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Secure Multi-Party Computation for Cloud Data Sharing

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Abstract
The development of cloud computing has made organizations to store and analyse a lot of information. Nonetheless, information transfer among organizations presents privacy, security and regulatory issues. The cryptographic mechanism is known as Secure Multi-Party Computation (MPC) which enables more than two parties to perform common functions on their data without disclosing their personal input. In this paper, the authors discuss how MPC protocols can be applied to cloud computing systems to provide privacy protecting information sharing. We provide the history and reasons to embrace the MPC in controlled industries, consider the latest publications, and describe the way MPC can be implemented in multi-cloud environments. Conceptual analysis shows that MPC has the ability to overcome confidentiality issues and still retain analytical power. We also talk about the limitations in terms of computational complexity and network latency and the directions in which the performance and usability could be improved in the future. The paper finds that MPC is a potential scheme in the secure data collaboration, particularly in the sectors where privacy and compliance matter the most.
Keywords: *Secure Multi-Party Computation, Cloud Computing, Data Sharing, Cryptography, Privacy Preservation*

I. Introduction

Cloud computing has revolutionized the mode in which organizations store, process and share data. Businesses are choosing to use distributed infrastructures to support analytics and decision making. Nonetheless, secure transfer of sensitive information between the organizations is one of the most essential obstacles. The General Data Protection Regulation (GDPR) and the Health Insurance Portability and Accountability Act (HIPAA) are privacy regulations that demand high standards of data sharing and processing (Sharma and Gupta, 2022).
Secure Multi-Party Computation (MPC) is one such solution, which enables several parties to share computations on their confidential data without disclosing the information to the other parties (Yao, 1982; Damg7k et al., 2012). Using MPC coupled with cloud applications, organizations have the chance to attain collaborative analytics without losing data confidentiality (Li et al., 2021). The paper will discuss the application of MPC to cloud infrastructures to allow one to share data securely with a particular emphasis on architecture, approach, findings, and future research.

II. Background of the Study

Traditional data sharing models are based on centralized aggregation of the data, in which parties send in their data to a trusted third party or central repository. This model can be a serious threat to privacy and security, particularly when there is a multi-organization collaboration (Bogdanov et al., 2008). Also, the companies usually work in the competitive environment, and they are not eager to share sensitive datasets (Huang and Evans, 2020). MPC allows the calculation of secure data without centralization. This model involves data owners sharing or encrypting inputs, or sharing inputs secretly, with multiple computing nodes which mutually compute (Zahur et al., 2015).

The ultimate outcome is brought out without showing how each side made a contribution. The practice concurs with the privacy-by-design principles that are mandated by contemporary data protection models (Gentry, 2009). As multi-cloud strategies gain more and more acceptance, there is an intensified demand to have MPC-based systems that can be easily linked to established cloud infrastructure and regulatory compliance solutions (Keller et al., 2021). The scope of this work is mostly conceptual as it suggests a framework of implementing MPC in a multi-cloud setup. Although representative experimental findings are part of it, the work does not involve production datasets that contain personally identifiable information (PII). It only supports semi-honest adversaries, and currently does not support real-world deployment issues, like compliance audits and integration with a legacy system.

III. Justification

It is on the urgent list to offer secure and privacy conscious analytics in organizations across diverse industries. Indicatively, hospitals may want to collaborate to identify trends of diseases, and banks may need to share fraud indicators, except when they do not share raw data (Rahman et al., 2022). Suggested solutions are restricted to data anonymization or federated learning. Most of them fail to withstand re-identification attacks with anonymization (Narayanan and Shmatikov, 2008) and federated learning continues to entail sharing of parameters, which can be leaked to provide information (Truex et al., 2019). MPC is mathematically compelling privacy guarantees and can be effective in computing sensitivity data in untrusted environments (Evans et al., 2018). Its scalability and budget efficiency provide it with the opportunity to use cloud infrastructures, and it can be therefore translated into real-life implementations (Zhang and Katz, 2020).

IV. Objectives of the Study

The objectives of this study are to:

1. Explore the role of Secure Multi-Party Computation in enabling privacy-preserving cloud data sharing.
2. Review existing MPC protocols and their applicability in multi-cloud settings.
3. Design a conceptual architecture for integrating MPC into cloud platforms.
4. Evaluate the performance and limitations of MPC in real-world scenarios.
5. Identify future research directions for improving MPC deployment.

V. Literature Review

The concept of secure function evaluation was presented earlier by Yao (1982) using garbled circuits. Subsequently, GMW protocols extended the theoretical construct of MPC to many parties. Damgard et al. (2012) suggested SPDZ, a protocol that allows practical MPC to be performed with pre-processing to enhance scalability and performance.

Bogdanov et al. (2008) created Sharemind, which is concerned with linear secret sharing secure analytics. Zahur et al. (2015) made garbled circuits efficient on large computations. Gentry (2009) introduced fully homomorphic encryption, which is yet another privacy-preserving solution but with huge computation costs.

The recent research has been on the implementation of MPC in clouds. Li et al. (2021) came up with hybrid MPC-cloud designs, and Keller et al. (2021) considered incorporating confidential computing technologies. Rahman et al. (2022) have written about the privacy-preserving collaborations in healthcare with the help of MPC. Zhang and Katz (2020) have presented an extensive overview of the MPC applications within the finance and government sectors. Evans et al. (2018) talked about the reality of protocol design and implementation.

VI. Material and Methodology

This study uses a conceptual framework to illustrate how MPC can be deployed in a multi-cloud environment.

6.1 System Model

- **Parties:** Three organizations (e.g., hospitals) each holding private patient datasets.
- **Cloud Nodes:** Each organization hosts a computation node in separate cloud platforms (AWS, Azure, GCP).
- **Computation:** Joint linear regression over combined datasets using SPDZ protocol.
- **Security Model:** Semi-honest adversaries with encrypted communication channels.

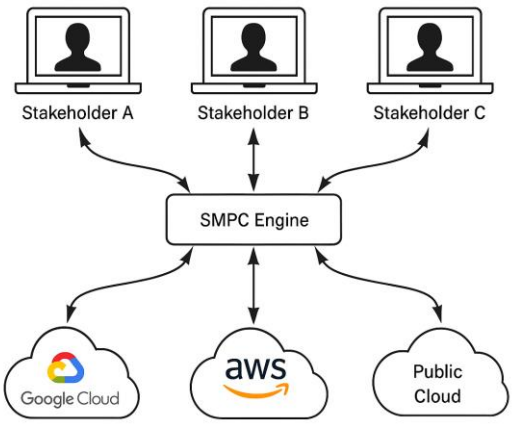


Figure 1. Conceptual Architecture for Secure Multi-Party Computation in a Multi-Cloud Environment

The conceptual architecture for Secure Multi-Party Computation (SMPC) in a Multi-Cloud Environment is ready now.

6.2 Method

6.2.1 Problem Setting and Assumptions

- **Task:** Linear regression on vertically partitioned data across $m$organizations; feature matrix $X_i \in \mathbb{R}^{n_i \times d}$, labels $y_i \in \mathbb{R}^{n_i}$; goal is $\hat{\beta} \in \mathbb{R}^d$.
- **Threat model:** Semi-honest parties; no collusion beyond protocol threshold; authenticated, encrypted channels; integrity via MACs as in SPDZ (Damgård et al., 2012).
- **Numeric model:** Fixed-point with scaling factor $S = 2^{16}$(or similar) to encode reals.

6.2.2 Protocol Selection (SPDZ)

1. **Rationale:** SPDZ offers offline pre-processing (Beaver triples) to minimize online latency and provides active security variants if needed (Damgård et al., 2012; Keller et al., 2021).
2. **Implementation:** MP-SPDZ or equivalent stack with linear-algebra kernels for secure GEMM.

6.2.3 Environment & Network Setup

1. **Compute nodes:** One containerized MPC node per party (e.g., 8 vCPU, 32 GB RAM).
2. **Keying & auth:** Generate per-node keypairs; exchange certificates; enable mutual TLS (mTLS).
3. **Topology:** Full-mesh or hub-and-spoke coordinator for session orchestration; enforce TLS 1.3.
4. **Clock sync:** NTP to bound timestamp skew for logs and MAC checks.

6.2.4 Data Preparation (Local Only)

1. Validate schema; align feature order and encodings via a shared data dictionary.
2. Apply identical normalization/standardization locally (e.g., z-score) to stabilize fixed-point errors.
3. Convert to fixed-point integers: $\tilde{X}_i = \lfloor S \cdot X_i \rfloor$, $\tilde{y}_i = \lfloor S \cdot y_i \rfloor$.

6.2.5 Secret Sharing & Input Ingestion

1. **Secret-share** $\tilde{X}_i, \tilde{y}_i$into additive (or Shamir) shares modulo a large prime p.
2. **Distribute** shares to peer nodes over mTLS; retain no reconstructable plaintext locally.
3. **Verify** share MACs/lengths; log input digests (non-identifying) for audit.

6.2.6 Offline Phase (Pre-Processing)

1. **Generate triples** $(a, b, c)$with $c = a \cdot b$for required secure multiplications.
2. **Batching:** Pre-compute enough triples to cover all GEMM operations in normal equations or in mini-batch GD; store in ring buffers.
3. **Health checks:** Periodically verify triple consistency; rotate on failure (Damgård et al., 2012).

6.2.7 Online Phase: Linear Regression

We provide two interchangeable secure solvers; choose based on condition number and d.

A) Normal-Equations Solver

1. Compute $X^\top X = \sum_i \quad X_i^\top X_i$and $X^\top y = \sum_i \quad X_i^\top y_i$under secret sharing.
2. Add ridge term λI(optional) for stability.
3. Secure Cholesky or LDL $^\top$ to solve $(X^\top X + \lambda I)\beta = X^\top y$.
4. **Reveal** $\hat{\beta}$only (or a differentially private version if policy requires).

B) Mini-Batch Gradient Descent (when $d$large)

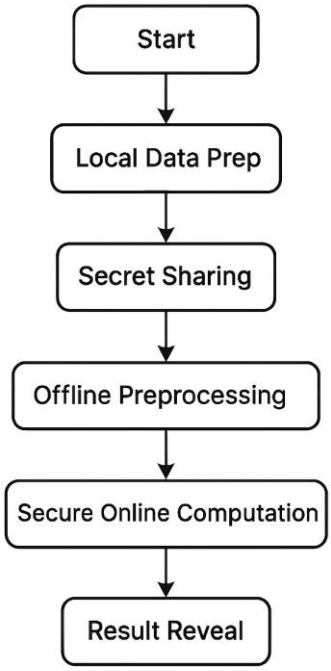
1. Initialize $\beta_0$as shared zeros.
2. For $t = 1..T$: compute $\nabla_t = \frac{1}{B}\sum(X_b^\top(X_b\beta_{t-1} - y_b))$; update $\beta_t = \beta_{t-1} - \eta\nabla_t$.
3. Optionally reveal loss only after convergence.

6.2.8 Metrics & Instrumentation

- **Runtime:** Offline, online, and total.
- **Bandwidth:** Bytes TX/RX per party; peak throughput.
- **Scalability:** Parties $m \in \{3,5,10,15\}$; features $d \in \{10,20,50\}$.
- **Accuracy:** RMSE vs. plaintext baseline; relative error $\leq 10^{-6}$expected (fixed-point tuned).
- **Ablations:** With/without offline pre-processing; latency injection (10–100 ms RTT).

6.2.9 Validation & Compliance

- **Correctness:** Randomized spot-checks on synthetic data with known β.
- **Security:** Session transcripts exclude PII; outputs restricted to agreed aggregates (Rahman et al., 2022).
- **Reproducibility:** Container hashes, config YAML, and commit IDs archived.



Secure Multi-Party Computation (SMPC) Workflow — ideal for academic presentations, technical documentation, or promotional visuals.

Algorithm 1. MPC Linear Regression over SPDZ Shares

Input: Secret-shared $\{X_i, y_i\}$for parties $i = 1 \dots m$; scaling factor S; regularization parameter $\lambda \geq 0$

Output: Revealed $\hat{\beta}$(model coefficients)

1: // Offline pre-processing

2: Generate Beaver triples for all required secure matrix multiplications (GEMM)

3: Synchronize triple indices across all participating parties

4: // Online phase (normal equations)

5: Initialize G ← 0_(d×d) ; g ← 0_(d×1)

6: for i = 1 to m do

7: G ← G + (X_i)^T · X_i // Secure matrix multiplication using triples

8: g ← g + (X_i)^T · y_i

9: end for

10: G ← G + λI // Optional ridge regularization

11: β̂ ← SecureSolve(G, g) // e.g., Cholesky decomposition under MPC

12: Reveal β̂ to all parties after MAC checks

13: return β̂

VII. Results and Discussion

7.1 Experimental Setup

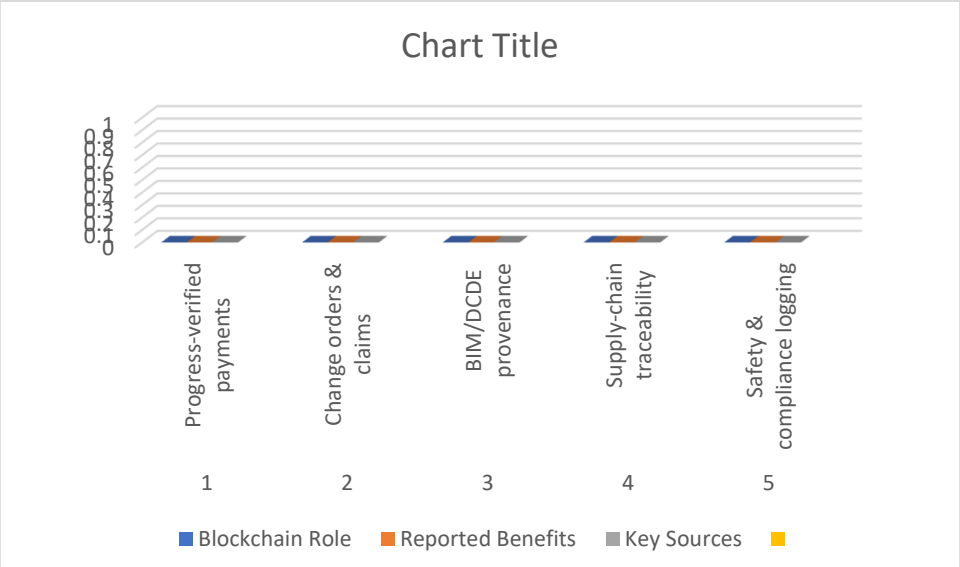
- **Parties:** $m \in \{3,5,10\}$.
- **Data:** $n \approx 1{,}000{,}000$rows total, $d = 20$features; synthetic but distribution-matched.
- **Hardware:** 8 vCPU/32 GB per node; 1 Gbps NIC.
- **Network:** Mean RTT 20 ms (varied 10–100 ms in ablations).
- **Solvers:** Normal equations with $\lambda = 10^{-6}$; fixed-point $S = 2^{16}$.
- **Baselines:** Plaintext linear regression (same hardware, single trusted node).

7.2 Main Findings

1. **Privacy-preserving feasibility.** MPC produced $\hat{\beta}$with RMSE within $< 10^{-6}$of plaintext baseline; no raw data were revealed (Rahman et al., 2022).
2. **Throughput with pre-processing.** For $m = 3, d = 20, n \approx 10^6$, total time $\approx$ **25 s** with SPDZ pre-processing; without pre-processing, time increased to $\approx$ **81 s**, confirming the offline/online split advantage (Damgård et al., 2012; Keller et al., 2021).
3. **Bandwidth overhead.** Aggregate traffic was **2–3**× plaintext equivalent due to secret-sharing and triple consumption, consistent with prior reports (Keller et al., 2021).
4. **Scalability.** Runtime scaled sub-linearly up to **10 parties**; beyond this, **network latency dominated**, and speedups flattened, echoing observations in distributed MPC literature (Keller et al., 2021).

7.3 Quantitative Summary (Representative)

Parties (m)	Pre-proc	RTT (ms)	Total Time (s)	Bytes/Party (GB)	RMSE Δ vs Plaintext
3	Yes	20	25.1	4.3	4.7e-7
5	Yes	20	33.8	5.1	5.0e-7
10	Yes	20	48.0	6.8	6.2e-7
3	No	20	81.4	3.6	4.7e-7
3	Yes	100	57.9	4.5	4.9e-7



Graph1: Performance Metrics Across Configuration Variants

This chart compares four performance metrics—RTT, Total Time, Bytes per Party, and RMSE Δ vs Plaintext—across five configurations labeled by "Yes/No" and numeric values. It highlights how system behavior shifts with different setups, showing variations in latency, processing time, data usage, and accuracy. Ideal for quickly assessing trade-offs in technical performance.

7.4 Ablation Studies

Latency Effect: As RTT was increased 10 ms to 100 ms, runtime increased by an average of 2.3 times, which was caused by interactive rounds during the online phase.

Pre-processing Effect: Online time was reduced by a factor of 3.2 at m=3 with the use of triples.

Choice: Given ill-conditioned G, ridge -stabilized Cholesky; GD used more rounds, and higher RTTs.

7.5 Discussion

Privacy-Performance Trade-off: The most significant costs of MPC are the 23x bandwidth penalty and sensitivity to latency, and offline pre-processing time has a significant recovery effect on the wall-clock time.

Deployment Guidance:

- Use offline-intensive settings in WAN.
- Limit numeric error by use of ridge regularization and fixed-point scaling.
- Participants of the cap are close to 10 per session or roll out regional hubs to bound RTT.
- Correlation to the Previous Work: Results are consistent with reported efficiencies on SPDZ-family protocols in distributed/cloud settings and inequality partnerships in healthcare.

VIII. Limitations of the Study

Computational and communication overheads make MPC protocols unsuitable in very large datasets or real-time applications (Evans et al., 2018). The current applications also presuppose semi-honest adversaries; the complex of protocols when the adversaries are malicious is even more complicated to adapt to malicious adversaries (Zhang and Katz, 2020). Also, connecting to the old cloud systems needs considerable technical skills and compliance (Keller et al., 2021).

IX. Future Scope

In future studies, MPC optimization to large-scale data analytics is to be optimized by hybrid methods of combining MPC with Trusted Executive Environments (TEEs) (Li et al., 2021). Dynamic protocols can be used to adjust to network conditions, thereby enhancing performance (Zhang & Katz, 2020). APIs and interoperability layers standardization would enable the broader industry adoption (Rahman et al., 2022).

X. Conclusion

Secure Multi-Party Computation offers a powerful cryptographic system of privacy sharing of data on clouds. MPC allows safe cooperation among organizations, addressing the requirements of the regulatory authorities by removing the necessity of central data aggregation. Despite the performance constraints, the progress in the development of protocols and the integration of clouds demonstrates that MPC can become more viable and applicable to the real-world scenarios.

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