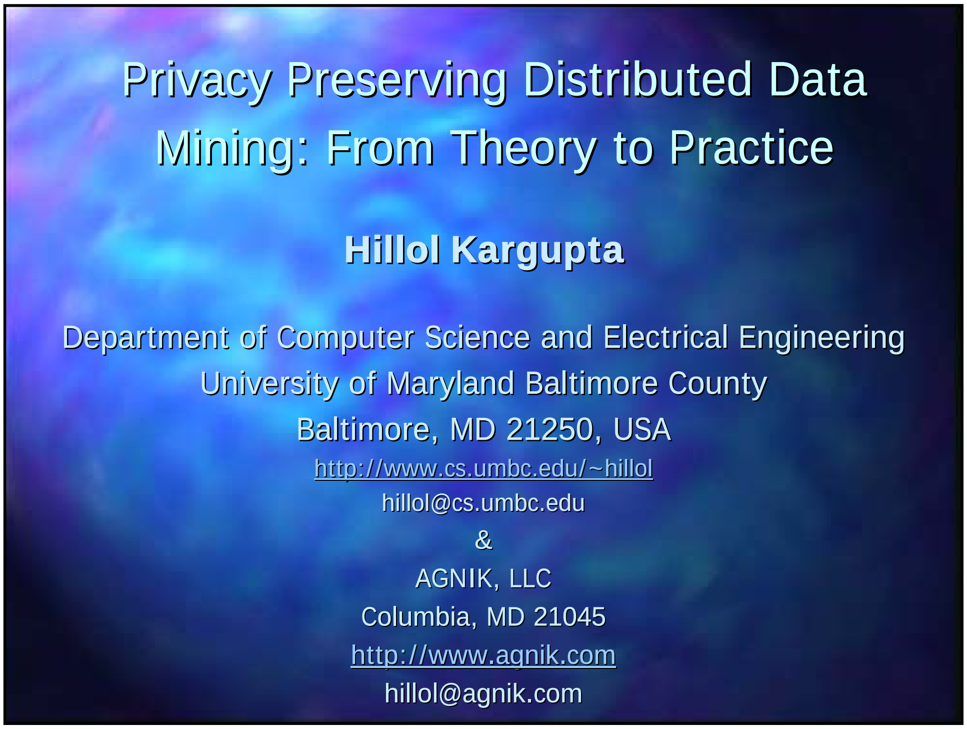

Privacy Preserving Distributed Data Mining: From Theory to Practice

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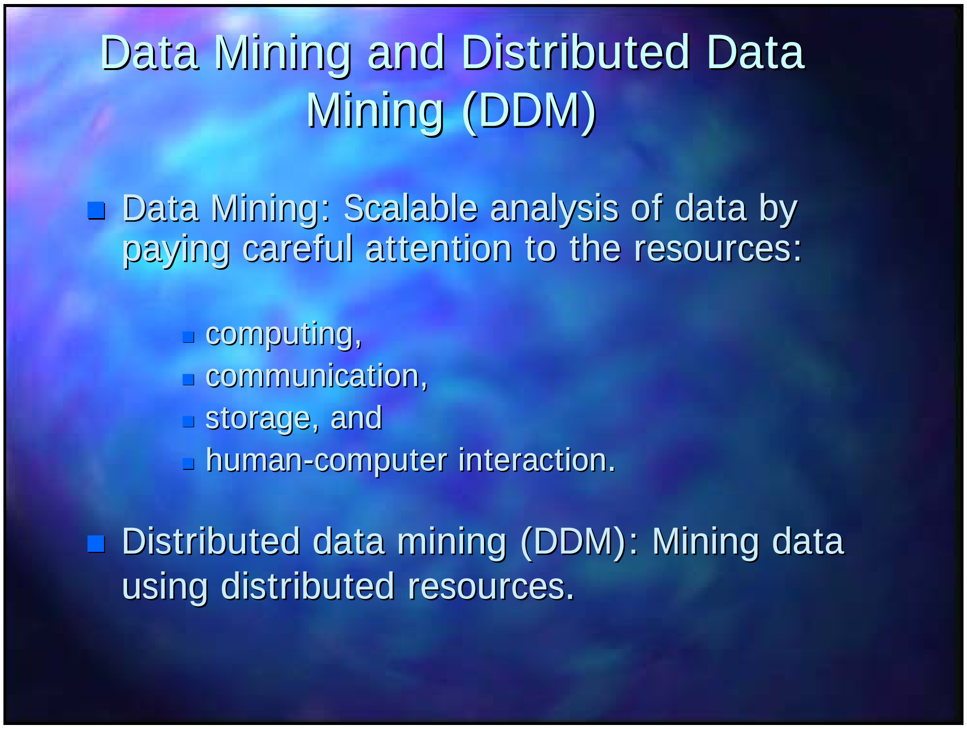
Roadmap

- Introduction
- Distributed Data Mining (DDM): An Overview
- Privacy Issues in DDM
- Protecting Privacy in DDM: Algorithmic Solutions
- Conclusions

Research & Development at UMBC DIADIC Laboratory and AGNIK, LLC

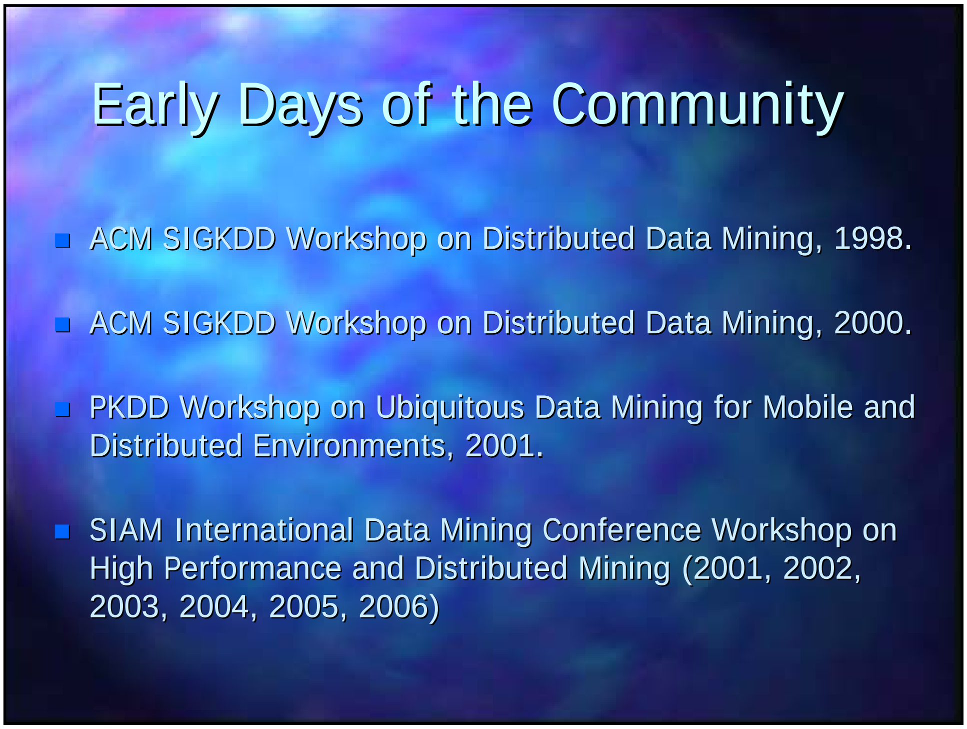
- Distributed and mobile data mining.
- Supported by Department of Homeland Security, NASA, US National Science Foundation CAREER award and other grants, US Air Force, TRW Research Foundation, Maryland Technology Development Council, and others.
- Agnik, LLC: A Spin-off from DIADIC Lab, specializing on mobile and distributed data mining and management.

2002 C-Coupe



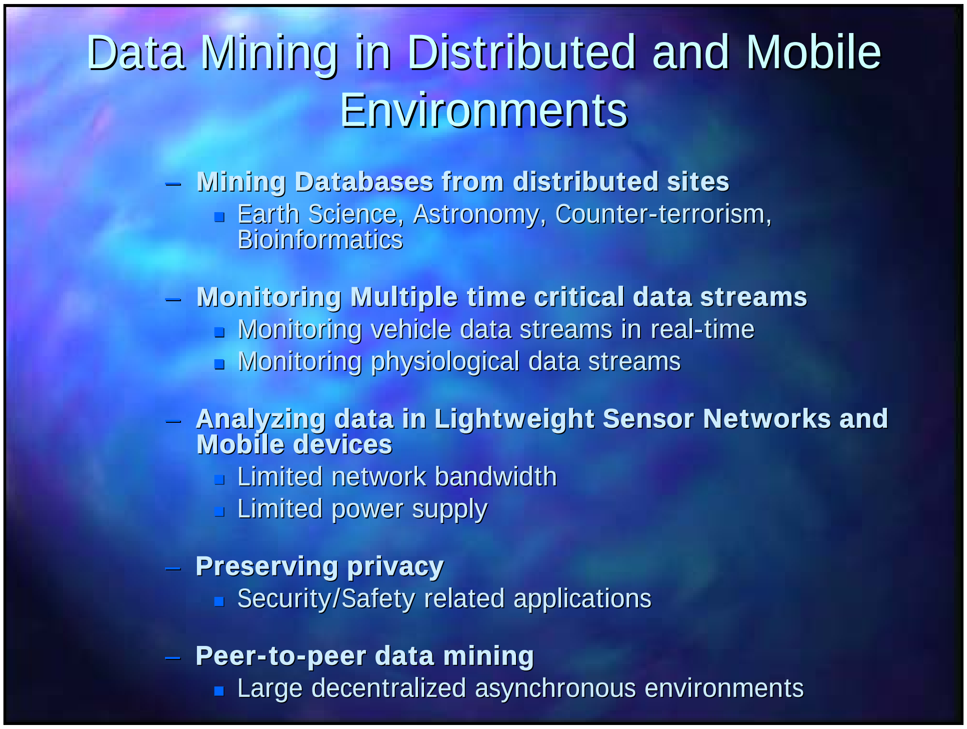
Data Mining and Distributed Data Mining (DDM)

- Data Mining: Scalable analysis of data by paying careful attention to the resources:
  - computing,
  - communication,
  - storage, and
  - human-computer interaction.
- Distributed data mining (DDM): Mining data using distributed resources.



Early Days of the Community

- ACM SIGKDD Workshop on Distributed Data Mining, 1998.
- ACM SIGKDD Workshop on Distributed Data Mining, 2000.
- PKDD Workshop on Ubiquitous Data Mining for Mobile and Distributed Environments, 2001.
- SIAM International Data Mining Conference Workshop on High Performance and Distributed Mining (2001, 2002, 2003, 2004, 2005, 2006)



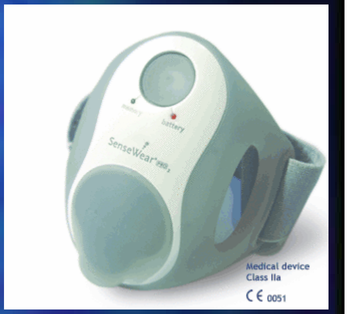
Data Mining in Distributed and Mobile Environments

- **Mining Databases from distributed sites**
  - Earth Science, Astronomy, Counter-terrorism, Bioinformatics
- **Monitoring Multiple time critical data streams**
  - Monitoring vehicle data streams in real-time
  - Monitoring physiological data streams
- **Analyzing data in Lightweight Sensor Networks and Mobile devices**
  - Limited network bandwidth
  - Limited power supply
- **Preserving privacy**
  - Security/Safety related applications
- **Peer-to-peer data mining**
  - Large decentralized asynchronous environments

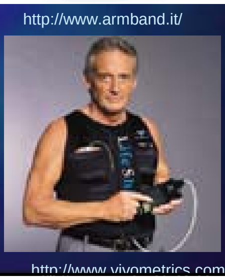
Resource-Constrained Real-time Physiological Data Stream Monitoring

- Wearable sensors available in the market
  - SenseWear Armband from BodyMedia
  - Wearable West[1]
  - LifeShirt Garment from Vivometrics
- SenseWear armband can measure heat flux, accelerometer, galvanic skin response, skin temperature, near body temperature
- Arm band can store up to about 5 days of data.

[1] www.smartextiles.info

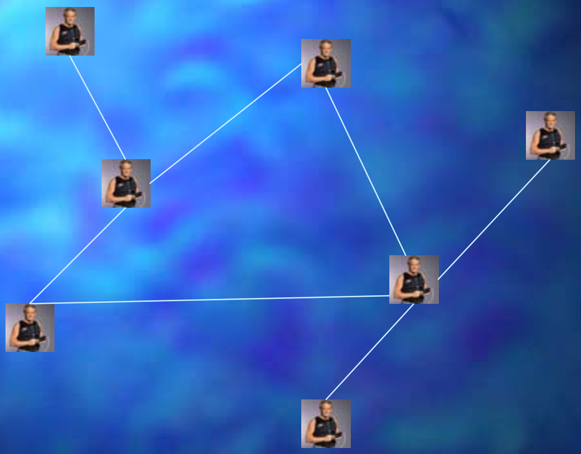


http://www.armband.it/

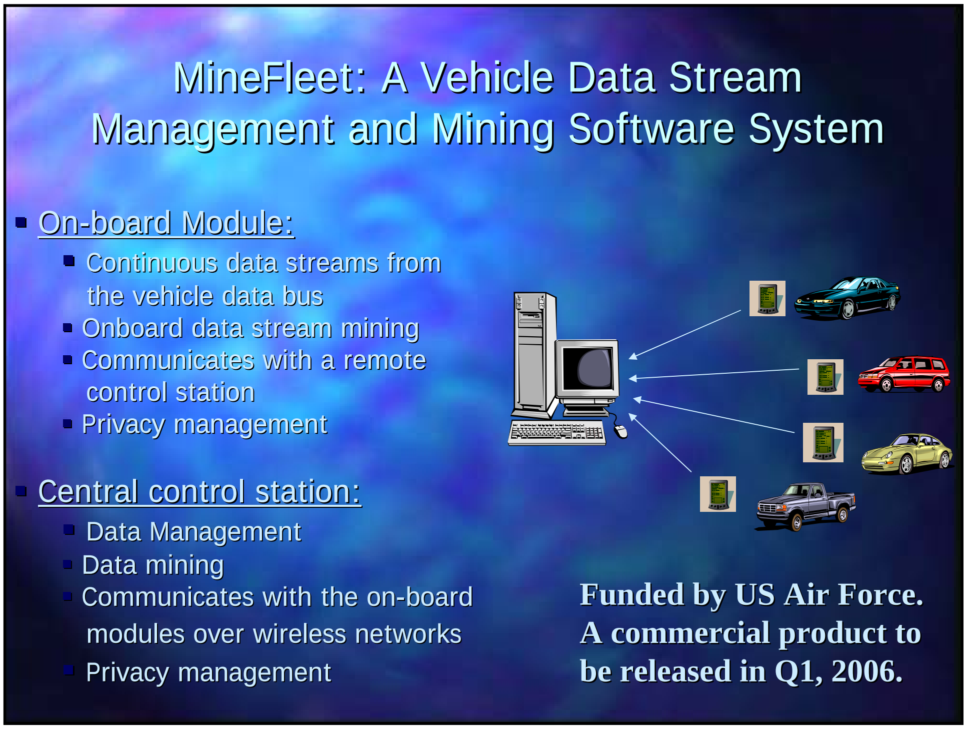


http://www.vivometrics.com

A Network of Physiological Data Stream Monitoring Devices



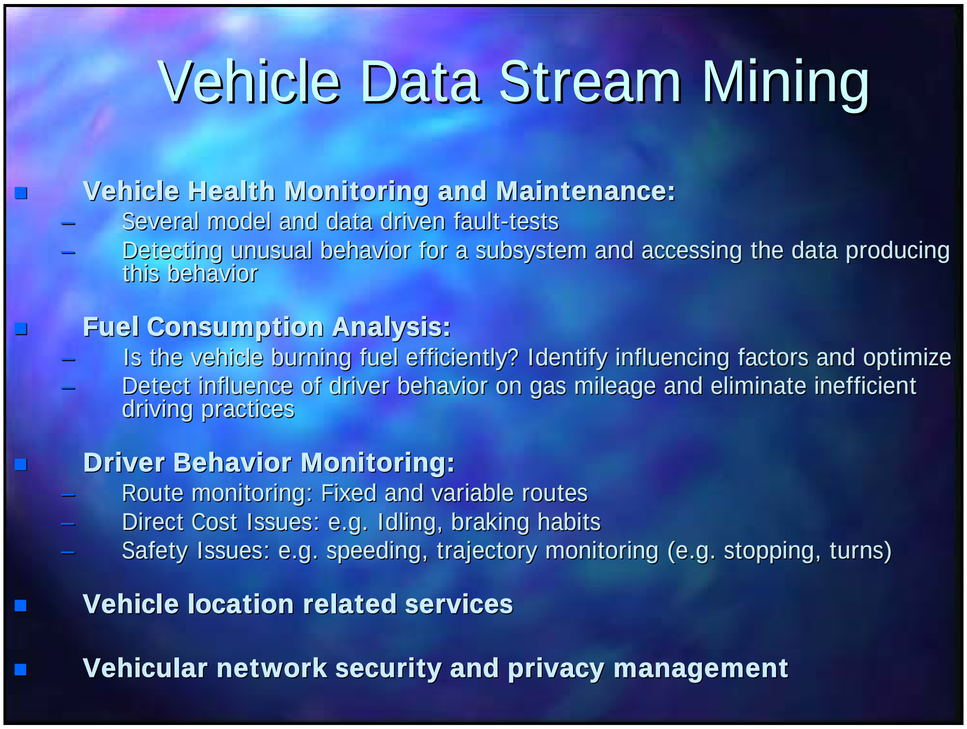
Detecting emerging patterns in a group of health workers, soldiers, elderly individuals, animals.



MineFleet: A Vehicle Data Stream Management and Mining Software System

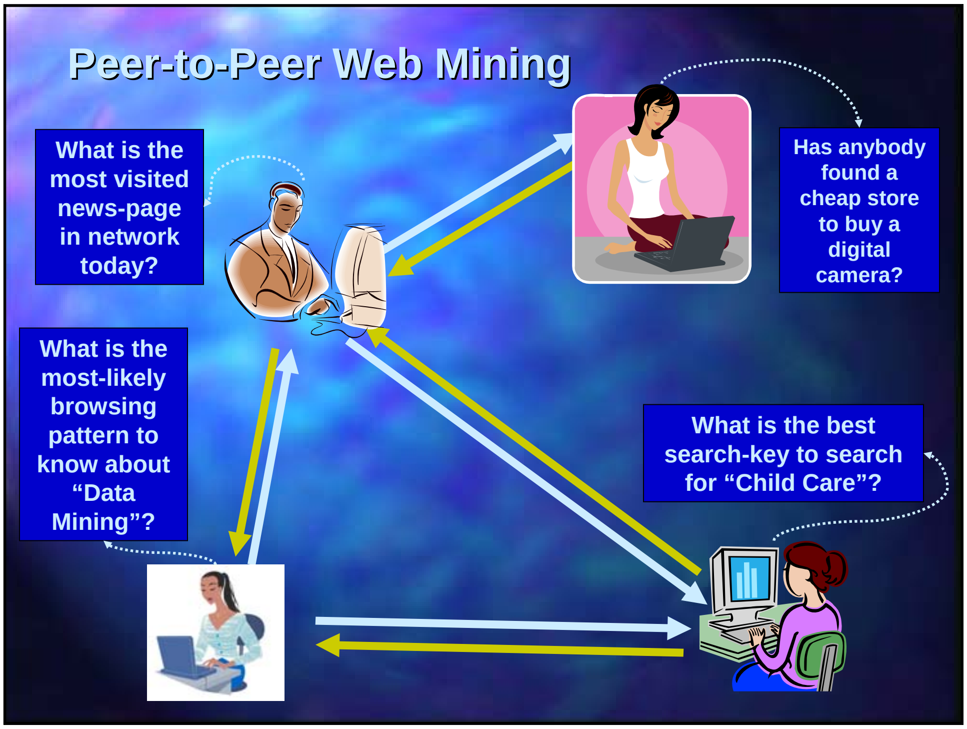
- On-board Module:
  - Continuous data streams from the vehicle data bus
  - Onboard data stream mining
  - Communicates with a remote control station
  - Privacy management
- Central control station:
  - Data Management
  - Data mining
  - Communicates with the on-board modules over wireless networks
  - Privacy management

Funded by US Air Force. A commercial product to be released in Q1, 2006.



Vehicle Data Stream Mining

- **Vehicle Health Monitoring and Maintenance:**
  - Several model and data driven fault-tests
  - Detecting unusual behavior for a subsystem and accessing the data producing this behavior
- **Fuel Consumption Analysis:**
  - Is the vehicle burning fuel efficiently? Identify influencing factors and optimize
  - Detect influence of driver behavior on gas mileage and eliminate inefficient driving practices
- **Driver Behavior Monitoring:**
  - Route monitoring: Fixed and variable routes
  - Direct Cost Issues: e.g. Idling, braking habits
  - Safety Issues: e.g. speeding, trajectory monitoring (e.g. stopping, turns)
- **Vehicle location related services**
- **Vehicular network security and privacy management**



Peer-to-Peer Web Mining

What is the most visited news-page in network today?

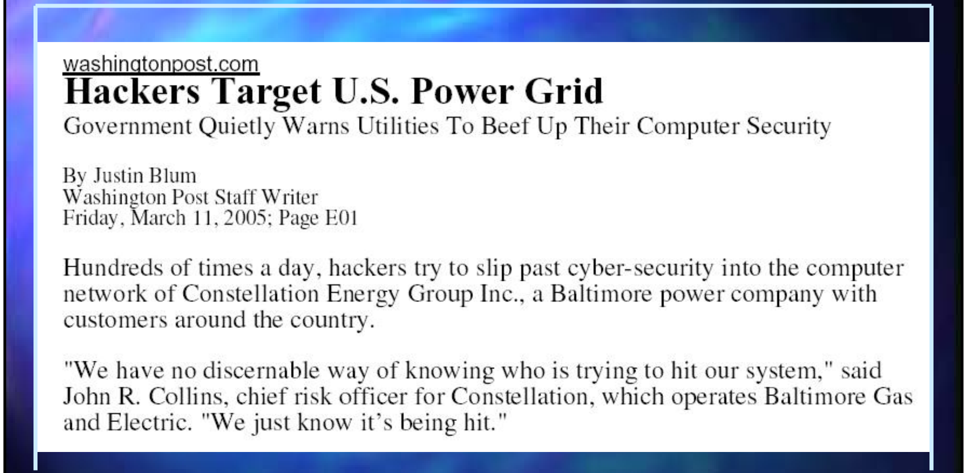
Has anybody found a cheap store to buy a digital camera?

What is the most-likely browsing pattern to know about “Data Mining”?

What is the best search-key to search for “Child Care”?

Useful Browser Data

1. Web-browser history
2. Browser cache
3. Click-stream data stored at browser (browsing pattern)
4. Search queries typed in the search engine
5. User profile
6. Bookmarks



washingtonpost.com

Hackers Target U.S. Power Grid

Government Quietly Warns Utilities To Beef Up Their Computer Security

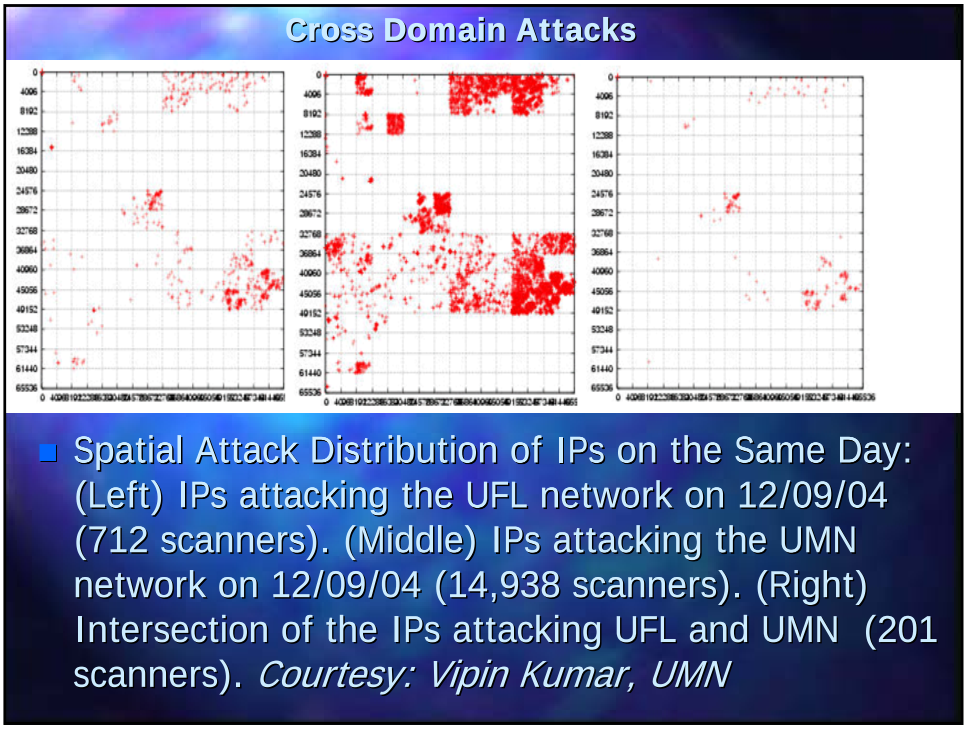
By Justin Blum
Washington Post Staff Writer
Friday, March 11, 2005; Page E01

Hundreds of times a day, hackers try to slip past cyber-security into the computer network of Constellation Energy Group Inc., a Baltimore power company with customers around the country.

"We have no discernable way of knowing who is trying to hit our system," said John R. Collins, chief risk officer for Constellation, which operates Baltimore Gas and Electric. "We just know it's being hit."

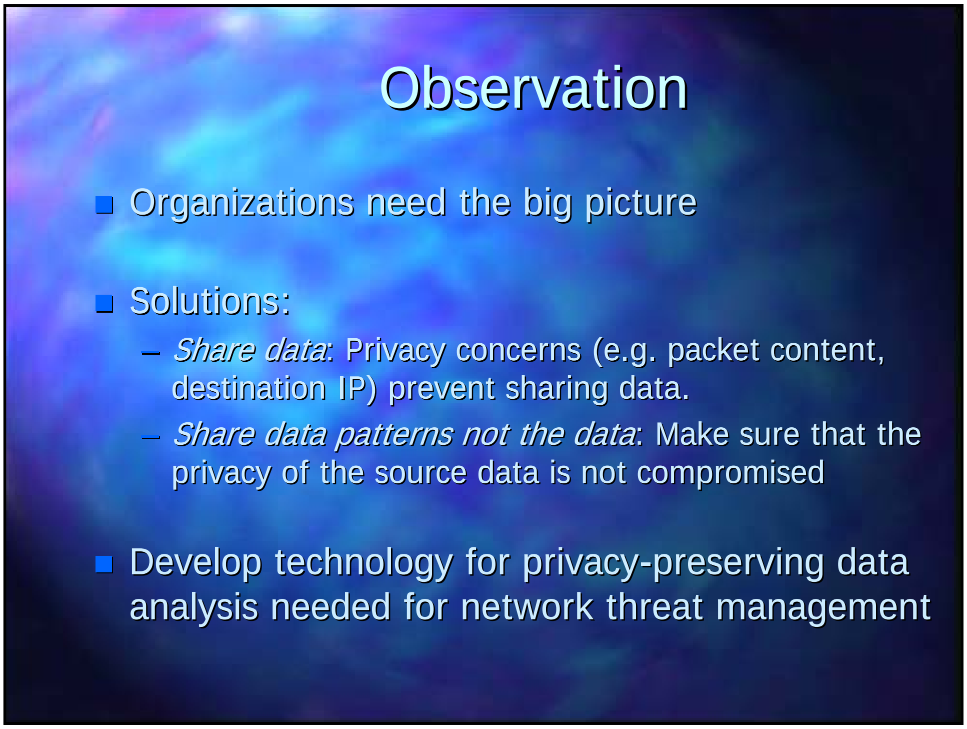
PURSUIT: Privacy-Sensitive Cross-Domain Intrusion Detection

- Cross-Domain Network Attack Detection system using Privacy-Preserving Distributed Data Mining
  - Detecting stealth attacks
  - Identifying botnets
  - Identifying cross-domain attack patterns, worm classification
- Sponsor: US Department of Homeland Security
- Partners:
  - Agnik, Army High Performance Research Center, University of Minnesota, and Tresys Inc.
- PURSUIT Consortium:
  - Purdue University
  - Ohio State University
  - Stevens University
  - SRI International
  - University of Illinois at Urbana-Champaign



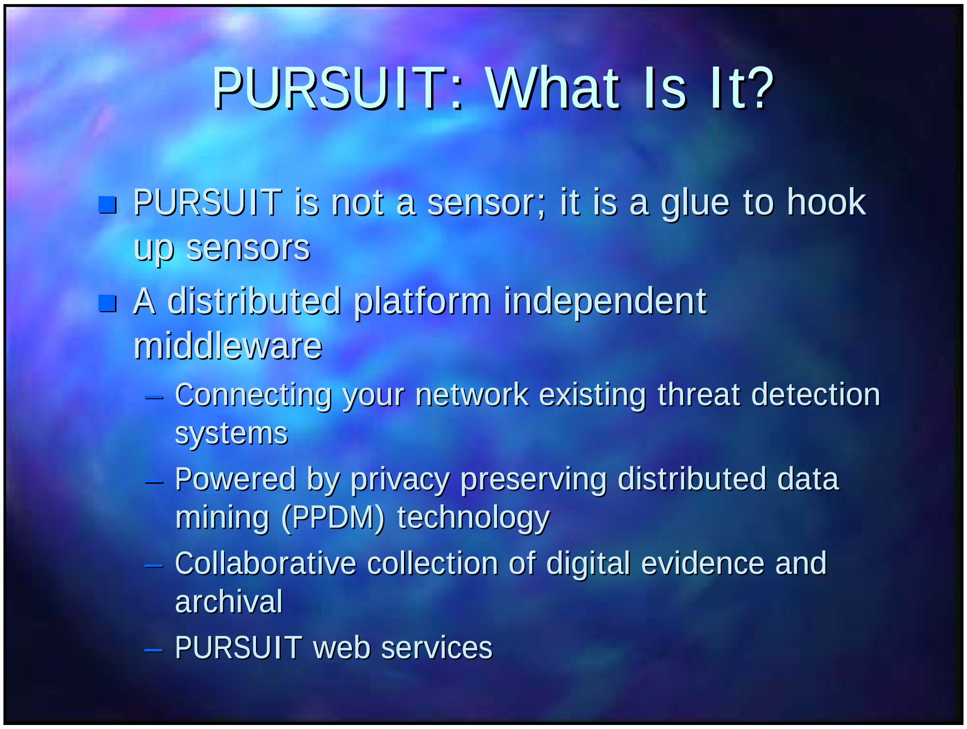
Cross Domain Attacks

- Spatial Attack Distribution of IPs on the Same Day: (Left) IPs attacking the UFL network on 12/09/04 (712 scanners). (Middle) IPs attacking the UMN network on 12/09/04 (14,938 scanners). (Right) Intersection of the IPs attacking UFL and UMN (201 scanners). *Courtesy: Vipin Kumar, UMN*



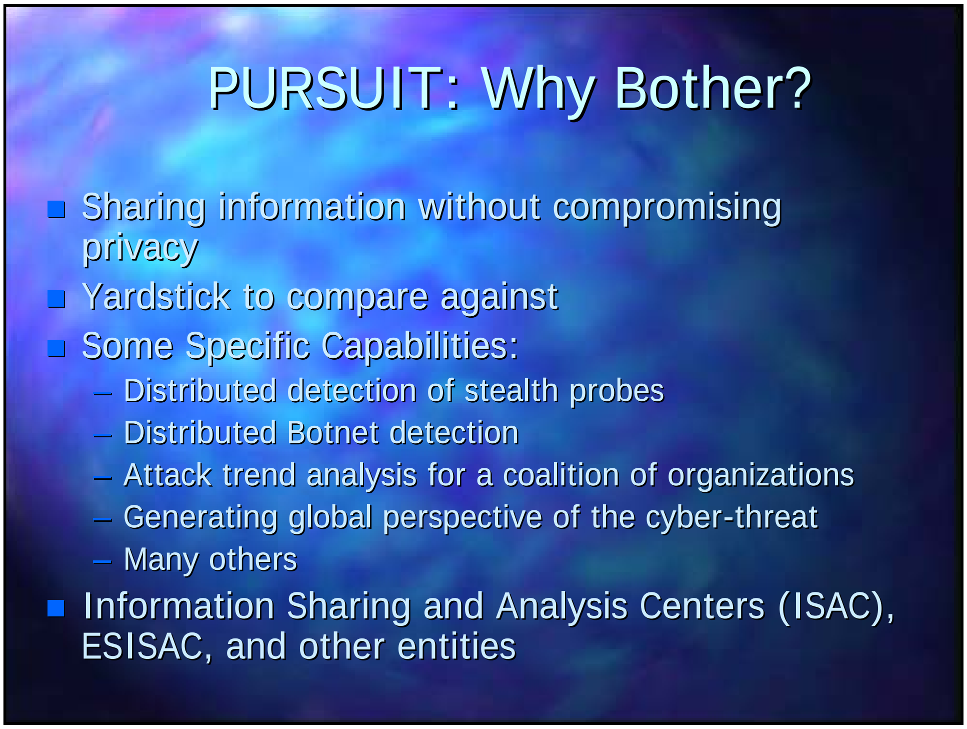
Observation

- Organizations need the big picture
- Solutions:
  - *Share data*: Privacy concerns (e.g. packet content, destination IP) prevent sharing data.
  - *Share data patterns not the data*: Make sure that the privacy of the source data is not compromised
- Develop technology for privacy-preserving data analysis needed for network threat management



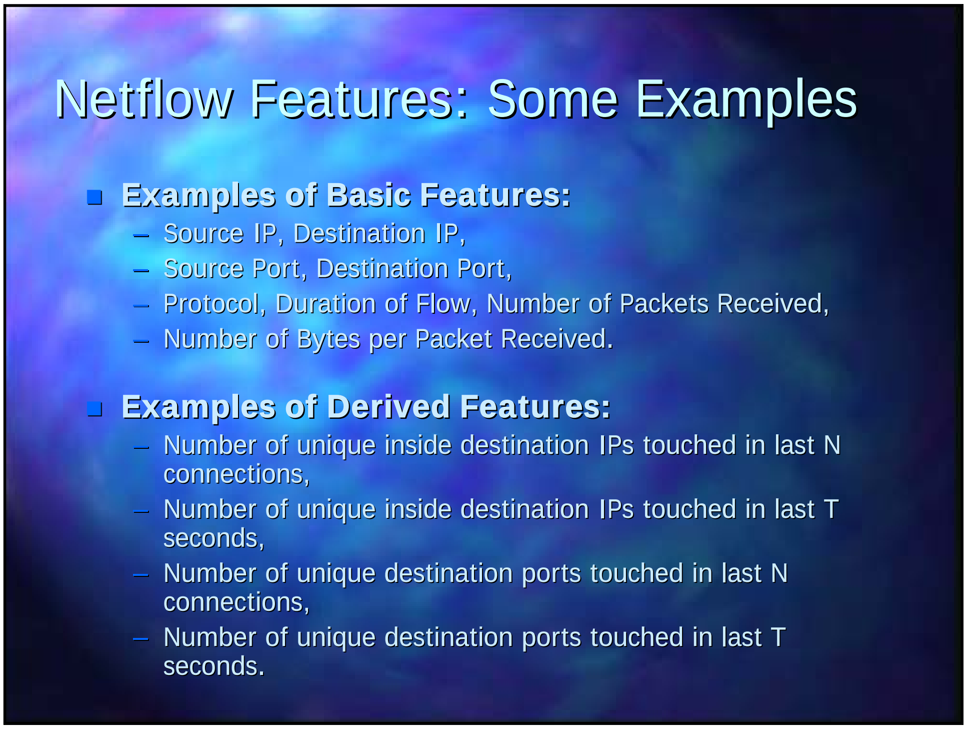
PURSUIT: What Is It?

- PURSUIT is not a sensor; it is a glue to hook up sensors
- A distributed platform independent middleware
  - Connecting your network existing threat detection systems
  - Powered by privacy preserving distributed data mining (PPDM) technology
  - Collaborative collection of digital evidence and archival
  - PURSUIT web services



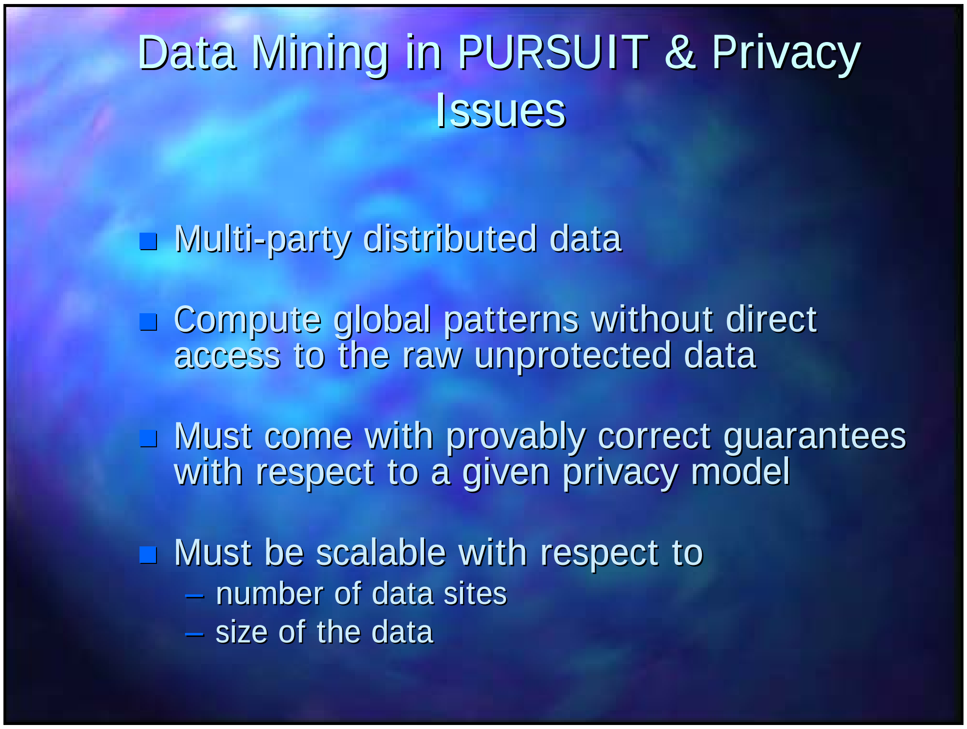
PURSUIT: Why Bother?

- Sharing information without compromising privacy
- Yardstick to compare against
- Some Specific Capabilities:
  - Distributed detection of stealth probes
  - Distributed Botnet detection
  - Attack trend analysis for a coalition of organizations
  - Generating global perspective of the cyber-threat
  - Many others
- Information Sharing and Analysis Centers (ISAC), ESISAC, and other entities



Netflow Features: Some Examples

- **Examples of Basic Features:**
  - Source IP, Destination IP,
  - Source Port, Destination Port,
  - Protocol, Duration of Flow, Number of Packets Received,
  - Number of Bytes per Packet Received.
- **Examples of Derived Features:**
  - Number of unique inside destination IPs touched in last N connections,
  - Number of unique inside destination IPs touched in last T seconds,
  - Number of unique destination ports touched in last N connections,
  - Number of unique destination ports touched in last T seconds.



Data Mining in PURSUIT & Privacy Issues

- Multi-party distributed data
- Compute global patterns without direct access to the raw unprotected data
- Must come with provably correct guarantees with respect to a given privacy model
- Must be scalable with respect to
  - number of data sites
  - size of the data

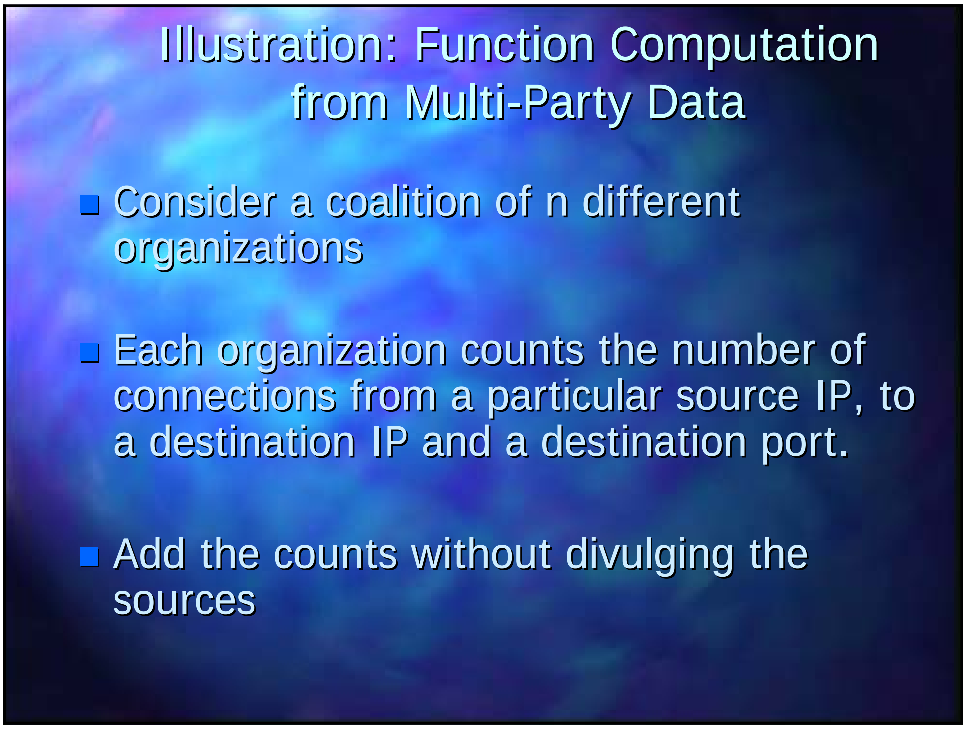


Illustration: Function Computation from Multi-Party Data

- Consider a coalition of n different organizations
- Each organization counts the number of connections from a particular source IP, to a destination IP and a destination port.
- Add the counts without divulging the sources

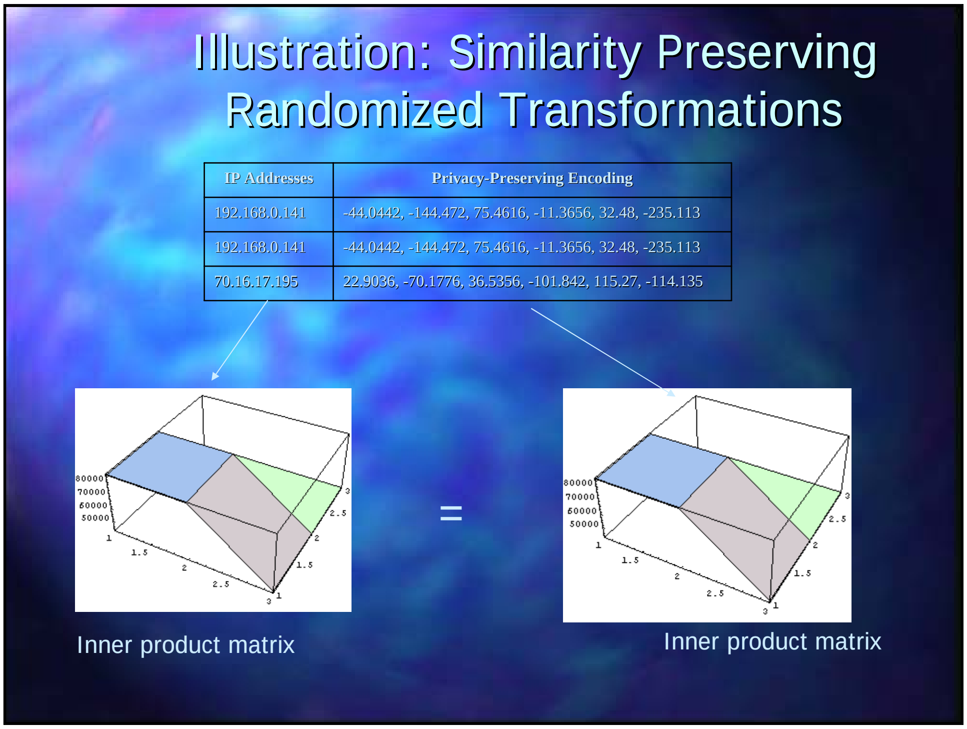
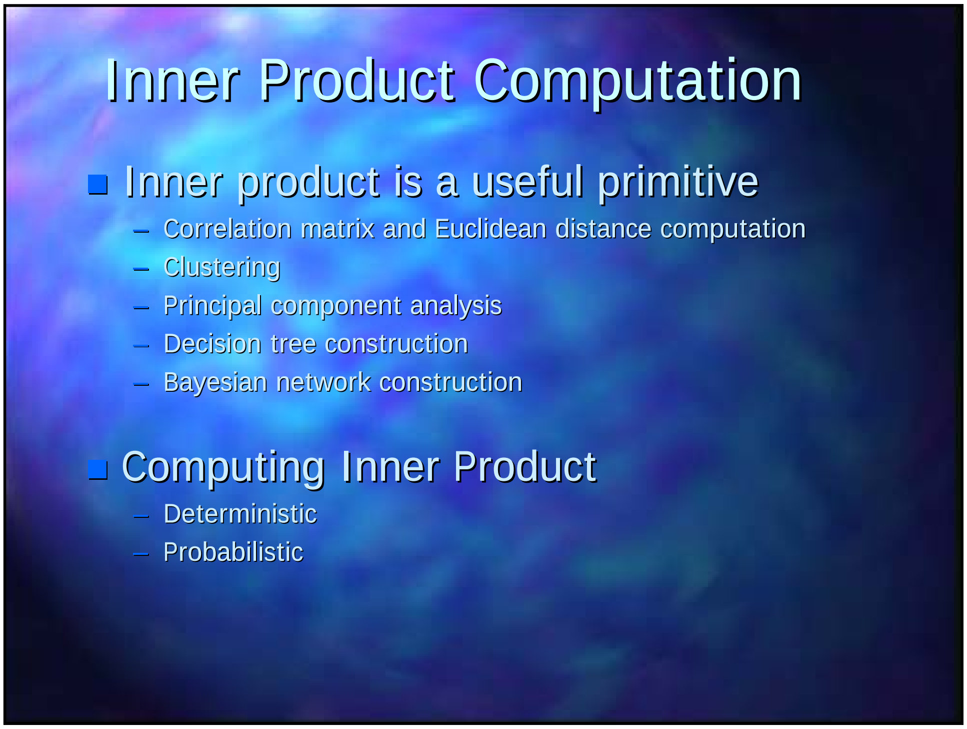


Illustration: Similarity Preserving Randomized Transformations

IP Addresses	Privacy-Preserving Encoding
192.168.0.141	-44.0442, -144.472, 75.4616, -11.3656, 32.48, -235.113
192.168.0.141	-44.0442, -144.472, 75.4616, -11.3656, 32.48, -235.113
70.16.17.195	22.9036, -70.1776, 36.5356, -101.842, 115.27, -114.135

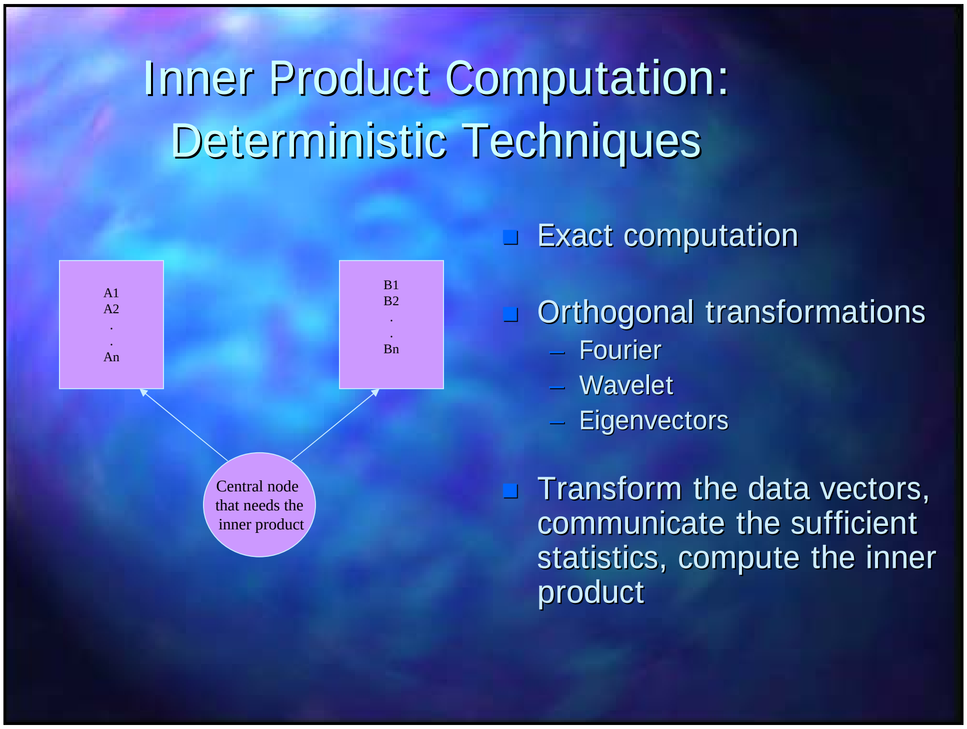
Inner product matrix

Inner product matrix



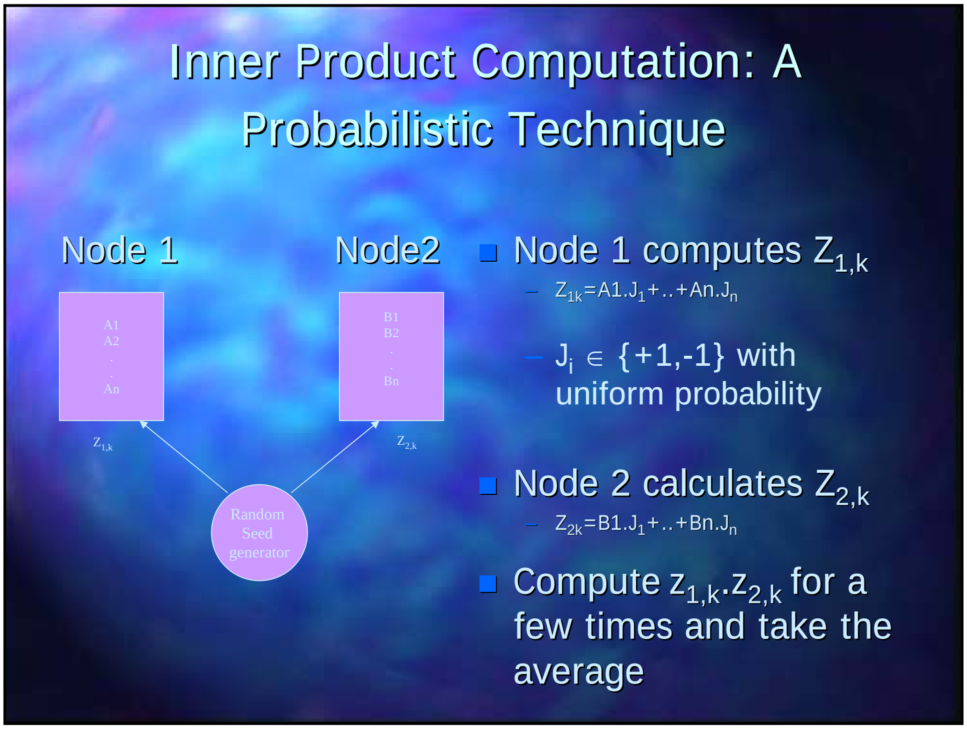
Inner Product Computation

- Inner product is a useful primitive
  - Correlation matrix and Euclidean distance computation
  - Clustering
  - Principal component analysis
  - Decision tree construction
  - Bayesian network construction
- Computing Inner Product
  - Deterministic
  - Probabilistic



Inner Product Computation: Deterministic Techniques

- Exact computation
- Orthogonal transformations
  - Fourier
  - Wavelet
  - Eigenvectors
- Transform the data vectors, communicate the sufficient statistics, compute the inner product



Inner Product Computation: A Probabilistic Technique

Node 1

A1
A2
.
.
An

$Z_{1,k}$

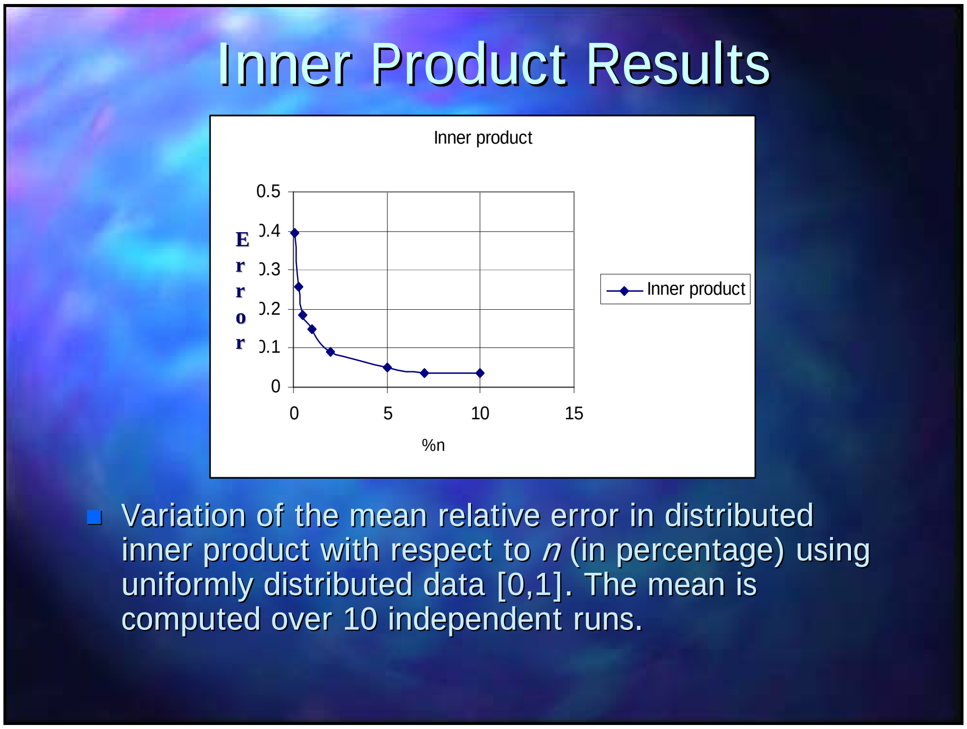
Node2

B1
B2
.
.
Bn

$Z_{2,k}$

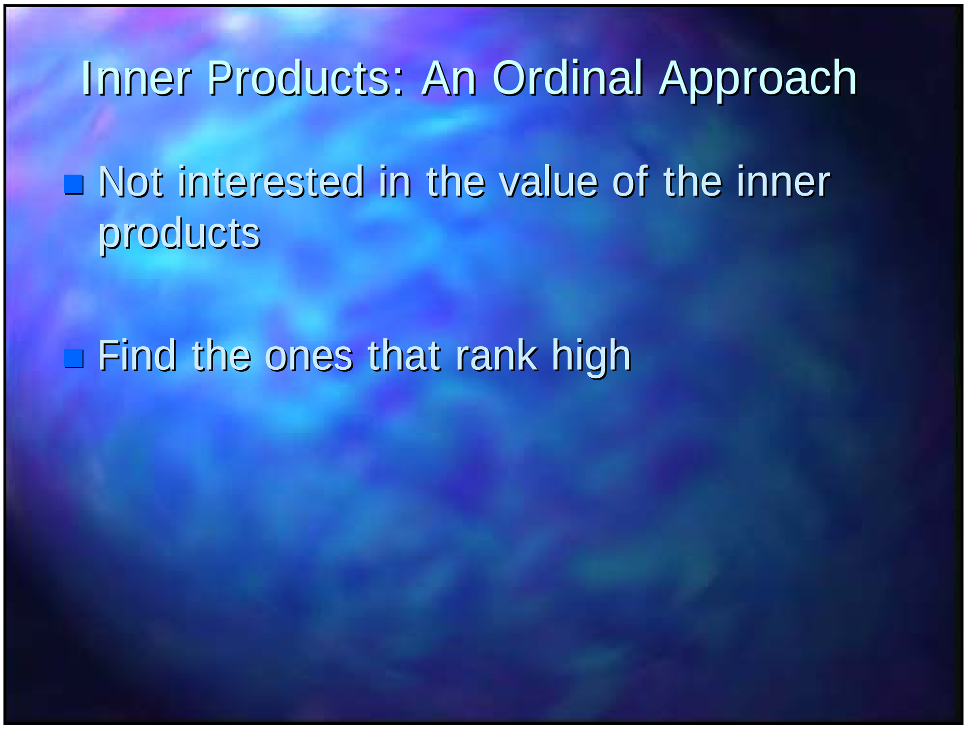
Random Seed generator

- Node 1 computes $Z_{1,k}$
  - Z_{1k}=A1.J_1+..+An.J_n
  - $J_i \in \{+1,-1\}$ with uniform probability
- Node 2 calculates $Z_{2,k}$
  - Z_{2k}=B1.J_1+..+Bn.J_n
- Compute $z_{1,k}.z_{2,k}$ for a few times and take the average



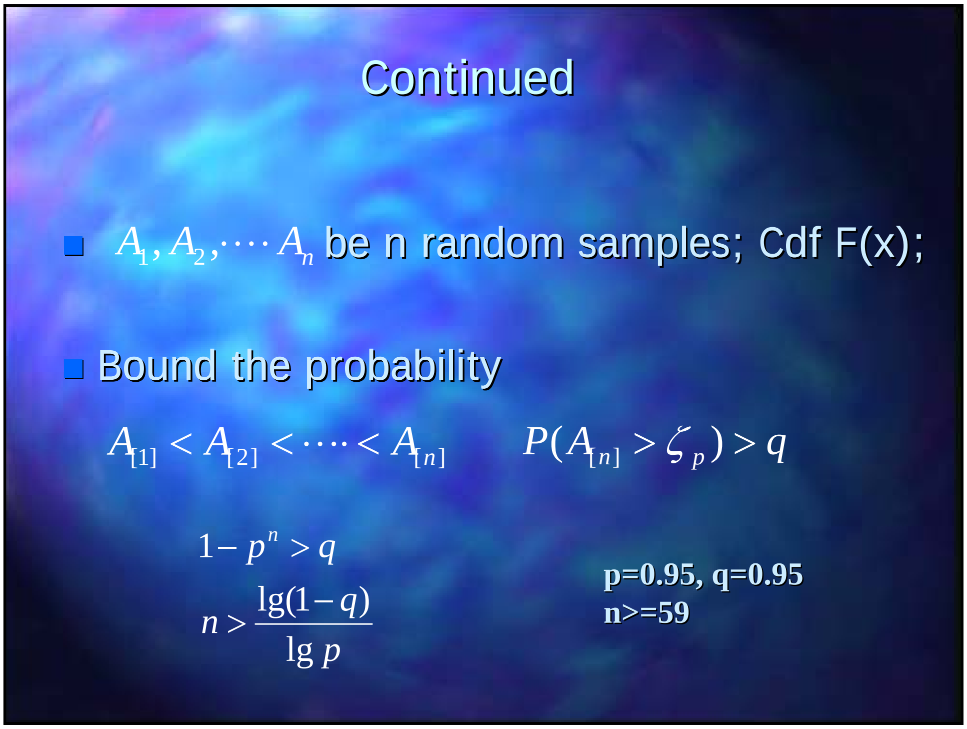
Inner Product Results

- Variation of the mean relative error in distributed inner product with respect to *n* (in percentage) using uniformly distributed data [0,1]. The mean is computed over 10 independent runs.



Inner Products: An Ordinal Approach

- Not interested in the value of the inner products
- Find the ones that rank high



Continued

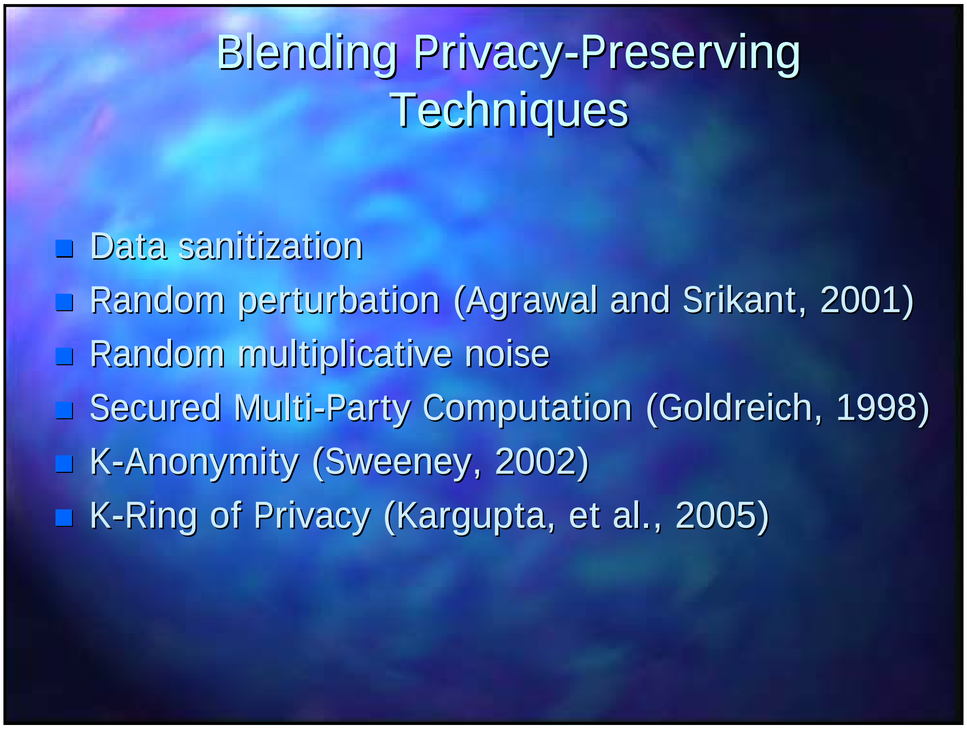
- $A_1, A_2, \cdots A_n$ be n random samples; Cdf F(x);
- Bound the probability

$$A_{[1]} < A_{[2]} < \cdots < A_{[n]} \qquad P(A_{[n]} > \zeta_p) > q$$

$$1 - p^n > q$$

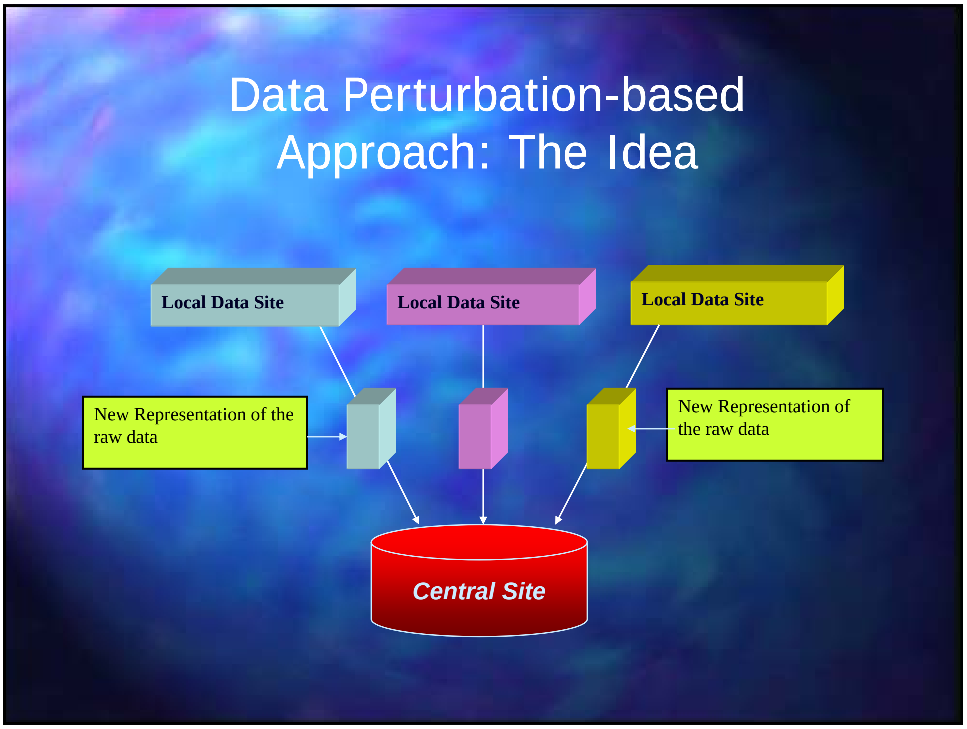
$$n > \frac{\lg(1-q)}{\lg p}$$

p=0.95, q=0.95
n>=59



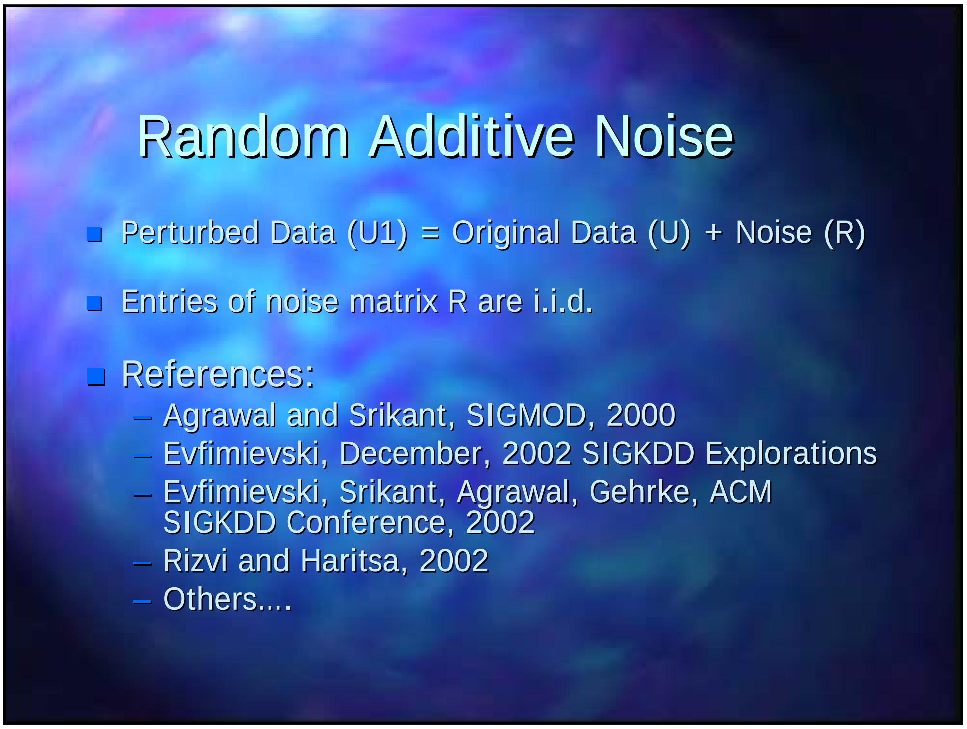
Blending Privacy-Preserving Techniques

- Data sanitization
- Random perturbation (Agrawal and Srikant, 2001)
- Random multiplicative noise
- Secured Multi-Party Computation (Goldreich, 1998)
- K-Anonymity (Sweeney, 2002)
- K-Ring of Privacy (Kargupta, et al., 2005)



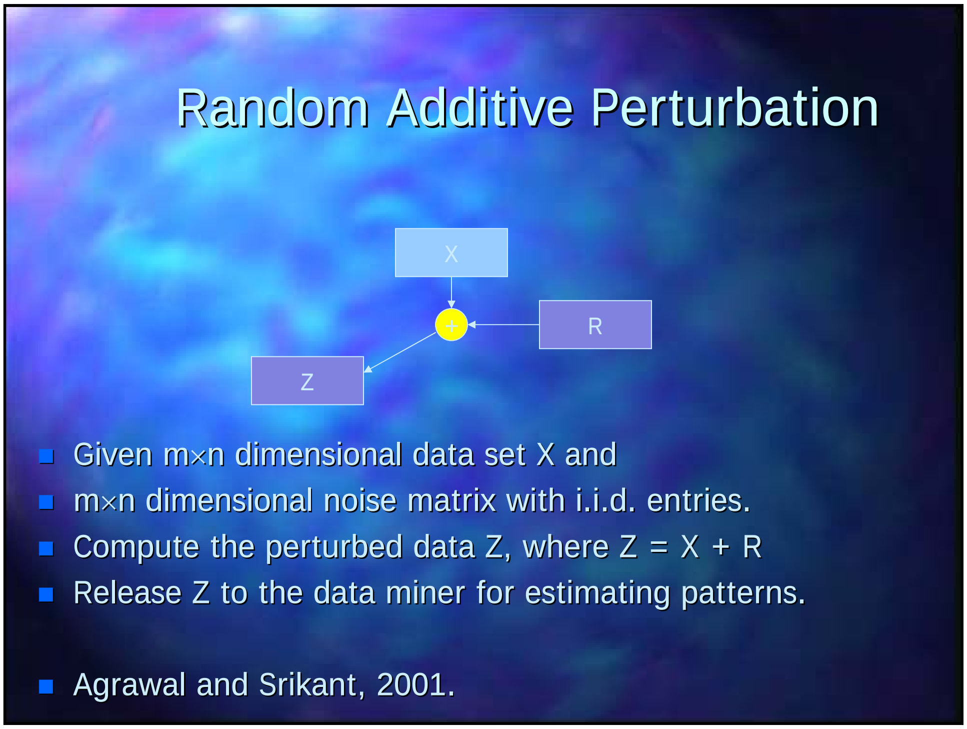
Data Perturbation-based Approach: The Idea

Local Data Site
Local Data Site
Local Data Site
New Representation of the raw data
New Representation of the raw data
Central Site



Random Additive Noise

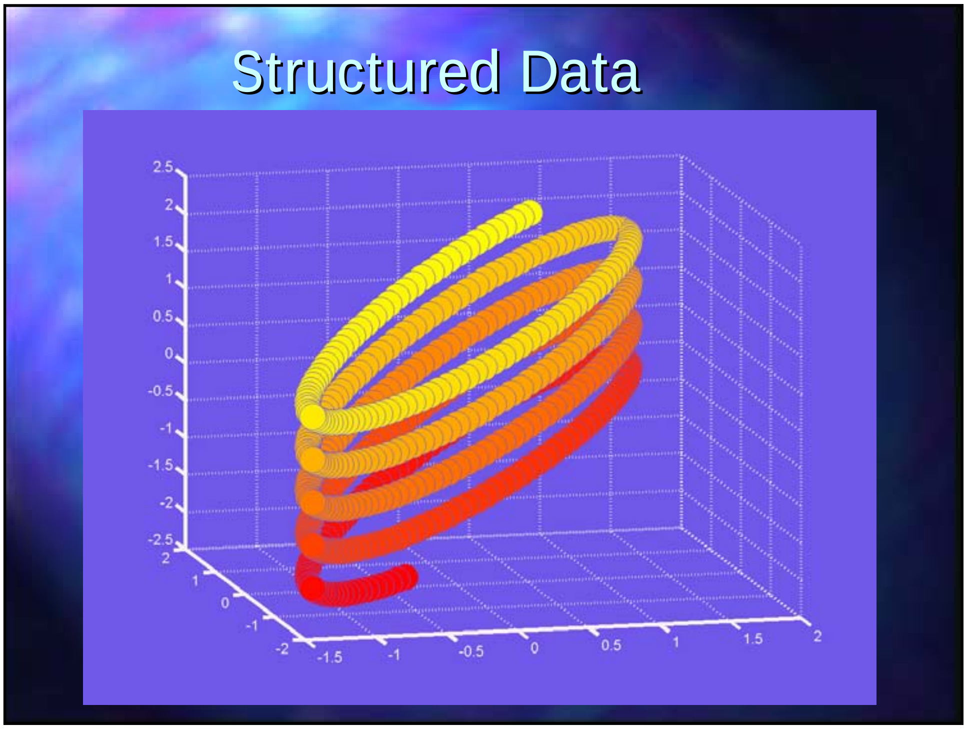
- Perturbed Data (U1) = Original Data (U) + Noise (R)
- Entries of noise matrix R are i.i.d.
- References:
  - Agrawal and Srikant, SIGMOD, 2000
  - Evfimievski, December, 2002 SIGKDD Explorations
  - Evfimievski, Srikant, Agrawal, Gehrke, ACM SIGKDD Conference, 2002
  - Rizvi and Haritsa, 2002
  - Others....



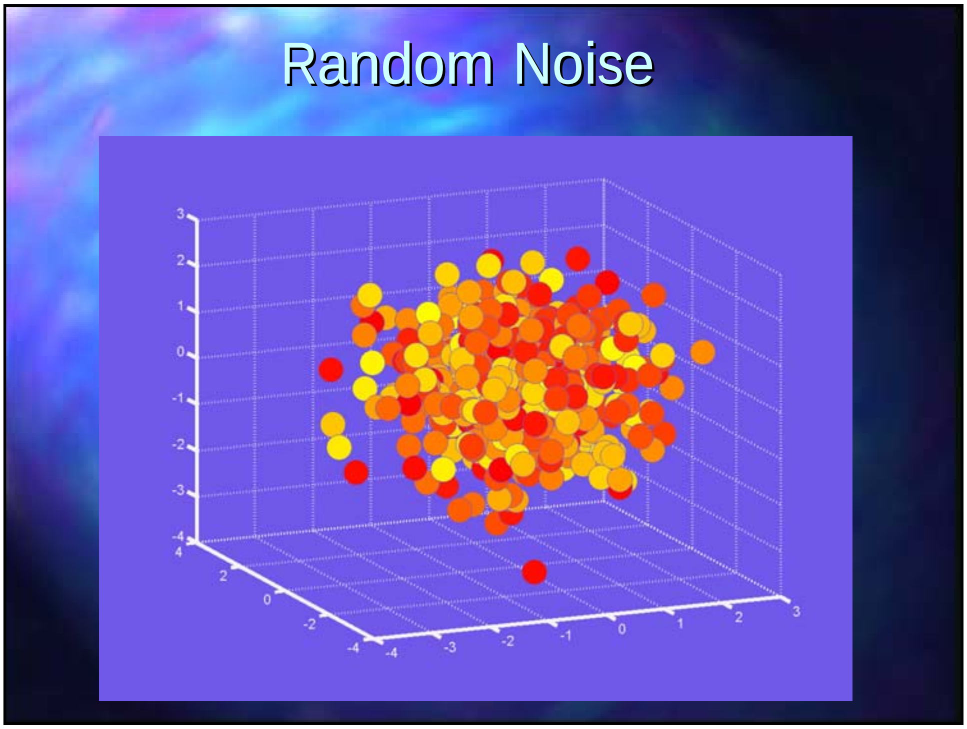
Random Additive Perturbation

- Given m×n dimensional data set X and
- m×n dimensional noise matrix with i.i.d. entries.
- Compute the perturbed data Z, where Z = X + R
- Release Z to the data miner for estimating patterns.

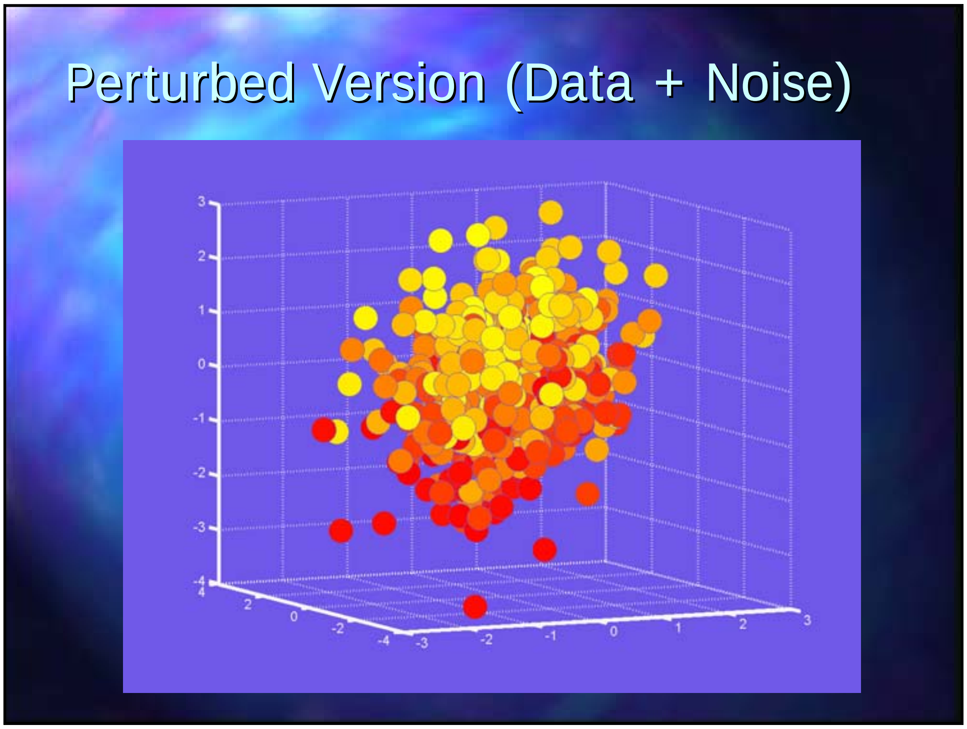
- Agrawal and Srikant, 2001.



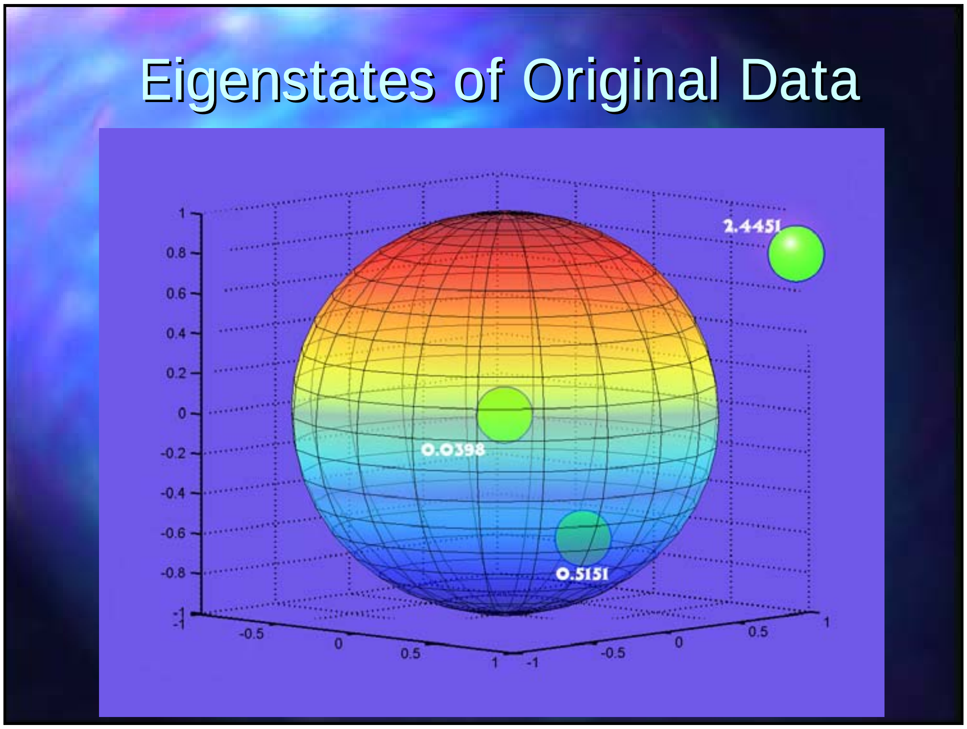
Structured Data



Random Noise

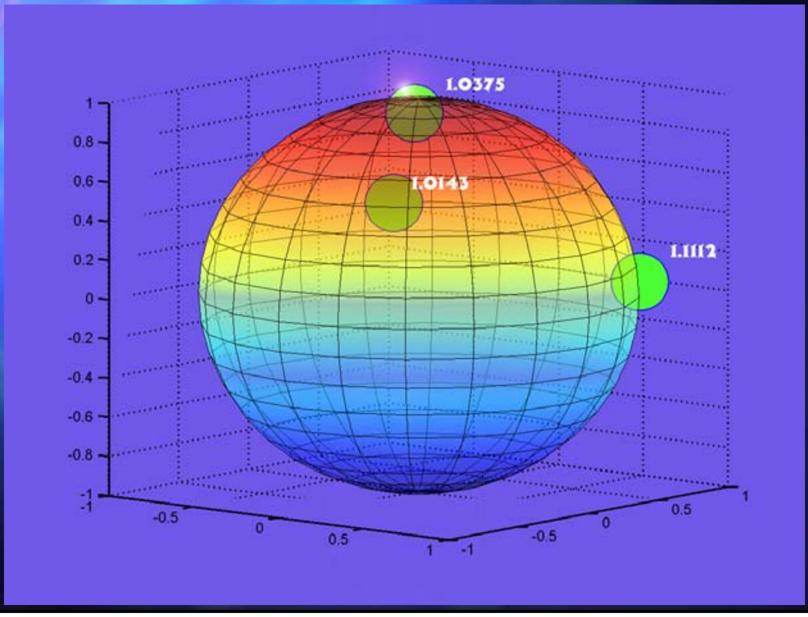


Perturbed Version (Data + Noise)



Eigenstates of Original Data

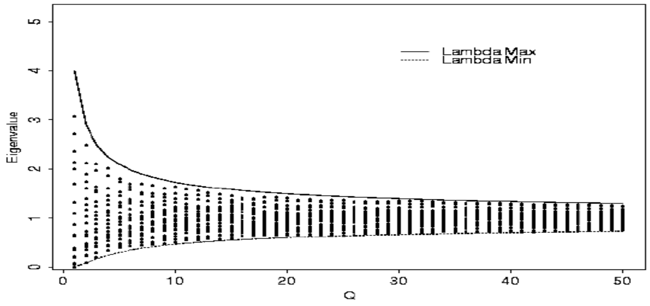
Eigenstates of the Random Noise



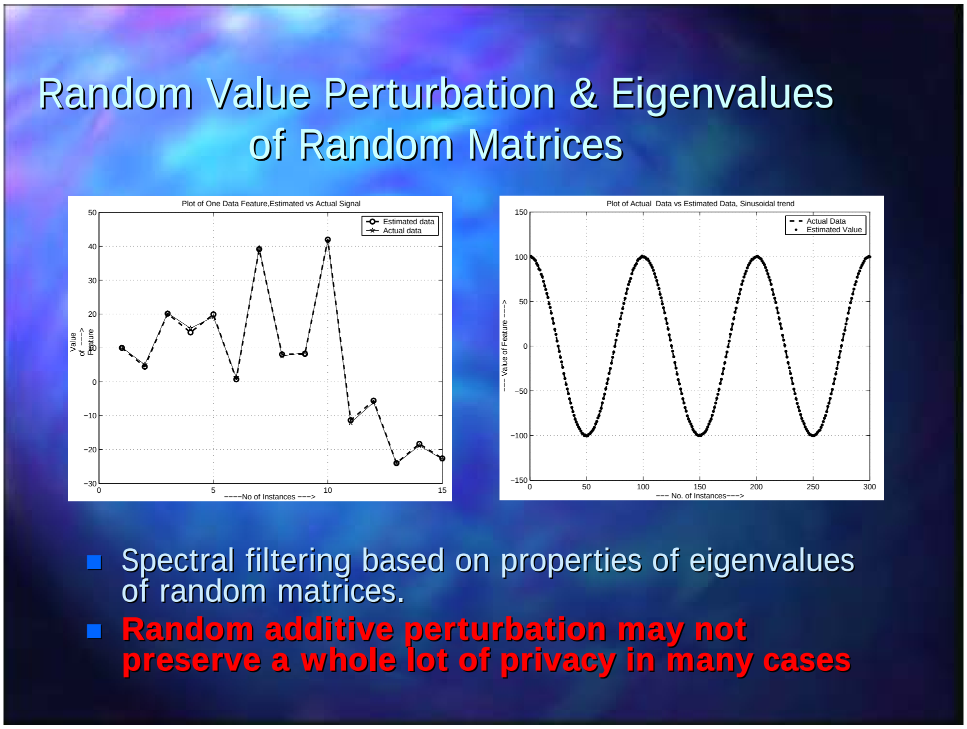
Eigenvalues of Random Matrices

Bounds of the eigenvalues:

$$\lambda_{\min} = \sigma^2(1 - 1/\sqrt{Q})^2.$$
$$\lambda_{\max} = \sigma^2(1 + 1/\sqrt{Q})^2.$$

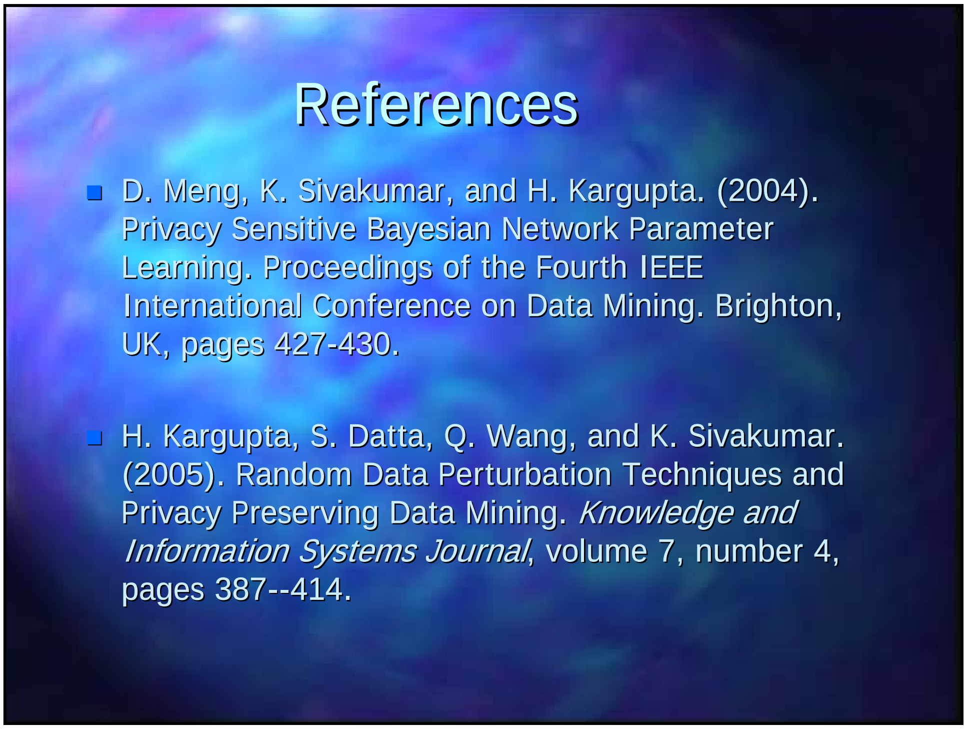


Q=number of rows/number of columns.
σ^2 = variance of entries in the noise matrix.



Random Value Perturbation & Eigenvalues of Random Matrices

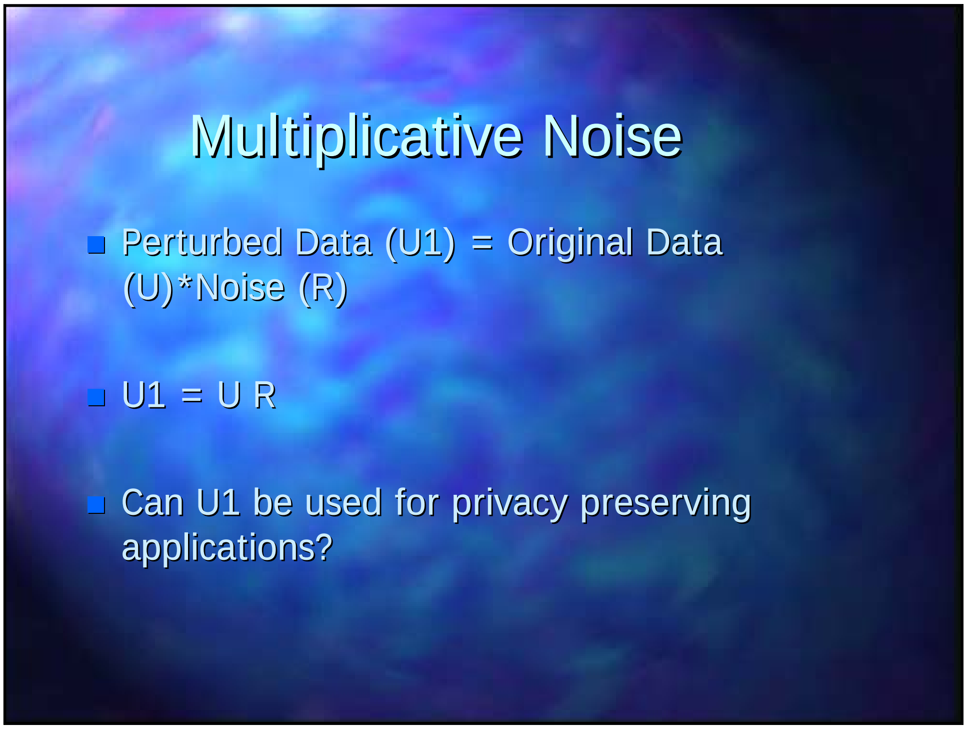
- Spectral filtering based on properties of eigenvalues of random matrices.
- **Random additive perturbation may not preserve a whole lot of privacy in many cases**



References

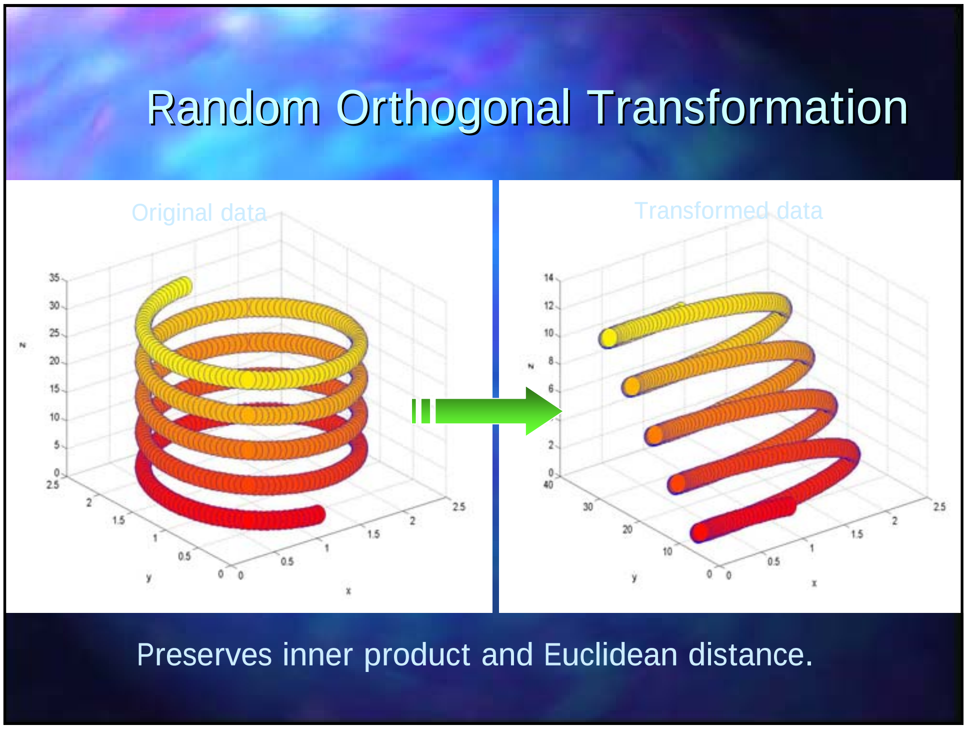
- D. Meng, K. Sivakumar, and H. Kargupta. (2004). Privacy Sensitive Bayesian Network Parameter Learning. Proceedings of the Fourth IEEE International Conference on Data Mining. Brighton, UK, pages 427-430.

- H. Kargupta, S. Datta, Q. Wang, and K. Sivakumar. (2005). Random Data Perturbation Techniques and Privacy Preserving Data Mining. *Knowledge and Information Systems Journal*, volume 7, number 4, pages 387--414.



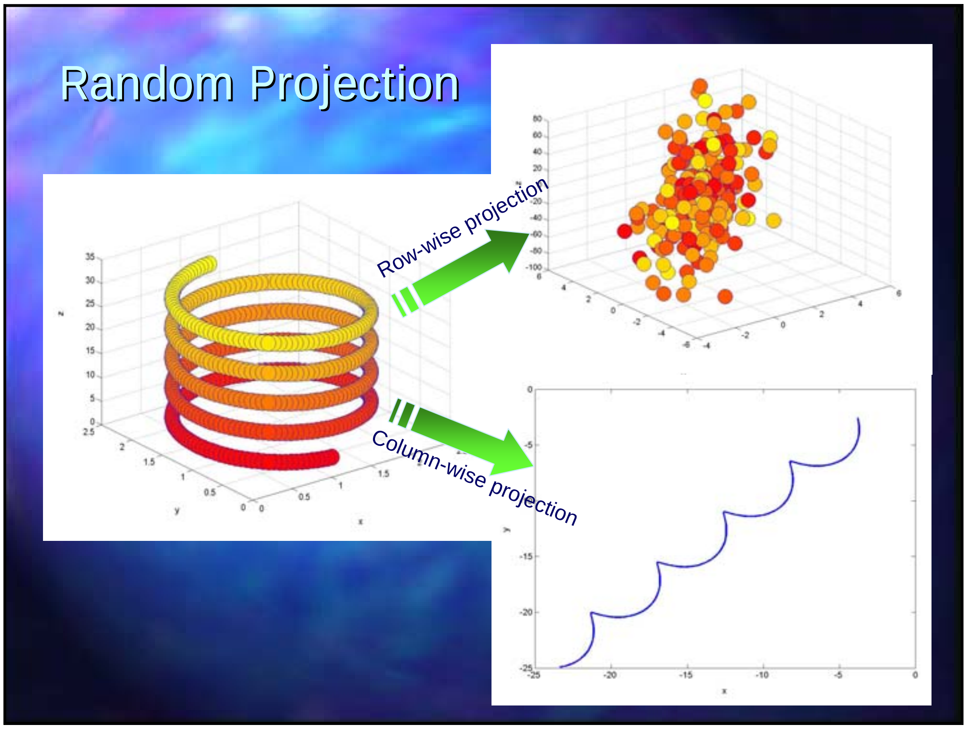
Multiplicative Noise

- Perturbed Data (U1) = Original Data (U)*Noise (R)
- U1 = U R
- Can U1 be used for privacy preserving applications?

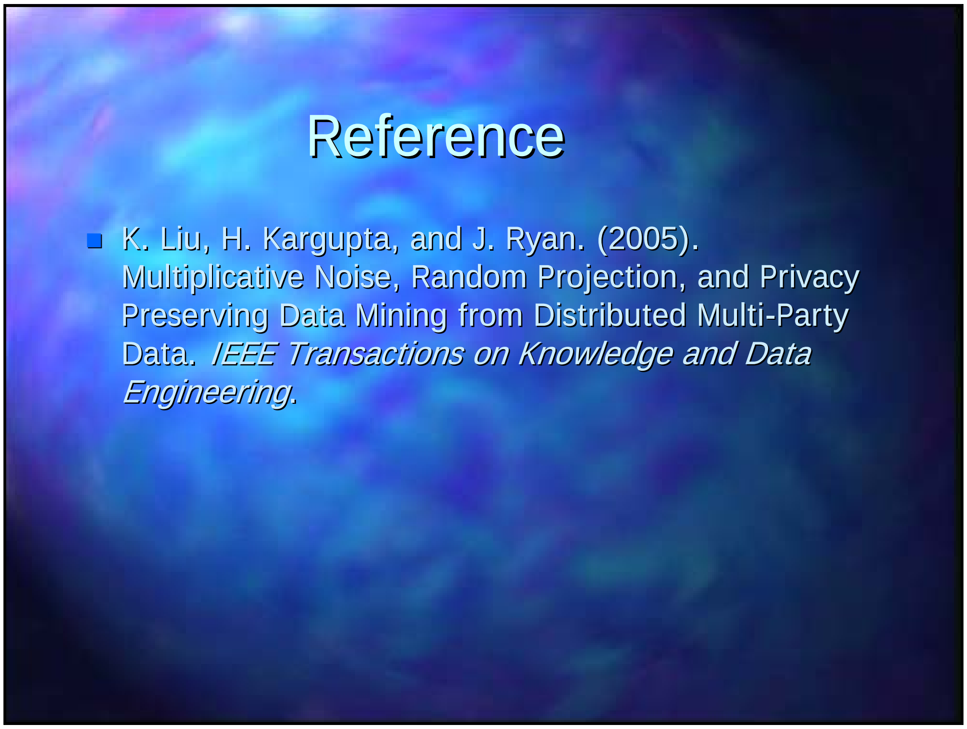


Random Orthogonal Transformation

Preserves inner product and Euclidean distance.

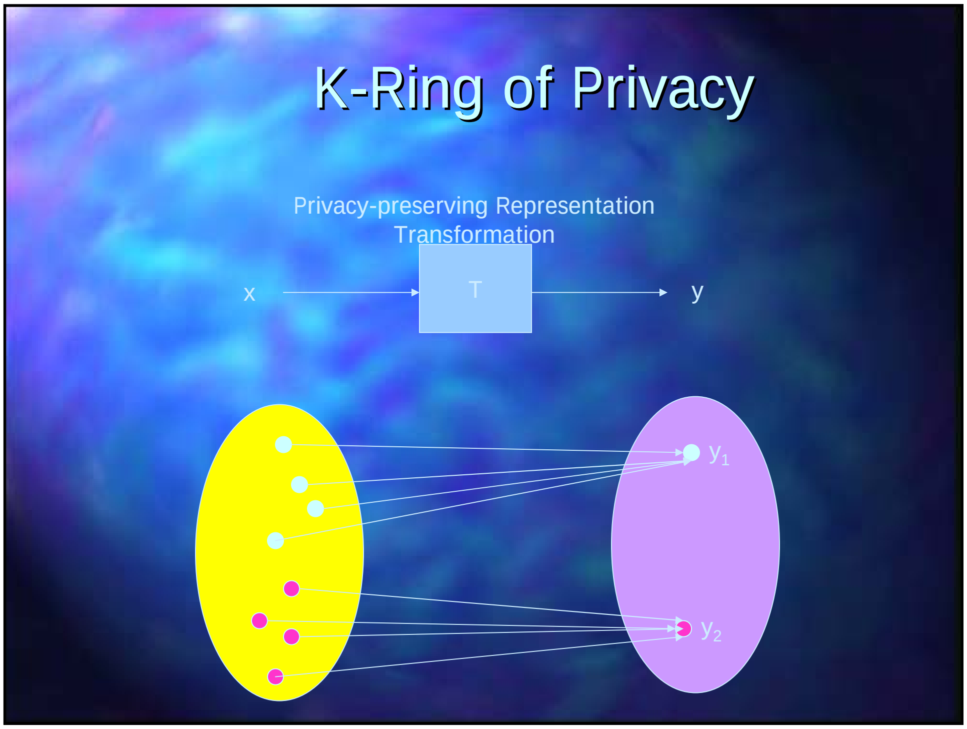


Random Projection



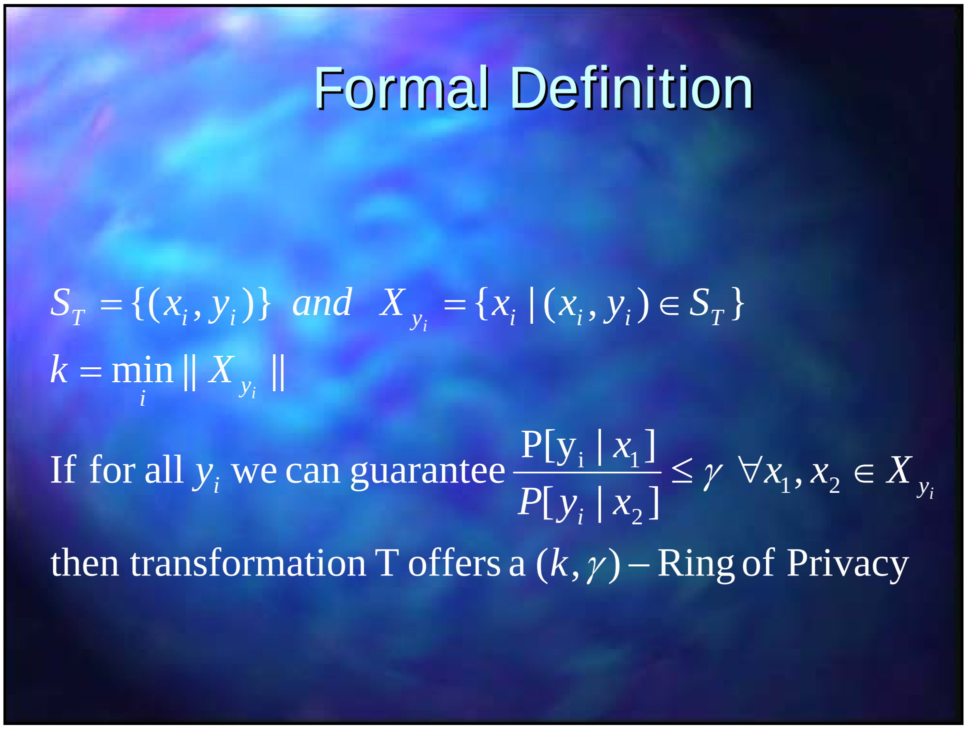
Reference

- K. Liu, H. Kargupta, and J. Ryan. (2005). Multiplicative Noise, Random Projection, and Privacy Preserving Data Mining from Distributed Multi-Party Data. *IEEE Transactions on Knowledge and Data Engineering.*



K-Ring of Privacy

Privacy-preserving Representation Transformation



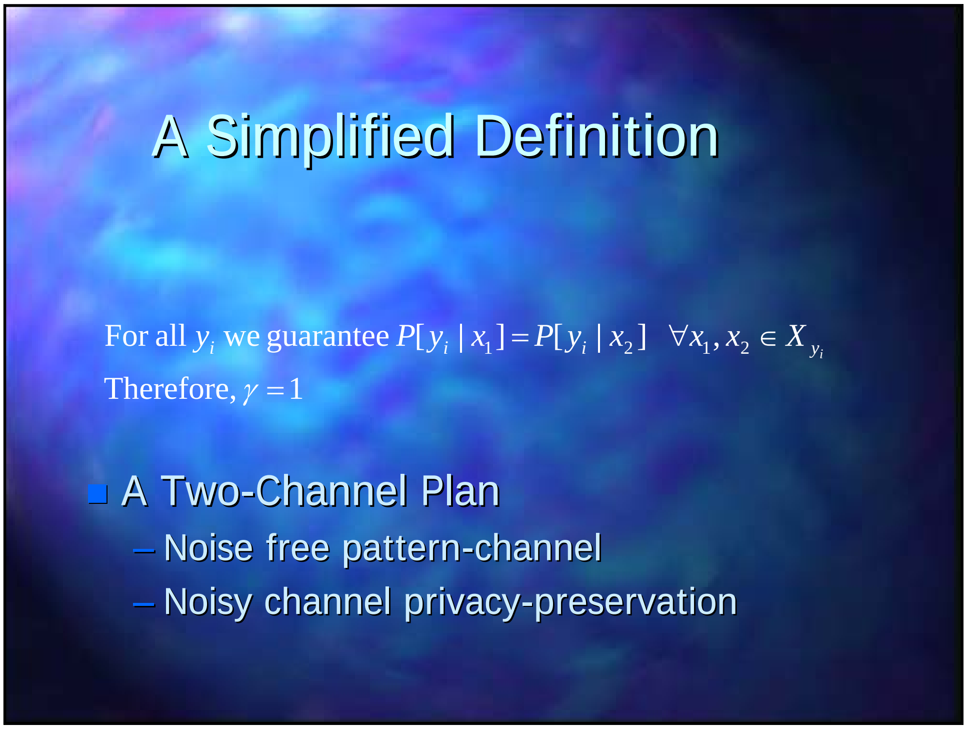
Formal Definition

$$S_T = \{(x_i, y_i)\} \quad \textit{and} \quad X_{y_i} = \{x_i \mid (x_i, y_i) \in S_T\}$$

$$k = \min_i \| X_{y_i} \|$$

$$\text{If for all } y_i \text{ we can guarantee } \frac{\mathrm{P}[\mathrm{y_i} \mid x_1]}{P[y_i \mid x_2]} \le \gamma \ \ \forall x_1, x_2 \in X_{y_i}$$

$$\text{then transformation T offers a } (k, \gamma) - \text{Ring of Privacy}$$

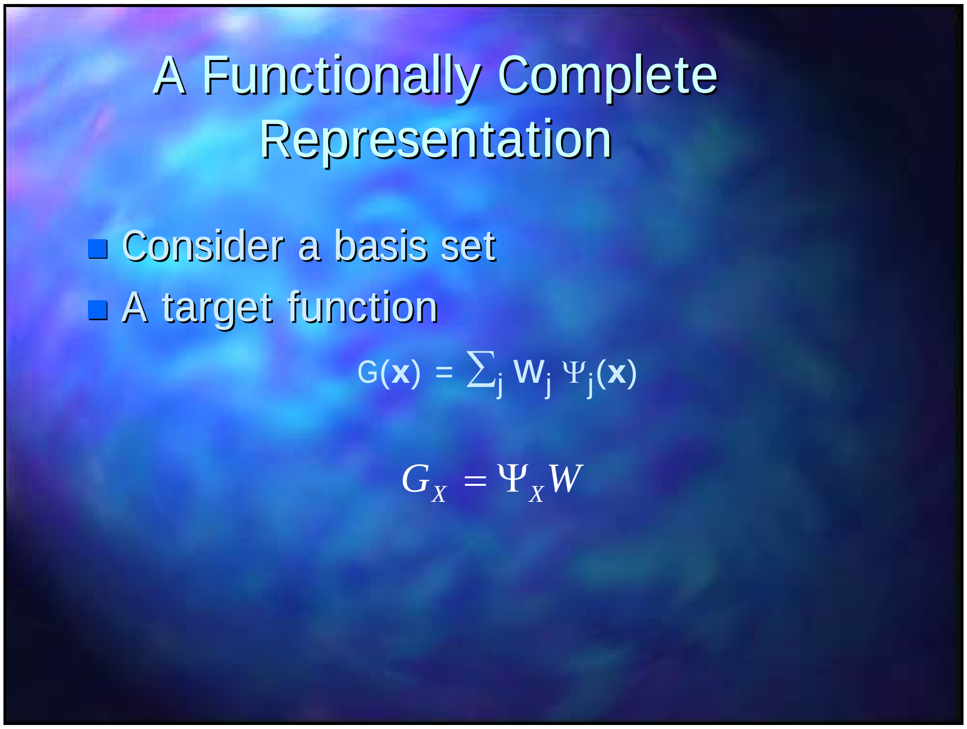


A Simplified Definition

For all y_i we guarantee $P[y_i \mid x_1] = P[y_i \mid x_2] \quad \forall x_1, x_2 \in X_{y_i}$

Therefore, $\gamma = 1$

- A Two-Channel Plan
  - Noise free pattern-channel
  - Noisy channel privacy-preservation

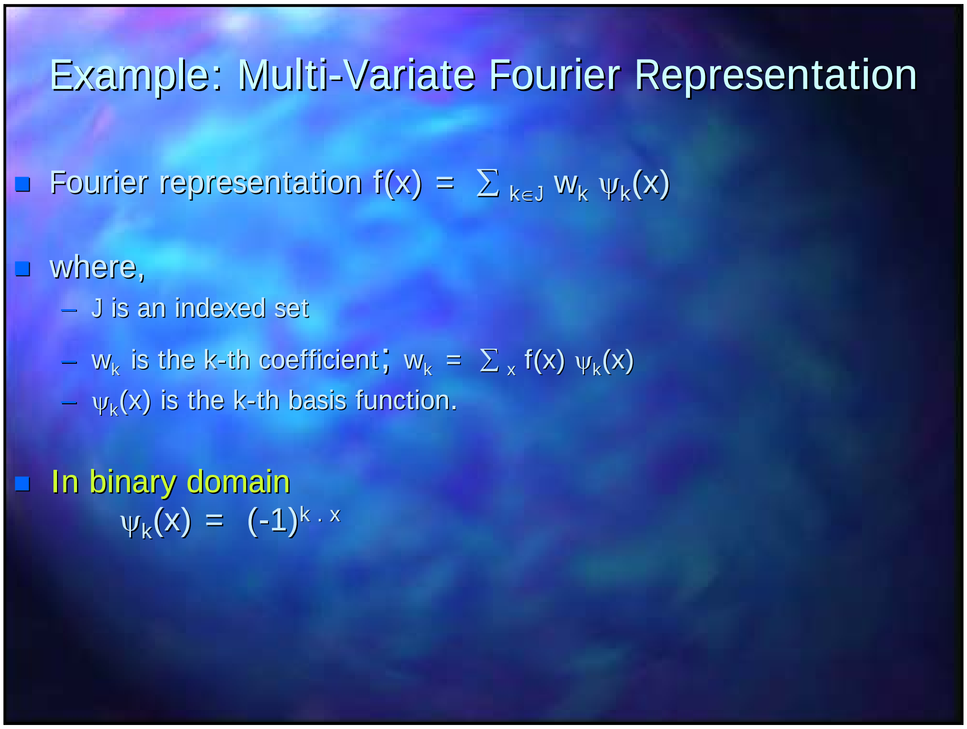


A Functionally Complete Representation

- Consider a basis set
- A target function

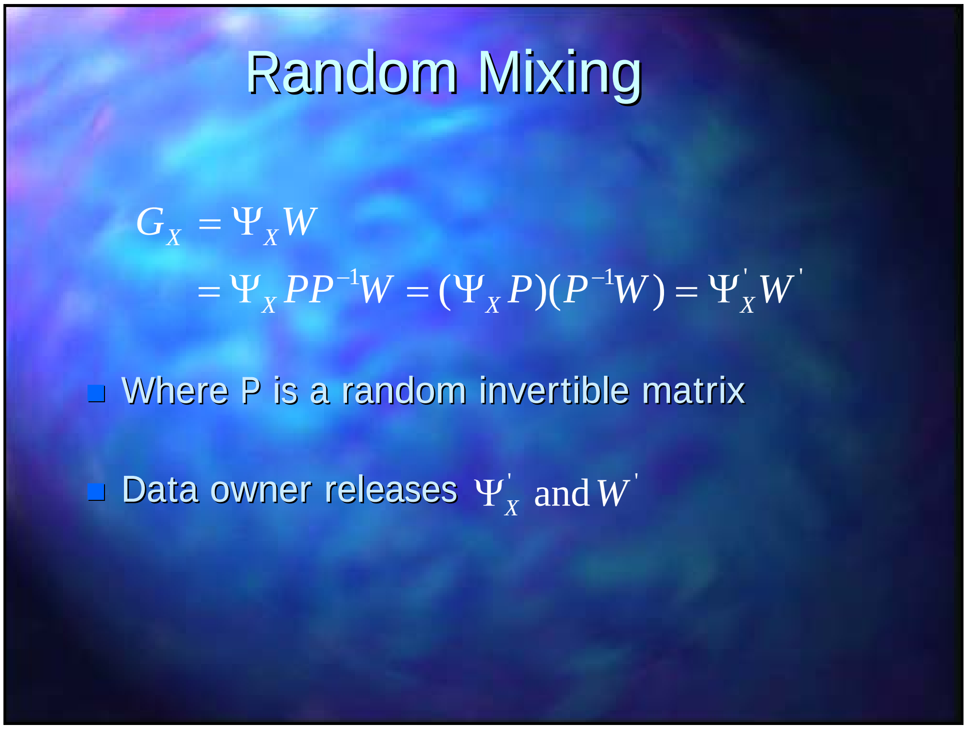
$$G(\mathbf{x}) = \sum_j W_j \Psi_j(\mathbf{x})$$

$$G_X = \Psi_X W$$



Example: Multi-Variate Fourier Representation

- Fourier representation $f(x) = \sum_{k \in J} w_k \psi_k(x)$
- where,
  - J is an indexed set
  - w_k is the k-th coefficient; $w_k = \sum_x f(x) \psi_k(x)$
  - $\psi_k(x)$ is the k-th basis function.
- In binary domain
  $\psi_k(x) = (-1)^{k . x}$



Random Mixing

$$G_X = \Psi_X W$$
$$= \Psi_X P P^{-1} W = (\Psi_X P)(P^{-1} W) = \Psi'_X W'$$

- Where P is a random invertible matrix
- Data owner releases Ψ'_X and W'

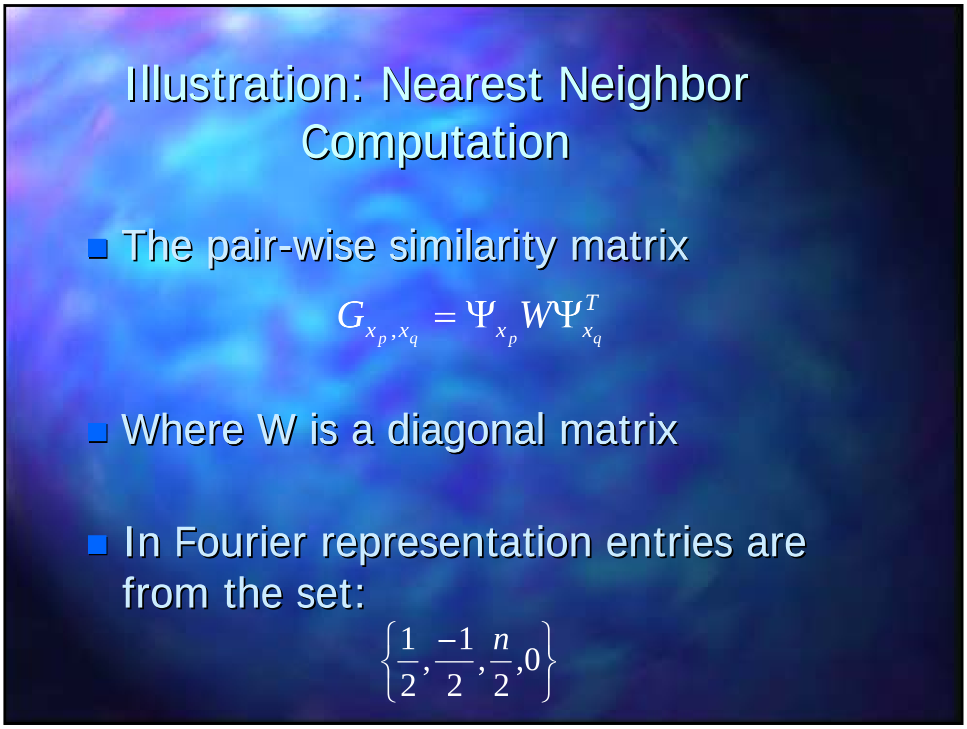


Illustration: Nearest Neighbor Computation

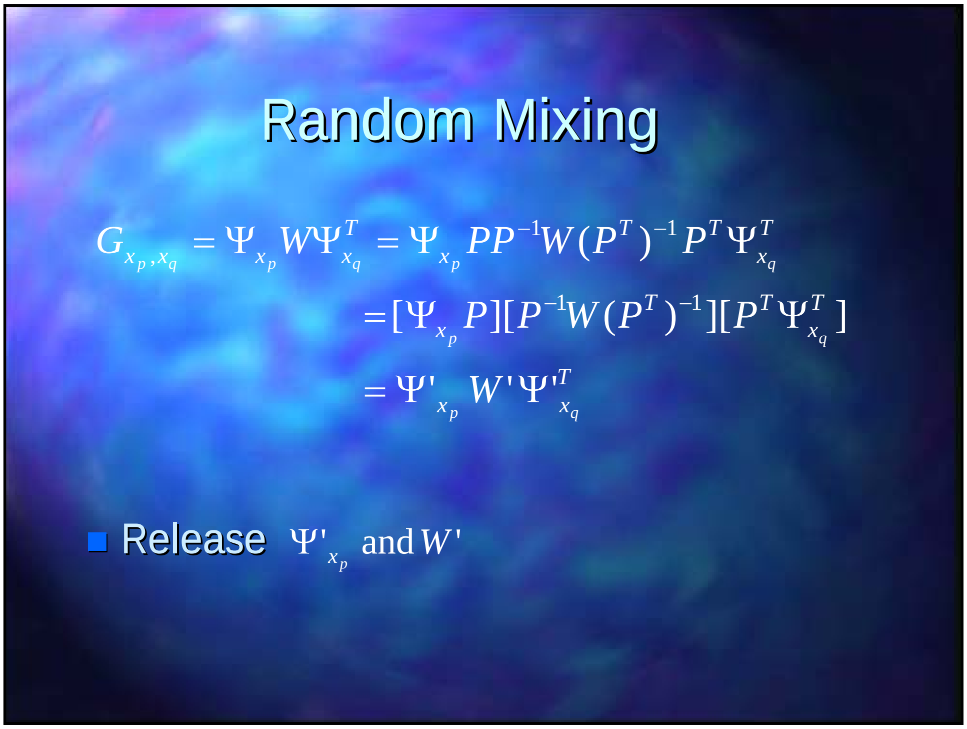
- The pair-wise similarity matrix

$$G_{x_p,x_q} = \Psi_{x_p} W \Psi^T_{x_q}$$

- Where W is a diagonal matrix

- In Fourier representation entries are from the set:

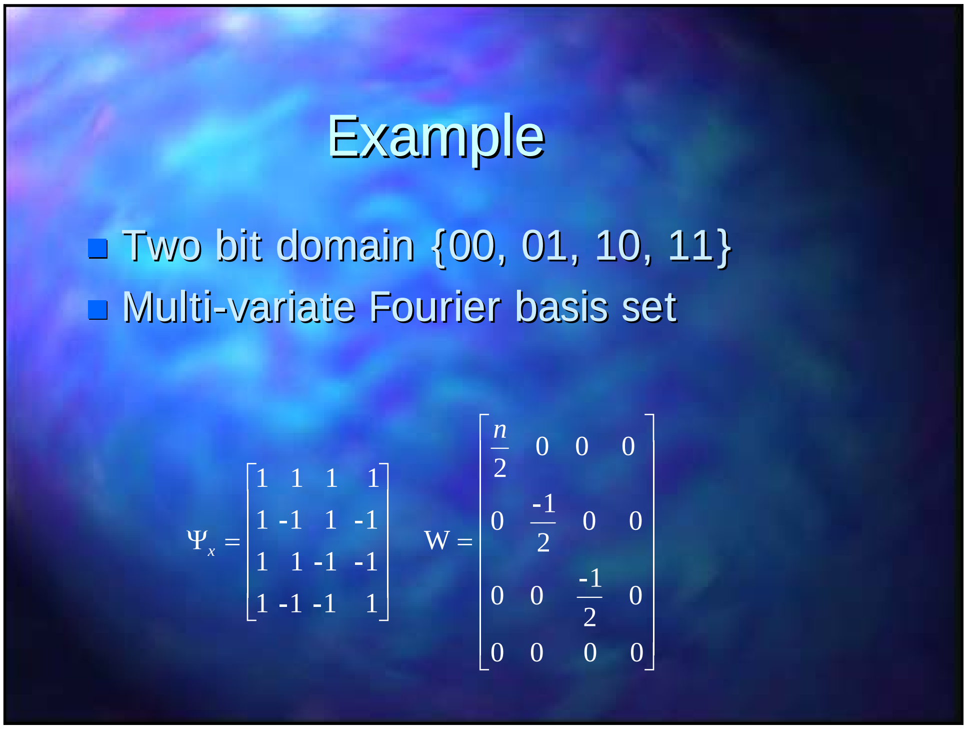
$$\left\{ \frac{1}{2}, \frac{-1}{2}, \frac{n}{2}, 0 \right\}$$



Random Mixing

$$\begin{aligned} G_{x_p,x_q} = \Psi_{x_p} W \Psi^T_{x_q} &= \Psi_{x_p} P P^{-1} W (P^T)^{-1} P^T \Psi^T_{x_q} \\ &= [\Psi_{x_p} P][P^{-1} W (P^T)^{-1}][P^T \Psi^T_{x_q}] \\ &= \Psi'_{x_p} W' \Psi'^T_{x_q} \end{aligned}$$

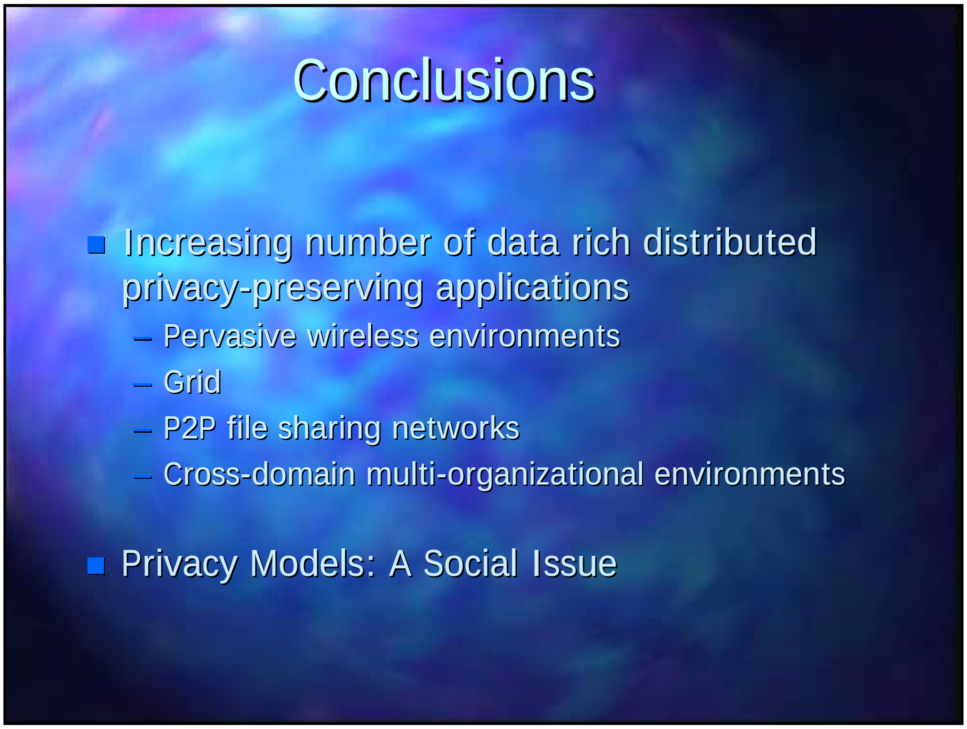
- Release Ψ'_{x_p} and W'



Example

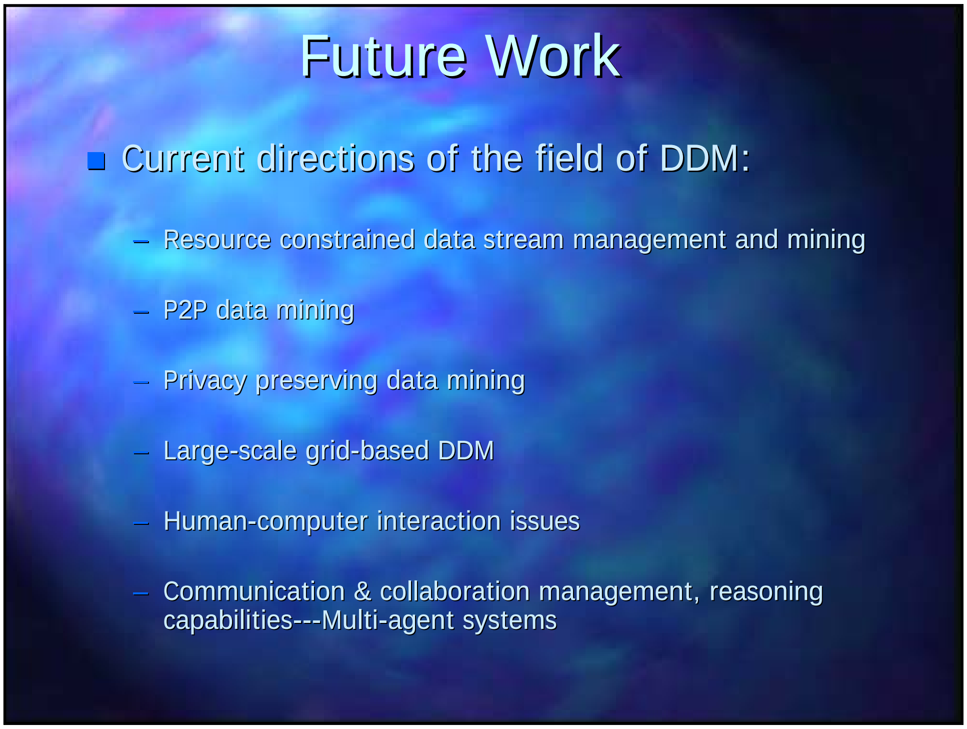
- Two bit domain {00, 01, 10, 11}
- Multi-variate Fourier basis set

$$\Psi_x = \begin{bmatrix} 1 & 1 & 1 & 1 \\ 1 & -1 & 1 & -1 \\ 1 & 1 & -1 & -1 \\ 1 & -1 & -1 & 1 \end{bmatrix} \qquad W = \begin{bmatrix} \frac{n}{2} & 0 & 0 & 0 \\ 0 & \frac{-1}{2} & 0 & 0 \\ 0 & 0 & \frac{-1}{2} & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$



Conclusions

- Increasing number of data rich distributed privacy-preserving applications
  - Pervasive wireless environments
  - Grid
  - P2P file sharing networks
  - Cross-domain multi-organizational environments
- Privacy Models: A Social Issue



Future Work

- Current directions of the field of DDM:
  - Resource constrained data stream management and mining
  - P2P data mining
  - Privacy preserving data mining
  - Large-scale grid-based DDM
  - Human-computer interaction issues
  - Communication & collaboration management, reasoning capabilities---Multi-agent systems