult to integrate data from several sources while maintaining privacy. Cooperation and standardisation amongst data suppliers may be necessary. Regulatory Compliance: Adhering to privacy-preserving data analysis techniques is crucial when it comes to complying with data privacy requirements such as GDPR or HIPAA.

VI. Empowering Privacy with Secure Multi-Party Computation (MPC)

“Secure Multi-Party Computation (MPC): Facilitating Collaborations That Protect Privacy” At the nexus of data analysis and encryption lies the intriguing topic of Secure Multi-Party Computation, or MPC. It enables several participants to maintain the confidentiality of their private inputs while collaboratively computing functions over them. This introduction will go over what MPC is, how important it is for protecting privacy, and what terms and ideas are important to know about this technology. An explanation of MPC is provided in **1. Fundamentally, Secure Multi-Party Computation (MPC) is a cryptographic method that permits many parties to analyse data together without disclosing the raw data to any other party. Put more simply, it allows several parties to collaborate on data while maintaining the privacy of their respective datasets.

A. Privacy-Preserving Collaboration: Secure Multi-Party Computation

Fundamentally, Secure Multi-Party Computation (MPC) is a cryptographic method that permits many parties to analyse data together without disclosing the raw data to any other party. Put more simply, it allows several parties to collaborate on data while maintaining the privacy of their respective datasets. Completing calculations on sensitive data while shielding it from other analysis participants is the main objective of MPC.

In order to do this, MPC uses cryptographic protocols that enable data to be encrypted so that calculations can be performed on the encrypted data and results may be received in an encrypted format. The final findings can only be decrypted and accessed by authorised persons. This guarantees the confidentiality of sensitive data.

B. Privacy-Preserving Data Analysis with MPC

MPC's primary function in data analysis is to protect privacy. Privacy problems are significant in an era where data sharing is necessary for cooperative research, decision-making, and a variety of applications. MPC solves this problem by enabling collaboration between entities, persons, and organisations while maintaining the privacy of sensitive data.

Imagine a situation where several hospitals want to analyse patient data to find patterns in diseases, but they don't want to share specific patient information. By using MPC, hospitals may work together to compute aggregate statistics or derive insights from the pooled data, all while maintaining the privacy of patient information. In fields where privacy is crucial, such as healthcare, banking, and research, this approach is priceless.

C. Keys of Secure Multi-Party Computation (MPC)

Private Inputs: These are the unique datasets that each MPC participant provides. Throughout the calculation, these inputs are kept private. Cryptographic protocols are mathematical rules that control how secret inputs are computed and interacted with securely. The Yao's Millionaires' Problem, Garbled Circuits, and Beaver Triple protocol are examples of common protocols. A fundamental idea in MPC is Secure Function Evaluation (SFE), in which participants jointly assess a function over their private inputs while maintaining privacy. SFE makes sure that parties are only aware of the computation's outcome and not its inputs. Malevolent Adversaries: MPC is built to withstand assaults from malevolent individuals attempting to jeopardise other people's privacy. Even in cases when some parties are unwilling to cooperate, strong procedures can stop data leaks. An encryption technique called homomorphic.

VII. Analysis of Secure MPC Protocols: Pros and Cons

The foundation of privacy-preserving collaborative data analysis is provided by Secure Multi-Party Computation (MPC) protocols, which allow parties to cooperatively calculate functions over their private inputs without disclosing those inputs to one another. We will cover the fundamentals of several secure MPC protocols, examine one prominent protocol in detail, and assess the advantages and disadvantages of various strategies in this talk. A Synopsis of Different Secure MPC Protocols: Several secure MPC protocols have been created, each with the intention of meeting certain security criteria and use cases. Together, these protocols provide a wide range of tools for computing that protects privacy. Several popular protocols consist of: “The Protocol for Yao's Millionaires' Problem” This protocol, which was first created to address a particular issue, served as the model for contemporary MPC.

A. *Exploring Secure Multi-Party Computation Protocols*

Several secure MPC protocols have been created, each with the intention of meeting certain security criteria and use cases. Together, these protocols provide a wide range of tools for computing that protects privacy. Several popular protocols consist of: Yao's Protocol for the Millionaires' Problem: This protocol, which was first created to address a particular issue, served as the model for contemporary MPC. To calculate functions safely, it uses a mechanism known as garbled circuits. Garbled Circuits: With this protocol, users may design a circuit that specifies the calculation they want to do. Then, in order to conceal its information and allow computation, they jumble this circuit. This strategy is popular and adaptable. The Beaver Triple Protocol works by creating random triples of values to help with safe multiplication, which is a vital computation in many cases.

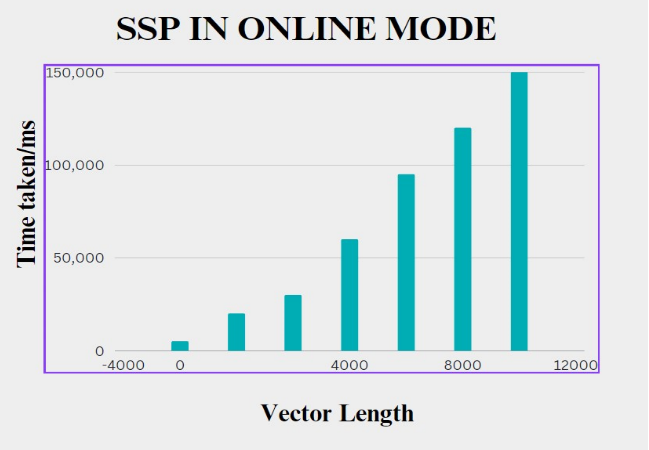

Fig. 4. Online Secure Scalar Product Protocol

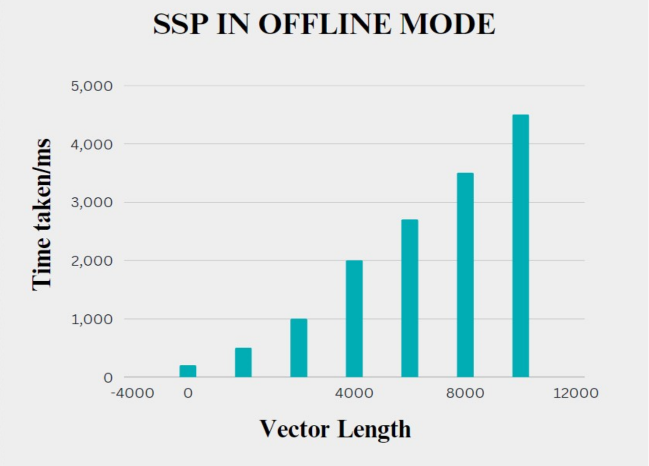

Fig. 5. Offline Secure Scalar Product Protocol

B. *Garbled Circuits in MPC*

Let's examine Garbled Circuits in more detail. This is one of the most popular and adaptable MPC protocols. In jumbled circuits, participants work together to build a circuit that symbolises the needed calculation. The internal workings of this circuit have been "garbled" to facilitate secure examination. In order to assess the circuit and calculate the outcome without disclosing their inputs, parties communicate encrypted data. The versatility of garbled circuits is well known, as they may be used for a wide range of activities, including intricate calculations.

C. *Pros and Cons of MPC Protocols*

Every MPC protocol has a unique mix of advantages and disadvantages that make them appropriate for certain situations:

Advantages:

Versatility: Homomorphic Encryption-Based Protocols and Garbled Circuits are adaptable and suitable for a variety of calculations.

Security: Because of the strong privacy protection provided by these protocols, it is very difficult for nefarious parties to access the data.

Drawbacks:

Computation Overhead: A protocol's processing time may rise if it is computationally demanding, as is the case with homomorphic encryption-based protocols.

Communication Costs: In MPC, parties may have to communicate a lot in order to transmit secure data.

Complexity: Certain MPC protocols, such as Garbled Circuits, can be difficult to implement and comprehend without the right knowledge.

VIII. Empowering Data Privacy with Secure MPC

When privacy and sharing sensitive data are top priorities, Secure Multi-Party Computation (MPC) provides a potent option for data analysis. Here, we examine the various professional uses for secure MPC and the noteworthy advantages it offers the field of data analysis. Secure MPC is widely used in the healthcare industry, where patient privacy is crucial. It is possible for several hospitals or research facilities to work together on patient data analysis without disclosing specific medical information. MPC, for instance, permits research on treatment results or illness patterns within a network of healthcare providers without jeopardising personal privacy. Financial firms frequently have to analyse transaction data in tandem in order to identify fraudulent activity and evaluate risk indicators.

Healthcare Collaboration: Secure MPC: Be safe MPC is often used in the healthcare industry, where patient privacy is extremely important. It is possible for several hospitals or research facilities to work together on patient data analysis without disclosing specific medical information. MPC, for instance, permits research on treatment results or illness patterns within a network of healthcare providers without jeopardising personal privacy.

Financial Data Analysis: Secure MPC Collaboration: Financial firms frequently have to analyse transaction data in tandem in order to identify fraudulent activity and evaluate risk indicators. Banks may exchange and examine financial data via secure MPC without revealing private client information. This strengthens their capacity to work together to prevent financial fraud.

Genomic Research Advancements: Secure MPC: Researchers in domains like as epidemiology and genomics may use secure MPC to analyse genetic data from several sources together. This advances personalised treatment by making it possible to identify genetic markers for various illnesses.

Data Privacy Compliance: Secure MPC: Secure MPC guarantees compliance with data privacy and security laws like HIPAA and GDPR in highly regulated sectors like healthcare and finance.

Versatile Secure MPC Applications: From straightforward aggregations to intricate computations, a broad range of data processing jobs can benefit from the use of secure MPC. It is appropriate for a variety of application scenarios due to its versatility.

IX. Practical Challenges in Secure MPC Implementation

Although Secure Multi-Party Computation (MPC) is an effective technique for data analysis that protects privacy, its real-world use presents a special set of difficulties. We will look at information on using MPC in real-world situations as well as the issues and problems that come up in this review. There are several important procedures and things to keep in mind while using MPC in real-world circumstances. The first important consideration is selecting a suitable MPC methodology. The particular use case, the number of participants, and the required level of security and privacy all influence this choice. Various trade-offs are available in terms of efficiency and security for protocols such as Homomorphic Encryption, Garbled Circuits, and Yao's Protocol. The calculation must be set up securely by all parties participating in the MPC. Usually, this entails exchanging cryptographic keys.

Choosing the Right MPC Protocol: The first important consideration is selecting a suitable MPC methodology. The particular use case, the number of participants, and the required level of security and privacy all influence this choice. Various trade-offs are available in terms of efficiency and security for protocols such as Homomorphic Encryption, Garbled Circuits, and Yao's Protocol.

Secure Setup for MPC: The calculation must be set up securely by all parties participating in the MPC. In order to thwart such assaults, this usually entails exchanging cryptographic keys and confirming the integrity of each party's setup. Another essential part of this stage is setting up a secure communication route.

Data Preprocessing for Secure MPC: It could be necessary to preprocess the data before starting the computation. To make sure the data is in a format appropriate for safe computing, this involves data cleansing, normalisation, and transformation.

Expertise for Effective MPC: Effective MPC implementation requires knowledge of secure configuration, protocol management, and cryptography. It could be necessary for organisations to spend money on staff training or working with subject matter experts.

X. Conclusion

We have covered many aspects of safe data mining, effective matrix operations, and secure data aggregation in our thorough review of privacy-preserving data analysis. In light of the rising concerns over data privacy and the necessity of collaborative data analysis, it is imperative to include privacy-preserving solutions. We began by going over the basic issues with data analysis, highlighting the need to find a balance between protecting individual privacy and gaining insights from data. Many industries, including healthcare, banking, marketing, and research, have privacy issues. As a result, sophisticated methods must be used to protect sensitive data.

The investigation of privacy-preserving techniques revealed a multitude of obstacles, such as the trade-off between privacy and accuracy, related computational and communication costs, difficulty with data integration, and the critical requirement for regulatory compliance. These difficulties highlighted how important it is to put strong privacy-preserving methods into practise, including Secure Multi-Party Computation (MPC). One important component in maintaining privacy is Secure Multi-Party Computation. Its many uses were demonstrated in a variety of fields, including genomics research, financial data analysis, and healthcare collaboration. Organisations may work together on data analysis while maintaining data privacy by utilising MPC to protect individual-level information. This encourages the exchange of insights. The report also included a detailed breakdown of the processes needed to apply MPC in real-world situations. Key concerns were choosing an acceptable MPC protocol, securing the system, preparing the data, and emphasising the importance of expertise.

The research concluded with an in-depth examination of Secure Multi-Party Computation (MPC) protocols, with a particular emphasis on Garbled Circuits, a well-liked and flexible approach for data processing that protects privacy. It further demonstrated the use of MPC in guaranteeing adherence to laws like HIPAA and GDPR and underlined the critical relevance of complying with data privacy standards. In conclusion, in today's data-driven society, integrating privacy-preserving approaches is crucial, particularly Secure Multi-Party Computation. Organisations may leverage collaborative data analysis capabilities without sacrificing individual privacy by utilising MPC.

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