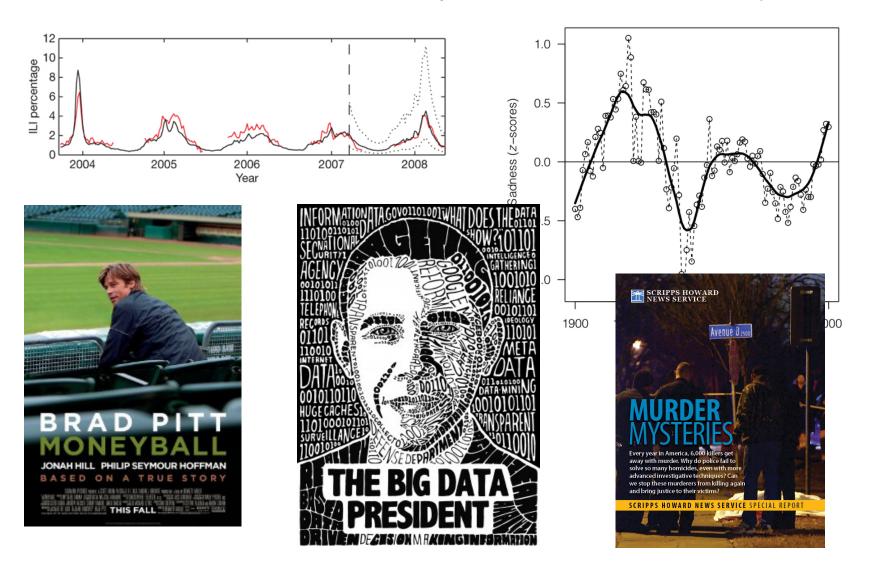
Privacy in Data Analysis

Everything Data CompSci 216 Spring 2015



Data and _____ your favorite subject



Where is all this data coming from?



Where is all this data coming from?

- Census surveys
- IRS Records

- Photos
- Videos

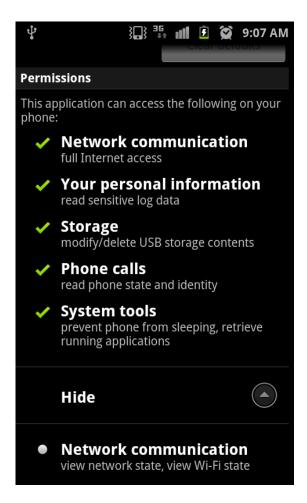
- Browse logs
- Shopping histories
- Insurance records ve Mobility trajectories

 Start phone Sensors

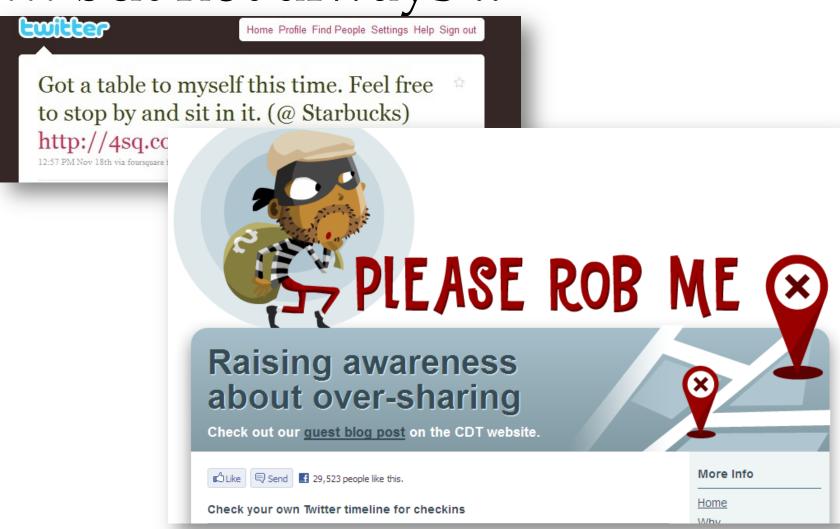
 Mobility trajectories

Sometimes users can know and control who sees their information

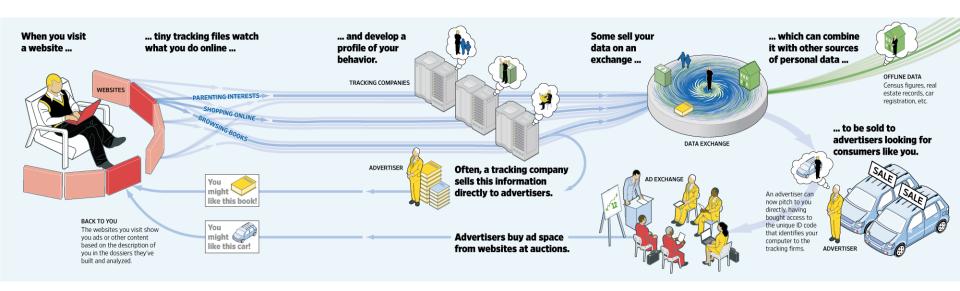




... but not always!!



Example: Targeted Advertising



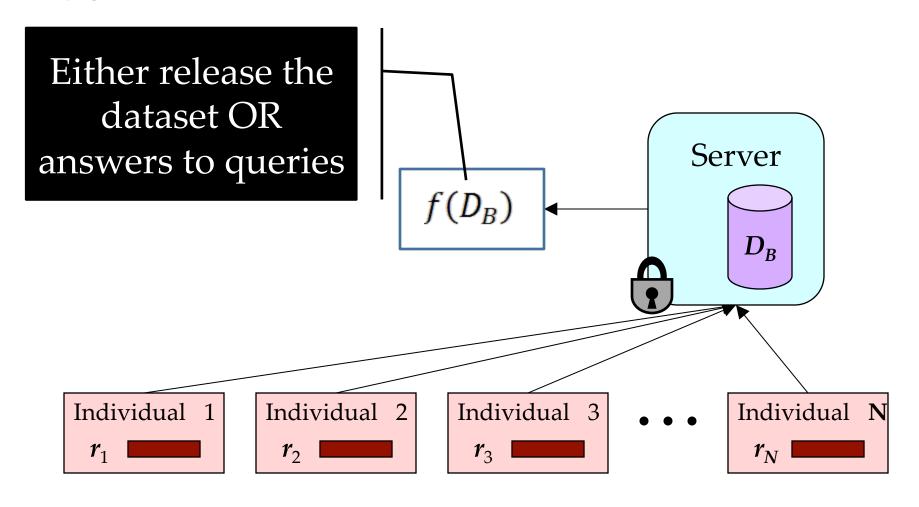
http://graphicsweb.wsj.com/documents/divSlider/media/ecosystem100730.png

What websites track your behavior?

Site	Exposure Index	Trackers
dictionary.com	Very High	234
merriam-webster.com	High	131
comcast.net	High	151
careerbuilder.com	High	118
photobucket.com	High	127
msn.com	High	207
answers.com	Medium	120
yp.com	Medium	89
msnbc.com	Medium	117
yahoo.com	Medium	106
aol.com	Medium	133
wiki.answers.com	Medium	72
cnn.com	Medium	72
about.com	Medium	83
cnet.com	Medium	81
verizonwireless.com	Medium	90
imdb.com	Medium	55
live.com	Medium	115
att.com	Medium	58
walmart.com	Medium	66
bbc.co.uk	Medium	45
ebay.com	Medium	42
ehow.com	Medium	55

http://blogs.wsj.com/wtk/

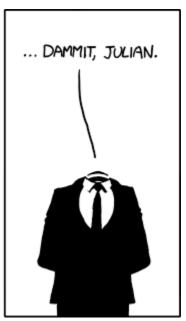
Servers track your information ... so what?



Does it matter ... I am anonymous, right?







Source (http://xkcd.org/834/)

What if we ensure our names and other identifiers are never released?

- Name
- •SSN

- Zip
- Visit Date
- Diagnosis
- Birth date
- Procedure
- Medication Sex
- Total Charge

Medical Data

- Name
- •SSN
- Visit Date
- Diagnosis
- Procedure
- Medication Sex
- Total Charge

- Name
- Address
- DateRegistered
- Party affiliation
- Date last voted

Medical Data Voter List

• Zip

Birth

date

- Name
- •SSN
- Visit Date
- Diagnosis
- Procedure
- Medication Sex
- Total Charge

- Name
- Address
- DateRegistered
- Party affiliation
- Date last voted

Governor of MA
 uniquely identified
 using ZipCode,
 Birth Date, and Sex.

Name linked to Diagnosis

Medical Data Voter List

• Zip

• Birth

date

- Name
- •SSN
- Visit Date
- Diagnosis
- Procedure
- Medication Sex
- Total Charge

- Name
- Address
- DateRegistered
- Party
 - affiliation
- Date last voted

0112

Medical Data Voter List

• Zip

• Birth

date

Quasi Identifier

87 % of US population

uniquely identified

Birth Date, and Sex.

using ZipCode,

AOL data publishing fiasco



AOL data publishing fiasco ...

G

Ashwin222 | Uefa cup

Ashwin222 Uefa champions league

Ashwin222 Champions league final

Ashwin222 Champions league final 2013

Jun156 exchangeability

Jun156 Proof of deFinitti's theorem

Brett12345 Zombie games

Brett12345 | Warcraft

Brett12345 Beatles anthology

Brett12345 Ubuntu breeze

Austin222 Python in thought

Austin222 | Enthought Canopy

User IDs replaced with random numbers

4

865712345	Uefa cup
865712345	Uefa champions league
865712345	Champions league final
865712345	Champions league final 2013
236712909	exchangeability
236712909	Proof of deFinitti's theorem
112765410	Zombie games
112765410	Warcraft
112765410	Beatles anthology
112765410	Ubuntu breeze
865712345	Python in thought
865712345	Enthought Canopy

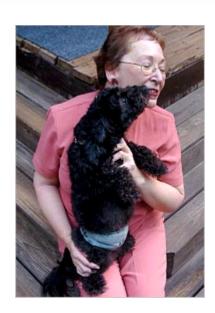
Privacy Breach

[NYTimes 2006]

A Face Is Exposed for AOL Searcher No. 4417749

By MICHAEL BARBARO and TOM ZELLER Jr. Published: August 9, 2006





Privacy violations from Facebook



http://article.wn.com/view/2012/08/28/ Facebooks_new_app_bazaar_violates_punters_privacy _lobbyists/

Inference from Impressions: Sexual Orientation

[Korolova JPC 2011]



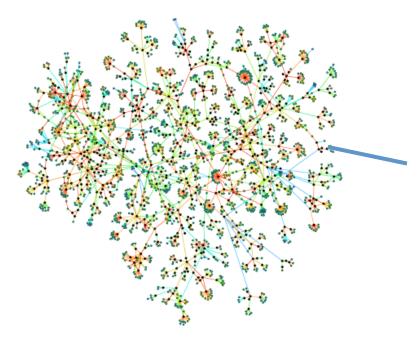
Facebook uses private information to predict match to ad

Reason for Privacy Breach

- Anyone can run a campaign with strict targeting criteria
 - Zip, birthdate and sex uniquely identify 87% of US population
- "Private" and "Friends only" profile infoused to determine match
- Default privacy settings lead to users having many publicly visible features
 - Default privacy setting for Likes, location, work place, etc. is public

Can Facebook release its graph?

• Suppose we release just release the nodes and edges in the Facebook graph ...

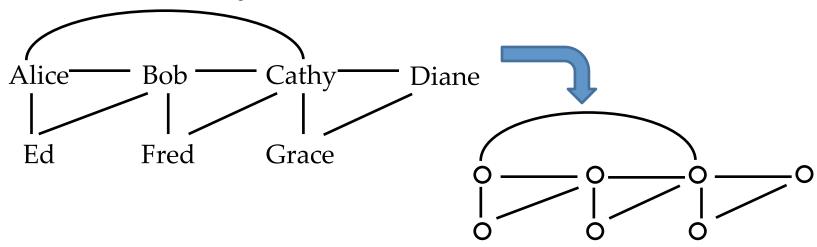


Mobile communication networks [J. Onnela et al. PNAS 07]

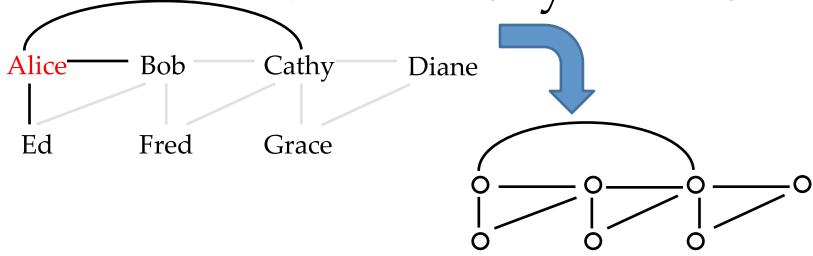
Sexual & Injection Drug Partners [Potterat et al. STI 02]



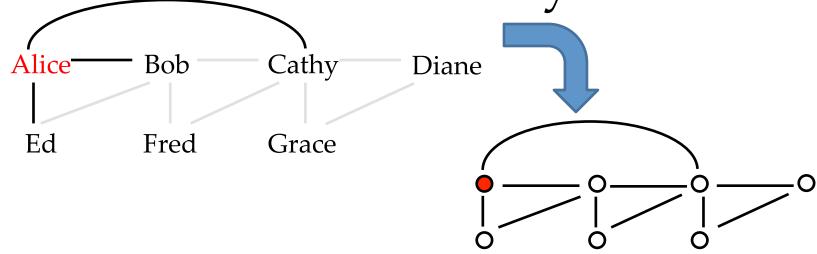
Naïve anonymization



- Consider the above email communication graph
 - Each node represents an individual
 - Each edge between two individuals indicates that they have exchanged emails
- Replace node identifiers with random numbers.

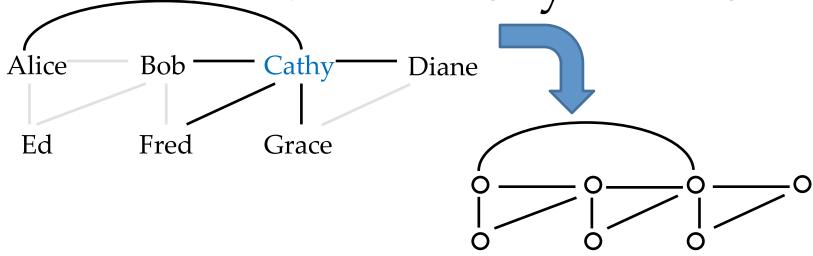


Alice has sent emails to three individuals only

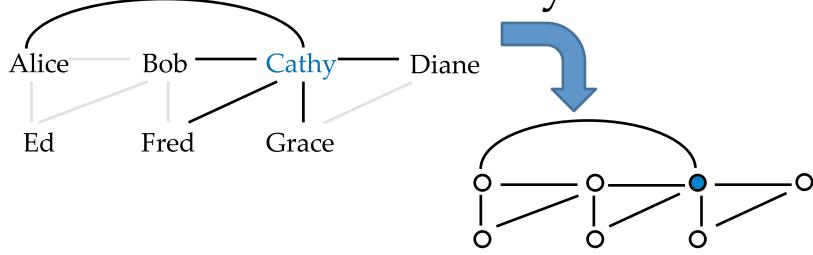


- Alice has sent emails to three individuals only
- Only one node in the anonymized network has a degree three
- Hence, Alice can re-identify herself

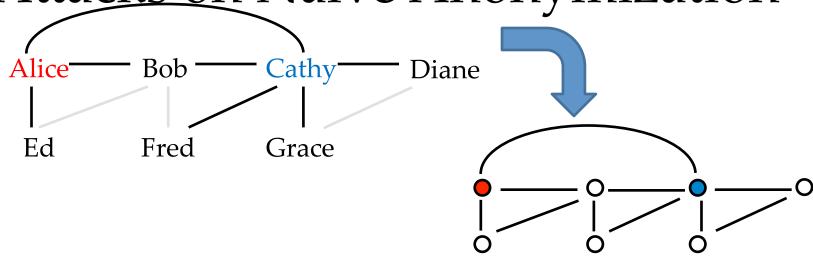
Lecture 2:590.03 Fall 13



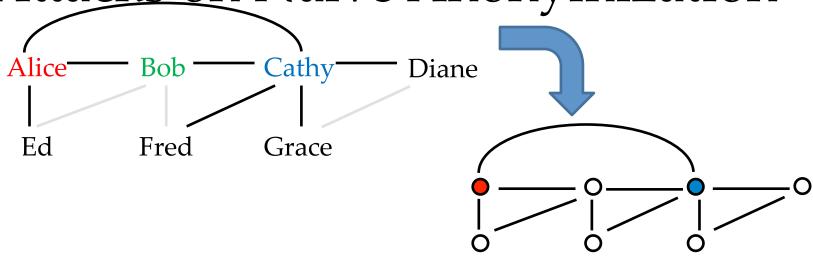
Cathy has sent emails to five individuals



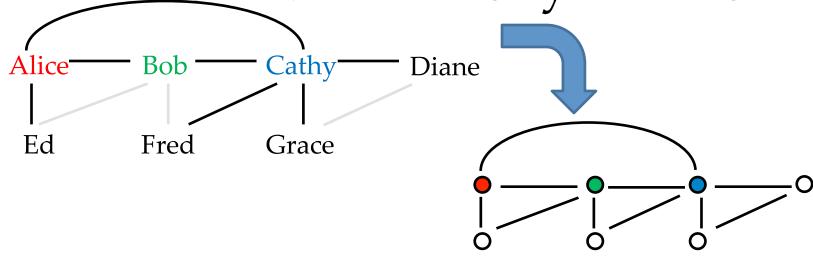
- Cathy has sent emails to five individuals
- Only one node has a degree five
- Hence, Cathy can re-identify herself



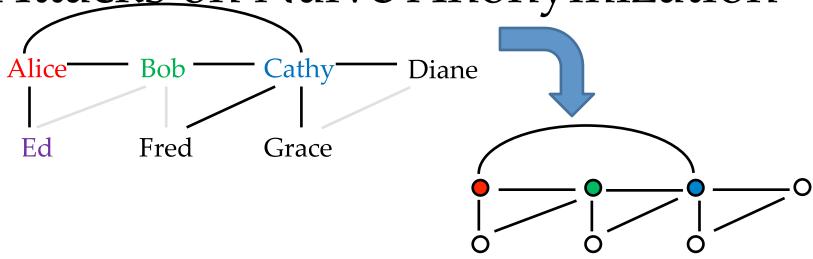
- Now consider that Alice and Cathy share their knowledge about the anonymized network
- What can they learn about the other individuals?



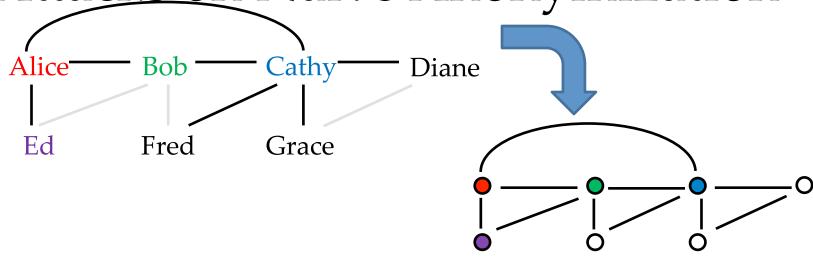
 First, Alice and Cathy know that only Bob have sent emails to both of them



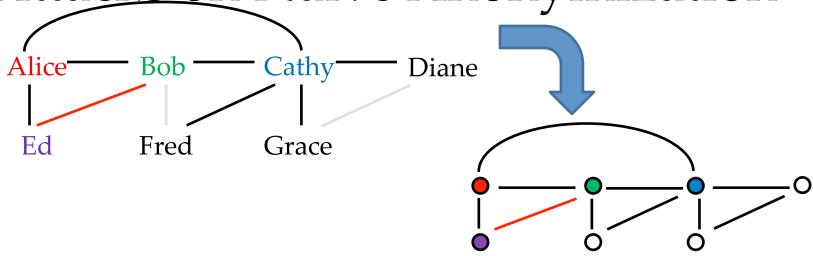
- First, Alice and Cathy know that only Bob have sent emails to both of them
- Bob can be identified



Alice has sent emails to Bob, Cathy, and Ed only



- Alice has sent emails to Bob, Cathy, and Ed only
- Ed can be identified



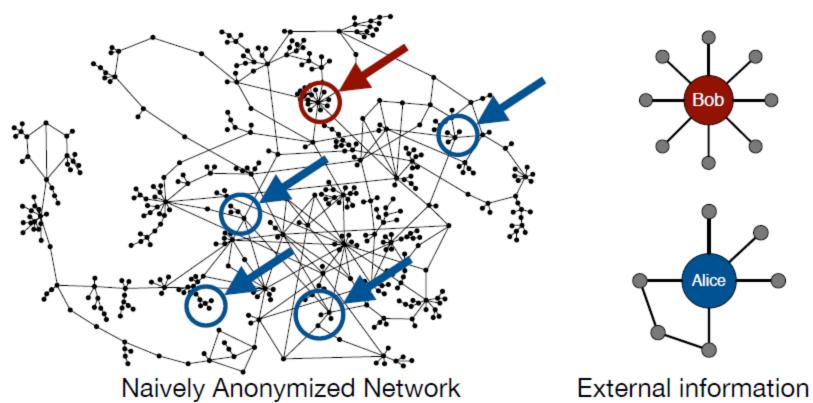
Alice and Cathy can learn that Bob and Ed are connected

Lecture 2:590.03 Fall 13

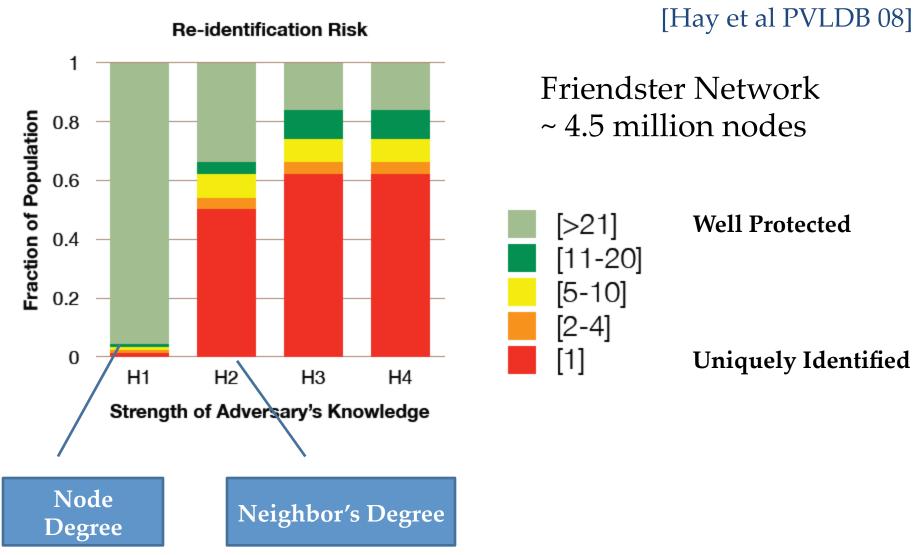
Attacks

Matching attack: the adversary matches external information to a naively anonymized network.

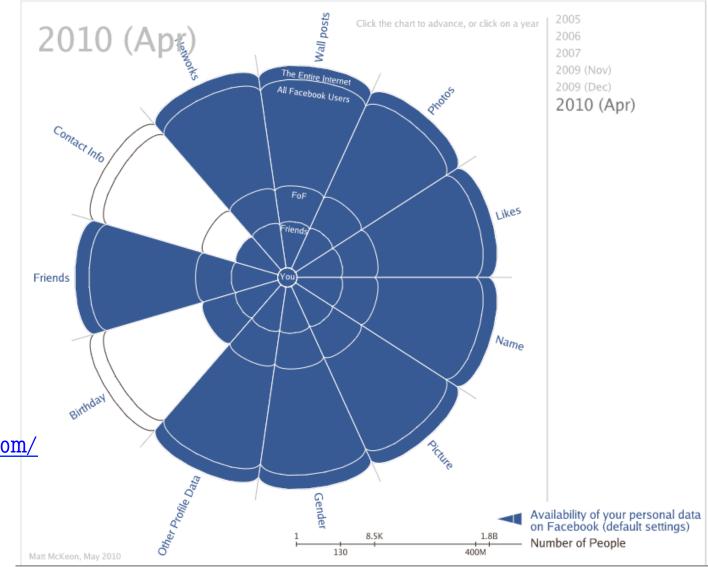
unique or partial node re-identification



Local structure is highly identifying



Sensitive values in social networks



http://mattmckeon.com/ facebook-privacy/

Sensitive values in social networks

- Some people are privacy conscious (like you)
- Most people are lazy and keep the default privacy settings (i.e., no privacy)

 Can infer your sensitive attributes based on the sensitive attribute of public individuals ...

Servers track your information ... and you are not anonymous

A Face Is Exposed for AOL Searcher No. 4417749

By MICHAEL BARBARO and TOM ZELLER Jr. Published: August 9, 2006

SIGN IN TO E



Why 'Anonymous' Data Sometimes Isn't

By Bruce Schneier 🖂

12.13.07

Last year, Netflix published 10 million movie rankings by 500,000 customers, as part of a challenge for people to come up with better recommendation systems than the one the company was using.





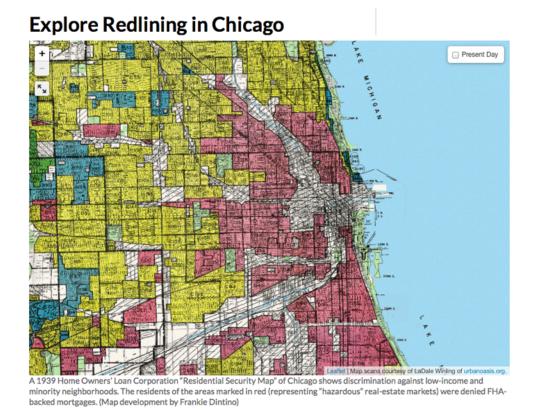


TECH | 2/16/2012 @ 11:02AM | 837,678 views

How Target Figured Out A Teen Girl Was Pregnant Before Her Father Did

Why care about privacy?

• **Redlining:** the practice of denying, or charging more for, services such as banking, insurance, access to health care, or even supermarkets, or denying jobs to residents in particular, often racially determined, areas.



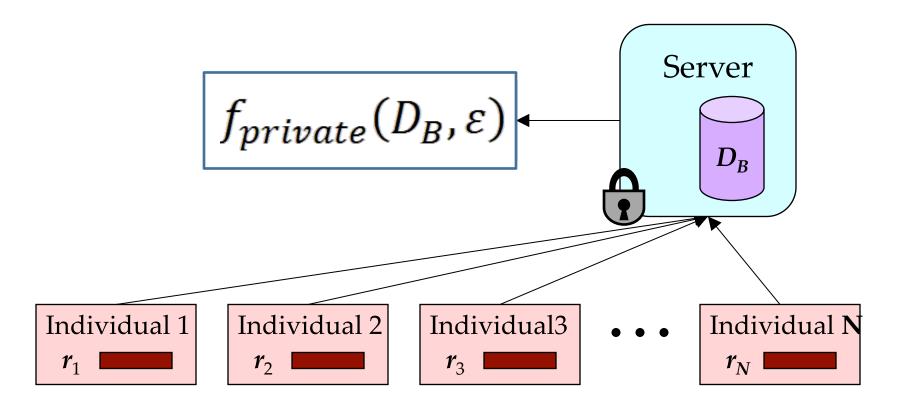
Can data analysis be done without breaching the privacy of individuals?



Private data analysis problem

Utility: $f_{private}$ approximates f

Privacy: No breach about any individual



Private data analysis examples

Application	Data Collector	Third Party (adversary)	Private Informatio n	Function (utility)
Medical	Hospital	Epidemiologi st	Disease	Correlation between disease and geography
Genome analysis	Hospital	Statistician/ Researcher	Genome	Correlation between genome and disease
Advertising	Google/FB/ Y!	Advertiser	Clicks/ Browsing	Number of clicks on an ad by age/region/gender
Social Recommen- dations	Facebook	Another user	Friend links / profile	Recommend other users or ads to users based on social network
Location Services	Verizon/ AT&T	Verizon/ AT&T	Location	Local Search

Private data analysis methods

• Bare Minimum protection: K-anonymity

• Ideal (state-of-the-art): Differential Privacy

K-Anonymity

• If every row corresponds to one individual, then ...

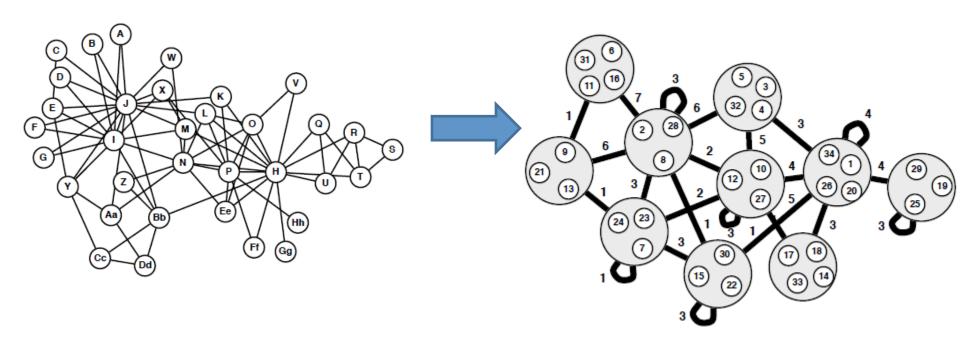
... every row should look like k-1 other rows based on the *quasi-identifier* attributes

K-Anonymity

Zip	Age	Nationality	Disease
13053	28	Russian	Heart
13068	29	American	Heart
13068	21	Japanese	Flu
13053	23	American	Flu
14853	50	Indian	Cancer
14853	55	Russian	Heart
14850	4 7	American	Flu
14850	59	American	Flu
13053	31	American	Cancer
13053	3 7	Indian	Cancer
13068	36	Japanese	Cancer
13068	32	American	Cancer

Zip	Age	Nationality	Disease
130**	<30	*	Heart
130**	<30	*	Heart
130**	<30	*	Flu
130**	<30	*	Flu
1485*	>40	*	Cancer
1485*	>40	*	Heart
1485*	>40	*	Flu
1485*	>40	*	Flu
130**	30-40	*	Cancer
130**	30-40	*	Cancer
130**	30-40	*	Cancer
130**	30-40	*	Cancer

K-anonymity in graphs



Problem: Homogeneity

Bob has Cancer

Name	Zip	Age	Nat.
Bob	13053	35	??

Zip	Age	Nationality	Disease
130**	<30	*	Heart
130**	30-40	*	Cancer
130**	30-40	*	Cancer
130**	30-40	*	Cancer
130**	30-40	*	Cancer

Problem: Composition

Zip Code	Age	Income	Disease
130**	[25-30]	$\geq 50k$	None
130**	[25-30]	$\geq 50k$	Stroke
130**	[25-30]	$\geq 50k$	Flu
130**	[23-30]	$\geq 50k$	Cancer
902**	[60-70]	< 50k	Flu
902**	[60-70]	< 50k	Stroke
902**	[60-70]	< 50k	Flu
902**	[60-70]	< 50k	Cancer

Zip Code	Age	Nationality	Disease
130**	< 40	*	Cold
130**	< 40	*	Stroke
130**	< 40	*	Rash
1485*	≥ 40	*	Cancer
1485*	≥ 40	*	Flu
1485*	≥ 40	*	Cancer

If Bob is in both datasets, then Bob has Stroke!

Differential Privacy

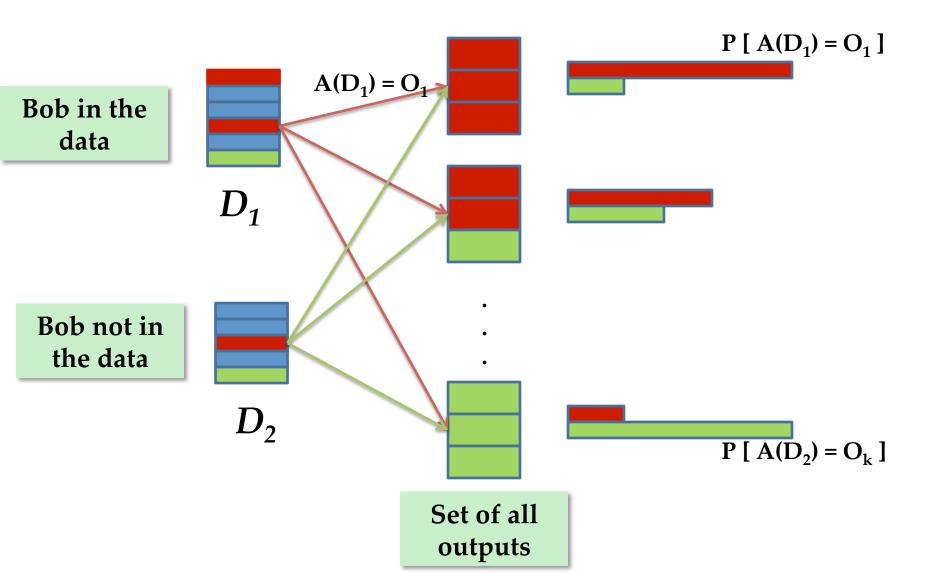
- Consider two datasets
 - With Bob as one of the participants
 - Without Bob
- Answers are roughly the same whether or not Bob is in the data

Differential Privacy

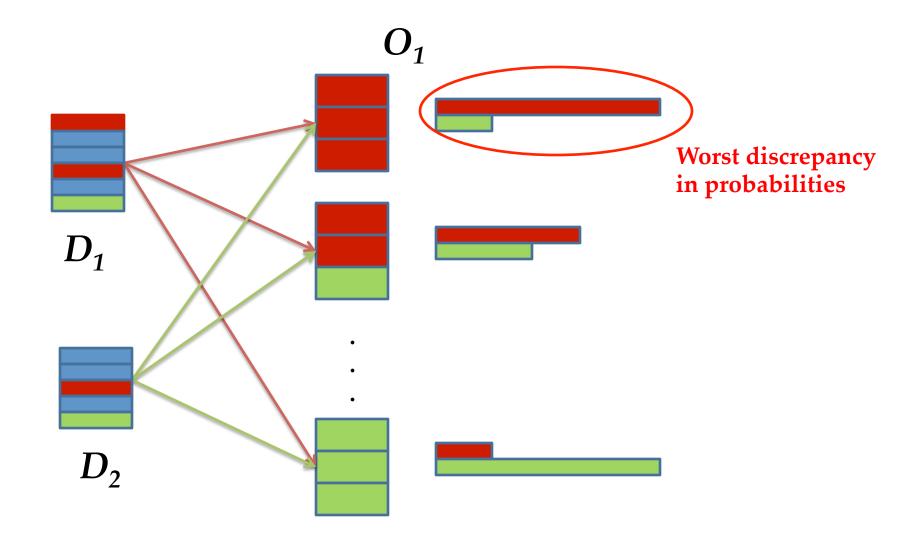
Algorithm A satisfies ε -differential privacy if: For **every pair** of *neighboring tables* D_1 , D_2 For **every output** O

$$Pr[A(D_1) = O] \le e^{\varepsilon} Pr[A(D_2) = O]$$

Meaning ...



Meaning ...



Privacy loss parameter ε

Algorithm A satisfies ε -differential privacy if: For **every pair** of *neighboring tables* D_1 , D_2 For **every output** O

$$Pr[A(D_1) = O] \le e^{\varepsilon} Pr[A(D_2) = O]$$

• Smaller the ε more the privacy (and better the utility)

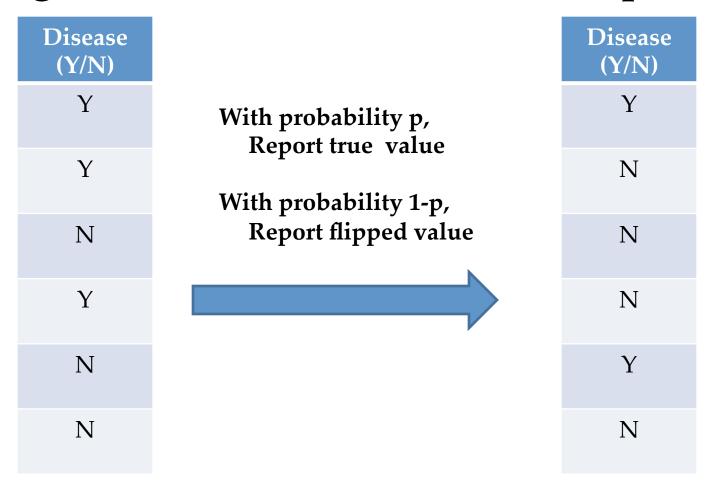
Differential Privacy

Algorithm A satisfies ε -differential privacy if: For every pair of neighboring tables D_1 , D_2 For every output O

$$Pr[A(D_1) = O] \le e^{\varepsilon} Pr[A(D_2) = O]$$

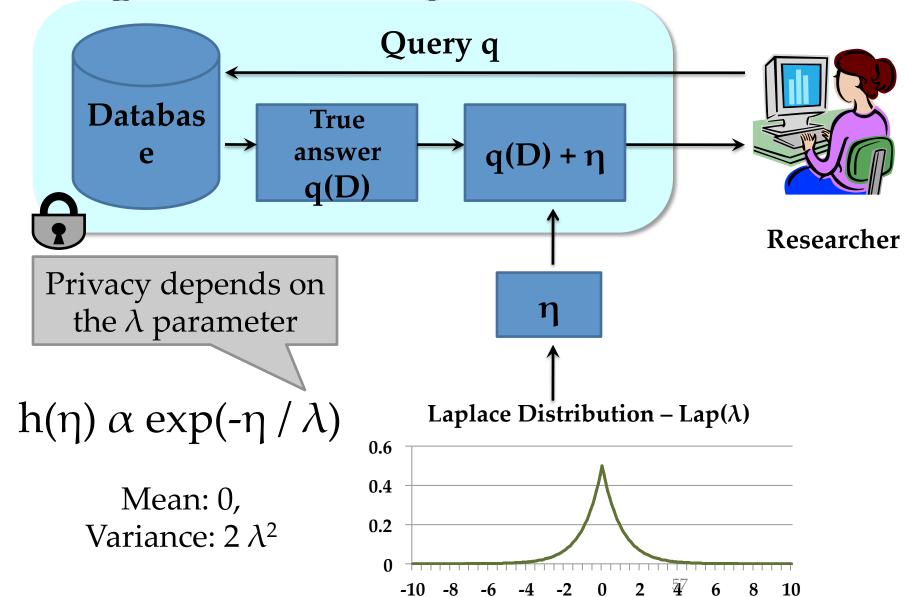
what the adversary learns about an individual is the same even if the individual is not in the data (or lied about his/her value)

Algorithm 1: Randomized Response



Can estimate the true proportion of Y in the data based on the perturbed values (since we know p)

Algorithm 2: Laplace Mechanism



Laplace Mechanism example

Qn: Release the histogram of admissions by diagnosis

Ans:

- Compute the true histogram
- Add noise to each count in the histogram using noise from Lap($1/\epsilon$)

Noisy count is within ± 1.38 of true count for $\varepsilon = 1$

Composition

Qn: Release 2 histograms of admissions (a) by diagnosis, and (b) age

Ans:

- Compute the true histograms
- Add noise to each count in the histograms using noise from Lap($1/\epsilon$)

Noisy counts are within ± 1.38 of true counts in both histograms ... but total privacy loss = 2

Differential Privacy summary

 Guarantees that the output of an analysis does not change much whether or not an individual is in the data

Very active area of research

- Many sophisticated algorithms for a variety of analyses (see my <u>other course</u>)
 - Used by the US Census to release data

Summary

• "Data-driven" revolution has transformed many fields ...

• ... but need to address the privacy problem

• Tools like differential privacy can foster 'safe' data collection, analysis and data sharing.