

# Novelty Assessment Report

**Paper:** Exponential-Wrapped Mechanisms: Differential Privacy on Hadamard Manifolds Made Practical

**PDF URL:** <https://openreview.net/pdf?id=ulCVfMOo30>

**Venue:** ICLR 2026 Conference Submission

**Year:** 2026

**Report Generated:** 2026-01-01

## Abstract

We propose a general and computationally efficient framework for achieving differential privacy (DP) on Hadamard manifolds, which are complete and simply connected Riemannian manifolds with non-positive curvature. Leveraging the Cartan-Hadamard theorem, we introduce Exponential-Wrapped Laplace and Gaussian mechanisms that achieve  $\epsilon$ -DP,  $(\epsilon, \delta)$ -DP, Gaussian DP (GDP), and Rényi DP (RDP) without relying on computationally intensive MCMC sampling. Our methods operate entirely within the intrinsic geometry of the manifold, ensuring both theoretical soundness and practical scalability. We derive utility bounds for privatized Fréchet means and demonstrate superior utility and runtime performances on both synthetic data and real-world data in the space of symmetric positive definite matrices (SPDM) equipped with three different metrics. To our knowledge, this work constitutes the first unified extension of multiple DP notions to general Hadamard manifolds with practical and scalable implementations.

### Disclaimer

This report is **AI-GENERATED** using Large Language Models and WisPaper (a scholar search engine). It analyzes academic papers' tasks and contributions against retrieved prior work. While this system identifies **POTENTIAL** overlaps and novel directions, **ITS COVERAGE IS NOT EXHAUSTIVE AND JUDGMENTS ARE APPROXIMATE**. These results are intended to assist human reviewers and **SHOULD NOT** be relied upon as a definitive verdict on novelty.

Note that some papers exist in multiple, slightly different versions (e.g., with different titles or URLs). The system may retrieve several versions of the same underlying work. The current automated pipeline does not reliably align or distinguish these cases, so human reviewers will need to disambiguate them manually.

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## Core Task Landscape

This paper addresses: **Differential Privacy on Hadamard Manifolds**

A total of **23 papers** were analyzed and organized into a taxonomy with **15 categories**.

### Taxonomy Overview

The research landscape has been organized into the following main categories:

- **Differential Privacy Mechanisms on Non-Euclidean Geometries**
- **Local Differential Privacy with Hadamard-Based Encoding**
- **Privacy-Preserving Graph and Hierarchical Data Embeddings**
- **Federated Learning and Privacy-Preserving Distributed Systems**
- **Application-Specific Privacy and Hyperbolic Geometry**
- **Auxiliary Topics in Privacy and Hyperbolic Geometry**

### Complete Taxonomy Tree

- Differential Privacy on Hadamard Manifolds Survey Taxonomy
- Differential Privacy Mechanisms on Non-Euclidean Geometries
  - Exponential-Wrapped Mechanisms for Hadamard Manifolds ★ (2 papers)
  - [0] Exponential-Wrapped Mechanisms: Differential Privacy on Hadamard Manifolds Made Practical (Anon et al., 2026) [View paper](#)
  - [17] Exponential-Wrapped Mechanisms for Differential Privacy on Hadamard Manifolds (Y Jiang, n.d.) [View paper](#)
  - Density-Aware and Conformal Transformation Mechanisms (1 papers)
  - [8] Density-Aware Noise Mechanisms for Differential Privacy on Riemannian Manifolds via Conformal Transformation (He Peilin, 2025) [View paper](#)
- Local Differential Privacy with Hadamard-Based Encoding
  - Frequency Oracles and Count Estimation (2 papers)
  - [1] Sarve: synthetic data and local differential privacy for private frequency estimation (Gatha Varma, 2022) [View paper](#)
  - [2] Practical Differential Privacy for Location Data Aggregation using a Hadamard Matrix (Patinya Sangiamchit, 2019) [View paper](#)
  - Frequent Itemset Mining (3 papers)
  - [6] Improving the Effect of Frequent Itemset Mining with Hadamard Response under Local Differential Privacy (Xuebin Ma, 2021) [View paper](#)
  - [10] Frequent Itemset Mining with Hadamard Response Under Local Differential Privacy (Haijiang Liu, 2020) [View paper](#)
  - [21] Hadamard Encoding Based Frequent Itemset Mining under Local Differential Privacy (Danting Zhao, 2023) [View paper](#)
- Privacy-Preserving Graph and Hierarchical Data Embeddings
  - Hierarchy-Aware Graph Embedding with Poincaré Differential Privacy (2 papers)
  - [4] Poincaré Differential Privacy for Hierarchy-Aware Graph Embedding | VIDEO (Fu, 2024) [View paper](#)
  - [7] Poincaré Differential Privacy for Hierarchy-Aware Graph Embedding (Yuecen Wei, 2024) [View paper](#)
  - Hyperbolic Embeddings for Text Privacy (1 papers)
  - [9] Leveraging hierarchical representations for preserving privacy and utility in text (Feyisetan, 2019) [View paper](#)
- Federated Learning and Privacy-Preserving Distributed Systems
  - Client-Specific Hyperbolic Federated Learning (1 papers)
  - [3] Client-specific hyperbolic federated learning (J Liu, 2024) [View paper](#)
  - Federated Generative Models for Synthetic Data (2 papers)
  - [19]  $\epsilon$  in a Federated Learning Framework for Generating Realistic, Non-Sensitive Data for Modatta: A Case Study of Recommendation Systems in Hyperbolic Space (Morais, 2023) [View paper](#)
  - [20] Training Tabular Generative Adversarial Networks in a Federated Learning Framework for Generating Realistic, Non-Sensitive Data for Modatta: A Case Study of  $\epsilon$  (Morais, 2023) [View paper](#)

- Application-Specific Privacy and Hyperbolic Geometry
  - Hyperbolic Routing and Cache Privacy (1 papers)
  - [5] Hyperbolic routing for cache privacy in information centric networking (Sean Cannan, 2023) [View paper](#)
  - Health Knowledge Graphs and Hyperbolic Embeddings (1 papers)
  - [13] Position: Hyperbolic Embeddings Are Essential for Health Knowledge Graphs in LLMs and Vector Databases (OU DENG, 2025) [View paper](#)
  - Population Genetics and Hyperbolic Geometry (1 papers)
  - [11] Hyperbolic geometry-based deep learning methods to produce population trees from genotype data (Aman Patel, 2022) [View paper](#)
- Auxiliary Topics in Privacy and Hyperbolic Geometry
  - Flexible Local Differential Privacy Strategies (1 papers)
  - [12] Fldp: Flexible Strategy For Local Differential Privacy (Dan Zhao, 2022) [View paper](#)
  - Performance Benchmarking and Randomness Efficiency (2 papers)
  - [15] Randomness efficient fast-johnson-lindenstrauss transform with applications in differential privacy and compressed sensing (Upadhyay, 2014) [View paper](#)
  - [16] Performance Benchmarking of Local Differential Privacy for Mobile Devices (Lucas Gallindo, 2022) [View paper](#)
  - Hyperbolic Network Generation and Analytics (3 papers)
  - [14] SENSE: sing Similarity eing Structure (N Malik, 2025) [View paper](#)
  - [22] Fast generation of dynamic complex networks with underlying hyperbolic geometry (Staudt, 2014) [View paper](#)
  - [23] E3. Initial report on ML-based analytics and privacy aspects (PDEU DE, n.d.) [View paper](#)
  - Hadamard Matrices in Imaging (1 papers)
  - [18] Imaging through scattering media using differential intensity transmission matrices with different Hadamard orderings. (Juan Liu, 2022) [View paper](#)

## Narrative

Core task: Differential privacy on Hadamard manifolds. This field addresses the challenge of protecting sensitive data that naturally resides in non-Euclidean spaces, particularly hyperbolic geometries where hierarchical and graph-structured information is often embedded. The taxonomy reveals several main branches: one focuses on designing differential privacy mechanisms tailored to non-Euclidean geometries, including exponential-wrapped approaches for Hadamard manifolds; another explores local differential privacy with Hadamard-based encoding schemes for decentralized settings; a third examines privacy-preserving embeddings of graphs and hierarchical data into hyperbolic spaces; and additional branches cover federated learning frameworks that leverage hyperbolic geometry, application-specific privacy solutions (such as recommendation systems and health data), and auxiliary topics bridging privacy with hyperbolic methods. Representative works like Hadamard Location Aggregation[2] and Hadamard Itemset Mining[6] illustrate how these geometric tools enable privacy guarantees while preserving the structural properties of complex data.

A particularly active line of work centers on exponential-wrapped mechanisms that adapt classical differential privacy noise to the curvature of Hadamard manifolds, balancing utility and privacy in non-flat spaces. Meanwhile, federated learning approaches such as Hyperbolic Federated[3] and application-driven studies like Hyperbolic Cache Privacy[5] explore how hyperbolic embeddings can reduce communication costs and improve model expressiveness under privacy constraints. The original paper, Exponential Wrapped Hadamard[0], sits squarely within the branch of exponential-wrapped mechanisms for Hadamard manifolds, contributing foundational theory for noise injection on curved spaces. Compared to nearby works like Density Aware Manifolds[8], which emphasizes adaptive noise calibration based on local geometry, Exponential Wrapped Hadamard[0] focuses on establishing rigorous privacy guarantees through exponential wrapping techniques. This positions it as a core theoretical contribution that underpins many application-specific extensions across hierarchical data, federated systems, and graph embeddings.

## Related Works in Same Category

The following **1 sibling papers** share the same taxonomy leaf node with the original paper:

### 1. Exponential-Wrapped Mechanisms for Differential Privacy on Hadamard Manifolds

**Authors:** Y Jiang, X Chang, L Ding, L Kong, B Jiang | **URL:** [View paper](#)

#### Abstract

â€œ the Differential Privacy (DP) framework to Hadamard manifolds, the class of complete and simply connected Riemannian manifolds with â€œ Inspired by the Cartanâ€œHadamard theorem, we â€œ

#### â€œ Similarity Notice

These papers appear to be different versions of the same work. Both have nearly identical titles (differing only slightly in word order), identical abstracts describing the same exponential-wrapped mechanisms for differential privacy on Hadamard manifolds, and the same technical content including the Cartan-Hadamard theorem approach and avoidance of MCMC sampling. The original is submitted to ICLR 2026 while the candidate is submitted to ICLR 2025, suggesting these are sequential submissions of the same research.

## Contributions Analysis

**Overall novelty summary.** The paper proposes a unified framework for differential privacy on Hadamard manifolds, introducing Exponential-Wrapped Laplace and Gaussian mechanisms that achieve multiple DP notions ( $\epsilon$ -DP,  $(\epsilon, \delta)$ -DP, GDP, RDP) without MCMC sampling. It resides in the 'Exponential-Wrapped Mechanisms for Hadamard Manifolds' leaf, which contains only two papers total. This is a notably sparse research direction within the broader taxonomy of 23 papers across differential privacy on non-Euclidean geometries, suggesting the work addresses a relatively underexplored niche in the field.

The taxonomy tree reveals that the paper's immediate sibling category, 'Density-Aware and Conformal Transformation Mechanisms,' contains only one paper focusing on local density calibration. Neighboring branches include local differential privacy with Hadamard-based encoding (5 papers across frequency oracles and itemset mining) and privacy-preserving graph embeddings (3 papers on hierarchical structures). The scope notes clarify that exponential-wrapped approaches differ fundamentally from density-aware methods by operating through distributional wrapping rather than adaptive noise calibration, positioning this work as methodologically distinct from its closest relatives.

Among 30 candidates examined, the contribution-level analysis shows mixed novelty signals. The 'Unified extension of multiple DP notions' examined 10 candidates with 1 appearing to provide overlapping prior work, suggesting some precedent exists for multi-notion DP frameworks on manifolds. However, the 'Exponential-Wrapped mechanisms avoiding MCMC' and 'General framework' contributions each examined 10 candidates with zero refutable matches, indicating these specific technical approaches appear more novel within the limited search scope. The statistics reflect a focused but not exhaustive literature review.

Based on the top-30 semantic matches examined, the work appears to occupy a sparsely populated research direction with limited direct competition. The taxonomy structure confirms that exponential-wrapped mechanisms for Hadamard manifolds constitute a small but

distinct methodological branch. While one contribution shows some prior overlap, the core technical mechanisms and general framework appear less anticipated by the examined literature, though the limited search scope precludes definitive claims about absolute novelty across the entire field.

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This paper presents **3 main contributions**, each analyzed against relevant prior work:

### Contribution 1: Unified extension of multiple DP notions to general Hadamard manifolds

**Description:** The authors present the first framework that extends multiple differential privacy notions—including  $(\epsilon, \delta)$ -DP, Gaussian DP, and Rényi DP—to general Hadamard manifolds. This represents the first RDP mechanism that works beyond Euclidean spaces.

This contribution was assessed against **10 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

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#### 1. FedGCN: Federated Learning-Based Graph Convolutional Networks for Non-Euclidean Spatial Data

URL: [View paper](#)

##### Brief Assessment

Federated Spatial GCN[33] focuses on federated learning for graph-structured data using graph convolutional networks. It does not address differential privacy mechanisms on Riemannian manifolds or Hadamard spaces, which is the core contribution of the original paper.

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#### 2. Conformal-DP: Differential Privacy on Riemannian Manifolds via Conformal Transformation

URL: [View paper](#)

##### Brief Assessment

Conformal Transformation Privacy[32] focuses on density-aware mechanisms using conformal transformations for complete Riemannian manifolds, not on extending multiple DP notions ( $\epsilon$ -DP, GDP, RDP) to Hadamard manifolds as the original paper does.

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#### 3. Federated Learning on Riemannian Manifolds with Differential Privacy

URL: [View paper](#)

##### Brief Assessment

Federated Riemannian Privacy[28] focuses on federated learning with differential privacy on Riemannian manifolds, not on extending multiple DP notions ( $\epsilon, \delta$ -DP, GDP, RDP) to Hadamard manifolds as the original paper does.

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#### 4. Almost sure convergence of differentially positive systems on a globally orderable Riemannian manifold

URL: [View paper](#)

##### Brief Assessment

Riemannian Manifold Convergence[35] focuses on differentially positive systems and convergence of orbits on Riemannian manifolds, not differential privacy mechanisms. The paper addresses dynamical systems theory rather than privacy-preserving data analysis.

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#### 5. Poincaré Differential Privacy for Hierarchy-Aware Graph Embedding

URL: [View paper](#)

##### Brief Assessment

Poincaré Hierarchy Embedding[7] focuses on differential privacy for hierarchical graph embeddings in hyperbolic space using the Poincaré ball model, not on extending multiple DP notions ( $\epsilon$ -DP,  $(\epsilon, \delta)$ -DP, GDP, RDP) to general Hadamard manifolds as the original paper does.

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#### 6. Differentially private Riemannian optimization

URL: [View paper](#)

##### Brief Assessment

Riemannian Optimization Privacy[24] focuses on gradient perturbation for empirical risk minimization on Riemannian manifolds, not on extending multiple DP notions ( $\epsilon, \delta$ -DP, GDP, RDP) to general Hadamard manifolds via exponential-wrapped mechanisms.

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#### 7. Differential privacy over riemannian manifolds

URL: [View paper](#)

##### Prior Art Analysis

Riemannian Manifolds Privacy[31] demonstrates that differential privacy mechanisms on Riemannian manifolds were already established prior to the original paper's claims. The candidate paper presents the Laplace mechanism for  $\epsilon$ -DP on general Riemannian manifolds and extends the framework to include  $(\epsilon, \delta)$ -DP through the Laplace distribution. While the candidate does not explicitly present Gaussian DP or Rényi DP mechanisms, it establishes the foundational framework for achieving differential privacy on Riemannian manifolds beyond Euclidean spaces, which directly challenges the novelty claim that the original paper is 'the first' to extend multiple DP notions to general Hadamard manifolds.

##### Evidence

Evidence 1 - **Rationale:** The candidate paper explicitly states it presents an extension of differential privacy mechanisms to Riemannian manifolds, which are more general than Hadamard manifolds. This establishes prior work on DP mechanisms beyond Euclidean spaces. - **Original:** we introduce the first mechanisms to extend  $(\epsilon, \delta)$ -dp, gaussian dp (gdp), and Rényi dp (rdp) to general hadamard manifolds. notably, this includes the first rdp mechanism applicable beyond euclidean spaces. - **Candidate:** in this work we consider the problem of releasing a differentially private statistical summary that resides on a riemannian manifold. we present an extension of the laplace or k-norm mechanism that utilizes intrinsic distances and volumes on the manifold.

Evidence 2 - **Rationale:** The original paper acknowledges that Reimherr et al. (2021) - which is the candidate paper - first extended DP to general Riemannian manifolds. This theorem shows the candidate established  $\epsilon$ -DP on manifolds, refuting the claim of being 'first' to extend DP notions to Hadamard manifolds. - **Original:** the differential privacy framework was first extended to general riemannian manifolds by reimherr et al. (2021), who introduced the riemannian laplace mechanism to achieve  $\epsilon$ -dp. - **Candidate:** theorem 1. let  $f : \mathcal{X} \rightarrow \mathcal{M}$  be a summary with global sensitivity  $\Delta$ . then the laplace mechanism with footpoint  $f(d)$  and rate  $\sigma = 2\Delta/\epsilon$  satisfies  $\epsilon$ -differential privacy. if the normalizing constant,  $c_{\eta, \sigma}$  does not depend on the footpoint,  $\eta$ , then one can take  $\sigma = \Delta/\epsilon$ .

Evidence 3 - **Rationale:** The candidate paper defines  $\epsilon$ -DP on general Riemannian manifolds (which include Hadamard manifolds as a special case), establishing the foundational framework that the original paper claims to be first in providing. - **Original:** to our knowledge, this work constitutes the first unified extension of multiple dp notions to general hadamard manifolds with practical and scalable implementations. - **Candidate:** denote the (random) sanitized version of  $f(d)$  as  $\tilde{f}(d)$ . we can then define what it means for  $\tilde{f}(d)$  to satisfy  $\epsilon$ -dp. definition 1. a family of randomized summaries,  $\{\tilde{f}(d) \in \mathcal{M} : d \in \mathcal{X}\}$ , is said to be differentially private with  $\epsilon > 0$ , if for any adjacent database  $d'$ , denoted as  $d \sim d'$ , differing in only ...

## 8. Metric differential privacy on the special orthogonal group SO (3)

URL: [View paper](#)

### Brief Assessment

Special Orthogonal Privacy[30] focuses specifically on SO(3) rotations using metric differential privacy with Laplace and Bingham mechanisms, not on general Hadamard manifolds or multiple DP notions ( $\epsilon, \delta$ )-DP, Gaussian DP, and Rényi DP.

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## 9. Algorithmic aspects of the log-Laplace transform and a non-Euclidean proximal sampler

URL: [View paper](#)

### Brief Assessment

Log Laplace Sampler[34] focuses on sampling algorithms using log-Laplace transforms for non-Euclidean geometries, not on extending differential privacy notions to Hadamard manifolds. The paper addresses sampling complexity rather than privacy mechanisms on manifolds.

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## 10. Gaussian Differential Privacy on Riemannian Manifolds

URL: [View paper](#)

### Brief Assessment

Gaussian Riemannian Privacy[29] focuses specifically on extending Gaussian DP to general Riemannian manifolds with bounded Ricci curvature, not on providing a unified framework for multiple DP notions ( $\epsilon$ -DP,  $(\epsilon, \delta)$ -DP, GDP, RDP) on Hadamard manifolds as claimed in the original paper.

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## Contribution 2: Exponential-Wrapped mechanisms avoiding MCMC sampling

**Description:** The authors develop Exponential-Wrapped Laplace and Gaussian mechanisms that achieve differential privacy without relying on computationally expensive MCMC sampling. Instead, these mechanisms use efficient sampling from tangent space distributions combined with the exponential map.

This contribution was assessed against **10 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

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### 1. Bayesian pseudo posterior mechanism under asymptotic differential privacy

URL: [View paper](#)

#### Brief Assessment

Bayesian Pseudo Posterior[39] focuses on synthetic data generation using pseudo posterior mechanisms with risk-based weighting for differential privacy, not on exponential map sampling techniques for Hadamard manifolds. The candidate employs MCMC sampling methods rather than avoiding them through exponential wrapping.

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### 2. Efficient mean estimation with pure differential privacy via a sum-of-squares exponential mechanism

URL: [View paper](#)

#### Brief Assessment

Sum of Squares Exponential[43] focuses on mean estimation using sum-of-squares methods to convert exponential mechanisms into polynomial-time algorithms, not on exponential-wrapped distributions via exponential maps on manifolds. The technical approaches are fundamentally different.

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### 3. Verifiable Exponential Mechanism for Median Estimation

URL: [View paper](#)

#### Brief Assessment

Verifiable Median Estimation[44] focuses on verifiable implementations using zk-SNARKs for the exponential mechanism, not on developing exponential-wrapped distributions that avoid MCMC through tangent space sampling and exponential maps on Hadamard manifolds.

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### 4. A Joint Exponential Mechanism For Differentially Private Top-

URL: [View paper](#)

#### Brief Assessment

Joint Exponential Top[37] focuses on top-k selection using exponential mechanism sampling from sequences, not on manifold-valued data with exponential map operations. The candidate's sampling involves Gumbel/exponential noise for count-based selection, fundamentally different from the original's tangent space sampling with exponential maps on Hadamard manifolds.

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### 5. Bayesian pseudo posterior mechanism under differential privacy

URL: [View paper](#)

#### Brief Assessment

Bayesian Pseudo Posterior[40] focuses on Bayesian inference with differential privacy using pseudo posterior mechanisms and exponential mechanisms for parameter estimation, not on exponential-wrapped distributions on Hadamard manifolds or avoiding MCMC through exponential map sampling as in the original paper.

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### 6. Implementing the exponential mechanism with base-2 differential privacy

URL: [View paper](#)

#### Brief Assessment

Base Two Exponential[36] focuses on implementing the exponential mechanism using base-2 arithmetic for numerical precision in floating-point systems, not on developing exponential-wrapped distributions on manifolds or avoiding MCMC through exponential map sampling techniques.

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### 7. InvisibleInk: High-Utility and Low-Cost Text Generation with Differential Privacy

URL: [View paper](#)

#### Brief Assessment

InvisibleInk Text[41] focuses on differential privacy for LLM-based text generation using the exponential mechanism over token distributions, not on general Hadamard manifolds or exponential-wrapped distributions with exponential maps as proposed in the original paper.

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## 8. Differential privacy without sensitivity

URL: [View paper](#)

### Brief Assessment

Privacy Without Sensitivity[42] focuses on differential privacy for Gibbs posteriors using Lipschitz and convexity properties, not on exponential-wrapped mechanisms or exponential map sampling on Hadamard manifolds. The candidate addresses unbounded sensitivity through different mathematical techniques (log-Sobolev inequalities) rather than the exponential map approach.

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## 9. FL2DP: Privacy-Preserving Federated Learning Via Differential Privacy for Artificial IoT

URL: [View paper](#)

### Brief Assessment

Federated IoT Privacy[45] uses the exponential mechanism for gradient perturbation in federated learning, not for sampling from manifold distributions. The original paper's exponential-wrapped mechanisms operate on Hadamard manifolds via the exponential map, while this candidate applies the exponential mechanism to gradient noise in Euclidean space for federated learning contexts.

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## 10. Utility-aware exponential mechanism for personalized differential privacy

URL: [View paper](#)

### Brief Assessment

Utility Aware Exponential[38] focuses on personalized differential privacy using exponential mechanisms for discrete query outputs in standard privacy settings, not on Riemannian manifolds or avoiding MCMC through exponential map sampling techniques.

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## Contribution 3: General framework for differential privacy on Hadamard manifolds

**Description:** The authors propose a general and computationally efficient framework that achieves differential privacy on Hadamard manifolds by leveraging the Cartan-Hadamard theorem and operating entirely within the intrinsic geometry of the manifold.

This contribution was assessed against **10 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

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## 1. Frequent Itemset Mining with Hadamard Response Under Local Differential Privacy

URL: [View paper](#)

### Brief Assessment

Hadamard Itemset Mining[10] focuses on local differential privacy for frequent itemset mining using Hadamard response algorithms, not on developing differential privacy frameworks for Hadamard manifolds using intrinsic geometry.

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## 2. Randomness efficient fast-johnson-lindenstrauss transform with applications in differential privacy and compressed sensing

URL: [View paper](#)

### Brief Assessment

Johnson Lindenstrauss Transform[15] focuses on randomness-efficient fast transformations for compressed sensing applications. The candidate's brief mentions of differential privacy appear in the context of showing that certain JL transforms fail to preserve differential privacy, rather than proposing a framework for achieving it on Hadamard manifolds.

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## 3. Federated Learning on Riemannian Manifolds with Differential Privacy

URL: [View paper](#)

### Brief Assessment

Federated Riemannian Privacy[28] proposes a federated learning framework on Riemannian manifolds with privacy guarantees, which is a different application domain than the original paper's general DP framework using exponential-wrapped mechanisms and intrinsic geometry.

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## 4. Improved differentially private Riemannian optimization: Fast sampling and variance reduction

URL: [View paper](#)

### Brief Assessment

Fast Riemannian Sampling[25] focuses on efficient sampling procedures and variance reduction for differentially private Riemannian optimization, not on establishing a general DP framework for Hadamard manifolds using intrinsic geometry and the Cartan-Hadamard theorem.

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## 5. Density-Aware Noise Mechanisms for Differential Privacy on Riemannian Manifolds via Conformal Transformation

URL: [View paper](#)

### Brief Assessment

Density Aware Manifolds[8] focuses on density-aware mechanisms using conformal transformations for complete Riemannian manifolds, addressing non-uniform data distributions. The original paper proposes exponential-wrapped mechanisms specifically for Hadamard manifolds without density adaptation, representing a different technical approach.

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## 6. Improving the Effect of Frequent Itemset Mining with Hadamard Response under Local Differential Privacy

URL: [View paper](#)

### Brief Assessment

Hadamard Itemset Mining[6] focuses on frequent itemset mining using Hadamard response under local differential privacy, not on developing differential privacy frameworks for Hadamard manifolds using intrinsic geometry. The term 'Hadamard' refers to different concepts in each paper.

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## 7. Supplemental to Differential Privacy Over Riemannian Manifolds

URL: [View paper](#)

### Brief Assessment

Riemannian Manifolds Supplement[27] is a supplemental document to the original paper itself, not a prior work. It contains additional proofs and experimental details supporting the same research, so it cannot refute the novelty of the original contribution.

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## 8. Fldp: Flexible Strategy For Local Differential Privacy

URL: [View paper](#)

## Brief Assessment

Flexible Local Privacy[12] focuses on local differential privacy (LDP) for frequency oracles with domain splitting, not on Hadamard manifolds or Riemannian geometry. The candidate addresses a fundamentally different problem space (local privacy in data collection) compared to the original's framework for differential privacy on Hadamard manifolds using intrinsic geometry.

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## 9. Differentially private Riemannian optimization

URL: [View paper](#)

### Brief Assessment

Riemannian Optimization Privacy[24] proposes tangent space Gaussian mechanisms for gradient perturbation in optimization, not a general framework operating entirely within intrinsic geometry via exponential-wrapped distributions and the Cartan-Hadamard theorem.

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## 10. Shape And Structure Preserving Differential Privacy

URL: [View paper](#)

### Brief Assessment

Shape Structure Privacy[26] focuses on positively curved manifolds (Kendall's shape space, spheres) using gradient-based mechanisms, while the original paper addresses Hadamard manifolds (non-positive curvature) with exponential-wrapped distributions. These are fundamentally different geometric settings with distinct technical approaches.

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## Appendix: Text Similarity Detection

Textual similarity detection checked 29 papers and found 3 similarity segment(s) across 1 paper(s).

The following **1 paper(s)** were detected to have high textual similarity with the original paper. These may represent different versions of the same work, duplicate submissions, or papers with substantial textual overlap. Readers are advised to verify these relationships independently.

### 1. Exponential-Wrapped Mechanisms for Differential Privacy on Hadamard Manifolds

**Detected in:** Core Task (sibling)

△ **Note:** This paper shows substantial textual similarity with the original paper. It may be a different version, a duplicate submission, or contain significant overlapping content. Please review carefully to determine the nature of the relationship.

## References

- [0] Exponential-Wrapped Mechanisms: Differential Privacy on Hadamard Manifolds Made Practical [View paper](#)
- [1] Sarve: synthetic data and local differential privacy for private frequency estimation [View paper](#)
- [2] Practical Differential Privacy for Location Data Aggregation using a Hadamard Matrix [View paper](#)
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- [30] Metric differential privacy on the special orthogonal group SO (3) [View paper](#)
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- [33] FedGCN: Federated Learning-Based Graph Convolutional Networks for Non-Euclidean Spatial Data [View paper](#)
- [34] Algorithmic aspects of the log-Laplace transform and a non-Euclidean proximal sampler [View paper](#)
- [35] Almost sure convergence of differentially positive systems on a globally orderable Riemannian manifold [View paper](#)
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