Disclosure Risks of Distance Preserving Data Transformations

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SSDBM, Hong Kong
July 9, 2008

Outline

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Data Analysis and Sharing

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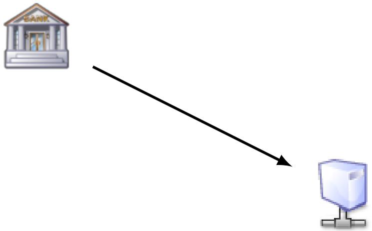
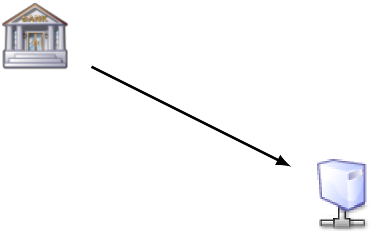


- Outsourcing

Data Analysis and Sharing



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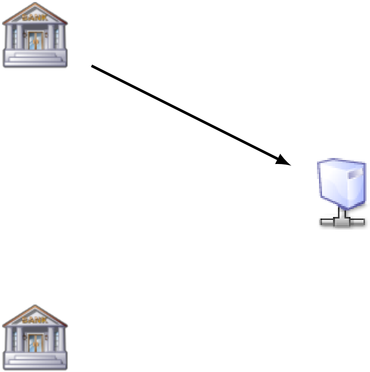

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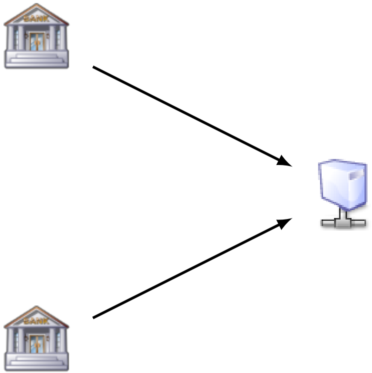

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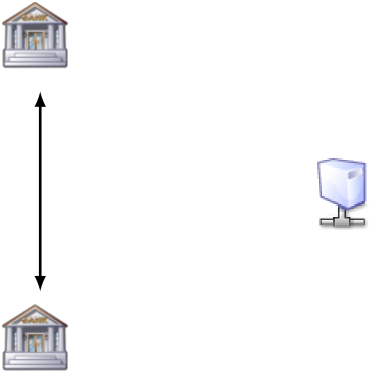

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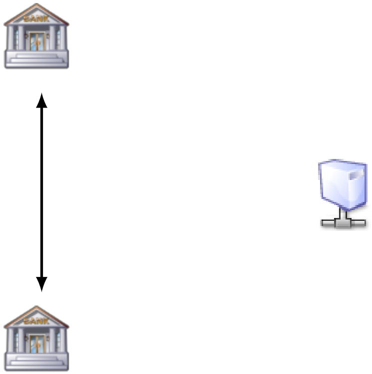

- Outsourcing — can the statistician be trusted?
- Sharing — can they trust each other?

Data Transformations

Data Transformations — a way to get rid of trust.

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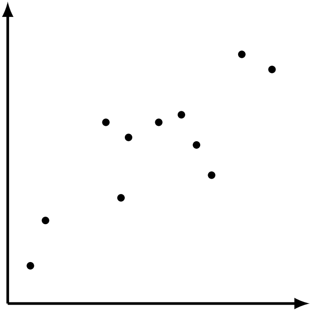

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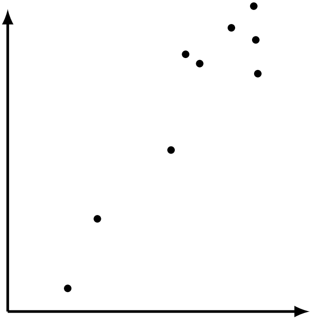

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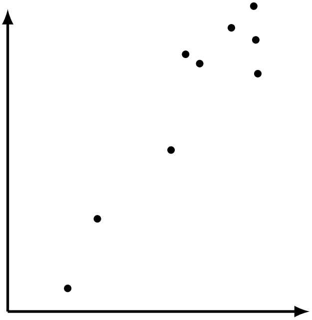

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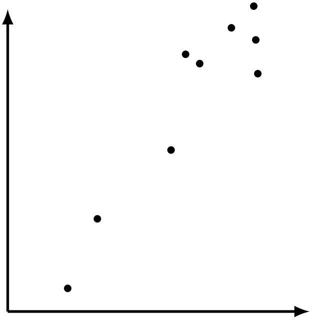

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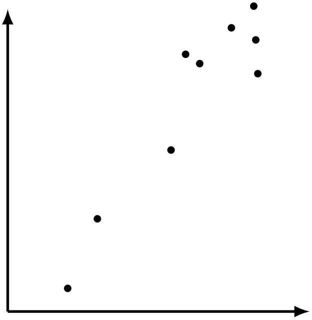

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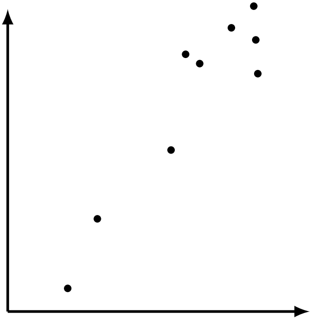

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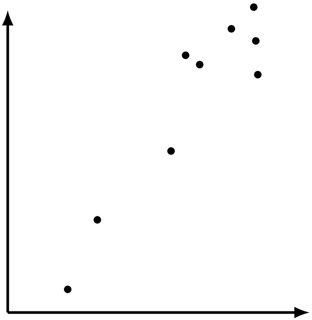

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Claim Do not leak private information. Wrong!

Attack Scenarios

Things an attacker might know:

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Things an attacker might know:

Data sample

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Probability distribution

- National statistical institutes
- Previous studies
- Qualified guess

An Example

	p_1	p_2	p_3	p_4	p_5
p_1	-	1.3	0.9	1.2	0.3
p_2	1.3	-	1.1	0.2	1.0
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p_4	1.2	0.2	0.5	-	0.9
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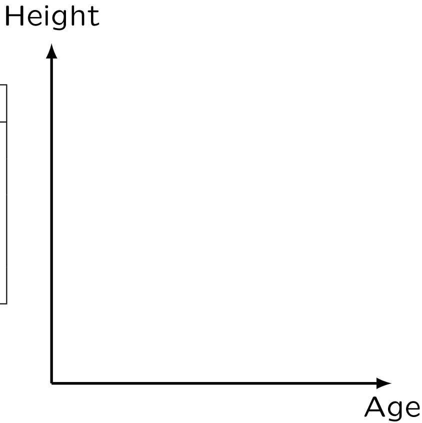

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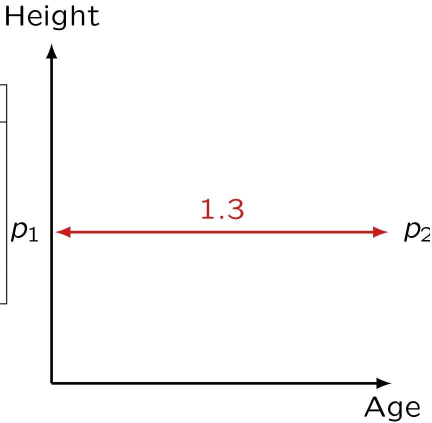

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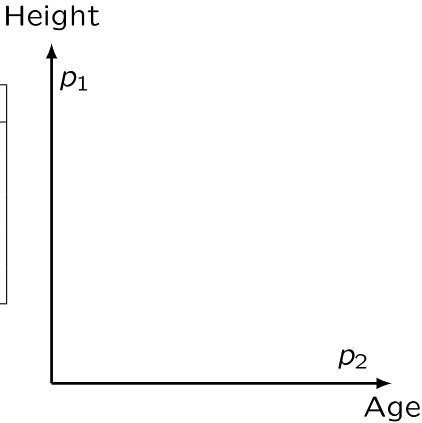

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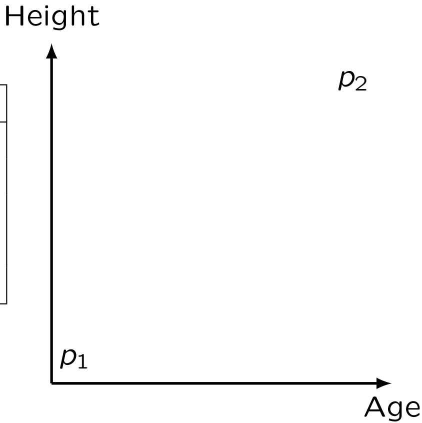

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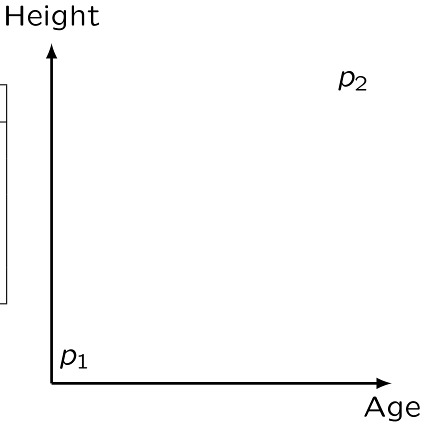

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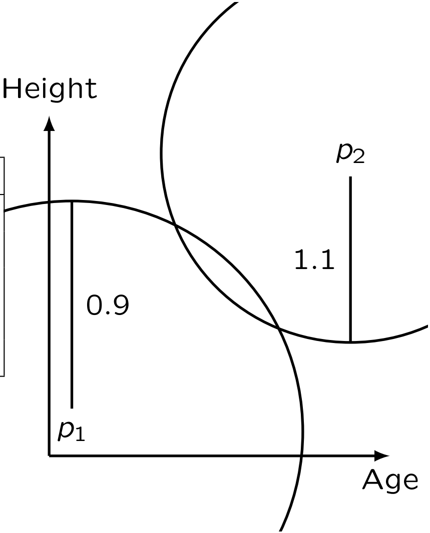

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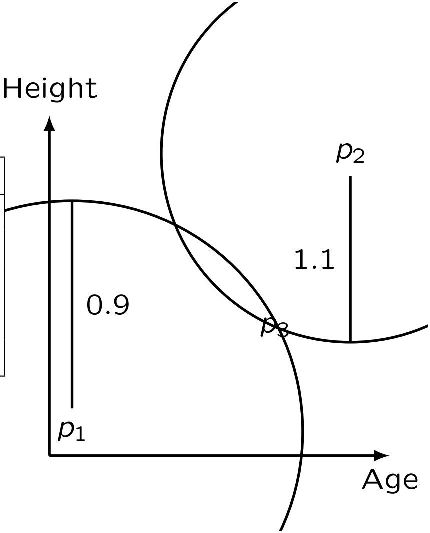

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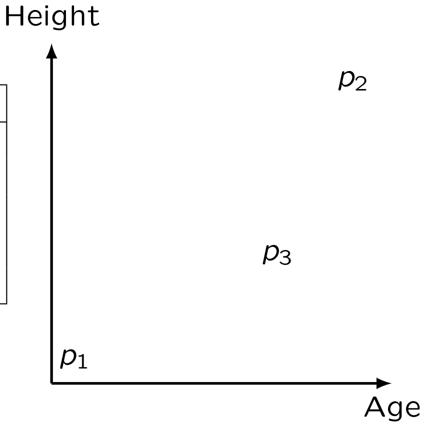

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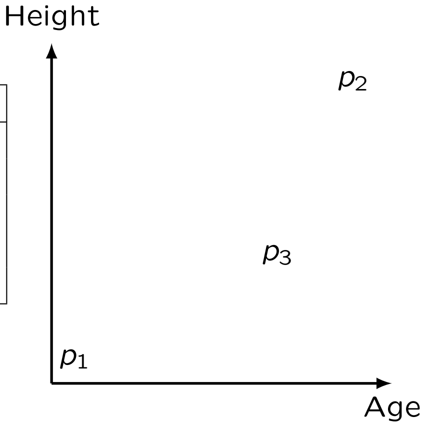

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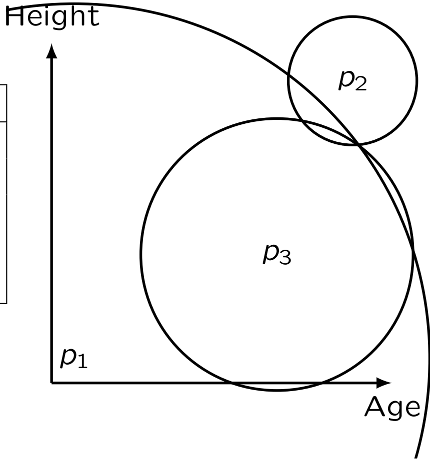

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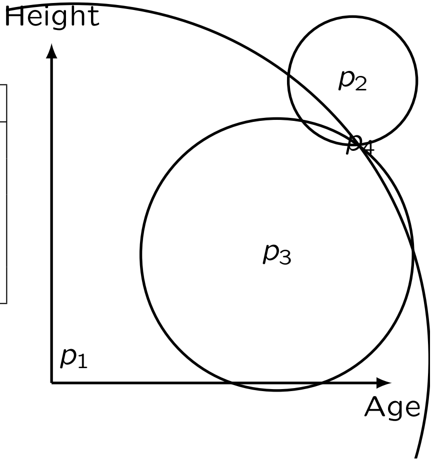

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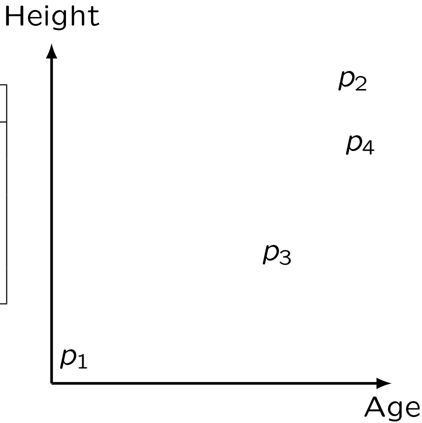

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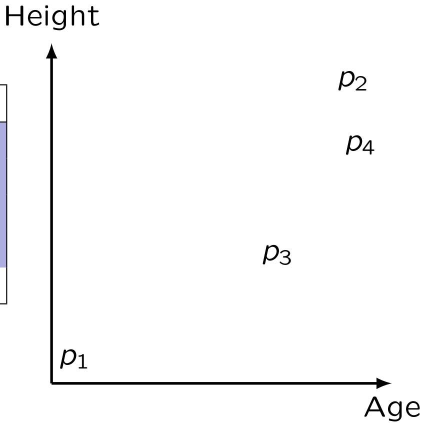

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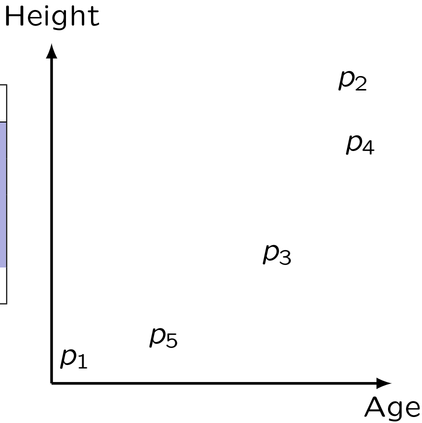

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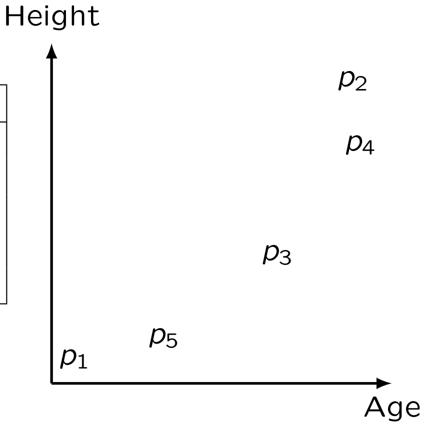

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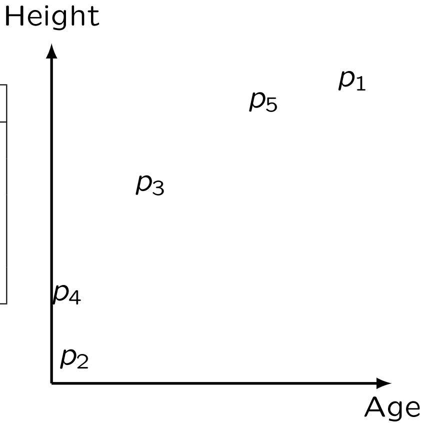

Outline

Motivation

The Attack

Conclusion

Attack Outline

Database n objects with d attributes

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Published Distances between objects

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Database	n objects with d attributes
Published	Distances between objects
Attacker	Knows probability distribution

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1. Guess $d + 1$ objects.

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The attack:

1. Guess $d+1$ objects.
2. Use lateration to fix remaining objects.
3. Rotate and mirror to fit known distribution.

Hyper-lateration

Known points $\overline{p}_1, \ldots, \overline{p}_n \in \mathbb{R}^d$

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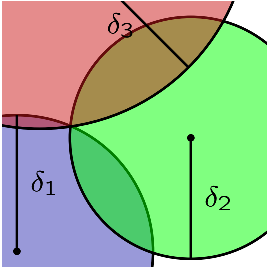

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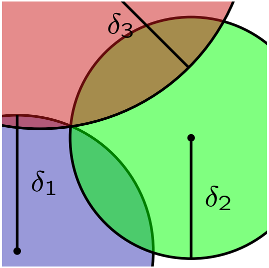

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$n - 1$ linear equations:

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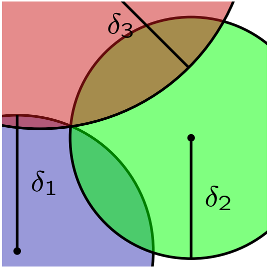

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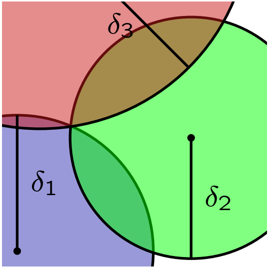

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If $n > d$ and $span\{\overline{p}_i\}_i = \mathbb{R}^d$, solution is unique.

Principal Component Analysis

Hyper-lateration Unique up to orthogonal transform.

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PCA Recognizes orientation of data

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Hyper-lateration: Unique up to orthogonal transform.

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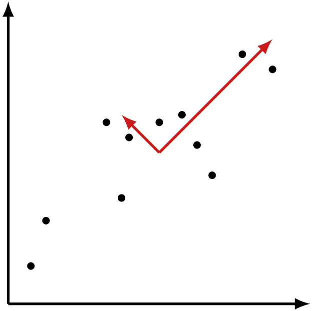

Principal Component Analysis

Hyper-lateration Unique up to orthogonal transform.

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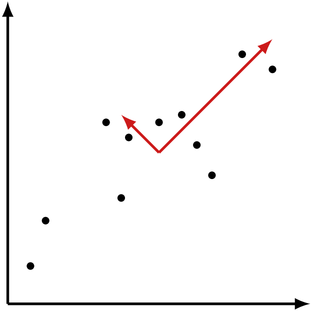
Covariance matrix:

$$\Sigma = \begin{bmatrix} Cov(A_1, A_1) & \cdots & Cov(A_1, A_d) \\ \vdots & & \vdots \\ Cov(A_d, A_1) & \cdots & Cov(A_d, A_d) \end{bmatrix},$$

$$Cov(A, B) = E[(A - \mu)(B - \nu)].$$



Principal Component Analysis

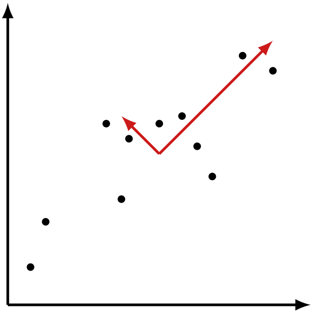
Hyper-lateration Unique up to orthogonal transform.

PCA Recognizes orientation of data (does not recognize mirroring).

Covariance matrix:

$$\Sigma = \begin{bmatrix} Cov(A_1, A_1) & \cdots & Cov(A_1, A_d) \\ \vdots & & \vdots \\ Cov(A_d, A_1) & \cdots & Cov(A_d, A_d) \end{bmatrix},$$

$Cov(A, B) = E[(A - \mu)(B - \nu)]$.
Eigenvectors, and values:
$(\overline{e}_1, \lambda_1), \ldots, (\overline{e}_d, \lambda_d)$.



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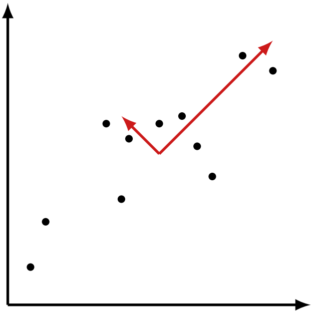

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Do this for both hyper-laterated points and sample drawn from known distribution.

The Attack

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   (unique up to rotation and mirroring)

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2. Find remaining objects with lateration
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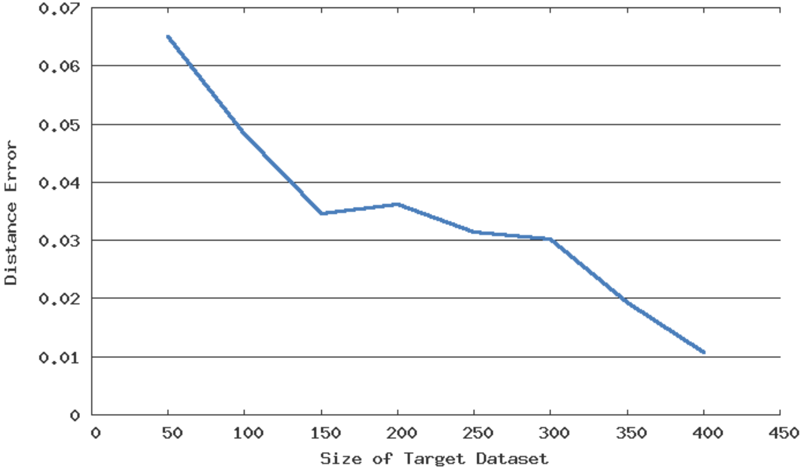
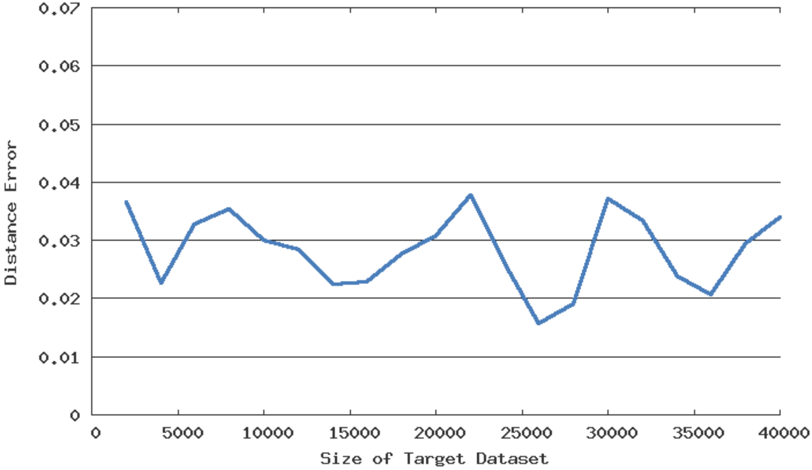
4. Rotate to match principal components of known probability distribution
5. Find best mirroring (optimized)

Attack Accuracy (1)



Auto Miles per Gallon (using 5 attributes)

Attack Accuracy (2)



US Adult Census (using 4 attributes)

Outline

Motivation

The Attack

Conclusion

Conclusion

Known	**Leaked**
Sample of $d+1$ objects	Everything
Probability distribution	Everything with high fidelity

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Never publish distances between data points!

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Thank You