PURDUE UNIVERSITY


# Privacy-Preserving Data Mining

*How do we mine data when we can't even look at it?*

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CERIAS Center for Education and Research in Information Assurance and Security

Indiana Center for Database Systems

## Privacy and Security Constraints

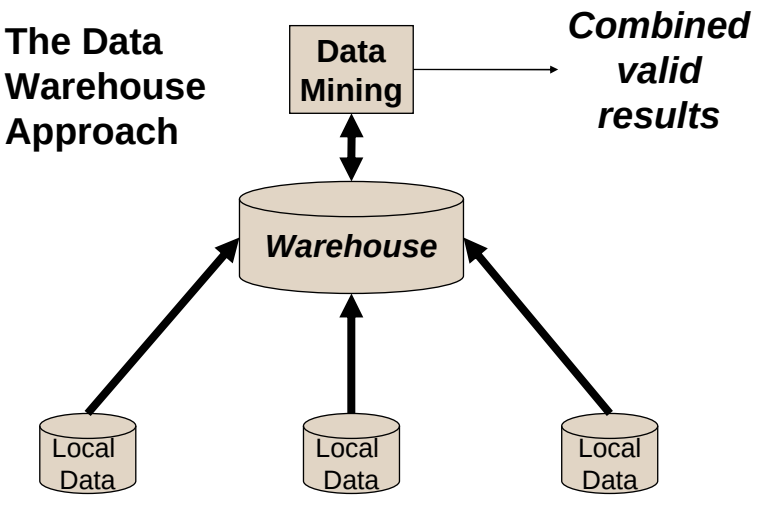
- Individual Privacy
  - Nobody should know more about any entity after the data mining than they did before
  - Approaches: Data Obfuscation, Value swapping
- Organization Privacy
  - Protect knowledge about a collection of entities
    - Individual entity values may be known to all parties
    - Which entities are at which site may be secret

# Privacy constraints don't prevent data mining

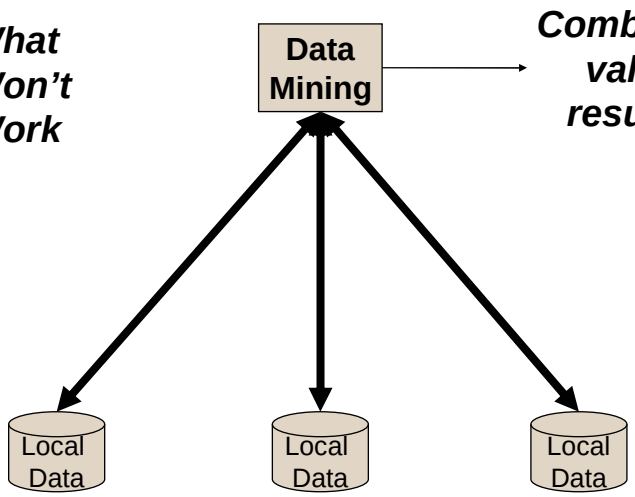
- Goal of data mining is summary results
  - Association rules
  - Classifiers
  - Clusters
- The results alone need not violate privacy
  - Contain no individually identifiable values
  - Reflect overall results, not individual organizations

*The problem is computing the results without access to the data!*

# Distributed Data Mining: The "Standard" Method



# Private Distributed Mining: What is it?

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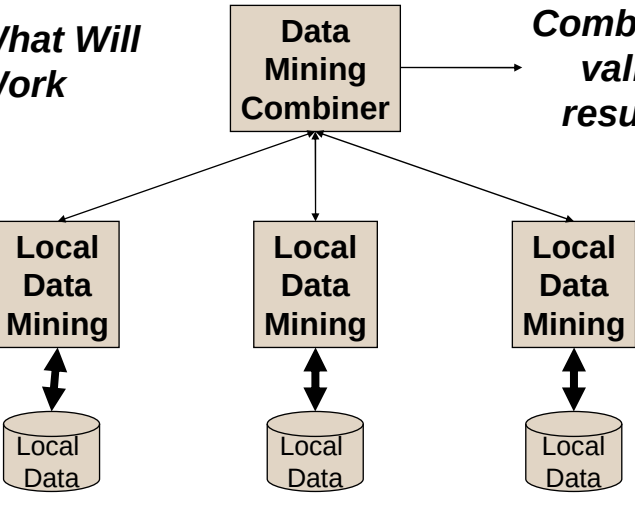
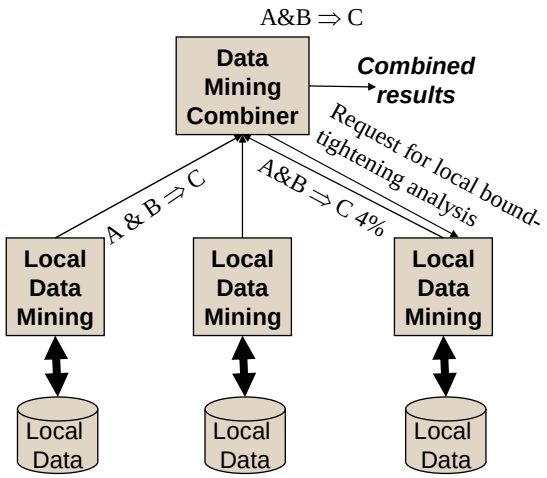


# Example: *Association Rules*

- Assume data is horizontally partitioned
  - Each site has complete information on a set of entities
  - Same attributes at each site
- If goal is to avoid disclosing entities, problem is easy
- Basic idea: Two-Phase Algorithm
  - First phase: Compute candidate rules
    - Frequent globally ⇒ frequent at some site
  - Second phase: Compute frequency of candidates

# Association Rules in Horizontally Partitioned Data



# Privacy-Preserving Data Mining: Who?

- Government / public agencies. Example:
  - The Centers for Disease Control want to identify disease outbreaks
  - Insurance companies have data on disease incidents, seriousness, patient background, etc.
  - But can/should they release this information?
- Industry Collaborations / Trade Groups. Example:
  - An industry trade group may want to identify best practices to help members
  - But some practices are trade secrets
  - How do we provide "commodity" results to all (Manufacturing using chemical supplies from supplier X have high failure rates), while still preserving secrets (manufacturing process Y gives low failure rates)?

# Privacy-Preserving Data Mining: Who?

- Multinational Corporations
  - A company would like to mine its data for globally valid results
  - But national laws may prevent transborder data sharing
- Public use of private data
  - Data mining enables research studies of large populations
  - But these populations are reluctant to release personal information

# Outline

- Privacy and Security Constraints
  - Types: Individual, collection, result limitation
  - Sources: Regulatory, Contractual, Secrecy
- Classes of solutions
  - Data obfuscation
  - Summarization
  - Data separation
- When do we address these issues?

*Break*

# Outline (after the break): Technical Solutions

- Data Obfuscation based techniques
  - Reconstructing distributions for developing classifiers
  - Association rules from modified data
- Data Separation based techniques
  - Overview of Secure Multiparty Computation
  - Secure decision tree construction
  - Secure association rules
  - Secure clustering
- What if the secrets are in the results?

## Individual Privacy: Protect the "record"

- Individual item in database must not be disclosed
- Not necessarily a person
  - Information about a corporation
  - Transaction record
- Disclosure of parts of record may be allowed
  - Individually identifiable information

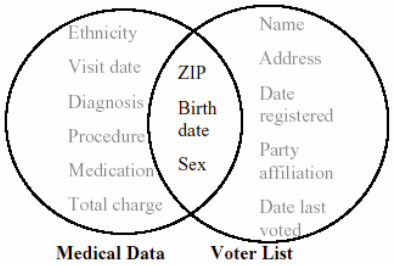
## Individually Identifiable Information

- Data that can't be traced to an individual not viewed as private
  - Remove "identifiers"
- But can we ensure it can't be traced?
  - Candidate Key in non-identifier information
  - Unique values for some individuals

*Data Mining enables such tracing!*

# Re-identifying "anonymous" data (Sweeney '01)

- 37 US states mandate collection of information
- She purchased the voter registration list for Cambridge Massachusetts
  - 54,805 people
- 69% unique on postal code and birth date
- 87% US-wide with all three



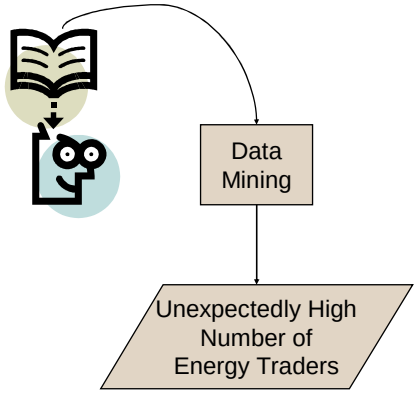

- Solution: *k*-anonymity
  - Any combination of values appears at least *k* times
- Developed systems that guarantee k-anonymity
  - Minimize distortion of results

# Collection Privacy

- Disclosure of individual data may be okay
  - Telephone book
  - De-identified records
- Releasing the whole collection may cause problems
  - Trade secrets – corporate plans
  - Rules that reveal knowledge about the holder of data

# Collection Privacy Example: Corporate Phone Book

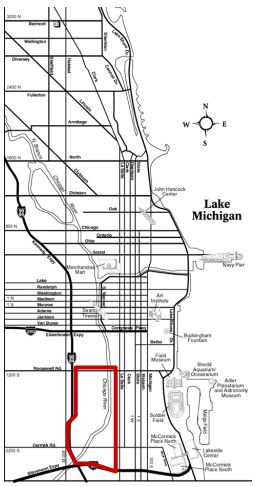
- Telephone Directory discloses how to contact an individual
  - *Intended use*
- Data Mining can find more
  - Relative sizes of departments
  - *Use to predict corporate plans?*
- Possible Solution: Obfuscation
  - Fake entries in phone book
  - *Doesn't prevent intended use*
- Key: Define Intended Use
  - *Not always easy!*




# Restrictions on Results

- Use of Call Records for Fraud Detection vs. Marketing
  - FCC § 222(c)(1) restricted use of individually identifiable information
    *Until overturned by US Appeals Court*
  - 222(d)(2) allows use for fraud detection
- Mortgage Redlining
  - Racial discrimination in home loans prohibited in US
  - Banks drew lines around high risk neighborhoods!!!
  - These were often minority neighborhoods
  - Result: Discrimination (redlining outlawed)

*What about data mining that "singles out" minorities?*



## Sources of Constraints

- Regulatory requirements
- Contractual constraints
  - Posted privacy policy
  - Corporate agreements
- Secrecy concerns
  - Secrets whose release could jeopardize plans
  - Public Relations – “bad press”

## Regulatory Constraints: Privacy Rules

- Primarily national laws
  - European Union
  - US HIPAA rules (www.hipaadvisory.com)
  - Many others: (www.privacyexchange.org)
- Often control transborder use of data
- Focus on intent
  - Limited guidance on implementation

# European Union Data Protection Directives

- Directive 94/46/EC
  - Passed European Parliament 24 October 1995
  - Goal is to ensure free flow of information
    - *Must preserve privacy needs of member states*
  - Effective October 1998
- Effect
  - Provides guidelines for member state legislation
    - Not directly enforceable
  - Forbids sharing data with states that don't protect privacy
    - Non-member state must provide adequate protection,
    - Sharing must be for "allowed use", or
    - Contracts ensure adequate protection
  - US "Safe Harbor" rules provide means of sharing (July 2000)
    - Adequate protection
    - But voluntary compliance
- Enforcement is happening
  - Microsoft under investigation for Passport (May 2002)
  - Already fined by Spanish Authorities (2001)

# EU 95/46/EC: Meeting the Rules

- Personal data is any information that can be traced directly *or indirectly* to a specific person
- Use allowed if:
  - Unambiguous consent given
  - Required to perform contract with subject
  - Legally required
  - Necessary to protect vital interests of subject
  - In the public interest, or
  - Necessary for legitimate interests of processor and doesn't violate privacy
- Some uses specifically proscribed
  - Can't reveal racial/ethnic origin, political/religious beliefs, trade union membership, health/sex life
- Must make data available to subject
  - Allowed to object to such use
  - Must give advance notice / right to refuse direct marketing use
- Limits use for automated decisions
  - Onus on processor to show use is legitimate

europa.eu.int/comm/internal_market/en/dataprot/law

## US Healthcare Information Portability and Accountability Act (HIPAA)

- Governs use of patient information
  - Goal is to protect the patient
  - Basic idea: Disclosure okay if anonymity preserved
- Regulations focus on outcome
  - A covered entity may not use or disclose protected health information, except as permitted or required…
    - To individual
    - For treatment (generally requires consent)
    - To public health / legal authorities
  - Use permitted where "there is no reasonable basis to believe that the information can be used to identify an individual"
- Safe Harbor Rules
  - Data presumed not identifiable if 19 identifiers removed (§ 164.514(b)(2)), e.g.:
    - Name, location smaller than 3 digit postal code, dates finer than year, identifying numbers
  - Shown not to be sufficient (Sweeney)
  - Also not necessary

*Moral: Get Involved in the Regulatory Process!*

## Regulatory Constraints: Use of Results

- Patchwork of Regulations
  - US Telecom (Fraud, not marketing)
    - Federal Communications Commission rules
    - Rooted in antitrust law
  - US Mortgage "redlining"
    - Financial regulations
    - Comes from civil rights legislation
- Evaluate on a per-project basis
  - Domain experts should know the rules
  - You'll need the domain experts anyway – ask the right questions

# Contractual Limitations

- Web site privacy policies
  - "Contract" between browser and web site
  - Groups support voluntary enforcement
    - TrustE – requires that web site DISCLOSE policy on collection and use of personal information
    - BBBonline
      - posting of an online privacy notice meeting rigorous privacy principles
      - completion of a comprehensive privacy assessment
      - monitoring and review by a trusted organization, and
      - participation in the programs consumer dispute resolution system
    - Unknown legal "teeth"
      - Example of customer information viewed as salable property in court!!!
  - P3P: Supports browser checking of user-specific requirements
    - Internet Explorer 6 – disallow cookies if non-matching privacy policy
    - PrivacyBird – Internet Explorer plug-in from AT&T Research
- Corporate agreements
  - Stronger teeth/enforceability
  - But rarely protect the individual

# Secrecy

- Governmental sharing
  - Clear rules on sharing of classified information
  - Often err on the side of caution
    - Touching classified data "taints" everything
    - Prevents sharing that wouldn't disclose classified information
- Corporate secrets
  - Room for cost/benefit tradeoff
  - Authorization often a single office
    - Convince the right person that secrets aren't disclosed and work can proceed
- Bad Press
  - Lotus proposed "household marketplace" CD (1990)
    - Contained information on US households from public records
    - Public outcry forced withdrawal
  - Credit agencies maintain public and private information
    - Make money from using information for marketing purposes
  - Key difference? *Personal information isn't disclosed*
    - Credit agencies do the mining
    - "Purchasers" of information don't see public data

## Classes of Solutions

- Data Obfuscation
  - Nobody sees the *real* data
- Summarization
  - Only the needed facts are exposed
- Data Separation
  - Data remains with trusted parties

## Data Obfuscation

- Goal:  Hide the protected information
- Approaches
  - Randomly modify data
  - Swap values between records
  - Controlled modification of data to hide secrets
- Problems
  - Does it really protect the data?
  - Can we learn from the results?

# Example: US Census Bureau Public Use Microdata

- US Census Bureau summarizes by census block
  - Minimum 300 people
  - Ranges rather than values
- For research, "complete" data provided for sample populations
  - Identifying information removed
    - Limitation of detail: geographic distinction, continuous → interval
    - Top/bottom coding (eliminate sparse/sensitive values)
  - Swap data values among similar individuals (Moore '96)
    - Eliminates link between potential key and corresponding values
    - If individual determined, sensitive values likely incorrect

    Preserves the privacy of the individuals, as no entity in the data contains actual values for any real individual.
  - Careful swapping preserves multivariate statistics
    - Rank-based: swap similar values (randomly chosen within max distance)

    Preserves dependencies with (provably) high probability
  - Adversary can estimate sensitive values if individual identified

    *But data mining results enable this anyway!*

# Summarization

- Goal: Make only innocuous summaries of data available
- Approaches:
  - Overall collection statistics
  - Limited query functionality
- Problems:
  - Can we deduce data from statistics?
  - Is the information sufficient?

# Example: Statistical Queries

- User is allowed to query protected data
  - Queries must use statistical operators that summarize results
    - Example: Summation of total income for a group doesn't disclose individual income
  - Multiple queries can be a problem
    - Request total salary for all employees of a company
    - Request the total salary for all employees but the president
    - Now we know the president's salary
- Query restriction – Identify when a set of queries is safe (Denning '80)
  - *query set overlap control* (Dobkin, Jones, and Lipton '79)
    - Result generated from at least *k* items
    - Items used to generate result have at most *r* items in common with those used for previous queries
    - At least 1+(*k*-1)/*r* queries needed to compromise data
  - Data perturbation: introducing noise into the original data
  - Output perturbation: leaving the original data intact, but introducing noise into the results

# Example: Statistical Queries

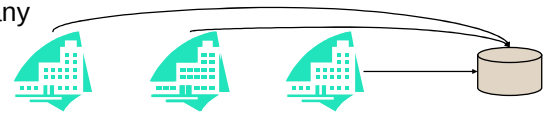
- Problem: Can approximate real values from multiple queries (Palley and Simonoff '87)
  - Create histograms for unprotected independent variables (e.g., job title)
  - Run statistical queries on the protected value (e.g., average salary)
  - Create a synthetic database capturing relationships between the unprotected and protected values
  - Data mining on the synthetic database approximate real values
- Problem with statistical queries is that the adversary creates the queries
  - Such manipulation likely to be obvious in a data mining situation
  - Problem: *Proving* that individual data not released

# Data Separation

- Goal: Only trusted parties see the data
- Approaches:
  - Data held by owner/creator
  - Limited release to trusted third party
  - Operations/analysis performed by trusted party
- Problems:
  - Will the trusted party be willing to do the analysis?
  - Do the analysis results disclose private information?

# Example: Patient Records

- My health records split among providers
  - Insurance company
  - Pharmacy
  - Doctor
  - Hospital



- Each agrees not to release the data without my consent
- Medical study wants correlations across providers
  - Rules relating complaints/procedures to "unrelated" drugs
- Does this need my consent?
  - *And that of every other patient!*
- It shouldn't!
  - Rules don't disclose my individual data

## When do we address these concerns?

- Must articulate that
  - A problem exists
    - There will be problems if we don't worry about privacy
  - We need to know the issues
    - Domain-specific constraints
  - A technical solution is feasible
    - Results valid
    - Constraints (provably) met

## What we need to know

- Constraints on release of data
  - Define in terms of Disclosure, not Privacy
  - What can be released, what mustn't
- Ownership/control of data
  - Nobody allowed access to "real" data
  - Data distributed across organizations
    - Horizontally partitioned: Each entity at a separate site
    - Vertically partitioned: Some attributes of each entity at each site
- Desired results: Rules? Classifier? Clusters?

# When to Address: CRISP-DM Stages

- Phase 1.2: Assess Situation
  - Capture privacy requirements while determining constraints
    *You've got the domain experts now – use them!*
- Phase 1.3: Determining data mining goals
  - Do the expected results violate constraints?
- Phase 2: Data understanding
  - Possible with non-private subset of data – Permission given or locally owned?
- Phase 3: Data preparation
  - 3.3: Will actual or derived (obfuscated) data be needed?
  - 3.4: Will warehouse-style integration be possible?
- Phase 4.1: Select modeling technique
  - Identify *(develop?)* technical solution
  - Document how solution meets constraints
- Phase 6.1: Plan deployment
  - Does the deployment satisfy constraints on use of results?

*CRoss Industry Standard Process for Data Mining*: www.crisp-dm.org

# Goal: Technical Solutions *that*

- Preserve privacy and security constraints
  - Disclosure Prevention that is
  - Provable, or
  - Disclosed data can be human-vetted
- Generate correct models: Results are
  - Equivalent to non-privacy preserving approach,
  - Bounded approximation to non-private result, or
  - Probabilistic approximation
- Efficient

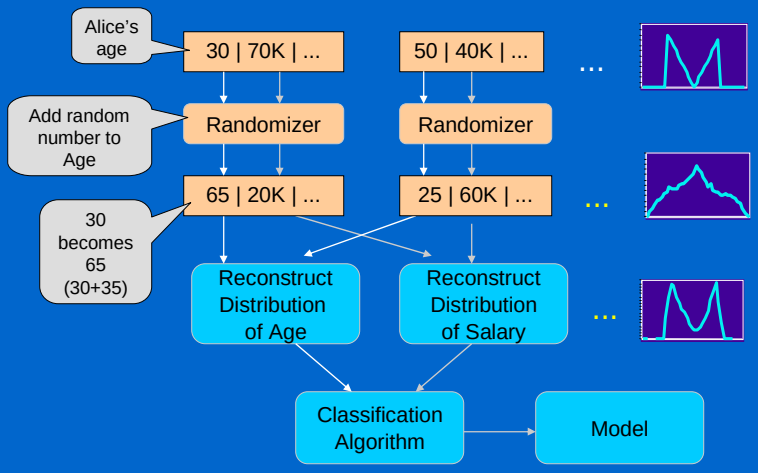
## Data Obfuscation Techniques

- Miner doesn't see the real data
  - Some knowledge of how data obscured
  - Can't reconstruct real values
- Results still valid
  - CAN reconstruct enough information to identify patterns
  - But not entities
- Example – *Agrawal & Srikant '00*

## Decision Trees
## *Agrawal and Srikant '00*

- Assume users are willing to
  - Give true values of certain fields
  - Give modified values of certain fields
- Practicality
  - 17% refuse to provide data at all
  - 56% are willing, as long as privacy is maintained
  - 27% are willing, with mild concern about privacy
- Perturb Data with Value Distortion
  - User provides $x_i+r$ instead of $x_i$
  - $r$ is a random value
    - Uniform, uniform distribution between $[-\alpha, \alpha]$
    - Gaussian, normal distribution with $\mu = 0, \sigma$

# Randomization Approach Overview



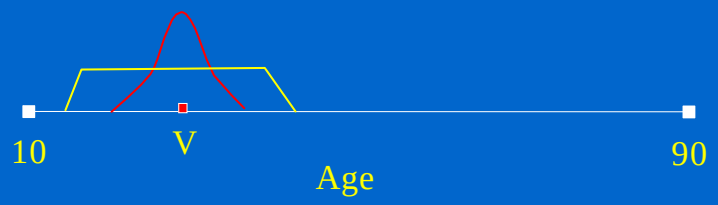

# Reconstruction Problem

- Original values $x_1, x_2, ..., x_n$
  - from probability distribution X (unknown)
- To hide these values, we use $y_1, y_2, ..., y_n$
  - from probability distribution Y
- Given
  - $x_1+y_1, x_2+y_2, ..., x_n+y_n$
  - the probability distribution of Y

  Estimate the probability distribution of X.

## Intuition (Reconstruct single point)

- Use Bayes' rule for density functions




Original distribution for Age
Probabilistic estimate of original value of V

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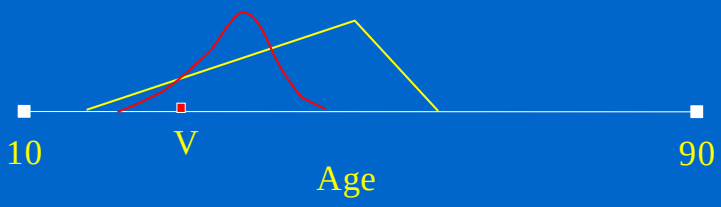
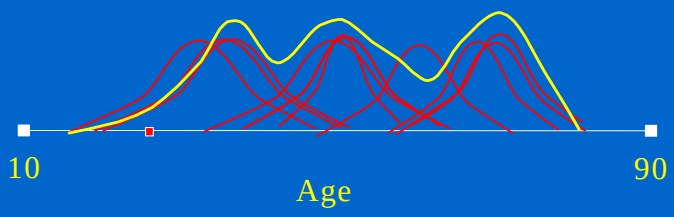



Original Distribution for Age
Probabilistic estimate of original value of V

## Reconstructing the Distribution

- Combine estimates of where point came from for all the points:
  - Gives estimate of original distribution.



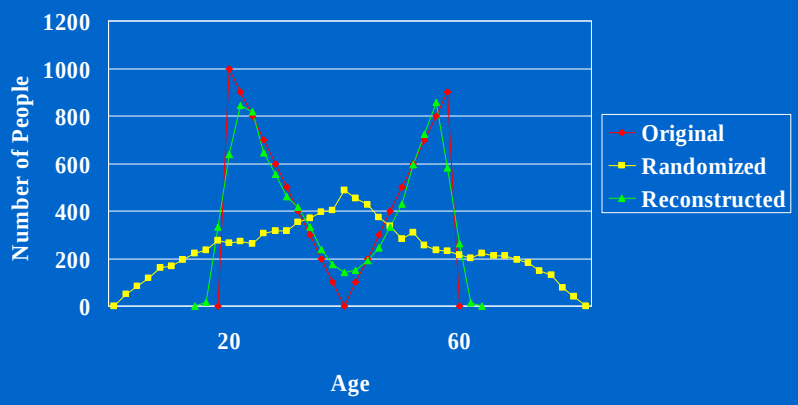

$$f_X = \frac{1}{n}\sum_{i=1}^{n} \frac{f_Y((x_i + y_i) - a)\, f_X^j(a)}{\int_{-\infty}^{\infty} f_Y((x_i + y_i) - a)\, f_X^j(a)}$$

## Reconstruction: Bootstrapping

$f_X^0$ := Uniform distribution
j := 0 // Iteration number
repeat
  $f_X^{j+1}(a) := \frac{1}{n}\sum_{i=1}^{n} \frac{f_Y((x_i + y_i) - a)\, f_X^j(a)}{\int_{-\infty}^{\infty} f_Y((x_i + y_i) - a)\, f_X^j(a)}$ (Bayes' rule)
  j := j+1
until (stopping criterion met)

- Converges to maximum likelihood estimate.
  - D. Agrawal & C.C. Aggarwal, PODS 2001.

## Works well




## Recap: Why is privacy preserved?

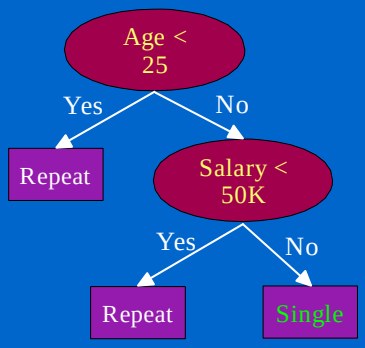
- Cannot reconstruct individual values accurately.
- Can only reconstruct distributions.

# Classification

- Naïve Bayes
  - Assumes independence between attributes.
- Decision Tree
  - Correlations are weakened by randomization, not destroyed.

# Decision Tree Example

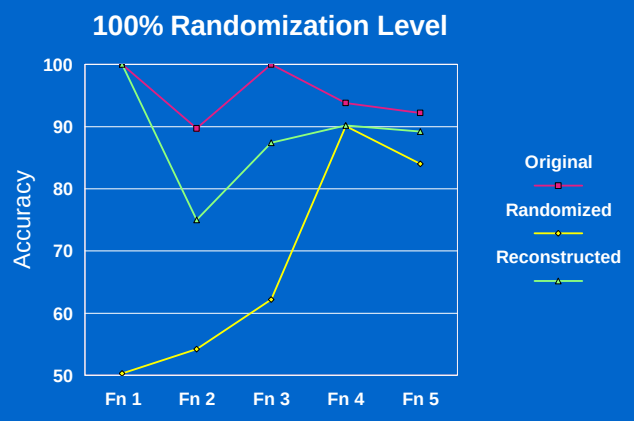
| Age | Salary | Repeat Visitor? |
|---|---|---|
| 23 | 50K | Repeat |
| 17 | 30K | Repeat |
| 43 | 40K | Repeat |
| 68 | 50K | Single |
| 32 | 70K | Single |
| 20 | 20K | Repeat |



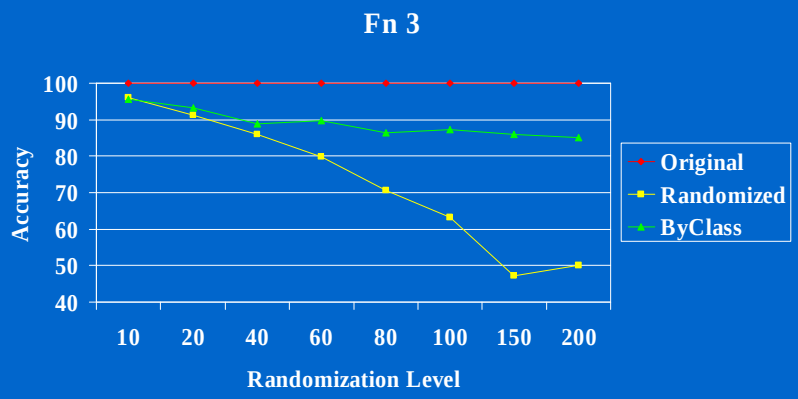
# Randomization Level

- Add a random value between -30 and +30 to age.
- If randomized value is 60
  - know with 90% confidence that age is between 33 and 87.
- Interval width ❝ amount of privacy.
  - Example: (Interval Width : 54) / (Range of Age: 100) ♏ 54% randomization level @ 90% confidence

# Decision Tree Experiments



## Accuracy vs. Randomization Level




## Quantification of Privacy
### *Agrawal and Aggarwal '01*

- Previous definition:

  If the original value can be estimated with c% confidence to lie in the interval [$\alpha_1$, $\alpha_2$], then the interval width ($\alpha_2$-$\alpha_1$) defines the amount of privacy at c% confidence level
- Ex: Interval width 2$\alpha$
  - confidence level 50% gives privacy $\alpha$
  - confidence level 100% gives privacy 2$\alpha$
- Incomplete in some situations

# Quantification of privacy II

Example: Attribute X with density function $f_X(x)$:

- $f_X(x) = 0.5, \quad 0 \leq x \leq 1$
- $f_X(x) = 0.5, \quad 4 \leq x \leq 5$
- $f_X(x) = 0, \quad$ otherwise

Perturbing attribute Y is distributed uniformly between [-1,1]

- Privacy 2 at 100% confidence level
- Reconstruction with enough data, and Y-distribution public: $Z \in [-1,2]$ gives $X \in [0,1]$ and $Z \in [3,6]$ gives $X \in [4,5]$
- This means privacy offered by Y at 100% confidence level is at most 1. (X can be localized to even shorter intervals, e.g. Z=-0.5 gives $X \in [0,0.5]$ )

# Intuition

- Intuition: A random variable distributed uniformly between [0,1] has half as much privacy as if it were in [0,2]
- In general: If fB(x)=2fA(2x) then B offers half as much privacy as A
- Also: if a sequence of random variable An, n=1, 2, … converges to random variable B, then privacy inherent in An should converge to the privacy inherent in B

## Differential entropy

- Based on differential entropy h(A):

$h(A) = -\int_{\Omega A} f_A(a) \log_2 f_A(a) da$ where $\Omega_A$ is the domain of A

- Random variable *U* distributed between 0 and a, h(*U*)=$\log_2$(a). For a=1, h(*U*)=0
- Random variables with less uncertainty then uniform distribution on [0,1] have negative differential entropy, more uncertainty →positive differential entropy

## Proposed metric

- Propose $\Pi(A)=2^{h(A)}$ as measure of privacy for attribute A
- Uniform *U* between 0 and a: $\Pi(U)=2^{\log_2(a)}=a$
- General random variable A, $\Pi$(A) denote length of interval, over which a uniformly distributed random variable has equal uncertainty as A
- Ex: $\Pi(A)=2$ means A has as much privacy as a random variable distributed uniformly in an interval of length 2

# Conditional privacy

- Conditional privacy – takes into account the additional information in perturbed values:

$$h(A \mid B) = -\int_{\Omega A,B} f_{A,B}(a,b) \log_2 f_{A|B=b}(a) da\, db$$

- Average conditional privacy of A given B:

$\Pi(A|B)=2^{h(A|B)}$

# Privacy loss

- Conditional privacy loss of A given B:

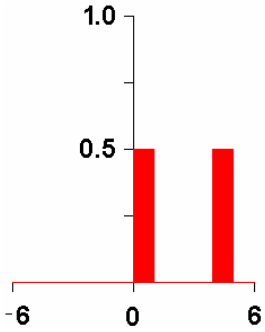
$P(A|B)=1-\Pi(A|B)/\Pi(A)=1-2^{h(A|B)}/2^{h(A)}=1-2^{-I(A;B)}$

Where $I(A;B)=h(A)-h(A|B)=h(B)-h(B|A)$

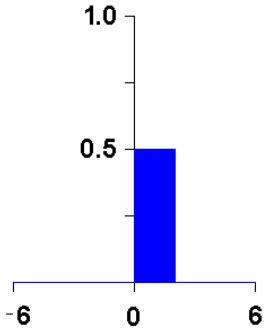
- I(A;B) is known as mutual information between random variables A and B
- $P(A|B)$ is the fraction of privacy of A which is lost by revealing B

# Example

- Look at earlier example:
- $f_X(x) = 0.5,\ 0 \le x \le 1$
- $f_X(x) = 0.5,\ 4 \le x \le 5$
- $f_X(x) = 0,$ otherwise




- Intuition from figures: X has as much privacy as a uniform variable over an interval of length 2 –
- Areas are the same:




# Distribution Reconstruction: Agrawal and Aggarwal

- Expectation Maximization-based algorithm for Distribution Reconstruction
  - Generalizes Agrawal-Srikant algorithm
  - Better worst-case performance

*500 data points, uniform on [2,4], perturbed from [-1,1]*

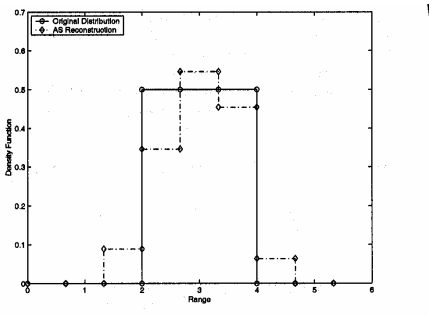



**Figure 2: Reconstructed Uniform Distribution (AS Algorithm)**

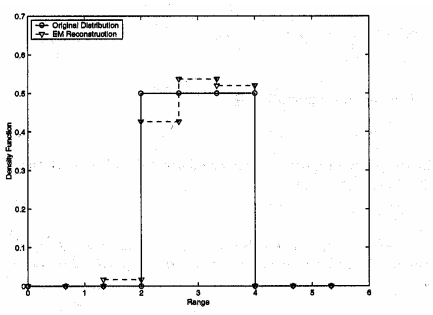



**Figure 3: Reconstructed Uniform Distribution (EM Algorithm)**

# Gaussian distribution

- Gaussian distribution, 500 data points, standard deviation of 2/πe
- Perturbing distribution – Gaussian, variance 1

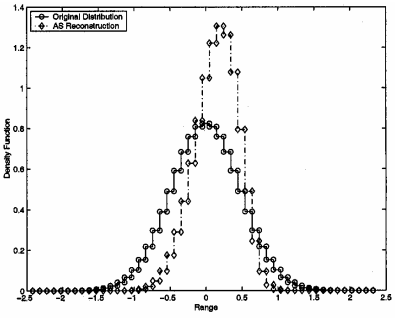



Figure 4: Reconstructed Gaussian Distribution (AS Algorithm)

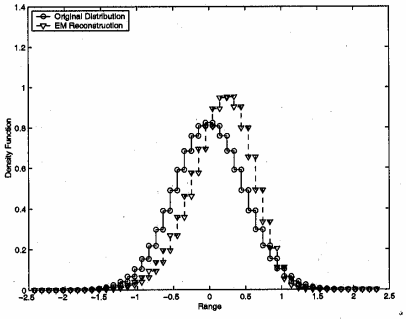



Figure 5: Reconstructed Gaussian Distribution (EM Algorithm)

# Information loss / privacy loss

- Gaussian – standard deviation of 2/pe
- Uniform distribution [-1,1] – same inherent privacy
- 500 data points

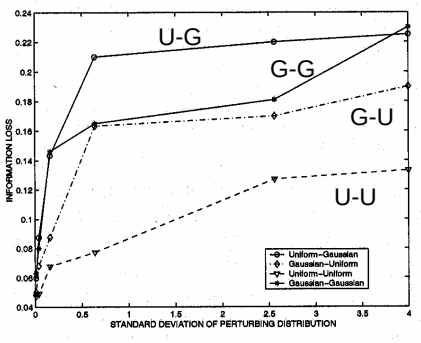



Figure 6: Information Loss with Standard Deviation of Perturbing Distribution

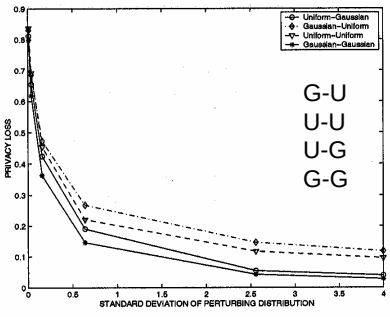


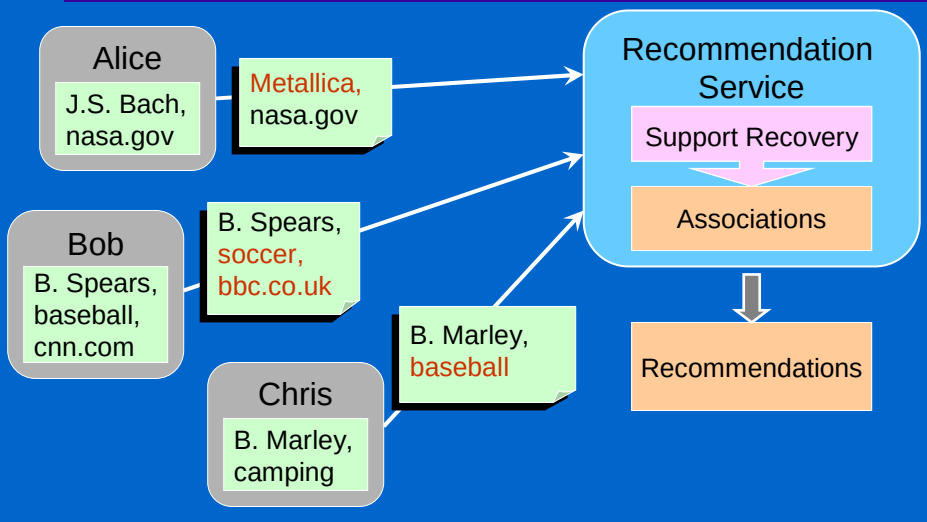

Figure 7: Privacy Loss with Standard Deviation of Perturbing Distribution

## Discovering Associations Over Privacy Preserved Categorical Data

A. Evfimievski, R. Srikant, R. Agrawal, J. Gehrke, "Privacy Preserving Mining of Association Rules", KDD 2002.

- A transaction ***t*** is a set of items
- Support ***s*** for an itemset ***A*** is the number of transactions in which ***A*** appears
- Itemset ***A*** is frequent if $s \geq s_{min}$
- Task: Find all frequent itemsets, while preserving the privacy of individual transaction.

## Recommendation Service



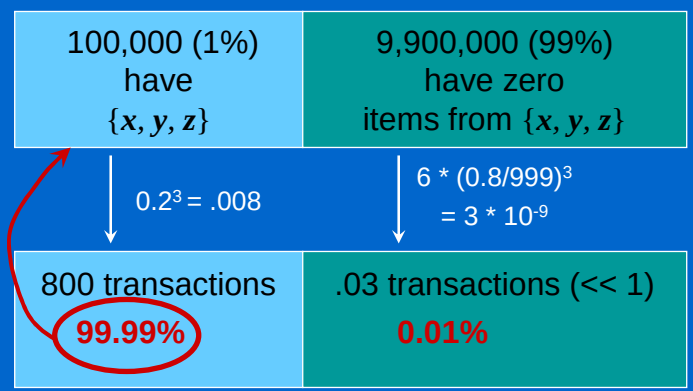
## Uniform Randomization

- Given a transaction,
  - keep item with 20% probability,
  - replace with a new random item with 80% probability.

Is there a problem?

## Example: $\{x, y, z\}$

10 M transactions of size 3 with 1000 items:




Uniform randomization: How many have $\{x, y, z\}$ ?

## Solution

"Where does a wise man hide a leaf? In the forest.
But what does he do if there is no forest?"
"He grows a forest to hide it in."

G.K. Chesterton

- Insert many false items into each transaction
- Hide true itemsets among false ones

## Cut and Paste Randomization

- Given transaction $t$ of size $m$, construct $t'$:
  - Choose a number $j$ between 0 and $K_m$ (cutoff);
  - Include $j$ items of $t$ into $t'$;
  - Each other item is included into $t'$ with probability $p_m$.

The choice of $K_m$ and $p_m$ is based on the desired level of privacy.

$t$ = a, b, c, u, v, w, x, y, z

$t'$ = b, v, x, z, œ, å, ß, ξ, ψ, €, ℵ, ъ, ħ, …

$j = 4$

## Partial Supports

To recover original support of an itemset, we need randomized supports of its subsets.

- Given an itemset ***A*** of size ***k*** and transaction size ***m***,
- A vector of partial supports of ***A*** is

$$\vec{s} = (s_0, s_1, \ldots, s_k), \text{ where}$$

$$s_l = \frac{1}{|T|} \cdot \#\{t \in T \mid \#(t \cap A) = l\}$$

  - Here $s_k$ is the same as the support of ***A***.
  - Randomized partial supports are denoted by $\vec{s}'$.

## Transition Matrix

- Let ***k*** = |***A***|, ***m*** = |***t***|.
- Transition matrix ***P*** = ***P*** (***k, m***) connects randomized partial supports with original ones:

$$\mathrm{E}\,\vec{s}' = P \cdot \vec{s}, \text{ where}$$

$$P_{l',l} = \Pr\left[\#(t' \cap A) = l' \mid \#(t \cap A) = l\right]$$

## The Estimators

- Given randomized partial supports, we can estimate original partial supports:

$$\vec{s}_{\text{est}} = Q \cdot \vec{s}', \quad \text{where} \quad Q = P^{-1}$$

- Covariance matrix for this estimator:

$$\text{Cov}\, \vec{s}_{\text{est}} = \frac{1}{|T|} \sum_{l=0}^{k} s_l \cdot Q\, D[l] Q^T,$$

$$\text{where} \quad D[l]_{i,j} = P_{i,l} \cdot \delta_{i=j} - P_{i,l} \cdot P_{j,l}$$

- To estimate it, substitute $\boldsymbol{s}_l$ with $(\boldsymbol{s}_{\text{est}})_l$.
  - Special case: estimators for support and its variance

## Privacy Breach Analysis

- How many added items are enough to protect privacy?
  - Have to satisfy Pr [$\boldsymbol{z} \in \boldsymbol{t} \mid \boldsymbol{A} \subseteq \boldsymbol{t'}$] < $\boldsymbol{\rho}$ ($\Leftrightarrow$ no privacy breaches)
  - Select parameters so that it holds for all itemsets.
  - Use formula ( $s_l^+ = \Pr\left[\#(t \cap A) = l, z \in t\right]$, $s_0^+ = 0$ ):

$$\Pr\left[z \in t \mid A \subseteq t'\right] = \sum_{l=0}^{k} s_l^+ \cdot P_{k,l} \Big/ \sum_{l=0}^{k} s_l \cdot P_{k,l}$$

- Parameters are to be selected in advance!
  - Enough to know maximal support of an itemset for each size.
  - Other parameters chosen for worst-case impact on privacy breaches.

## Can we still find frequent itemsets?

Privacy Breach level = 50%.

Soccer:

$s_{min} = 0.2\%$

| Itemset Size | True Itemsets | True Positives | False Drops | False Positives |
|---|---|---|---|---|
| 1 | 266 | 254 | 12 | 31 |
| 2 | 217 | 195 | 22 | 45 |
| 3 | 48 | 43 | 5 | 26 |

Mailorder:

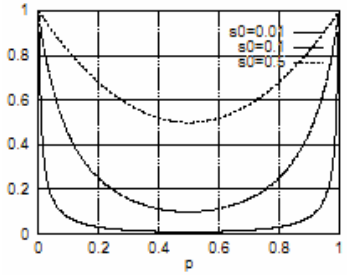
$s_{min} = 0.2\%$

| Itemset Size | True Itemsets | True Positives | False Drops | False Positives |
|---|---|---|---|---|
| 1 | 65 | 65 | 0 | 0 |
| 2 | 228 | 212 | 16 | 28 |
| 3 | 22 | 18 | 4 | 5 |

## Association Rules
### *Rizvi and Haritsa '02*

- "Market Basket" problem
  - Presence/absence of attributes in transactions
  - Few positive examples per transaction
- Bits "flipped" with probability *p*
  - Goal is low probability of knowing true value
  - Sparseness helps
- Mining the data
  - Get distorted data and *p*
  - $C^T = M^{-1}C^D$

$$M = \begin{bmatrix} p & 1-p \\ 1-p & p \end{bmatrix}, C = \begin{bmatrix} C_1 \\ C_0 \end{bmatrix}$$




Test: *p=0.9*, support=.25%

| *Length* | *Rules* | *Support Error* | *Missing* | *Extras* |
|---|---|---|---|---|
| 1 | 249 | 5.89 | 4.02 | 2.81 |
| 2 | 239 | 3.87 | 6.89 | 9.59 |
| 3 | 73 | 2.60 | 10.96 | 9.59 |
| 4 | 4 | 1.41 | 0 | 25.0 |

## Data Separation

- Data holders trusted with content
  - But only their own
- Mustn't share
  - But this doesn't prevent global models

## Secure Multiparty Computation
*It can be done!*

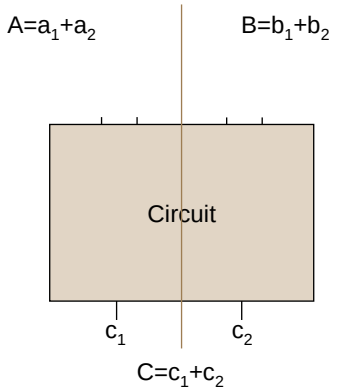
- Goal: Compute function when each party has some of the inputs
- Yao's Millionaire's problem *(Yao '86)*
  - Secure computation possible if function can be represented as a circuit
  - Idea: Securely compute gate
    - Continue to evaluate circuit
- Works for multiple parties as well *(Goldreich, Micali, and Wigderson '87)*

# Secure Multiparty Computation: Definitions

- Secure
  - Nobody knows anything but their own input and the results
  - Formally: ∃ polynomial time S such that {S(x,f(x,y))} ≡ {View(x,y)}
- Semi-Honest model: follow protocol, but remember intermediate exchanges
- Malicious: "cheat" to find something out

# How does it work?

- Each side has input, knows circuit to compute function
- Add random value to your input, give to other side
  - Each side has *share* of all inputs
- Compute share of output
  - Add results at end
- XOR gate: just add locally
- AND gate: send your share encoded in truth table
  - Oblivious transfer allows other side to get only correct value out of truth table




| value of $(a_2,b_2)$ | (0,0) | (0,1) | (1,0) | (1,1) |
|---|---|---|---|---|
| OT-input | 1 | 2 | 3 | 4 |
| value of output | $c_1+a_1b_1$ | $c_1+a_1(b_1+1)$ | $c_1+(a_1+1)b_1$ | $c_1+(a_1+1)(b_1+1)$ |

# Oblivious Transfer

- What is it?
  - *A* has inputs $a_i$
  - *B* makes choice
  - *A* doesn't know choice, *B* only sees chosen value.
- How?
  - *A* sends public key *p* to B
  - B selects 4 random values *b*
    - encrypts (only) $b_{choice}$ with $f_p$, sends all to *A*
  - *A* decrypts all with private key, sends to B:
    $c_i = a_i \oplus e(f_p^{-1}(b_i))$
  - B outputs $c_{choice} \oplus e(b_{choice}) = a_{choice} \oplus e(f_p^{-1}(f_p(b_{choice}))) \oplus e(b_{choice})$

# Decision Tree Construction *(Lindell & Pinkas '00)*

- Two-party horizontal partitioning
  - Each site has same schema
  - Attribute set known
  - Individual entities private
- Learn a decision tree classifier
  - ID3
- Essentially ID3 meeting Secure Multiparty Computation Definitions

# Key Assumptions/Limitations

- Protocol takes place in the semi-honest model
- Only Two-party case considered
  - Extension to multiple parties is not trivial
- Computes an ID3 approximation
  - Protocol for computation of $ID3_\delta \in ID3_\delta$
  - δ-approximation of ID3
  - δ has implications on efficiency
- Deals only with categorical attributes

# Cryptographic Tools

- Oblivious Transfer
  - 1-out-of-2 oblivious transfer. Two parties, sender and receiver. Sender has two inputs $<X_0,X_1>$ and the receiver has an input $\alpha \in (0,1)$. At the end of the protocol the receiver should get $X_\alpha$ and nothing else and the sender should learn nothing.
- Oblivious Evaluation of Polynomials
  - Sender has polynomial P of degree k over some finite field F and a receiver with an element z in F (the degree k is public). The receiver obtains P(z) without learning anything about the polynomial P and the sender learns nothing about z.
- Oblivious Circuit Evaluation
  - Two party Yao's protocol. A has input x and B has a function f and a combinatorial circuit that computes f. At the end of the protocol A outputs f(x) and learns no other information about f while B learns nothing at all.

# ID3

- R – the set of attributes
- C – the class attribute
- T – the set of transactions

**ID3**$(R, C, T)$

1. If $R$ is empty, return a leaf-node with the class value assigned to the most transactions in $T$.
2. If $T$ consists of transactions which all have the same value $c$ for the class attribute, return a leaf-node with the value $c$ (finished classification path).
3. Otherwise,
   (a) Determine the attribute that *best* classifies the transactions in $T$, let it be $A$.
   (b) Let $a_1, ..., a_m$ be the values of attribute $A$ and let $T(a_1), ..., T(a_m)$ be a partition of $T$ such that every transaction in $T(a_i)$ has the attribute value $a_i$.
   (c) Return a tree whose root is labeled $A$ (this is the test attribute) and has edges labeled $a_1, ..., a_m$ such that for every $i$, the edge $a_i$ goes to the tree ID3$(R - \{A\}, C, T(a_i))$.

# Privacy Preserving ID3

Step 1: *If R is empty, return a leaf-node with the class value assigned to the most transactions in T*

- Set of attributes is public
  – Both know if R is empty
- Run Yao's protocol for the following functionality:
  – Inputs $(|T_1(c_1)|,\ldots,|T_1(c_L)|)$, $(|T_2(c_1)|,\ldots,|T_2(c_L)|)$
  – Output *i* where $|T_1(c_i)|+|T_2(c_i)|$ is largest

# Privacy Preserving ID3

Step 2: *If T consists of transactions which have all the same value c for the class attribute, return a leaf node with the value c*

- Represent having more than one class (in the transaction set), by a fixed symbol different from $c_i$,
- Force the parties to input either this fixed symbol or $c_i$
- Check equality to decide if at leaf node for class $c_i$
- Various approaches for equality checking
  - Yao'86
  - Fagin, Naor '96
  - Naor, Pinkas '01

# Privacy Preserving ID3

- Step 3:(a) *Determine the attribute that best classifies the transactions in T, let it be A*
  - Essentially done by securely computing x*(ln x)
- (b,c) *Recursively call $ID3_\delta$ for the remaining attributes on the transaction sets $T(a_1),\ldots,T(a_m)$ where $a_1,\ldots, a_m$ are the values of the attribute A*
  - Since the results of 3(a) and the attribute values are public, both parties can individually partition the database and prepare their inputs for the recursive calls

# Determining the best attribute

- Let A have m possible values $a_1,\ldots,a_m$,
  C have l possible values $c_1,\ldots,c_l$
- $T(a_j)$ is transactions with attribute A set to $a_j$
  $T(a_j, c_i)$ is transactions with A set to $a_j$ and class $c_i$
- Conditional entropy is the weighted sum of entropies, which is simplified as follows:

$$\begin{aligned} H_C(T|A) &= \sum_{j=1}^{m} \frac{|T(a_j)|}{|T|} H_C(T(a_j)) \\ &= \frac{1}{|T|} \sum_{j=1}^{m} |T(a_j)| \sum_{i=1}^{\ell} -\frac{|T(a_j,c_i)|}{|T(a_j)|} \cdot \log(\frac{|T(a_j,c_i)|}{|T(a_j)|}) \\ &= \frac{1}{|T|} \left( -\sum_{j=1}^{m} \sum_{i=1}^{\ell} |T(a_j,c_i)| \log(|T(a_j,c_i)|) + \sum_{j=1}^{m} |T(a_j)| \log(|T(a_j)|) \right) \end{aligned}$$

# X ln X

- Taylor Series of natural logarithm:

$$\ln(1+\varepsilon) = \sum_{i=1}^{\infty} \frac{(-1)^{i-1}\varepsilon^i}{i} = \varepsilon - \frac{\varepsilon^2}{2} + \frac{\varepsilon^3}{3} - \frac{\varepsilon^4}{4} + \cdots \qquad \text{for } -1 < \varepsilon < 1$$

- Error for partial evaluation:

$$\left| \ln(1+\varepsilon) - \sum_{i=1}^{k} \frac{(-1)^{i-1}\varepsilon^i}{i} \right| < \frac{|\varepsilon|^{k+1}}{k+1} \cdot \frac{1}{1-|\varepsilon|}$$

- Error shrinks exponentially as k grows

$$\ln(x) = \ln(2^n(1+\varepsilon)) = n\ln 2 + \varepsilon - \frac{\varepsilon^2}{2} + \frac{\varepsilon^3}{3} - \frac{\varepsilon^4}{4} + \cdots$$

# Comparison

- Fully Generic solution |R|*|T|*logm oblivious transfers (for every bit)
- Semi generic protocol (uses circuit evaluation for x ln x)
  - Computes Taylor series (k multiplications)
  - $O(k^3 \log^2|T||S|)$ since multiplication is quadratic in terms of input size
- Their solution - O(klog|T|*|S|) bits
  - Order $O(k^2 \log|T|)$ more efficient

# Association Rule Mining: Horizontal Partitioning

- Distributed Association Rule Mining: Easy without sharing the individual data *[Cheung+'96] (Exchanging support counts is enough)*
- What if we do not want to reveal which rule is supported at which site, the support count of each rule, or database sizes?
  - Hospitals want to participate in a medical study
  - But rules only occurring at one hospital may be a result of bad practices
    - *Is the potential public relations / liability cost worth it?*

## Overview of the Method *(Kantarcioglu and Clifton '02)*

- Find the union of the locally large candidate itemsets securely
- After the local pruning, compute the globally supported large itemsets securely
- At the end check the confidence of the potential rules securely

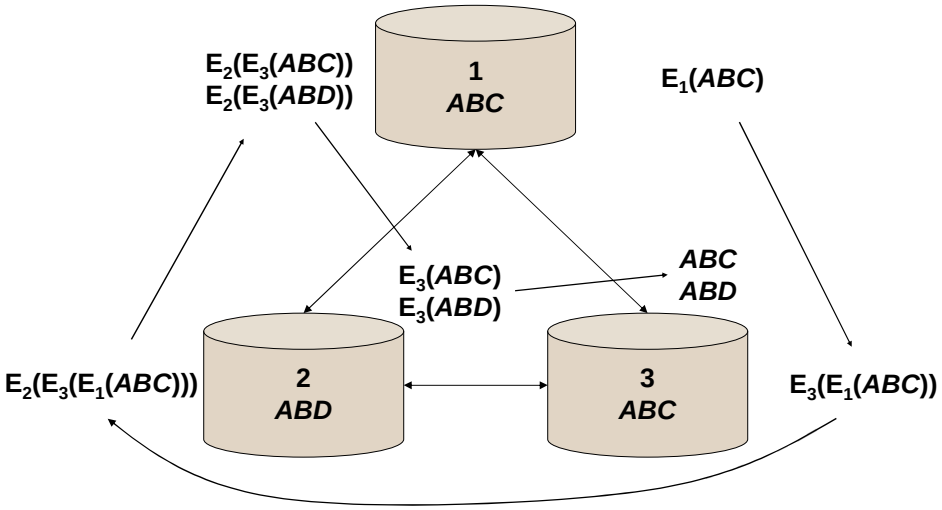
## Securely Computing Candidates

- Key: Commutative Encryption ($E_a(E_b(x)) = E_b(E_a(x))$)
  - Compute local candidate set
  - Encrypt and send to next site
    - Continue until all sites have encrypted all rules
  - Eliminate duplicates
    - Commutative encryption ensures if rules the same, encrypted rules the same, regardless of order
  - Each site decrypts
    - After all sites have decrypted, rules left
- Care needed to avoid giving away information through ordering/etc.

Redundancy maybe added in order to increase the security.

*Not fully secure according to definitions of secure multi-party*

# Computing Candidate Sets




# Compute Which Candidates Are Globally Supported?

- Goal: To check whether

$$X.\sup \geq s * \sum_{i=1}^{n} |DB_i| \quad (1)$$

$$\sum_{i=1}^{n} X.\sup_i \geq \sum_{i=1}^{n} s^* | DB_i | \quad (2)$$

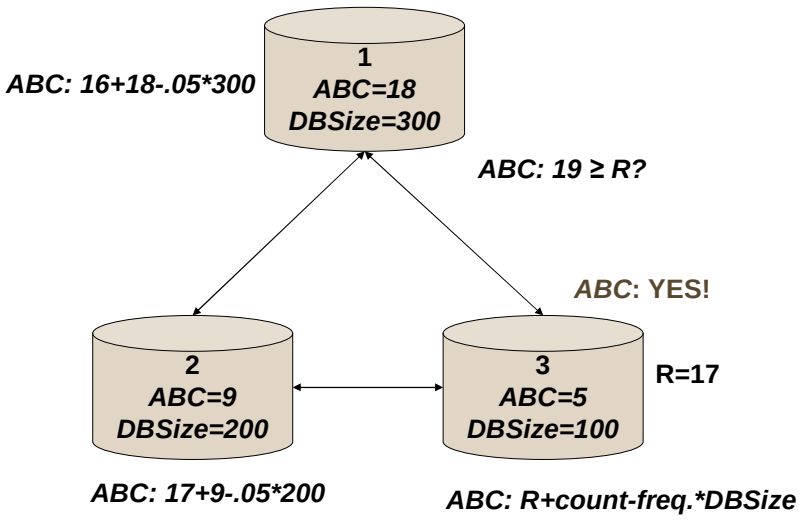
$$\sum_{i=1}^{n} (X.\sup_i - s^* | DB_i |) \geq 0 \quad (3)$$

Note that checking inequality (1) is equivalent to checking inequality (3)

## Which Candidates Are Globally Supported? (Continued)

- Now securely compute Sum ≥ 0:
  - Site$_0$ generates random *R*
    Sends *R+count*$_0$ *– frequency*dbsize*$_0$ to site$_1$
  - Site$_k$ adds *count*$_k$ *– frequency*dbsize*$_k$, sends to site$_{k+1}$
- Final result: Is sum at site$_n$ - *R* ≥ 0?
  - Use Secure Two-Party Computation
- This protocol is secure in the semi-honest model

## Computing Frequent: Is *ABC* ≥ 5%?



# Computing Confidence

- Checking confidence can be done by the previous protocol. Note that checking confidence for X $\Rightarrow$ Y

$$\frac{\{X \cup Y\}.\sup}{X.\sup} \geq c \Rightarrow \frac{\sum_{i=1}^{n} XY.\sup_i}{\sum_{i=1}^{n} X.\sup_i} \geq c$$

$$\Rightarrow \sum_{i=1}^{n} (XY.\sup_i - c * X.\sup_i) \geq 0$$

# Association Rules in Vertically Partitioned Data

- Two parties – Alice (A) and Bob (B)
- Same set of entities (data cleansing, join assumed done)
- A has *p* attributes, $A_1 \ldots A_p$
- B has *q* attributes, $B_1 \ldots B_q$
- Total number of transactions, *n*
- Support Threshold, *k*

| | | | | | | |
|---|---|---|---|---|---|---|
| JSV | Brain Tumor | Diabetic | *JSV* | *5210* | *Li/Ion* | *Piezo* |

# Vertically Partitioned Data *(Vaidya and Clifton '02)*

- Learn globally valid association rules
- Prevent disclosure of individual relationships
  - Join key revealed
  - Universe of attribute values revealed
- Many real-world examples
  - Ford / Firestone
  - FBI / IRS
  - Medical records

# Basic idea

- Find out if itemset $\{A_1, B_1\}$ is frequent (i.e., If support of $\{A_1, B_1\} \geq k$)

A

| Key | $A_1$ |
|---|---|
| $k_1$ | 1 |
| $k_2$ | 0 |
| $k_3$ | 0 |
| $k_4$ | 1 |
| $k_5$ | 1 |

B

| Key | $B_1$ |
|---|---|
| $k_1$ | 0 |
| $k_2$ | 1 |
| $k_3$ | 0 |
| $k_4$ | 1 |
| $k_5$ | 1 |

- Support of itemset is defined as number of transactions in which all attributes of the itemset are present
- For binary data, support $=|A_i \wedge B_i|$
- Boolean AND can be replaced by normal (arithmetic) multiplication.

# Basic idea

- Thus, $Support = \sum_{i=1}^{n} A_i \times B_i$
- This is the scalar (dot) product of two vectors
- To find out if an arbitrary (shared) itemset is frequent, create a vector on each side consisting of the component multiplication of all attribute vectors on that side (contained in the itemset)
- E.g., to find out if $\{A_1, A_3, A_5, B_2, B_3\}$ is frequent
  - A forms the vector X = $\prod A_1 A_3 A_5$
  - B forms the vector Y = $\prod B_2 B_3$
  - Securely compute the dot product of X and Y

# The algorithm

1. $L_1$ = {large 1-itemsets}
2. for (k=2; $L_{k-1} \neq \phi$; k++) do begin
3. $C_k$ = apriori-gen($L_{k-1}$);
4. for all candidates $c \in C_k$ do begin
5. if all the attributes in $c$ are entirely at A or B
6. that party independently calculates $c.count$
7. else
8. let A have $l$ of the attributes and B have the remaining $m$ attributes
9. construct $\vec{X}$ on A's side and $\vec{Y}$ on B's side where $\vec{X} = \prod_{i=1}^{l} \vec{A}_i$ and $\vec{Y} = \prod_{i=1}^{m} \vec{B}_i$
10. compute $c.count = \vec{X}.\vec{Y} = \sum_{i=1}^{n} x_i * y_i$
11. endif
12. $L_k = L_k \cup c | c.count \geq minsup$
13. end
14. end
15. Answer = $\cup_k L_k$

# Protocol

- A generates $n/2$ randoms, $R_1 \ldots R_{n/2}$
- A sends the following $n$ values to B

$$\left\langle x_1 + a_{1,1} * R_1 + a_{1,2} * R_2 + \cdots + a_{1,n/2} * R_{n/2} \right\rangle$$
$$\left\langle x_2 + a_{2,1} * R_1 + a_{2,2} * R_2 + \cdots + a_{2,n/2} * R_{n/2} \right\rangle$$
$$\vdots$$
$$\left\langle x_n + a_{n,1} * R_1 + a_{n,2} * R_2 + \cdots + a_{n,n/2} * R_{n/2} \right\rangle$$

- The $(n^2/2)$ $a_{i,j}$ values are known to both A and B

# Protocol (cont.)

- B multiplies each value he gets with the corresponding y value he has and adds all of them up to get a sum S, which he sends to A.

$$S = \left[ \begin{array}{l} y_1 * \{x_1 + (a_{1,1} * R_1 + a_{1,2} * R_2 + \cdots + a_{1,n/2} * R_{n/2})\} \\ + y_2 * \{x_2 + (a_{2,1} * R_1 + a_{2,2} * R_2 + \cdots + a_{2,n/2} * R_{n/2})\} \\ \vdots \\ + y_n * \{x_n + (a_{n,1} * R_1 + a_{n,2} * R_2 + \cdots + a_{n,n/2} * R_{n/2})\} \end{array} \right]$$

- Group the $x_i * y_i$ terms, and expand the equations

# Protocol (cont)

$$S = \sum_{i=1}^{n} x_i * y_i$$

$$x_1 * y_1 + x_2 * y_2 + \cdots + x_n * y_n$$

$$+\left( a_{1,1} * y_1 * R_1 + a_{1,2} * y_1 * R_2 + \cdots + a_{1,n/2} * y_1 * R_{n/2} \right)$$

$$+\left( a_{2,1} * y_2 * R_1 + a_{2,2} * y_2 * R_2 + \cdots + a_{2,n/2} * y_2 * R_{n/2} \right)$$

$$\vdots$$

$$+\left( a_{n,1} * y_n * R_1 + a_{n,2} * y_n * R_2 + \cdots + a_{n,n/2} * y_n * R_{n/2} \right)$$

Grouping components vertically and factoring out $R_i$

# Protocol (complete)

$$S = \sum_{i=1}^{n} x_i * y_i$$

$$+ R_1 * \left( a_{1,1} * y_1 + a_{2,1} * y_2 + \cdots + a_{n,1} * y_n \right)$$

$$+ R_2 * \left( a_{1,2} * y_1 + a_{2,2} * y_2 + \cdots + a_{n,2} * y_n \right)$$

$$\vdots$$

$$+ R_{n/2} * \left( a_{1,n/2} * y_1 + a_{2,n/2} * y_2 + \cdots + a_{n,n/2} * y_n \right)$$

- A already knows $R_1 \ldots R_{n/2}$
- Now, if B sends these n/2 values to A,
- *A can remove the baggage and get the scalar product*

# Security Analysis

- A sends to B
  - n values (which are linear equations in 3n/2 unknowns – the n x-values and n/2 R-values)
  - The final result (which reveals another linear equation in the n/2 R-values) (Note – this can be avoided by allowing A to only report if scalar product exceeds threshold)
- B sends to A
  - The sum, S (which is one linear equation in the n y-values)
  - n/2 values (which are linear equations in n unknowns – the n y-values)

# Security Analysis

- Security based on the premise of revealing less equations than the number of unknowns – possible solutions infinite!
- Security of both is symmetrical
- Just from the protocol, nothing can be found out
- Everything is revealed *only* when about half the values are revealed

## The Trouble with {0,1}

- Input values are restricted only to 0 or 1
- Parties reveal linear equation in values
  - Adversary could try all combinations of {0,1} and see which fits
- Solution: Eliminate unique solution
  - Create $a_{i,j}$ values so 0's and 1's paired
  - No way of knowing *which* is 0 or 1
- *Completely different approach for three or more parties*

## EM Clustering *(Lin & Clifton '03)*

- Goal: EM Clustering in Horizontally Partitioned Data
  - Avoid sharing individual values
  - Nothing should be attributable to individual site
- Solution: Partition estimation update
  - Each site computes portion based on it's values
  - Securely combine these to complete iteration

# Expectation Maximization

- log $L_c(\Psi)$ = log $f_c(\mathbf{x}; \Psi)$:
- E-Step: On the (t+1)st step, calculate the expected complete data log likelihood given observed data values.
  - $G(\Psi; \Psi^{(t)}) = E_{\Psi(t)}\{\log L_c(\Psi)||y\}$
- M-Step: Find $\Psi^{(t+1)}$ to maximize $G(\Psi; \Psi^{(t)})$
- For finite normal mixtures:

$$f(y,\Psi) = \sum_{i=1}^{k} \pi_i f_i(y;\theta_i) \text{ where } f_i(y;\theta_i) = (2\pi_i\sigma_i^2)^{-1/2} \exp\{k - \frac{(y-\mu_i)^2}{2\sigma_i^2}\}$$

# EM Clustering: Process

- Estimate $\mu_i$, $\pi$, and $\sigma^2$ at each iteration
  - $\mu_i^{(t+1)} = \sum_{j=1}^{n} z_{ij}^{(t)} y_j \,/\, \sum_{j=1}^{n} z_{ij}^{(t)}$
  - $\sigma_i^{2(t+1)} = \sum_{j=1}^{n} z_{ij}^{(t)} (y_j - \mu_i^{(t+1)})^2 \,/\, n$
  - $\pi_i^{(t+1)} = \sum_{j=1}^{n} z_{ij}^{(t)} \,/\, n$
- Each Sum can be partitioned across sites
  - Compute global sum securely *(Kantarcioglu and Clifton '02)*

## What if the Secrets are in the Results?

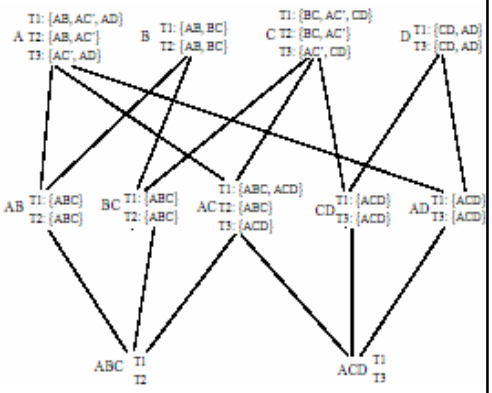
- Assume we want to make data available
  - Example: Telephone directory
- But the data contains rules we don't want people to learn
  - Areas of corporate expertise
- How do we hide the rules?
  - While minimizing effect on the data!

## Disclosure Limitation of Sensitive Rules *(Atallah et. al. '99)*

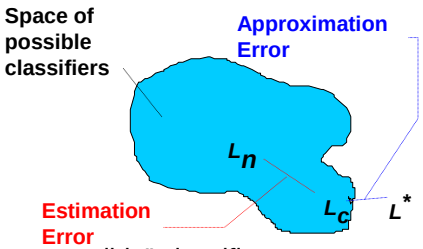
- Given a database and a set of "secret" rules, modify database to hide rules
  Change 1's to 0's and vice-versa to
  - Lower support
  - Lower confidence
- Goal: Minimize effect on non-sensitive rules
  - Problem shown to be NP-Hard!

# Heuristic Solution: Minimize effect on small itemsets

- Build graph of all supported itemsets
- To hide large itemset:
  - Go up tree to find item with lowest support
  - Select transaction affecting fewest 2-itemsets
  - Remove item from that transaction




# What if we don't know what we want to hide? *(Clifton '00)*




Total (mean-squared) error

$$\int ( c - L(a) )^2 P(a, c)\, da\, dc$$

- $L^*$ : "best possible" classifier
- $L_n$ : classifier learned from the sample
- $L_c$ : best classifier from those that can be described by the given classification model (e.g decision tree, neural network)

Goal: determine sample size so expected error is sufficiently large *regardless of technique used to learn classifier.*

## Sample size needed to classify when zero approximation error

- Let *C* be a class of discrimination functions with VC dimension $V \geq 2$. Let *X* be the set of all random variables *(X,Y)* for which $L_C = 0$. For $\delta \leq 1/10$ and $\varepsilon < 1/2$

$$N(\varepsilon,\delta) \geq \frac{V-1}{12\varepsilon}$$

*Intuition: This is difficult, because we must have a lot of possible classifiers for one to be perfect.*

## Sample size needed to classify when no perfect classifier exists

- Let *C* be a class of discrimination functions with VC dimension $V \geq 2$. Let *X* be the set of all random variables *(X,Y)* for which for fixed $L \in (0, ½)$

$$L = \inf_{g \in \boldsymbol{C}} \mathrm{P}\{g(X) \neq Y\}.$$

Then for every discrimination rule $g_n$ based on $X_1, Y_1, \ldots, X_n, Y_n$,

$$N(\varepsilon,\delta) \geq \frac{L(V-1)\mathrm{e}^{-10}}{32} \times \min\left(\frac{1}{\delta^2}, \frac{1}{\varepsilon^2}\right)$$

and also, for $\varepsilon \leq L$ ε ¼,

$$N(\varepsilon,\delta) \geq \frac{L}{4\varepsilon^2} \log \frac{1}{4\delta}$$

*Intuition: If the space of classifiers is small, getting the best one is easy (but it isn't likely to be very good).*

# Summary

- Privacy and Security Constraints can be impediments to data mining
  - Problems with access to data
  - Restrictions on sharing
  - Limitations on use of results
- Technical solutions possible
  - Randomizing / swapping data doesn't prevent learning good models
  - We don't need to share data to learn global results
  - References to more solutions in the tutorial notes
- *Still lots of work to do!*

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