Privacy and Data Mining: New Developments and Challenges

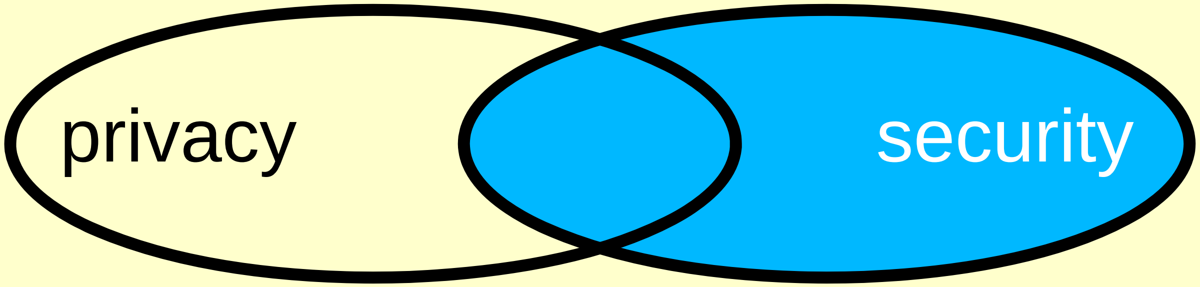
- Why privacy??
- Classification of Privacy-preserving Data Mining research (PPDM)
- Examples of current PPDM work
- Challenges

Why privacy and data mining?…

- Like any technology can be used for « good » and « bad » purposes …
- It's Computer Science that has developed these tools, so…
- A moral obligation to develop solutions that will alleviate [potential] abuses and problems

Privacy

- „fuzzy”, over-general concept
  - legal
  - economic
- Security?



Privacy

- Freedom from being watched ("*to be left alone*")
- …being able to control who knows what about us, and when [Moor]

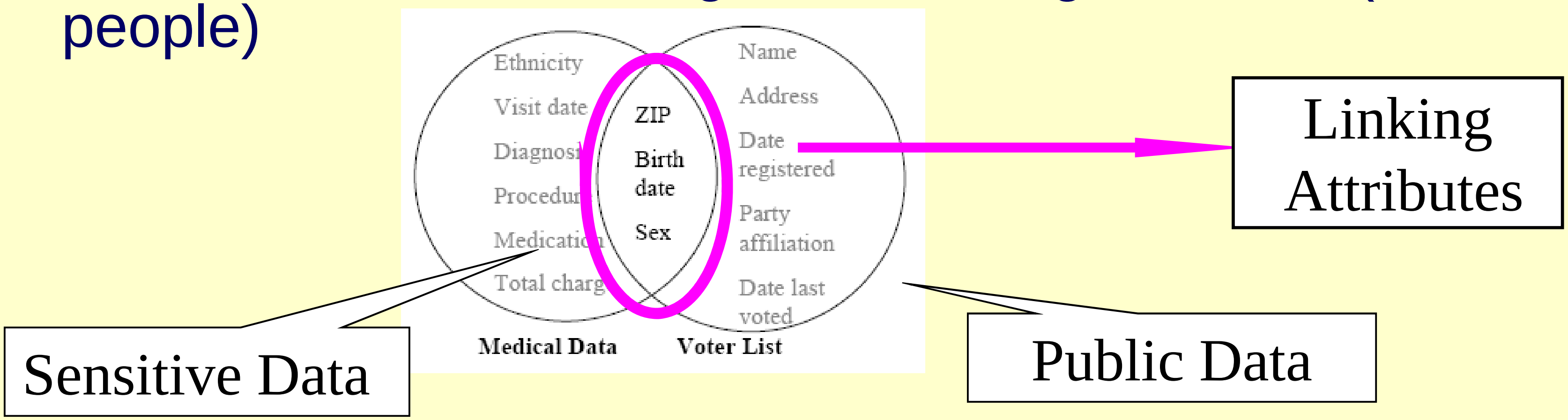
Privacy

- A CS « perspective»
  - I am a database
  - Privacy is the ability to control the *views*
- Threats to privacy due to:
  - The Internet
  - Distributed databases
  - Data mining
- « greased » data

…more precisely

- Privacy preservation: what does that mean?
- Given a table of instances (rows), we cannot associate any instance with a given person
- Naive anonymization…
- …is not sufficient, due to pseudo-identifiers

- L. Sweeney published this « attack » in 2001:
- <u>**anoymized**</u> (*de-linked*) health records of all 135,000 employees+families of the state of Massachussetts was placed on-line
- Electoral list of Cambridge, MA – bought for $20 (54 805 people)



- 69% records are unique wrt birthdate, ZIP; 87% are unique wrt to bday, ZIP, sex…
- Governor’s health records were identified
- …naive anonymization is not sufficient

Other privacy fiascos

- AOL search engine queries published

  2006

- Netflix publicly released a data set containing movie ratings of 500,000 Netflix subscribers *between December* 1999 and December 2005.
- By matching no more than 8 movie ratings and approximate dates, 96% of subscribers can be uniquely identified.

In statistics

- Statistical Disclosure Control
- A table is published, and the whole table has to be protected
- Risk/quality dilemma
- SDC ignores the use of the table
  - Classification
  - Associations
  - Distributed data

Privacy-preserving Data Mining PPDM

- Data sharing
- Data publishing
- Cloud
- Two main dimensions:
  - What is being protected: data, results?
  - Data centralized or distributed?

PPDM - dimensions

	Data centralized	Data distributed
Protecting the data	•generalization/suppression [Sweeney] •randomization [Du]/perturbation [Aggrawal]	•Horizontal/vertical: SMC-based [Clifton], •Homomorphic encryption [Wright], [Zhang Matwin]
Protecting the results	*k*-anonymization of results :[Gianotti/Pedreschi]	[Jiang, Atzior], [Felty, Matwin]

Privacy Goal: *k*-Anonymity

- Quasi-identifier (QID): The set of re-identification attributes.
- *k*-anonymity: Each record cannot be distinguished from at least *k-1* other records in the table wrt *QID*. [Sween98]

Raw patient table

Job	**Sex**	**Age**	**Disease**
Engineer	Male	36	Fever
Engineer	Male	38	Fever
Lawyer	Male	38	Hepatitis
Musician	Female	30	Flu
Musician	Female	30	Hepatitis
Dancer	Female	30	Hepatitis
Dancer	Female	30	Hepatitis

3-anonymous patient table

Job	**Sex**	**Age**	**Disease**
Professional	Male	[36-40]	Fever
Professional	Male	[36-40]	Fever
Professional	Male	[36-40]	Hepatitis
Artist	Female	[30-35]	Flu
Artist	Female	[30-35]	Hepatitis
Artist	Female	[30-35]	Hepatitis
Artist	Female	[30-35]	Hepatitis

Homogeneity Attack on *k*-anonymity

- A data owner wants to release a table to a data mining firm for classification analysis on *Rating*

Job	Country	Child	Bankruptcy	Rating	# Recs
Cook	US	No	Current	0G/4B	4
Artist	France	No	Current	1G/3B	4
Doctor	US	Yes	Never	4G/2B	6
Trader	UK	No	Discharged	4G/0B	4
Trader	UK	No	Never	1G/0B	1
Trader	Canada	No	Never	1G/0B	1
Clerk	Canada	No	Never	3G/0B	3
Clerk	Canada	No	Discharged	1G/0B	1
				Total:	24

- Inference: {Trader,UK} → fired
- Confidence = 4/5 = 80%
- An inference is sensitive if its confidence > threshold.

p-Sensitive k-Anonymity

- for each equivalence class EC there is at least p distinct values for each sensitive attribute
- **Similarity attack** occurs when the values of sensitive attribute in an EC are distinct but have similar sensitivity.

Age	Country	Zip Code	Health Condition
<30	America	142**	HIV
<30	America	142**	HIV
<30	America	142**	Cancer
<30	America	142**	Cancer
>40	Asia	130**	Hepatitis
>40	Asia	130**	Phthisis
>40	Asia	130**	Asthma
>40	Asia	130**	Heart Disease
3*	America	142**	Flu
3*	America	142**	Flu
3*	America	142**	Flu
3*	America	142**	Indigestion

2-Sensitive 4-Anonymity

l-Diversity

- every equivalence class in this table has at least l *well represented* values for the sensitive attribute
- **Distinct *l*-diversity**: the number of distinct values for a sensitive attribute in each equivalence class to be at least l.
- l -Diversity may be difficult and unnecessary to achieve and it may cause a huge information loss.

	Non-Sensitive			Sensitive
	Zip Code	Age	Nationality	Condition
1	1305*	≤ 40	$*$	Heart Disease
4	1305*	≤ 40	$*$	Viral Infection
9	1305*	≤ 40	$*$	Cancer
10	1305*	≤ 40	$*$	Cancer
5	1485*	> 40	$*$	Cancer
6	1485*	> 40	$*$	Heart Disease
7	1485*	> 40	$*$	Viral Infection
8	1485*	> 40	$*$	Viral Infection
2	1306*	≤ 40	$*$	Heart Disease
3	1306*	≤ 40	$*$	Viral Infection
11	1306*	≤ 40	$*$	Cancer
12	1306*	≤ 40	$*$	Cancer

3-diverse data [4]

t-closeness

- An equivalence class EC is said to have t-closeness if the distance between the distribution of a sensitive attribute in this class and the distribution of the attribute in the whole table is no more than a threshold *t*. [5].

- It solves the attribute disclosure problems of l-diversity, i.e. skewness attack and similarity attack, [6]

	ZIP Code	Age	Salary	Disease
1	4767*	≤ 40	3K	gastric ulcer
3	4767*	≤ 40	5K	stomach cancer
8	4767*	≤ 40	9K	pneumonia
4	4790*	≥ 40	6K	gastritis
5	4790*	≥ 40	11K	flu
6	4790*	≥ 40	8K	bronchitis
2	4760*	≤ 40	4K	gastritis
7	4760*	≤ 40	7K	bronchitis
9	4760*	≤ 40	10K	stomach cancer

0.167-closeness w.r.t. salary and

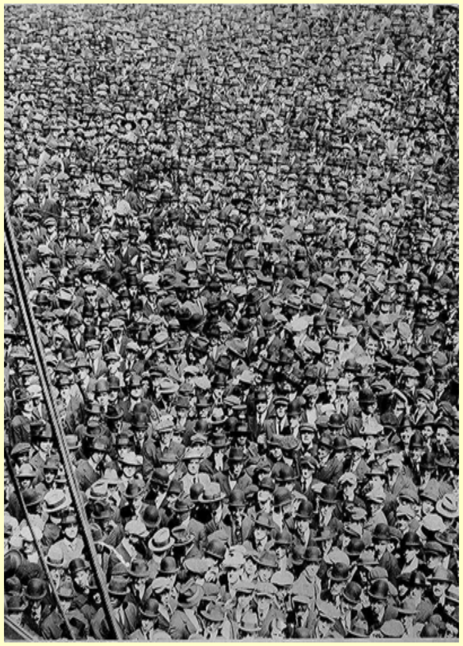
0.278-closeness w.r.t. Disease[5]

Two basic approaches

camouflage

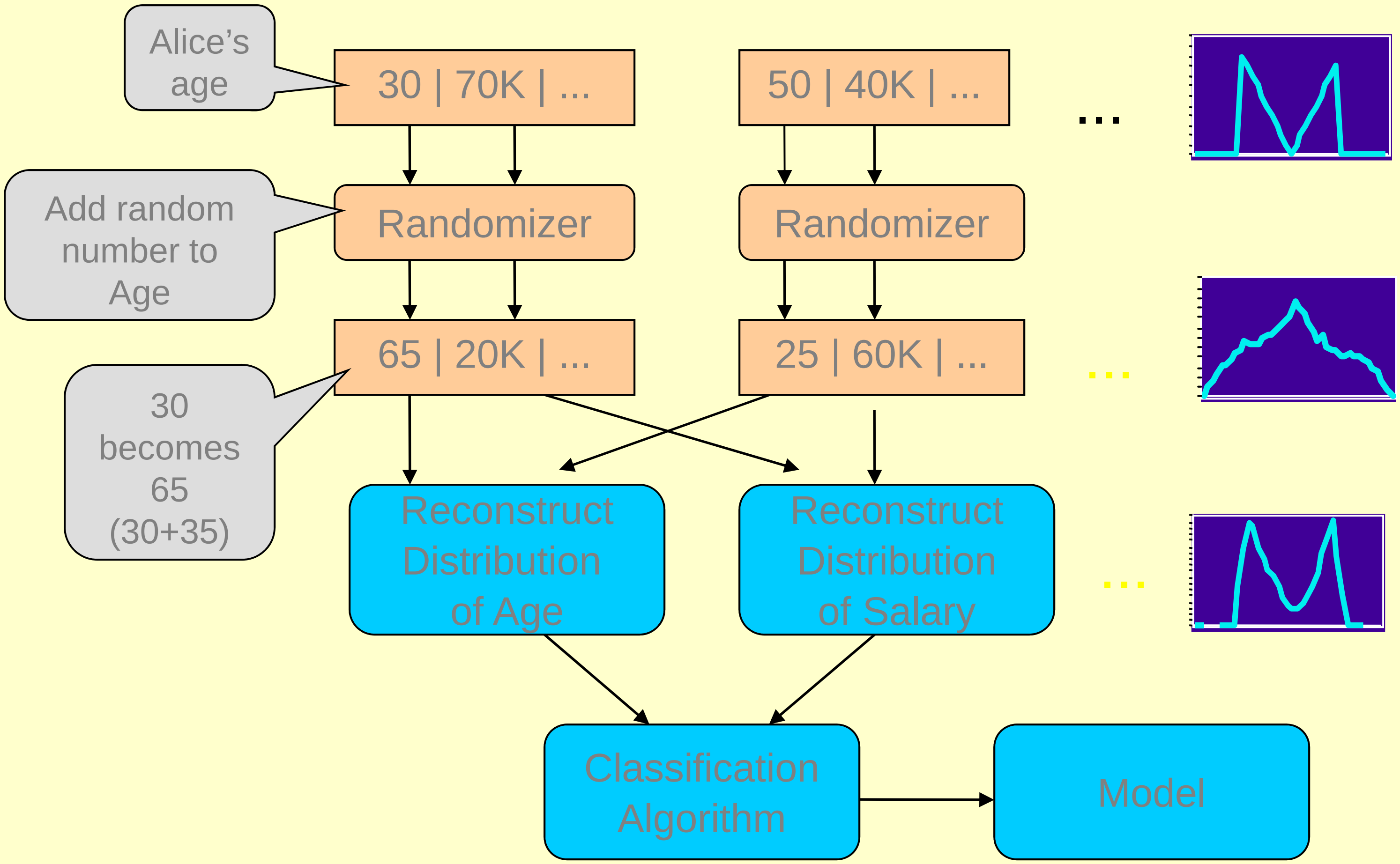
Data modification/perturbation

hiding in the crowd



k-anonymization

Randomization

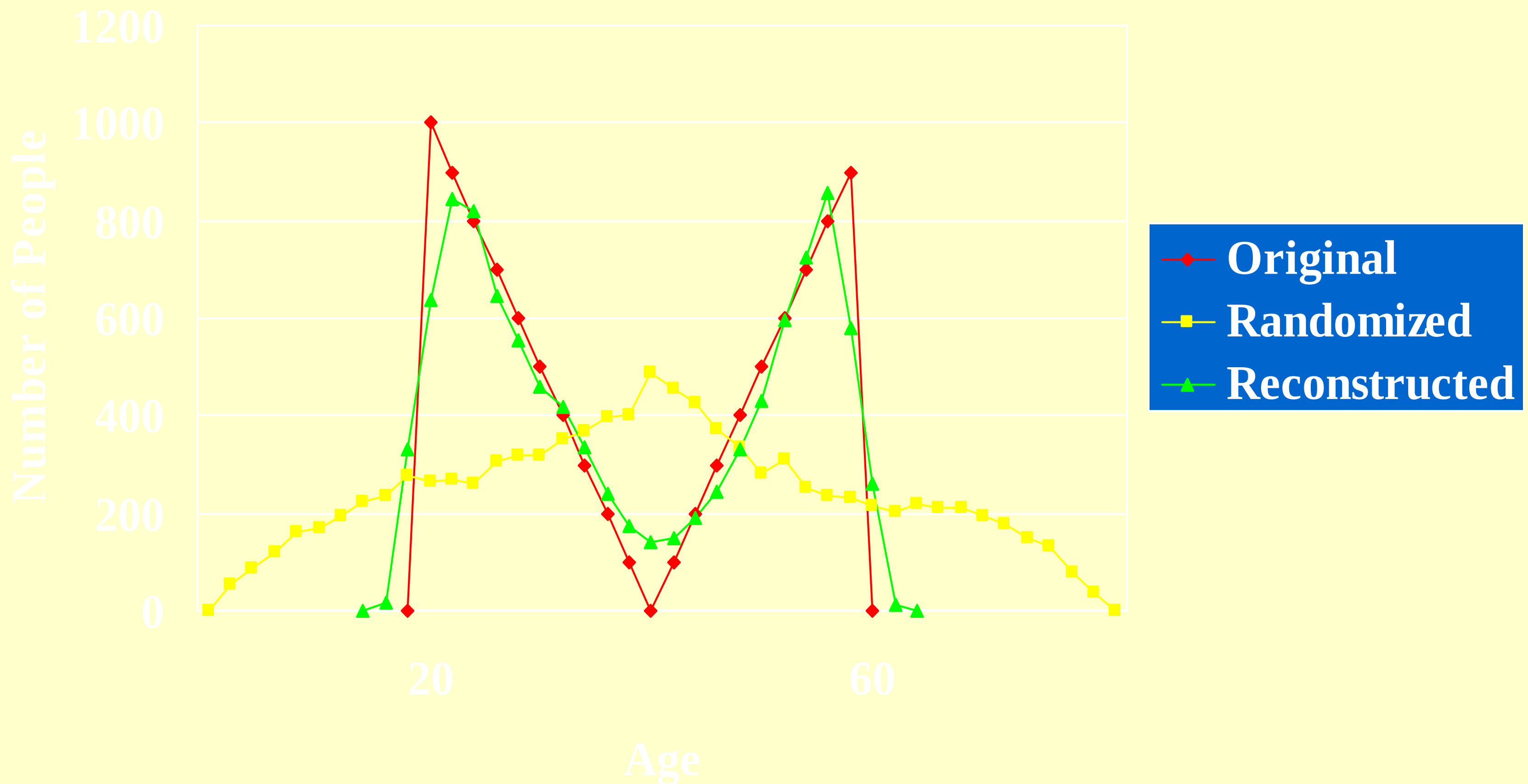


Reconstruction (*linking*)

- initial (confidential) values $x_1, x_2, ..., x_n$ have an (uknown) distribution X
- For protection, we perturb them with values $y_1, y_2, ..., y_n$ with a *known* distribution Y
- given
  - $x_1+y_1, x_2+y_2, ..., x_n+y_n$
  - distribution Y

Find an estimation of the distribution X.

Works well


1200
1000
800
600
400
200
0
Number of People
20
60
Age
Original
Randomized
Reconstructed

Privacy measure

If in the perturbed data, we can identify an original value x in an interval $[x_1, x_2]$ with probability c%, we have a c% confidence in the privacy of x

	confidence		
	50%	95%	99.9%
Discretization	0.5 x W	0.95 x W	0.999 x W
Uniform	0.5 x 2α	0.95 x 2α	0.999 x 2α
Gaussian	1.34 x σ	3.92 x σ	6.8 x σ

example

- Salary 20K - 150K
- 95% confidence
- 50% privacy for uniform distr.
- 2α = 0.5*130K / 0.95 = 68K

- For a high level of confidence, discretization hurts the results
- Gaussian distribution is better for higher confidence levels

privacy measures

- For modification methods
- First – wrt the interval to which we generalize a value
- We inject ”noise” with a random variable *A* with distribution *f*
- The privacy measure is

$$\prod(A) = 2^{-\int_{\Omega_A} f_A(a)\log_2 f_A(a)da}$$

- We measure entropy

Differential privacy

- The desideratum: “access to a database should not enable one to learn anything about individual that could not be learned without access” [Dalenius 77]: simlar to semantic security of Goldwasser & Micali
- Impossible because of auxiliary knowledge *(AK)*: database of avg height of people of different nationalities + *AK* = SM is 2 cm shorter than avg Israeli male

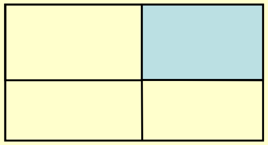
Differential privacy cont'd

- A randomized function K gives ε -differential privacy if for all data sets D_1 and D_2 differing on at most one element, and all $S \subseteq Range(K)$,
- $Pr[K(D_1) \in S] \leq \exp(\varepsilon) \times Pr[K(D_2) \in S]$
- A ***relative*** guarantee of non-disclosure: any disclosure is as likely whether or not the individual participates in *D*
- *K* is a protection ("sanitization") scheme, $\in S$ represents a query about a database

Differential privacy cont'd

- For every pair of inputs that differ in one value
- For every output
- Adversary should not be able to distinguish between any D1and D2 based on any O:

$$\log\left[\frac{\Pr(D_1 \rightarrow O)}{\Pr(D_2 \rightarrow O)}\right] < \varepsilon(\varepsilon > 1)$$



Distributed data

- Vehicle/accident data
- To discover the causes of accidents we need to know the attributrs of different components from different manufacturers (brakes, tires)
- They will nolt disclose these values in the open
- **Vertical** partition

Distributed data

- A medical study carried out in several hospitals
- Would like to *merge* the data for bigger impact of results (results on 20 000 patients instead of 5 000 each)
- For legal reasons, cannot just share then open data
- Horizontal partition

Association Rule Mining Algorithm [Agrawal et al. 1993]

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. compute ***c.count***
6. end
7. $L_k = \{c \in C_k \mid c.count \geq \min - \sup\}$
8. end
9. Return $L = \bigcup_k L_k$

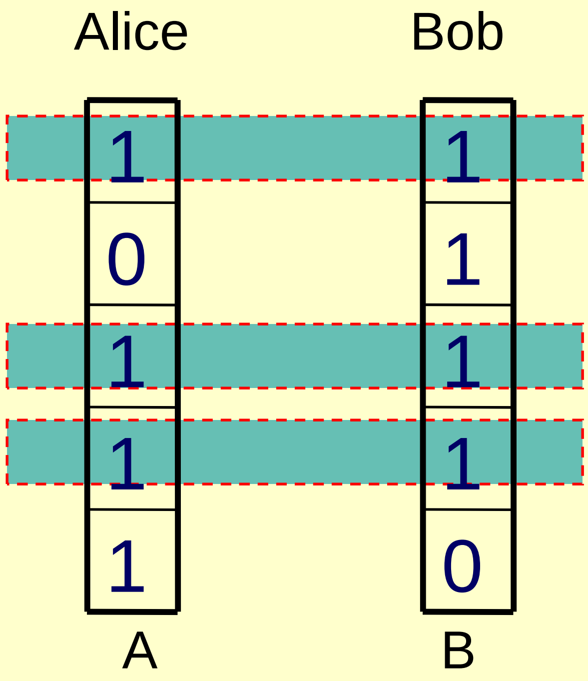
c.count is the frequency of an *itemset*.

to compute frequency, we need access to values of attributes belonging to different parties

Example

- c.count is the scalar product.
- A = Alice's attribute vector, B = Bob'
- AB is a candidate frequent itemset
- c.count = A • B = 3.

- How to perform the scalar product preserving the privacy of Alice and Bob?



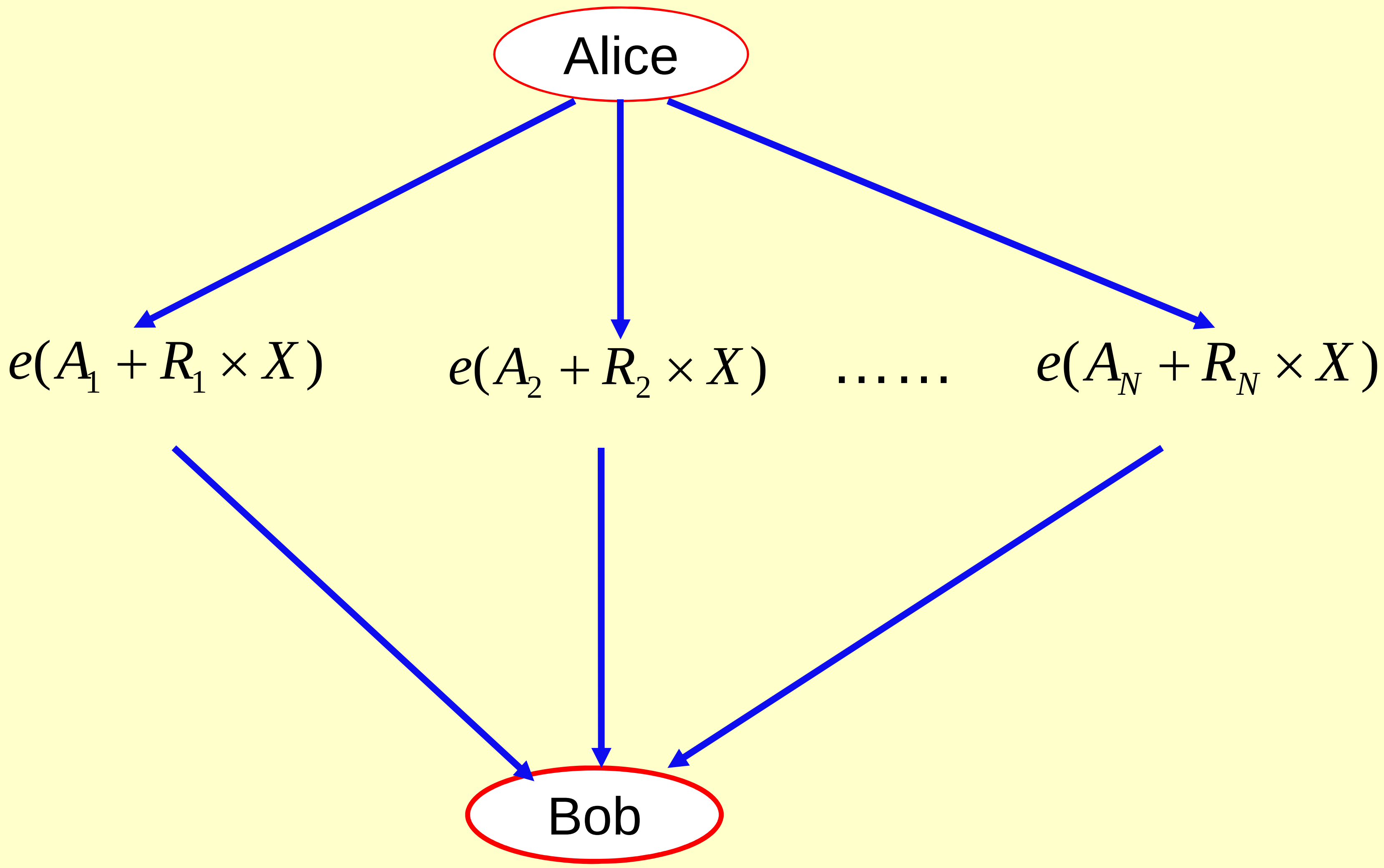
Homomorphic Encryption

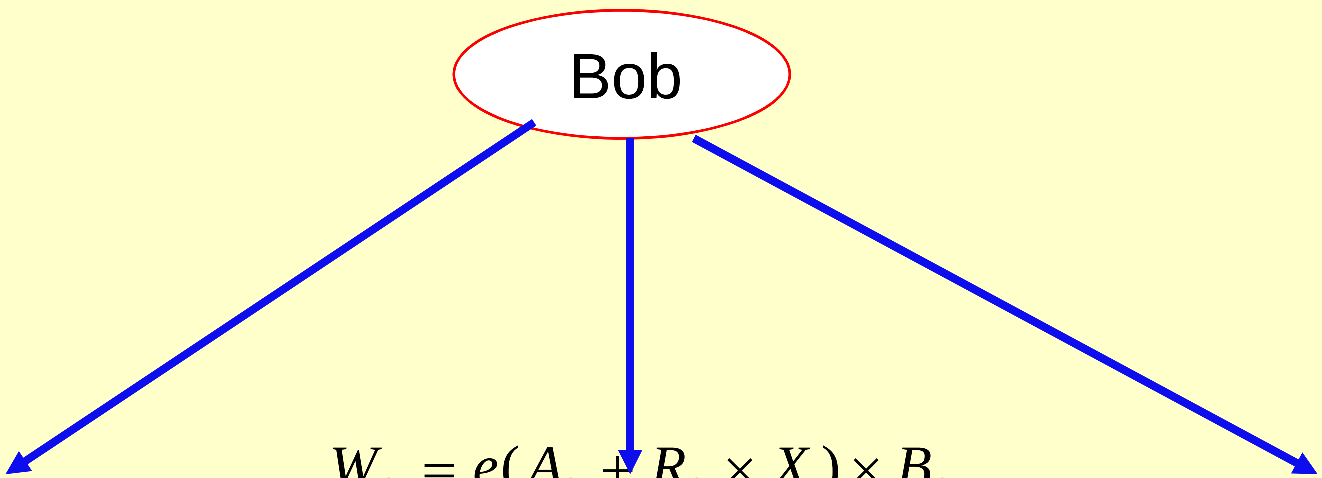
[Paillier 1999]

- Privacy-preserving protocol based on the concept of homomorphic encryption
- The homomorphic encryption property is

$$e(m_1) \times e(m_2) \times \cdots \times e(m_n) = e(m_1 + m_2 + \cdots + m_n)$$

- *e* is an encryption function $e(m_i) \neq 0$


Alice
$e(A_1 + R_1 \times X)$
$e(A_2 + R_2 \times X)$
……
$e(A_N + R_N \times X)$
Bob



$$W_1 = e(A_1 + R_1 \times X) \times B_1 \quad W_2 = e(A_2 + R_2 \times X) \times B_2 \quad \cdots \quad W_N = e(A_N + R_N \times X) \times B_N$$

$$B_i = 0 \Rightarrow W_i = 0$$

$$B_i = 1 \Rightarrow W_i = e(A_i + R_i \times X) \times B_i = e(A_i + R_i \times X)$$

Bob computes $W' = [\prod_{j \neq 0} W_j] \bmod X = [\prod_{j \neq 0} e(A_j + R_j \times X)] \bmod X = [e(A_{j_1} + \ldots A_{j_m} +,(R_{j_1} + \ldots R_{j_m}) \times X] \bmod X$
encrypts , sends to Alice

Last stage

- Alice decrypts W' and computes modulo X.

$$c.count$$
$$= d(e(A_1 + A_2 + \cdots + A_j + (R_1 + R_2 + \cdots + R_j + R') \times X)) \bmod X$$

$$(A_1 + A_2 + \cdots + A_j) \le N < X$$

$$((R_1 + R_2 + \cdots + R_j + R') \times X) \bmod X = 0$$

- She obtains $A_1 + A_2 + \cdots + A_j$ for these A_j whose corresponding B_j are not 0, which is = c.count
- Privacy analysis

Now looking at data mining results…

Can data mining results reveal personal information? In some cases, yes: [Atzori et al. 05]:

An association rule :

$$a_1 \wedge a_2 \wedge a_3 \Rightarrow a_4 [\sup = 80, conf = 98.7\%]$$

Means that $\sup(\{a_1, a_2, a_3, a_4\}) = 80$

So $\sup(\{a_1, a_2, a_3\}) = \frac{\sup(\{a_1, a_2, a_3, a_4\})}{0.987} = \frac{0.8}{.0987} = 81.05$

And $a_1 \wedge a_2 \wedge a_3 \wedge \neg a_4$ has support =1, and identifies a person!!

Protecting data mining results

- A *k-anonymous patterns* approach and an algorithm (*inference channels*) detect violations of *k*-anonymity of results

Discrimination and data mining

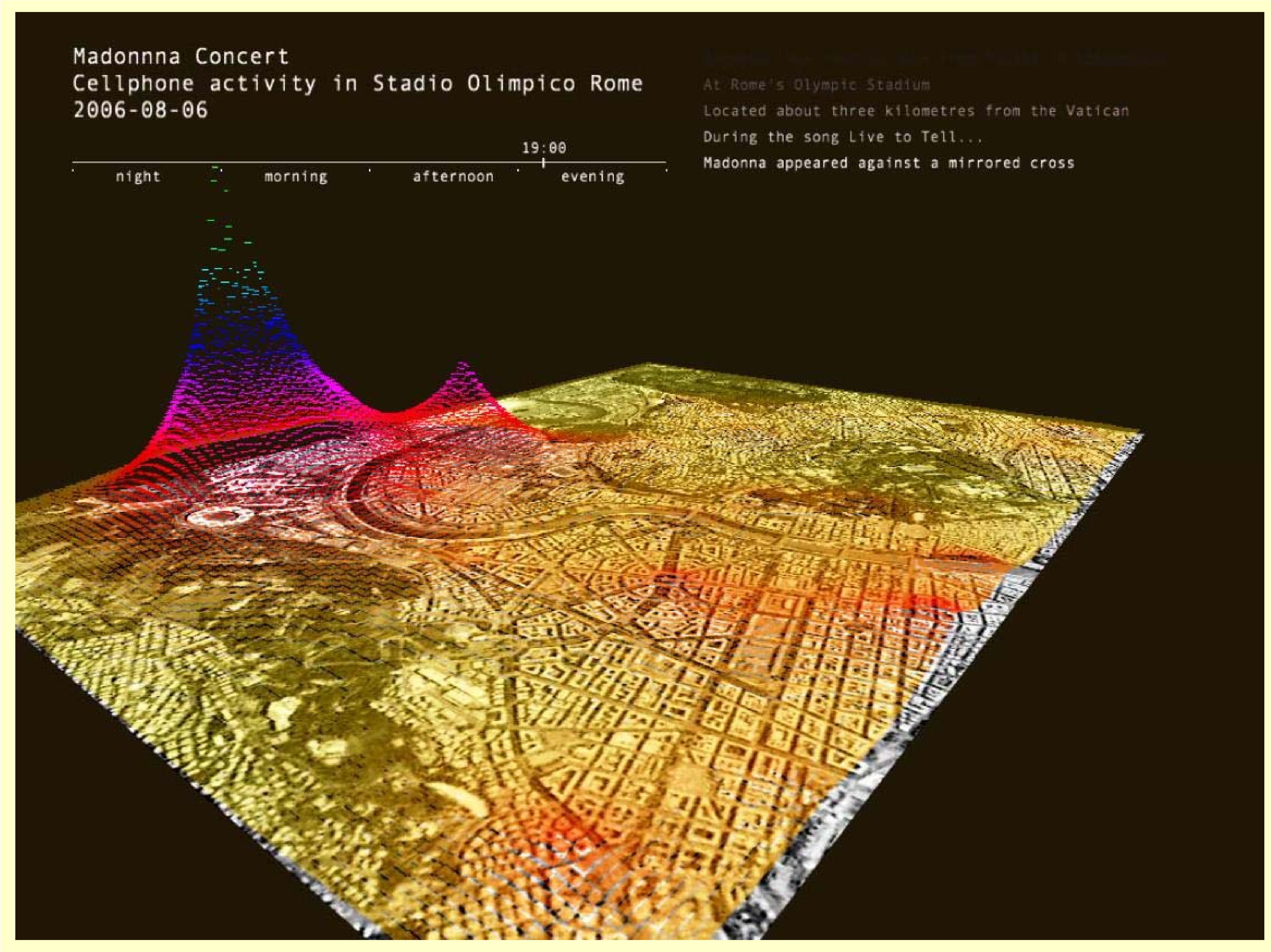
- [Pedreschi et al 07] shows how DM results can lead to discriminatory rules
- In fact, DM's goal is discrimination (between different sub-groups of data)
- They propose a measure of potential discrimination with lift : to what extent a sensitive is more assigned by a rule to a sensitive group than to an average group

Other challenges

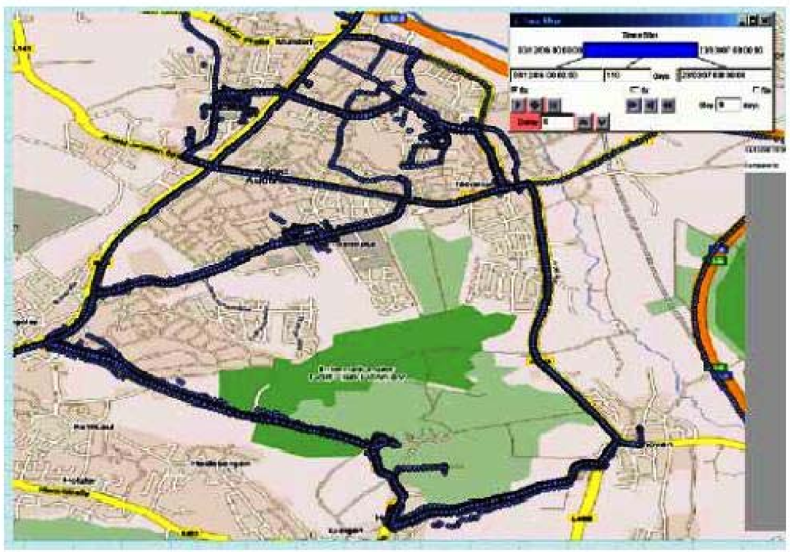
- Privacy and social networks
- Privacy definition – where to look for inspiration (economics?)
- Text data – perturbation/anonymization methods don’t work
- Medical data: trails [Malin], privacy of longitudinal data
- Mobile data -

GeoPKDD

- European project on Geographic Privacy-aware Knowledge Discovery and Delivery
- Data from GSM/UMTS and GPS


Madonnna Concert
Cellphone activity in Stadio Olimpico Rome
2006-08-06
19:00
night
morning
afternoon
evening
At Rome's Olympic Stadium
Located about three kilometres from the Vatican
During the song Live to Tell...
Madonna appeared against a mirrored cross

First obtaining spatio-temporal trajectories, then patterns

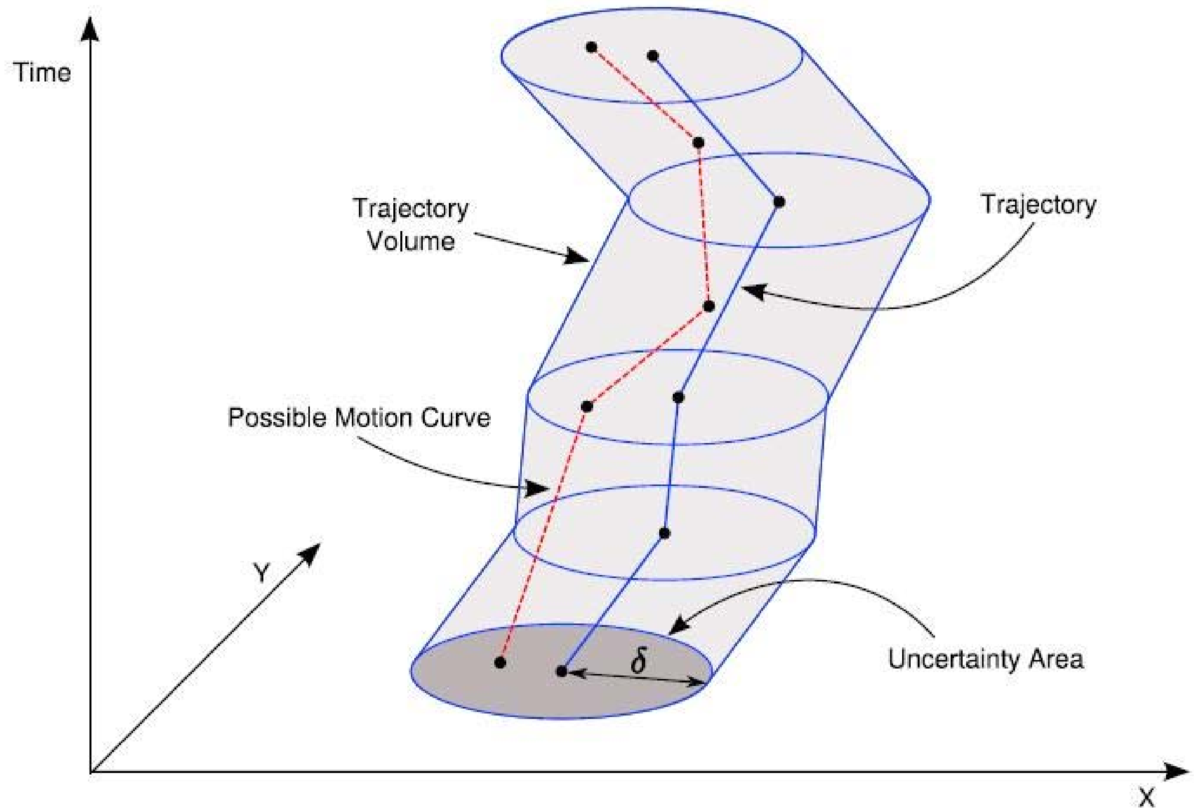


Trajectory = sequence of points visiteddans in a temporal order

pattern= set of frequent trajectories with similar transition times

Privacy of spatio-temporal data

- Modify the data in such a way each trajectory be indistinguishable from k other trajectories
- … by minimizing distorsion introduced into the data



Conclusion

- A major challenge for database/data mining research
- Lots of interesting contributions/papers, but lack of a systematic framework
- …?