

Privacy-Preserving Identification via Layered Sparse Code Design: Distributed Servers and Multiple Access Authorization

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Outline

Introduction

Proposed Framework

- Fundamentals

- Overview

- Sparse Data Representation

- Privacy-Preserving Identification

Results

Introduction

Privacy-preserving content identification

- Biometrics
- Physical object recognition and security
- Medical/clinical applications
- Privacy-sensitive multimedia records

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Recent Trends

Big Data & Distributed Applications

Services on outsourced
cloud-based systems

Introduction

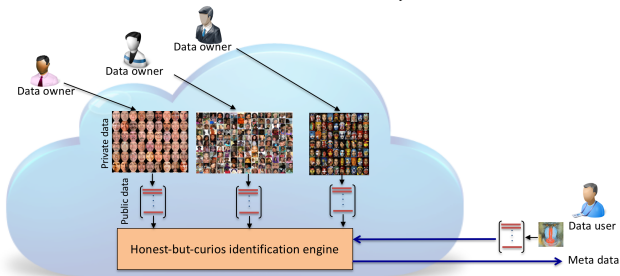
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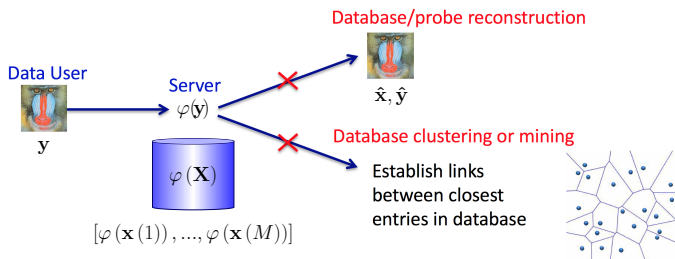
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Introduction

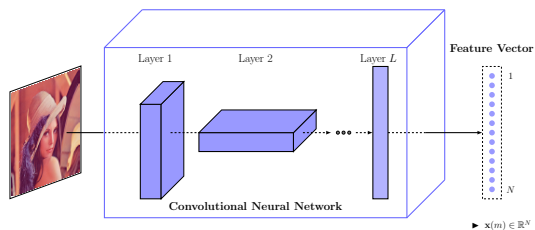
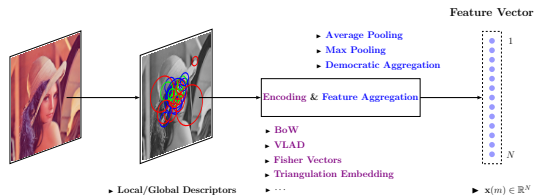
Problem Formulation

Goal of privacy protection in outsourced services



Introduction

How do we receive a feature vector?



Introduction

state-of-the-art

■ Cryptographic Methods - Homomorphic Encryption

- **Main Idea:** Similarity search in the encrypted domain
 - Brute force identification \implies huge complexity

■ Robust Hashing - a single hash from the whole content / local descriptors / last layer of CNN

- **Main Idea:** $x \longrightarrow (011011100110)$ and believed non-invertability
 - Loss in performance due to binarization
 - Unauthorized database clustering

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■ Group Testing / Memory Vectors

- **Main Idea:** Group testing by measuring the proximity to the group representative
 - Group representatives (memory vectors) should be stored in memory

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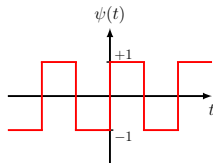
- **Main Idea:** Group testing by measuring the proximity to the group representative
 - Group representatives (memory vectors) should be stored in memory

Introduction

state-of-the-art

■ Universal Quantization

- **Main Idea:** projection with the dimension reduction and periodic quantization
 - Binary quantization: in the region of low projected magnitudes - high P_b
 - Ambiguization due to periodization of quantizer - no possibility to recover data even for the authorized users
 - Server still can cluster data - privacy leakages
 - Information preservation in general - no link to $R(d)$ and recovery is demonstrated so far



$$\mathbf{a} = \psi(\mathbf{W}\mathbf{x})$$

$$t_i = [\mathbf{W}\mathbf{x}]_i$$

Introduction

state-of-the-art

■ Sparse Approximation with Ambiguization

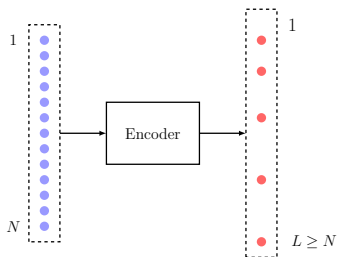
- **Main Idea:** obtain an information-preserving sparse ternary representation of the data, while ensuring privacy
 - Fast search / memory efficient
 - Difficult to accurately reconstruct from probe
 - Server cannot reveal a structure of the database

Part 1:

Sparse Data Representation

Sparsification

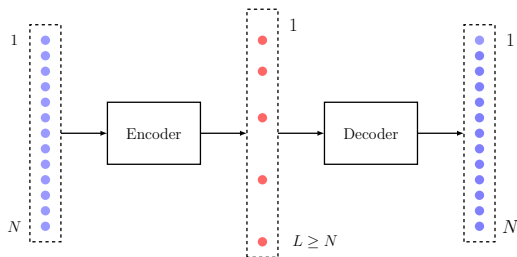
Main Idea



- ▶ $\mathbf{x}(m) \in \mathbb{R}^N$
- ▶ $\mathbf{x}(m) \sim p(\mathbf{x})$
- ▶ $\mathbf{u}(m) \in \{-1, 0, +1\}^L$
- ▶ $\|\mathbf{u}(m)\|_0 \leq S_x$
- ▶ Rate: $R = \frac{1}{L} \log_2 \left(\binom{L}{S_x} 2^{S_x} \right)$

Sparsification

Main Idea



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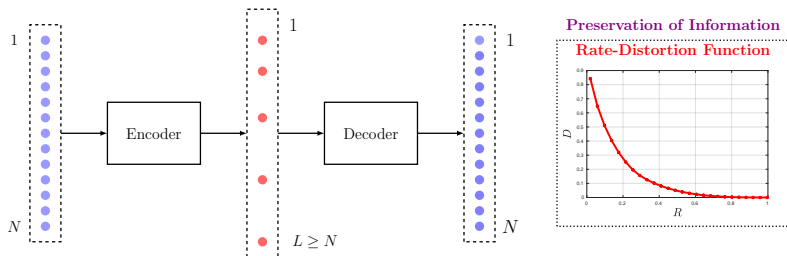
► Rate: $R = \frac{1}{L} \log_2 \left(\binom{L}{S_x} 2^{S_x} \right)$

► $\hat{\mathbf{x}}(m) \in \mathbb{R}^N$

► Distortion: $\frac{1}{N} \|\mathbf{x}(m) - \hat{\mathbf{x}}(m)\|_2^2 \leq D$

Sparsification

Main Idea



► $\mathbf{x}(m) \in \mathbb{R}^N$

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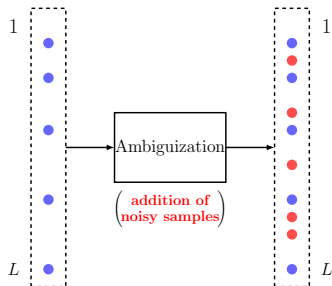
► Distortion: $\frac{1}{N} \|\mathbf{x}(m) - \hat{\mathbf{x}}(m)\|_2^2 \leq D$

Part 2:

Ambiguization

Ambiguization

Main Idea



► $\mathbf{u}(m) \in \{-1, 0, +1\}^L$

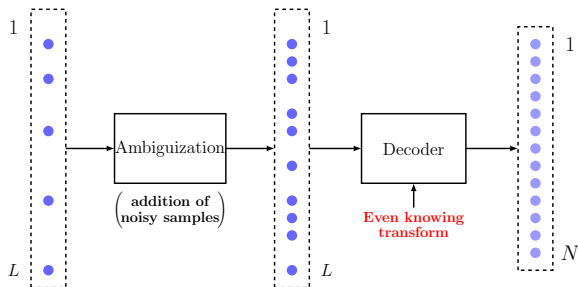
► $\|\mathbf{u}(m)\|_0 \leq S_x$

► **Public Domain**

► $\mathbf{u}(m) \oplus \mathbf{n}$

Ambiguization

Main Idea



▶ $\mathbf{u}(m) \in \{-1, 0, +1\}^L$

▶ **Public Domain**

▶ $\hat{\mathbf{x}}(m) \in \mathbb{R}^N$

▶ $\|\mathbf{u}(m)\|_0 \leq S_x$

▶ $\mathbf{u}(m) \oplus \mathbf{n}$

▶ $\|\mathbf{x}(m) - \hat{\mathbf{x}}(m)\|_2^2 \rightarrow \simeq 2N\sigma_x^2$

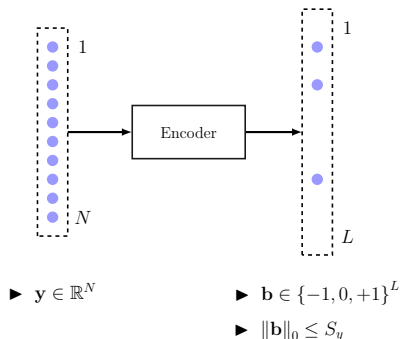
- ▶ Prevent reconstruction from $\mathbf{u}(m) \oplus \mathbf{n}$ and from probe \mathbf{y}
- ▶ Preclude server from discovering the structure of the database \mathcal{A}

Part 3:

Privacy-Preserving Identification

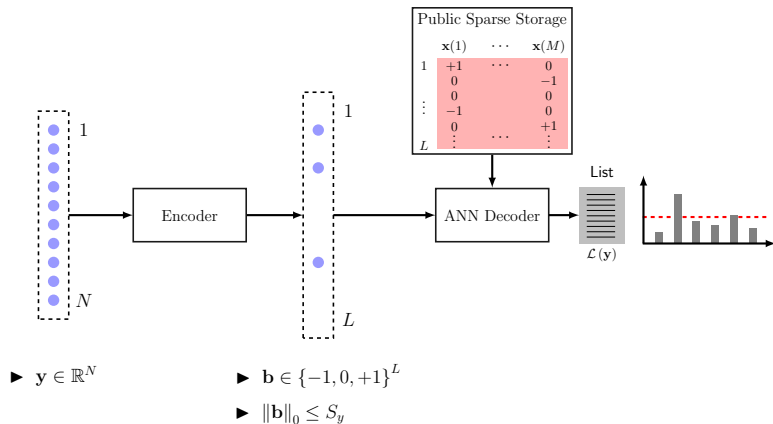
Privacy-Preserving Identification: Search Scheme I

Main Idea: User discloses his probe completely



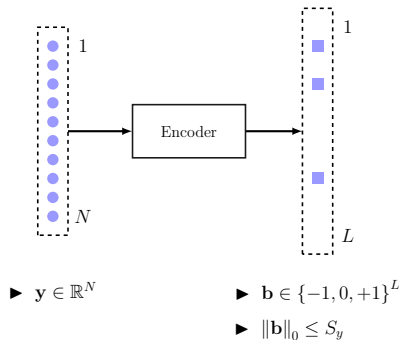
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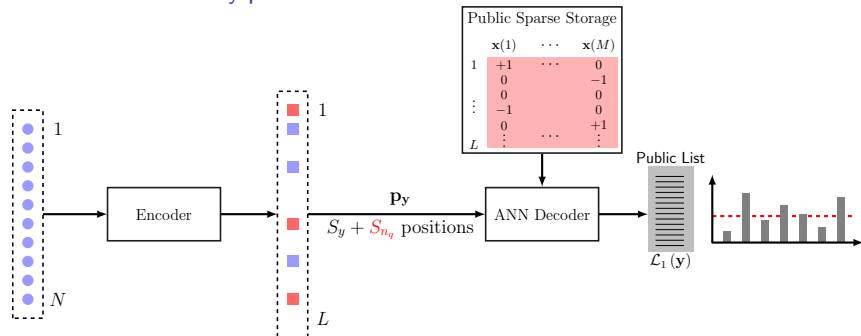
Privacy-Preserving Identification: Search Scheme II

Main Idea: User sends only positions of interest



Privacy-Preserving Identification: Search Scheme II

Main Idea: User sends only positions of interest



► $\mathbf{y} \in \mathbb{R}^N$

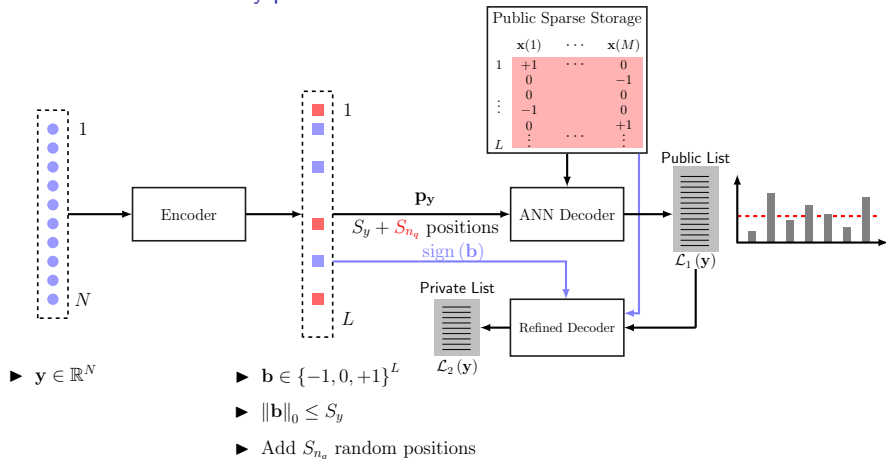
► $\mathbf{b} \in \{-1, 0, +1\}^L$

► $\|\mathbf{b}\|_0 \leq S_y$

► Add S_{n_q} random positions

Privacy-Preserving Identification: Search Scheme II

Main Idea: User sends only positions of interest

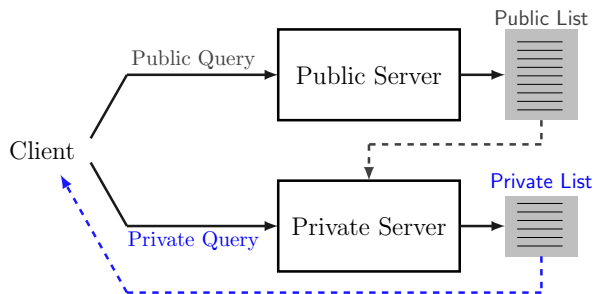


Proposed Framework Overview

Types of Decoders

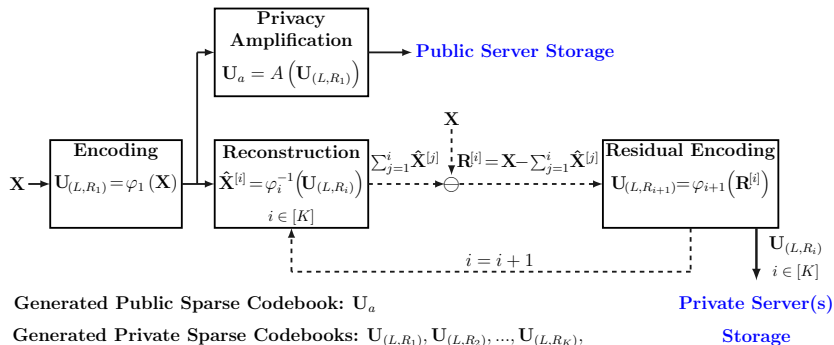
- **Type I:** search in the **quantized x** and **quantized y**
- **Type II:** search is based on **real y** and **reconstructed x** (just from one stage using simple pseudo-inverse of quantized x)
- **Type III:** search is based on **real y** and **successively reconstructed x** (from multiple stages as $\hat{x}^{[1]} + \dots + \hat{x}^{[K]}$) - *that what we propose here.*

General block diagram of the proposed framework



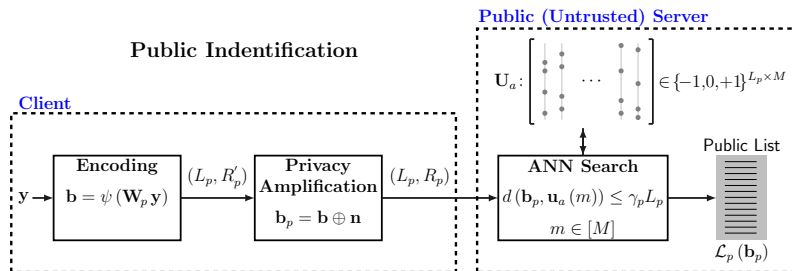
Successive Sparse Codebooks Generation Scheme

Proposed solution



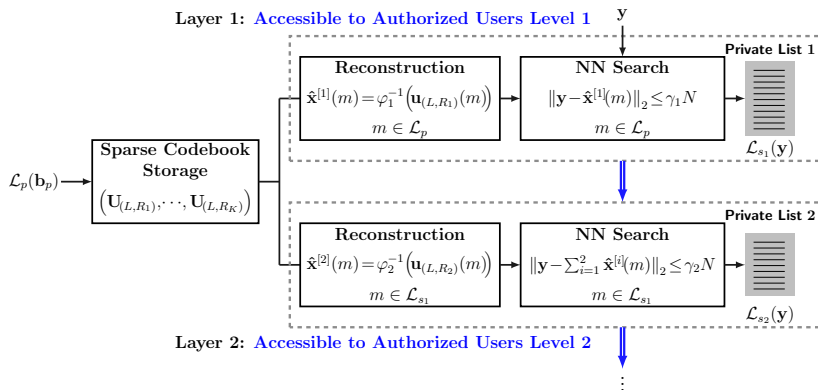
Public Identification Scheme

Proposed solution



Private Multiple-access Identification Scheme

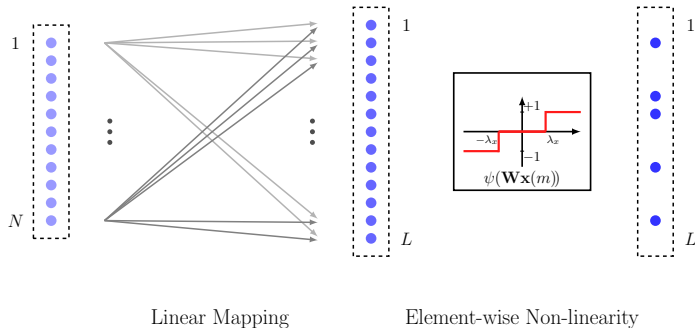
Proposed solution



- └ Proposed Framework
 - └ Sparse Data Representation

Sparsifying Transform

A Schematic Idea



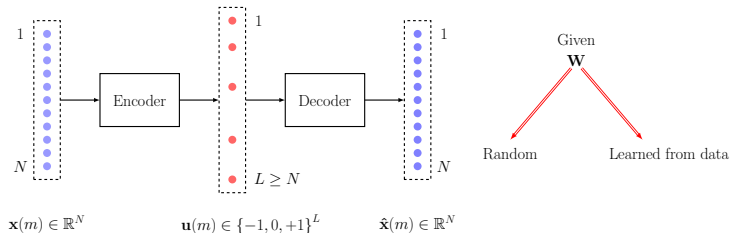
$$\mathbf{x}(m) \in \mathbb{R}^N \xrightarrow{\mathbf{W}} \mathbf{W}\mathbf{x}(m) \in \mathbb{R}^L \xrightarrow{\psi(\cdot)} \mathbf{u}(m) \in \{-1, 0, +1\}^L$$

$\xrightarrow{\varphi(\cdot)}$

- └ Proposed Framework
 - └ Sparse Data Representation

Sparsifying Transform

General Problem Formulation



Encoder:

$$\hat{\mathbf{a}}(m) = \psi(\mathbf{W}\mathbf{x}(m))$$

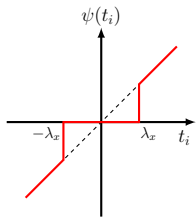
Decoder:

$$\hat{\mathbf{x}}(m) = \mathbf{W}^\dagger \hat{\mathbf{a}}(m)$$

Encoder: as a projection problem (for a fixed \mathbf{W})

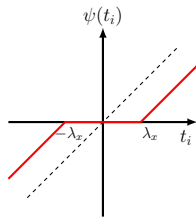
$$\hat{\mathbf{a}}(m) = \arg \min_{\mathbf{a}(m) \in \mathcal{A}^L} \|\mathbf{W}\mathbf{x}(m) - \mathbf{a}(m)\|_2^2 + \beta \Omega(\mathbf{a}(m)), \forall m \in [M]$$

- $\mathbf{W} \in \mathbb{R}^{L \times N}$, $\mathbf{x}(m) \in \mathbb{R}^N$, $\mathbf{a}(m) \in \mathbb{R}^L$
- Closed-form solution for: $\Omega(\cdot) = \|\cdot\|_0$ and $\Omega(\cdot) = \|\cdot\|_1$



Hard-thresholding operator

$$\Omega(\cdot) = \|\cdot\|_0$$



Soft-thresholding operator

$$\Omega(\cdot) = \|\cdot\|_1$$

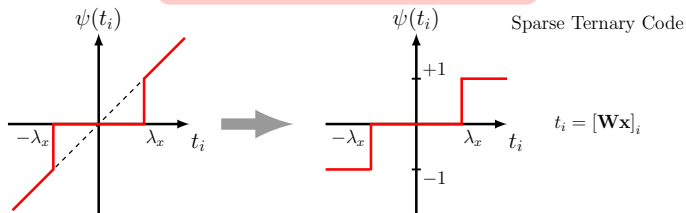
$$t_i = [\mathbf{W}\mathbf{x}]_i$$

$$\hat{\mathbf{a}}(m) = \psi(\mathbf{W}\mathbf{x}(m))$$

Encoder: Extra constraint on the alphabet

$$\hat{\mathbf{u}}(m) = \psi(\mathbf{W}\mathbf{x}(m))$$

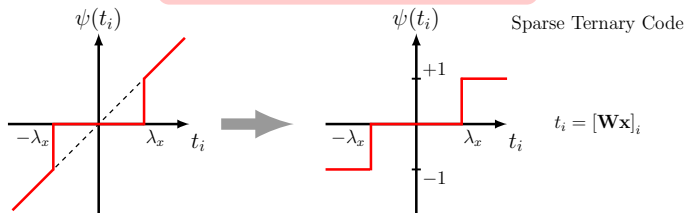
$$\text{s.t. } \mathbf{u}(m) \in \{-1, 0, +1\}$$



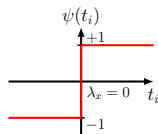
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**Remark:**

Binary hashing (like LSH) is the special case of our $\psi(\cdot)$ for $\lambda_x = 0$.



Learning Sparsifying Transform

General Formulation: joint learning

$$(\hat{\mathbf{W}}, \hat{\mathbf{A}}) = \arg \min_{(\mathbf{W}, \mathbf{A})} \|\mathbf{W}\mathbf{X} - \mathbf{A}\|_F^2 + \beta_W \Omega_W(\mathbf{W}) + \beta_A \Omega_A(\mathbf{A})$$

► **Sparse Coding Step** (Fixed \mathbf{W}):



$$\hat{\mathbf{A}} = \arg \min_{\mathbf{A}} \|\mathbf{W}\mathbf{X} - \mathbf{A}\|_F^2 + \beta_A \Omega_A(\mathbf{A})$$

$$\hat{\mathbf{a}}(m) = \psi(\mathbf{W}\mathbf{x}(m))$$

► **Transform Update Step** (Fixed \mathbf{A}):

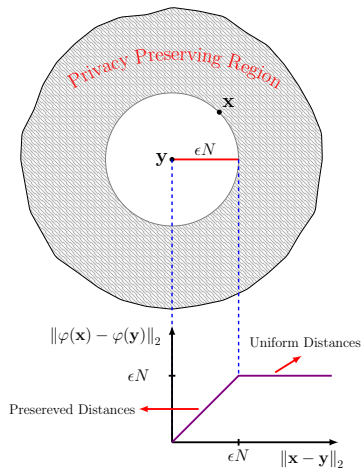
$$\hat{\mathbf{W}} = \arg \min_{\mathbf{W}} \|\mathbf{W}\mathbf{X} - \mathbf{A}\|_F^2 + \beta_W \Omega_W(\mathbf{W})$$

Linear Regression :
(with quadratic regularizer)

$$\hat{\mathbf{W}} = \mathbf{A}\mathbf{X}^T (\mathbf{X}\mathbf{X}^T + \beta_W \mathbf{I}_N)^{-1}$$

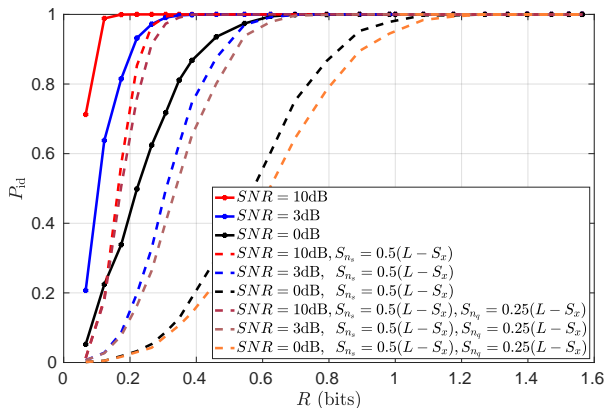
Desired property of mapping scheme

Distance preservation in the desired radius



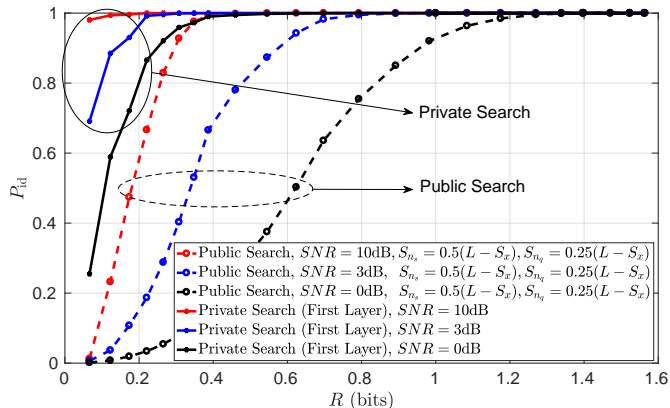
Probability of Correct Identification

Relation between probability of correct identification and encoding rate:



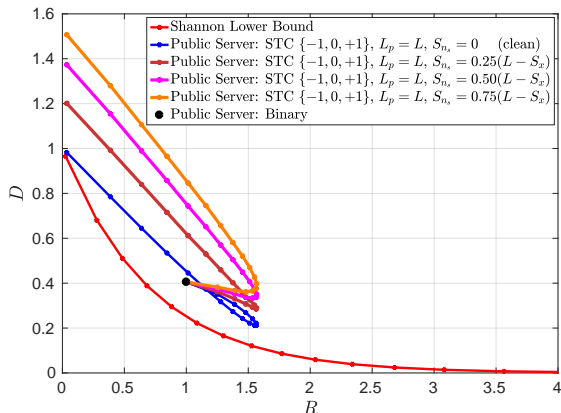
Probability of Correct Identification

Comparison between the probability of correct identification at the public server and private server:



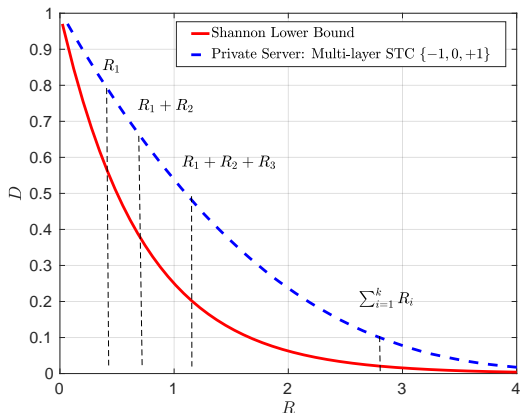
Information Loss

Distortion-rate behavior at the **public server**:



Information Loss

Distortion-rate behavior at the **private server**:



Conclusions:

- Fast search is performed on the public server
- Refined searches are performed on the distributed private server(s)
- Distributed security
- Accuracy of the private search is based on the authorization level of the clients

