Data Mining & Differential Privacy

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- only with 3-letters-organisations approval

Context :: Issues

- access to data strictly controlled
- data released with privacy issues (AOL click stream)

Society would benefit if we could publish useful data without worrying about privacy and access issues.

Privacy

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- AOL user 4417749 = Thelma Arnold

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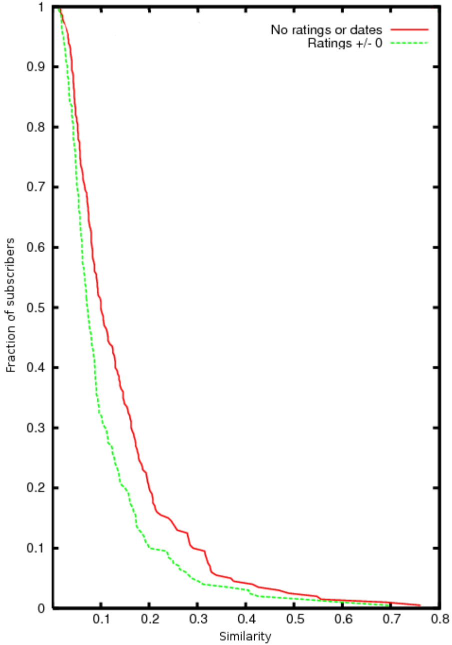
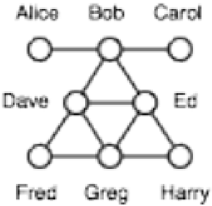
  - IMDB comments – Netflix reidentification


No ratings or dates
Ratings +/- 0
Fraction of subscribers
Similarity
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8

One customer . . . sued Netflix, saying she thought her rental history could reveal that she was a lesbian before she was ready to tell everyone.



Edges from call & email logs: what did they know and when did they know it?

Nodes

ID	Age	HIV
Alice	25	Pos
Bob	19	Neg
Carol	34	Pos
Dave	45	Pos
Ed	32	Neg
Fred	28	Neg
Greg	54	Pos
Harry	49	Neg

Edges

ID1	ID2
Alice	Bob
Bob	Carol
Bob	Dave
Bob	Ed
Dave	Ed
Dave	Fred
Dave	Greg
Ed	Greg
Ed	Harry
Fred	Greg
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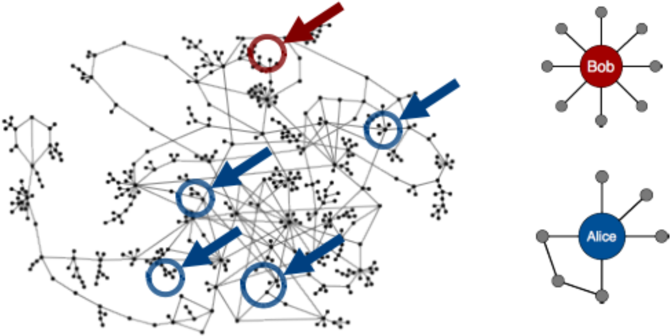
Bob
Alice

Important note

Just because data looks hard to re-identify, doesn't mean it *is*.

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privacy $\nearrow$, utility $\searrow$

Privacy protection needs

- membership disclosure: is X in Xs?
- sensitive attribute disclosure: has X a?
- identity disclosure: does i belong to X? are x and y the same?

k-anonymity

Your quasi-identifiers are indistinguishable from at least other k people's.

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- easy to understand
- easy to attack
  - doesn't say anything about operations done on data
  - join on other columns
  - no protection against background knowledge
  - updates (age) destroy protection

Other approaches

l-diversity : each group must have at least l distinct values

probabilistic l-diversity : frequency of the most frequent value in a class is bounded by $1/l$

entropy l-diversity : entropy of distribution of values inside a class is at least $\log(l)$

recursive (c, l)-diversity

$\ldots$ ($>$ 100 related approaches)

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$\ldots$ ($>$ 100 related approaches)

- hard to achieve
- underkill/overkill

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- insecure against attackers with too much background info
- no composition
- no meaningful definitions for privacy and utility
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Privacy is **not** a property of the data.

- privacy depends on the analysis done on the data
- identity transformation

Differential Privacy

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$$e^{-\epsilon} \leq \frac{Pr(\mathcal{A}(Q, D_1) = R)}{Pr(\mathcal{A}(Q, D_2) = R)} \leq e^{\epsilon}$$

Differential Privacy (2)

Add noise to analysis result.

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- sensibility of result (query)
- the more sensible the result, the more noise needs to be added
- sensibility is *worst-case* measure
- sensibility is independent of data in database
- sensibility of *how many people have this disease?* is 1
- sensibility of *what's the average salary of employees* is very high (sum, max, min, . . .)

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$$\Delta(f) = \max_{D_1, D_2} \|f(D_1) - f(D_2)\|$$

Differential Privacy (4)

Laplace mechanism

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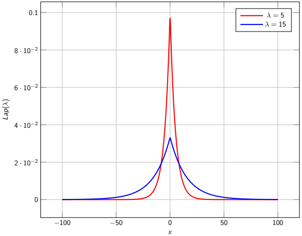
Laplace mechanism

$$\begin{aligned} \tilde{x} &= x + Lap(\lambda) \\ Lap(\lambda) &= \frac{1}{2\lambda}\exp(-\frac{|x|}{\lambda}) \\ \lambda &= \frac{\Delta(f)}{\epsilon} \end{aligned}$$



Laplace mechanism :: example

- How many users viewed more than 10 movies?

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- $\epsilon = 0.1$, $\lambda = 10$
- (possible) output: $\tilde{x} = 37$ (noise -5)

Differential Privacy (5)

Exponential mechanism

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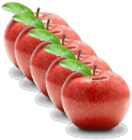
Exponential mechanism

- Laplace mechanism works for numerical data
- Exponential mechanism works for categorical data
- each item has a quality function $q(x)$
- randomly output item with probability $\sim \exp(\frac{q(x)}{\lambda})$
- $\lambda = \frac{2\Delta(q)}{\epsilon}$

Exponential mechanism :: example



Could set the price of apples at $1.00 for profit: $4.00

Could set the price of apples at $4.01 for profit $4.01

Best price: $4.01
2nd best price: $1.00
Profit if you set the price at $4.02: $0
Profit if you set the price at $1.01: $1.01

Differential Privacy (6)

Composability

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Composability

sequential composition $\epsilon_t = \epsilon_1 + \epsilon_2 + \ldots + \epsilon_k$

parallel composition $\epsilon_t = \max\{\epsilon_1, \epsilon_2, \ldots, \epsilon_k\}$

Differential Privacy (7)

How to use the mechanisms?

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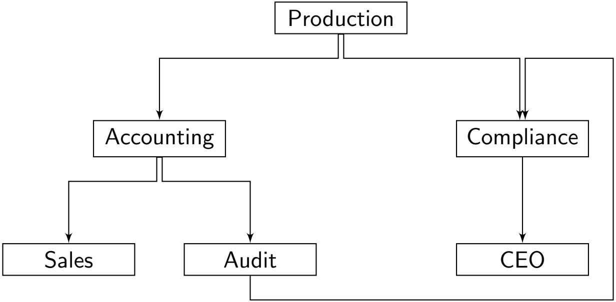
How to use the mechanisms?

- using them directly gives not so good results
- composability properties help
- we can generate synthetic data and apply all algorithms on that
- we can interleave dp mechanisms with the original data-mining algorithm
- optimization problems

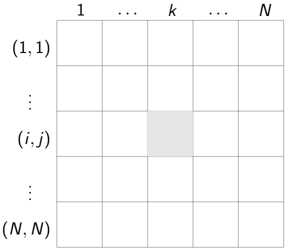
Workflow

Paths in organisation.



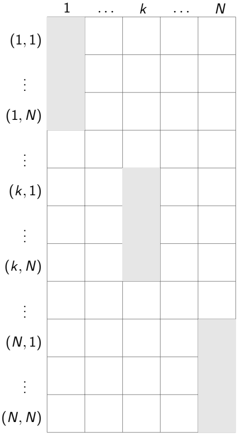
Workflow (2)

How many docs go through $i \to j \to k$



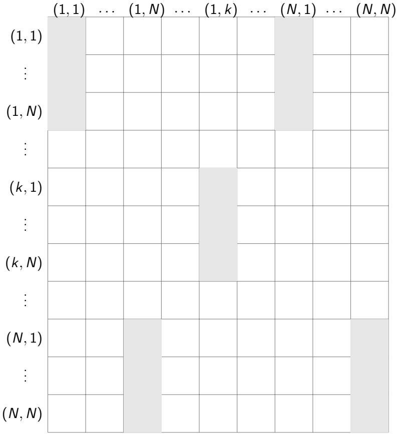
Workflow (3)

How many triangle paths $(i \to j \to i)$



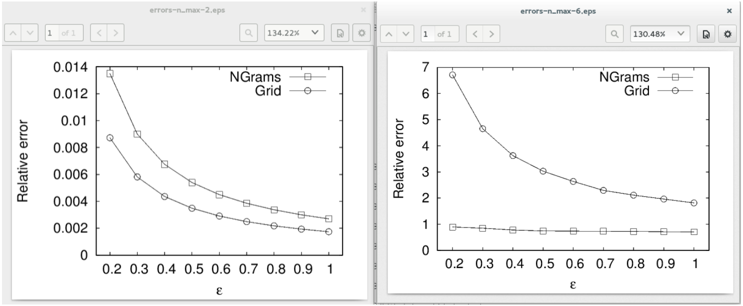
Workflow (4)

How many returned docs $(i \to \ldots j \to \ldots i)$



Workflow (5)

- n-gram model for higher dimensionality
- integrity constraints



Differential Privacy (8)

Limitations

- results are worse for higly-corellated data
- no extensions for complex models
- how to properly set ϵ
- expensive computations
- error bounds
- no direct relationship between utility and privacy
- inconsistencies