

Privacy preserving similarity detection for data analysis

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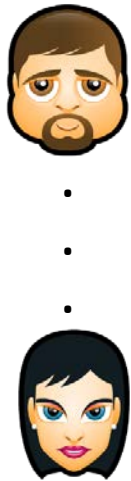
Privacy vs Utility



Personality test

Clustering

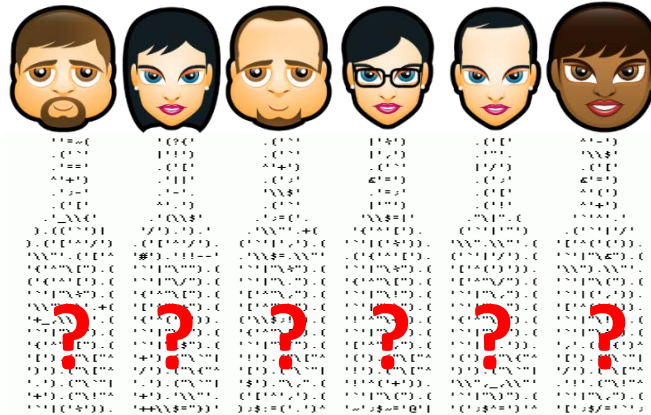
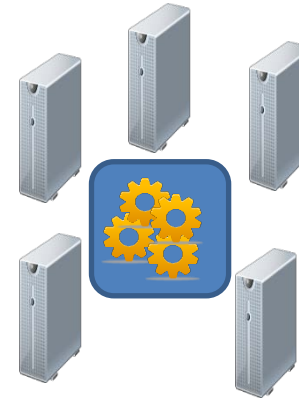
Similarity



Data $A_1, A_2, A_3, \dots, A_n$



Data $B_1, B_2, B_3, \dots, B_n$



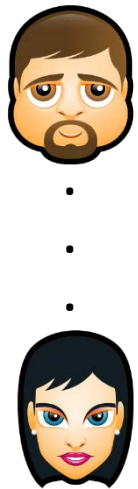
Privacy preserving similarity detection for data analysis

Naïve solutions

- Encrypt data with standard crypto
 - Renders operations infeasible.
- Data separation
 - Vertical separation is not always applicable.
- Anonymizing techniques
 - Don't protect individuals data.

Our Approach

- Combine crypto with data processing



Data $A'_1, A'_2, A'_3, \dots, A'_n$



$$F(A_1, \dots, A_n) = F(A'_1, \dots, A'_n)$$

Data $B'_1, B'_2, B'_3, \dots, B'_n$

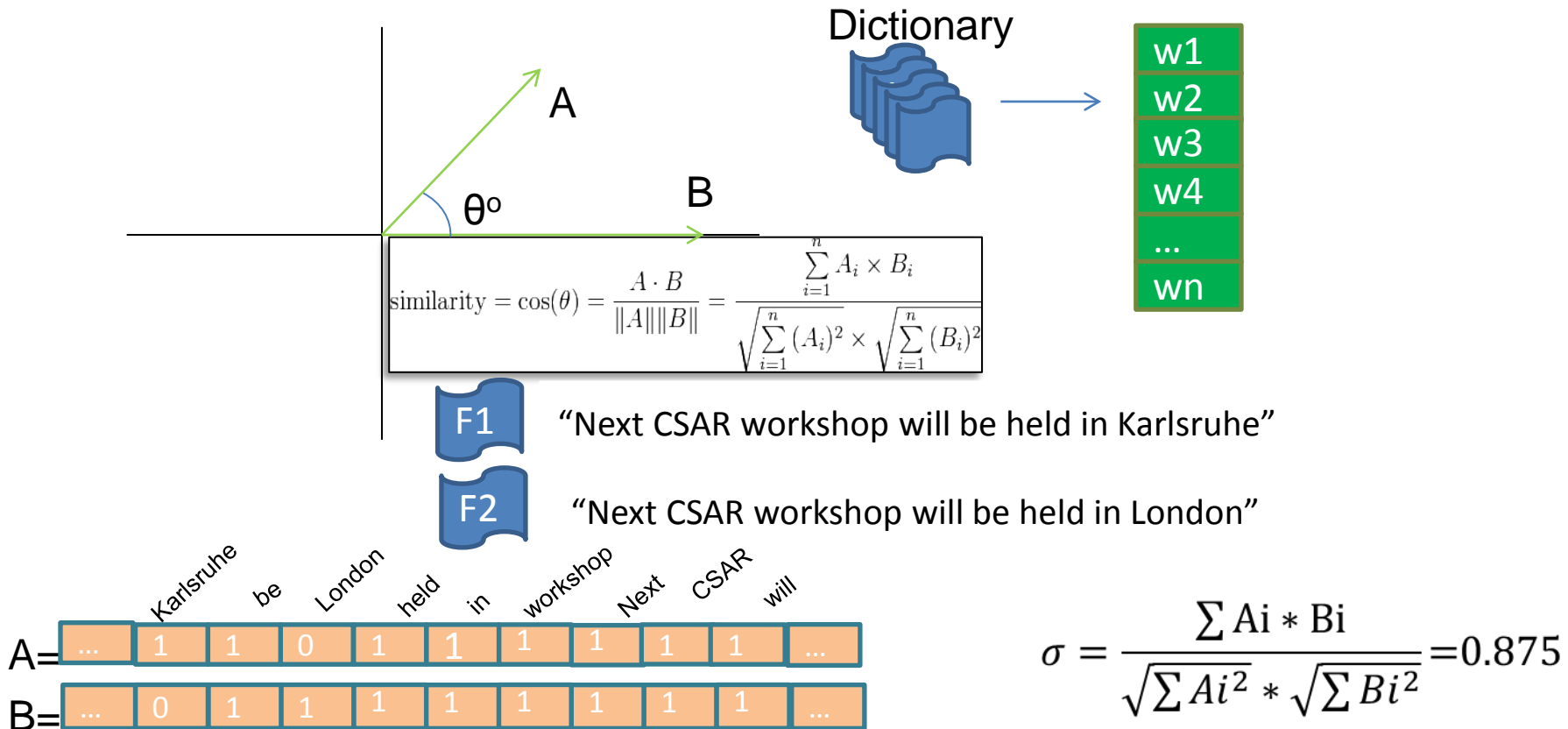


User	Data	Data analysis
Alice	A'_1, \dots, A'_n	$F(A'_1, \dots, A'_n)$
Bob	B'_1, \dots, B'_n	$F(B'_1, \dots, B'_n)$

Outline

- Our solution
 - Cosine similarity
 - Privacy with Geometrical Transformations
- Security Analysis
- Performance Evaluation
 - Hierarchical clustering
 - Results
- Looking Ahead

Cosine similarity



Random Scaling

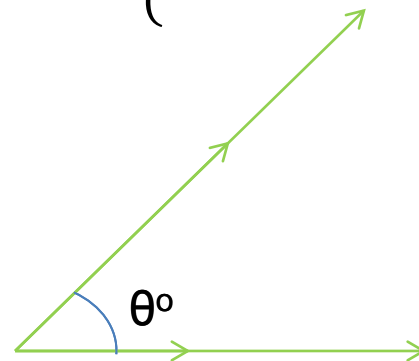
- Data encoded as unique vectors in \mathbb{R}^n
- $\varphi_r: \mathbb{R}^n \rightarrow \mathbb{R}^n$ s.t:

$$\cos(a, b) = \cos(\varphi_{r_1}(a), \varphi_{r_2}(b))$$

- Random scaling

- $r \leftarrow \mathbb{R}^n$

- $S(r, A) = r \cdot A = \begin{bmatrix} r & \dots & \\ \vdots & r & \vdots \\ & \dots & r \end{bmatrix} \cdot A$

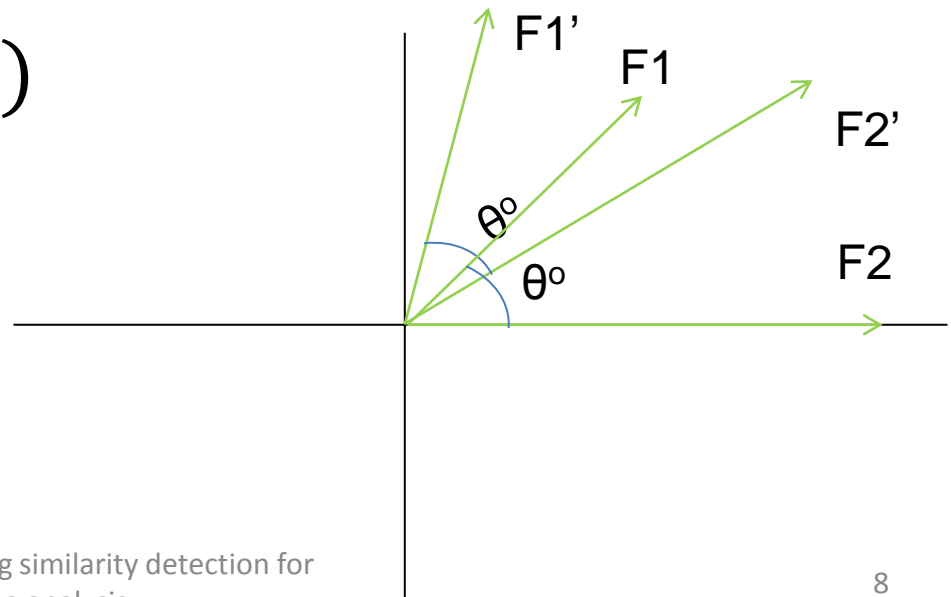


Vector Rotation

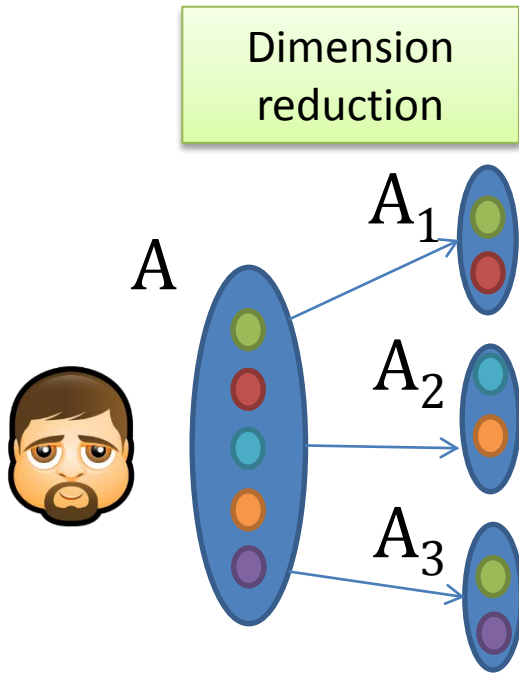
- Rotation by a common angle λ°

$$- R_{\lambda^\circ}(\mathbf{a}) = \mathbf{a} \cdot \begin{bmatrix} \cos(\lambda^\circ) & \cdots & \sin(\lambda^\circ) \\ \vdots & & \vdots \\ -\sin(\lambda^\circ) & \cdots & \cos(\lambda^\circ) \end{bmatrix}$$

- $\varphi_r = \mathbf{a} \cdot R_{\lambda^\circ}(\mathbf{a}) \cdot Sr(\mathbf{a})$



Our solution



Dimension
reduction

Random
Scaling

Rotation

$$S(r_1, A_1) = r_1 \cdot \begin{array}{c} \text{green} \\ \text{red} \end{array}$$

$$S(r_2, A_2) = r_2 \cdot \begin{array}{c} \text{cyan} \\ \text{orange} \end{array}$$

$$S(r_3, A_3) = r_3 \cdot \begin{array}{c} \text{green} \\ \text{purple} \end{array}$$

$$R_{\lambda^\circ}(r_1 \cdot A_1) = R_{\lambda^\circ} \cdot r_1 \cdot \begin{array}{c} \text{green} \\ \text{red} \end{array}$$

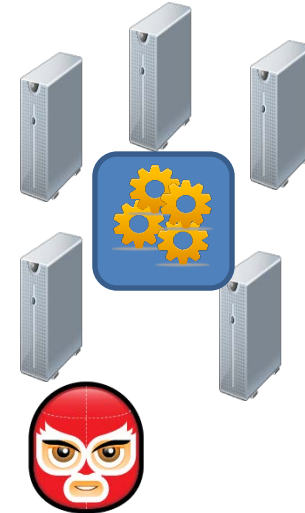
$$R_{\lambda^\circ}(r_2 \cdot A_2) = R_{\lambda^\circ} \cdot r_2 \cdot \begin{array}{c} \text{cyan} \\ \text{orange} \end{array}$$

$$R_{\lambda^\circ}(r_3 \cdot A_3) = R_{\lambda^\circ} \cdot r_3 \cdot \begin{array}{c} \text{green} \\ \text{purple} \end{array}$$

Security analysis



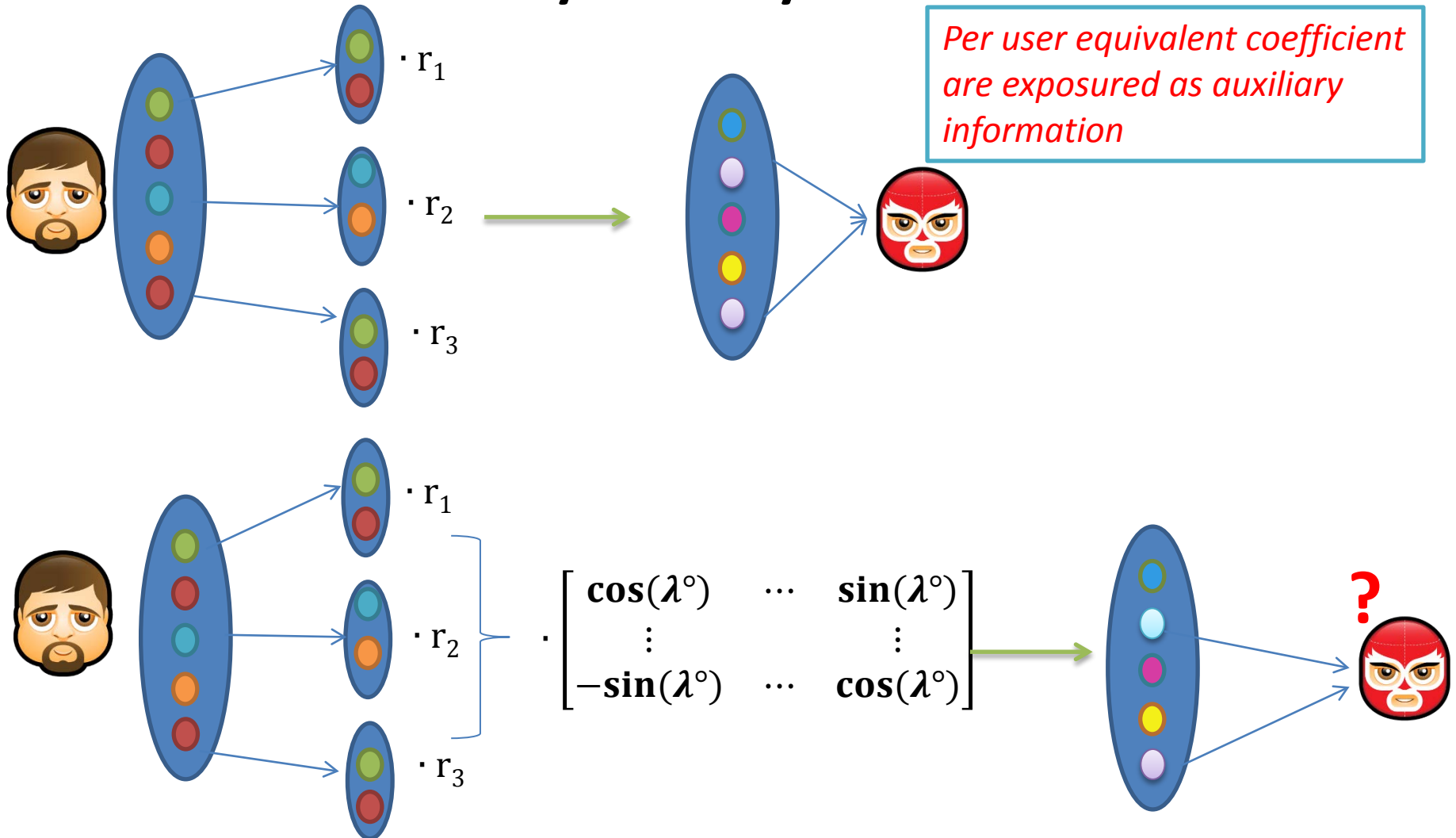
$$V'_1 = R_{\lambda^\circ} (S(r_1, d_1, d_2), S(r_2, d_3, d_4), S(r_3, d_1 d_5))$$



- External:
 - Rotation angle remains unknown.

- Internal:
 - Rotation angle is known.

Security analysis cont'd



Evaluation



4sqPersonality

- 173 users willing to run 4sqPersonality test
- 5 factor personality test
 - Openness, Conscientiousness, Extraversion, Agreeableness, Neuroticism.

Clustering approach

- Hierarchical Agglomerative clustering (HAC)
 - Input: n points and $N \times N$ similarity matrix
 - Output: Single cluster containing all n points

```
C=MakeSingletonClusters();
```

```
for i=0 to i=n:
```

```
    Find “closest” clusters c1,c2;
```

```
    Merge(c1,c2);
```

```
    RecomputeDistances(C);
```

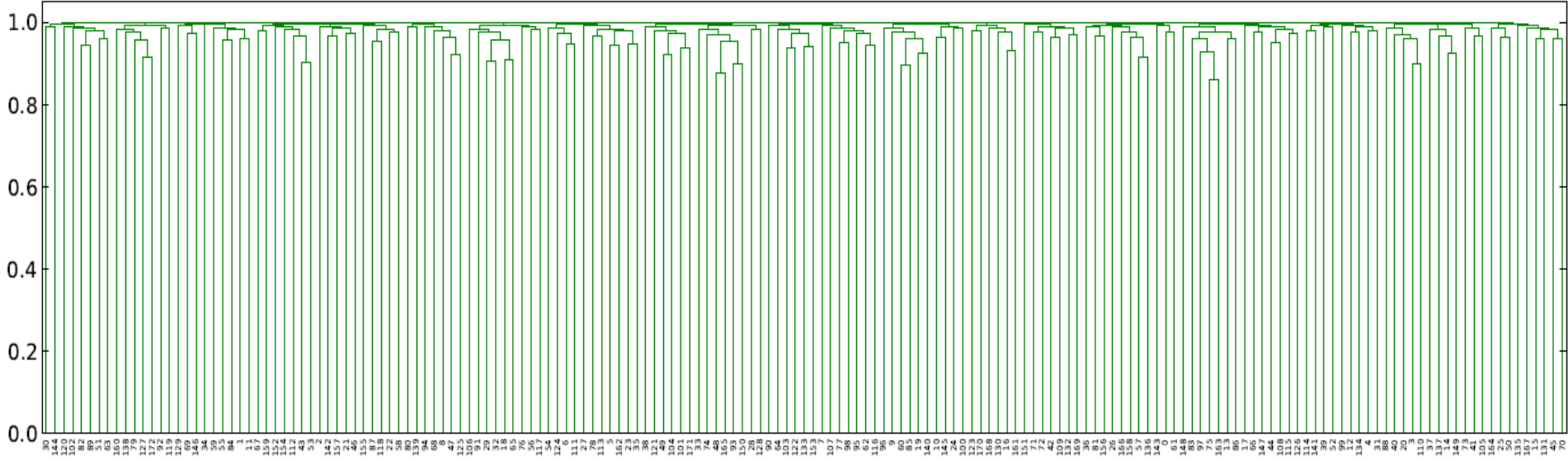
```
    if #C=1 exit();
```

Agglomerative: $O(n^3)$
Divisible: $O(2^n)$

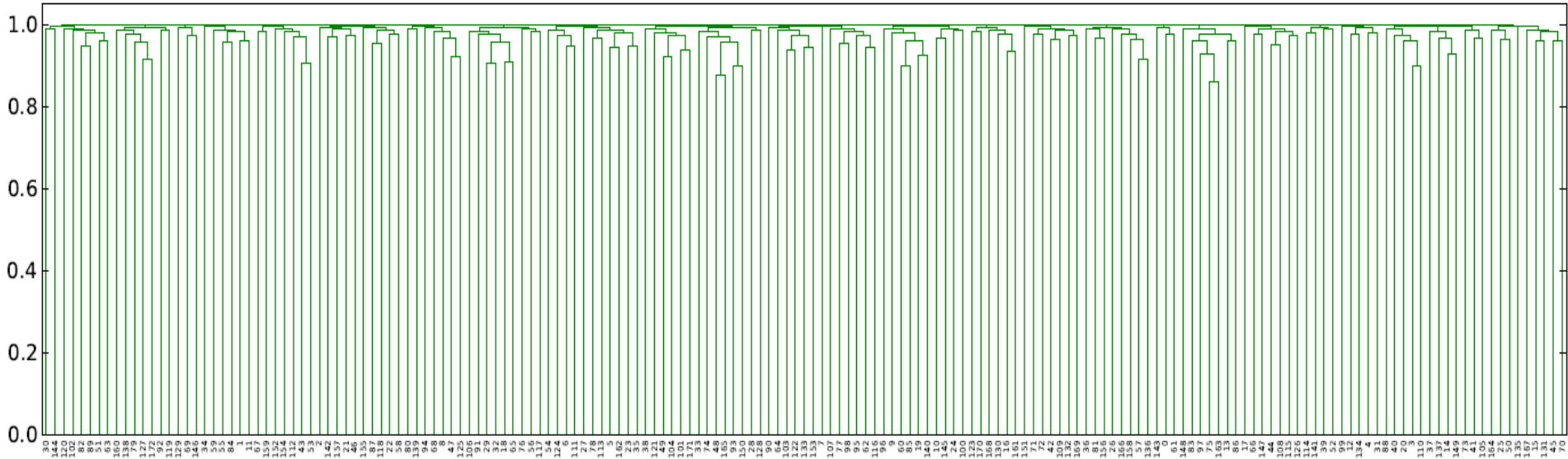
Cosine
Similarity

Results

Plaintext data



Encrypted data



Recap

1. Pairwise cosine similarity for multidimensional vectors.
2. Geometrical transformations compatible with cosine similarity.



Privacy preserving similarity detection for data analysis

Looking Ahead

- Other privacy preserving similarity detection algorithms.
- Privacy preserving data analysis algorithms:
 - MAX,MIN

Thank you!

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