Protecting Data Sources, Protecting Personal Data

Simson L. Garfinkel Senior Scientist, Confidentiality and Data Access U.S. Census Bureau

> 4th Kavli Symposium Tuesday, February 20 Austin, TX



Raise your hand if you use two-factor authentication to protect your email account



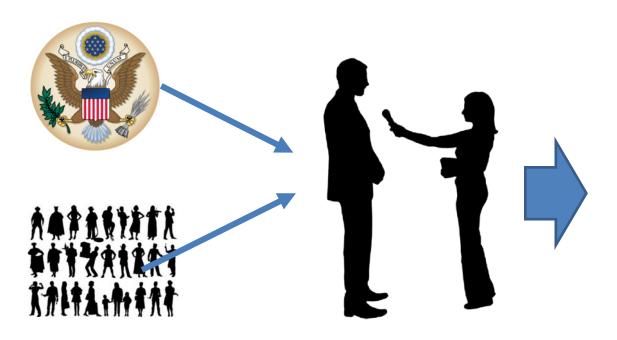
Two factor authentication







Protecting Data Sources, Protecting Personal Data



Sources

Collection

Communications Security



Processing

Storage Security



Dissemination

Publications Security

Outline

Communications security: How do you obtain confidential information from your sources?



Storage security: How do you maintain your secrets?



Publication security: How do you control the information released by your publication to prevent the inadvertent release of confidential information?

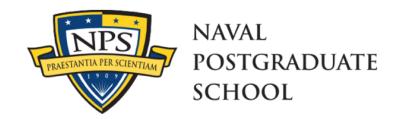


Bio: Simson L. Garfinkel

1987 Freelance science writer



2006 Associate Professor



2015 Computer Scientist



2017 Computer Scientist



I have spent 29 years trying to secure computers...



An Introduction to Computer Security

(Part 1)

Simson L. Garfinkel

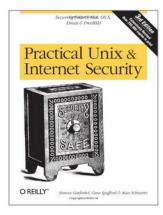
"Spies," "vandals," and "crackers" are out there, waiting to get into-or destroy-your databases.

ests and the interests of their clients. same way as lawyers now recognize

AWYERS MUST UNDERSTAND is- Lawyers today must automatically L sues of computer security, both recognize insecure computer systems for the protection of their own inter- and lax operating procedures in the

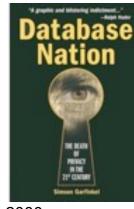
> The Practical Lawyer Sept. 1987

System Security



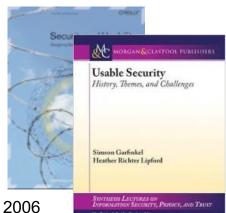
1991

Privacy Policy



2000

Usable Security



Internet of Things



2006

Today's systems are frequently less secure than those of the 1970s.

Poor security is inherent in many information systems.

- Attack is easier and cheaper than defense.
- Cyber "defense in depth" does not work a single vulnerability compromises.
- It's easier to break things than to fix them.



Network Connectivity makes it easier to exploit vulnerable computers.

Fortunately, most journalists have modest security needs.



A methodology for thinking about your security needs

Identify your critical assets and interactions — what you are trying to protect.

Identify potential threats — what you are trying to protect against.

Identify potential vulnerabilities — how your threat could be harmed

Identify risks — the potential for harm

Asset + Threat + Vulnerability = Risk

There are many risk equations

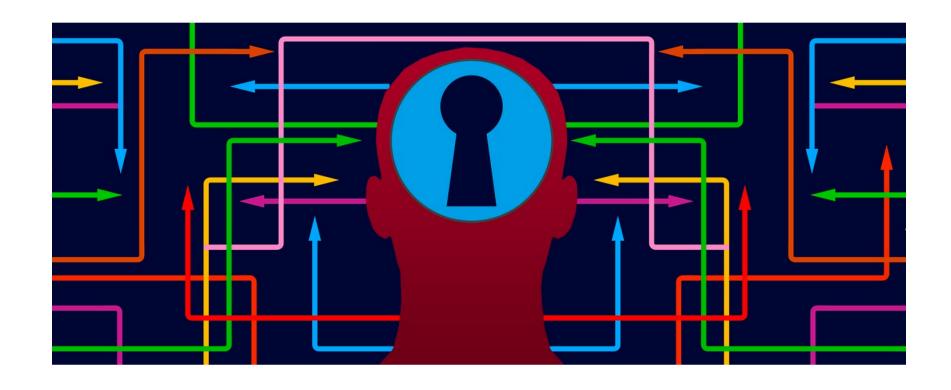
Asset + Threat + Vulnerability = Risk

Risk = Threat * Vulnerability * Consequences

Risk = Impact * Probability

These equations *shouldn't* be solved quantitatively.

Communications Security



Communications with sources: Securing data in flight

Primary risk: interception







Email

Phone

In-Person meeting

Asset: content & reputation

Which of these is has the most interception <u>risk</u>?







Answer depends on:

- Threat who is attacking?
- Vulnerability how are they attacking?
- Consequence what is the impact of an interception?

In-person meetings are risky



E HOME

Q SEARCH

The New York Times

TIMES INSIDER

'Isn't That the Trump Lawyer?': A Reporter's Accidental Scoop

查看简体中文版 查看繁體中文版

By KENNETH P. VOGEL SEPT. 19, 2017



The Acela Spy

The shocking things I've learned by eavesdropping on Amtrak.

By Amy Webb

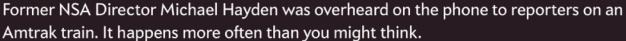
"On Amtrak, powerful people talk loudly and spill secrets.

"This is my conclusion based on five years' field research commuting on Amtrak's Acela between cities along the East Coast."









Eavesdropping email or phone requires access.

There are two points of access:

- 1. The end-point devices.
- 2. The network.



Primary threat: spyware and malware





Primary threat: interception

Encryption doesn't protect against malware

"https:" encryption protects data in flight against interception.



S/MIME and PGP (message encryption) also protects data at rest. See NIST SP800-188, "Trustworthy Email."

Storage Security

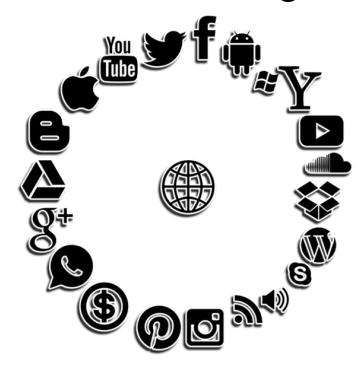


Storage Security

Local Storage



Cloud Storage



Issues: Physical Access • Logical Access

Most of the data crimes in recent years have been unauthorized access to stored data.

Asset?

Physical access:

Attacker physically removed the data.

Vulnerability?

Logical access:

Computer system allowed access

Data were not encrypted to the attacker.

Threat?

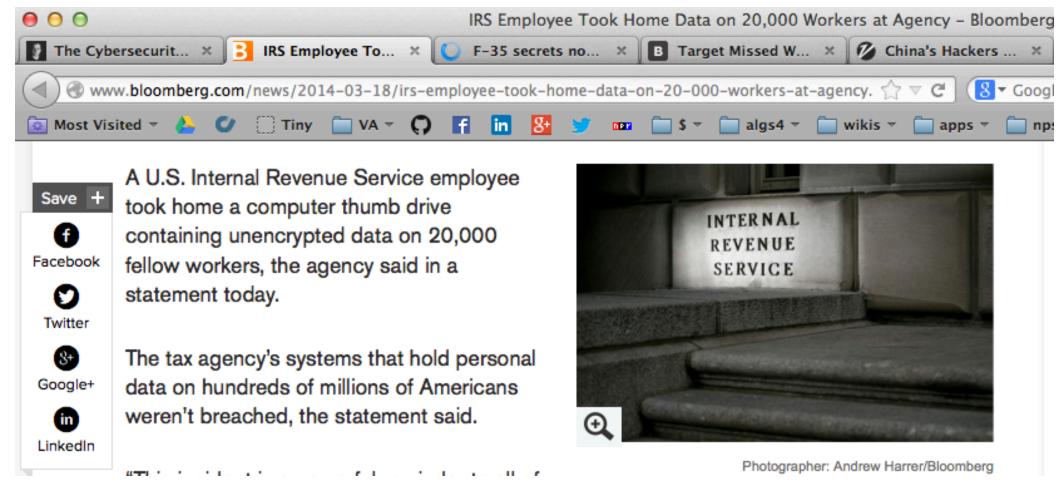
Consequence?

May 2013: Edward Snowden steals millions of documents from the US National Security Agency



March 2014:

IRS Employee Took Home Data on 20,000 Workers



March 2014: Stolen F-35 secrets show up in China's stealth Fighter



Sept. 2014: Celebrity photos stolen from iCloud

SEP 2, 2014 @ 04:06 PM

33,895 @

2 Free Issues of Forbes

Apple Admits Celebrity Photos Were Stolen In Targeted Hack



Protecting Local Storage

Physical security.

Disk encryption.

Off-site backups.



MacOS FileVault



Oakland CA fires, 1989

Protecting Network Storage

Two-factor access

Account recovery









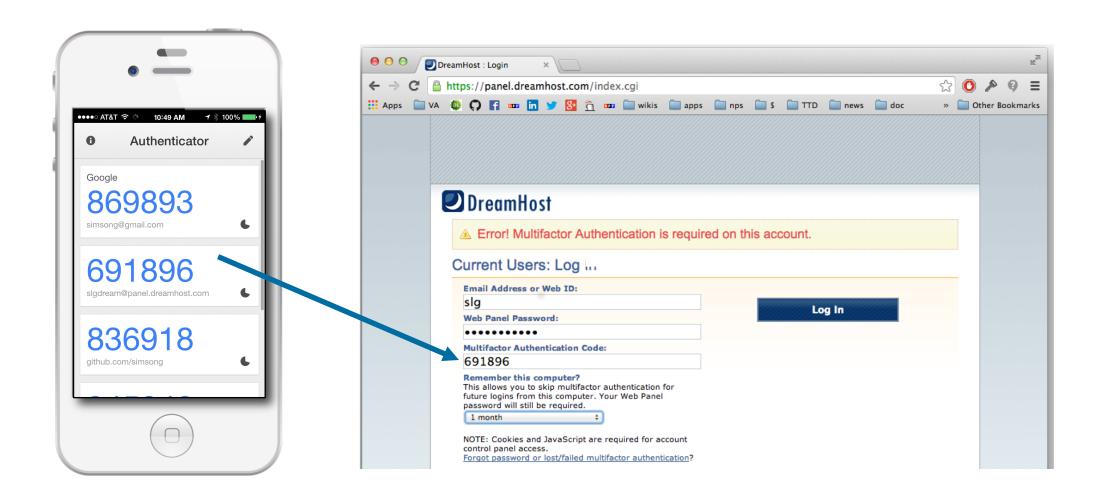
Google Drive

GMAIL

DropBox

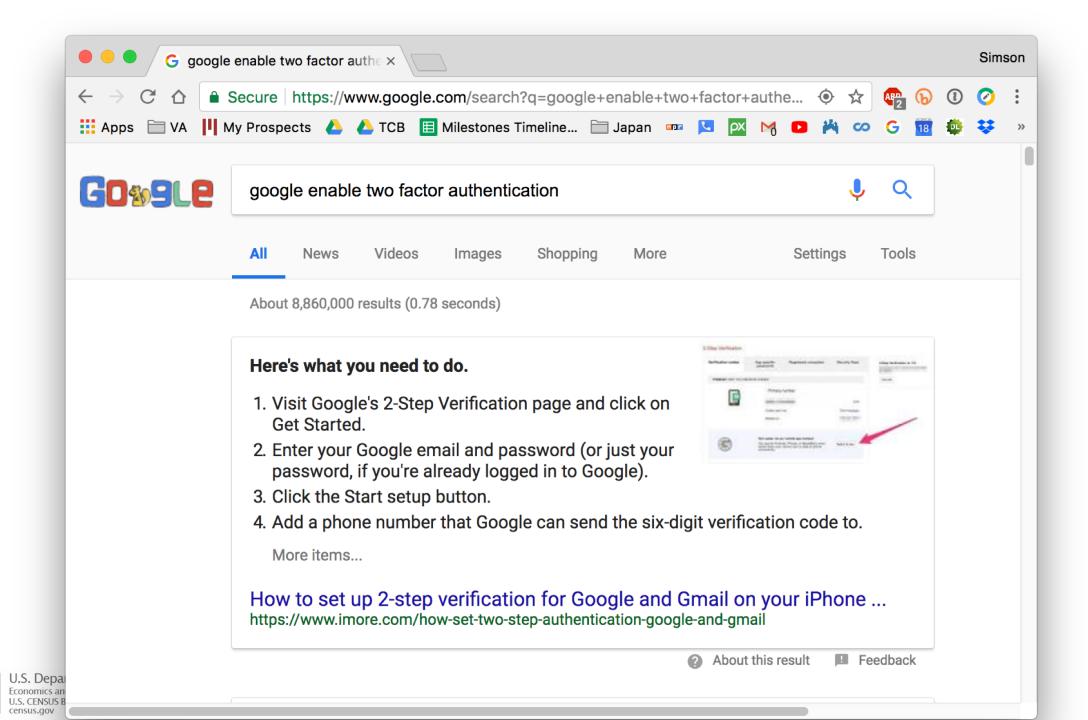
OneDrive

Example: Google Authenticator's 2-factor authentication protections against password stealing.

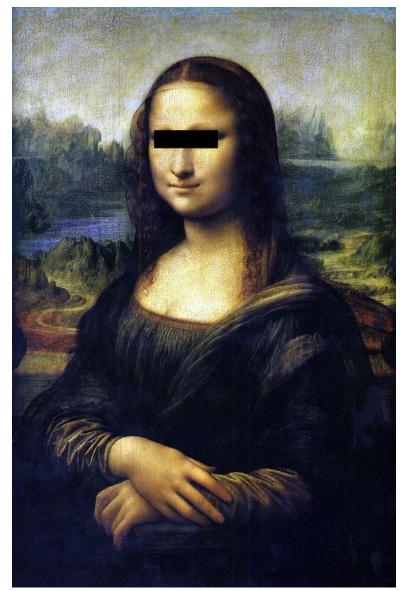


Universal Second Factor (U2F)





Publication Security



https://commons.wikimedia.org/wiki/ Commons:Photographs_of_identifiable_people

Problems with attempts at anonymisation







Black band over the eyes

Pixelated face

Cropped head

WORLD

SECRETS OF HISTORY: The C.I.A. in Iran -- A special report.; How a Plot Convulsed Iran in '53 (and in '79)

By JAMES RISEN APRIL 16, 2000











For nearly five decades, America's role in the military coup that ousted Iran's elected prime minister and returned the shah to power has been lost to history, the subject of fierce debate in Iran and stony silence in the United States. One by one, participants have retired or died without revealing key details, and the Central Intelligence Agency said a number of records of the operation -- its first successful overthrow of a foreign government -- had been destroyed.



June 16, 2000: the *New York Times* publishes on its Web site a leaked secret CIA report on its website.

Report published as a PDF.

The Times had attempted to redact the names Iranians who had assisted.

The Times "redacted" by putting black boxes over the PDF.

Cryptome.org removed the black boxes and re-published.

http://cryptome.org/cia-iran.htm

Date: Mon, 19 Jun 2000 08:19:45 -0400

To: intelforum@his.com

From: John Young jya@pipeline.com

Subject: Re: Complete CIA history of 1953 Iranian coup posted by New York Times

The digital means the NY Times used to black out names of persons it was advised might be put at risk by publication failed to do the job properly. All the deletions are readable. The unredacted report shall be published shortly on cryptome.org.

The unexpected consequences of digital security are worth pondering.



Date: Tue, 20 Jun 2000 11:04:29 -0400

To: John Young <jya@pipeline.com>

From: Rich Meislin <meislin@nytimes.com>

Subject: Re: CIA Iran Report

Dear Mr. Young, Thank you for informing us about the problem with this document. We are removing it from our site until we can delete the names in a more secure fashion. The names were obscured because of our concern for possible retribution against the families of the people named in this report, and we would strongly urge you to respect that judgment.

Sincerely, Rich Meislin





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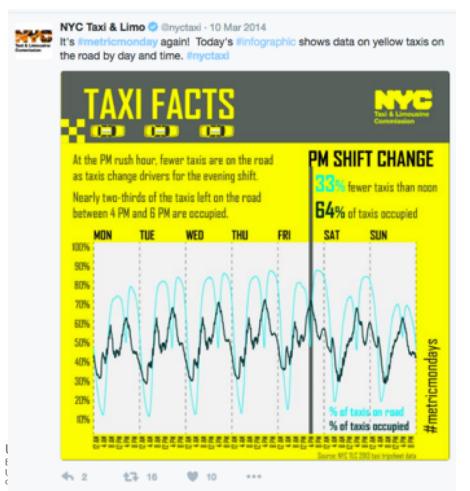






Data can be revealing, even without names.

In March 2014, the New York City Taxi & License Commission tweeted a "TAXI FACTS" infographic:





Chris Whong files a "Freedom of Information Law" request for all the data used to create the graphic.

NYC TLC provided Chris Whong with all of the data

175 million trips:

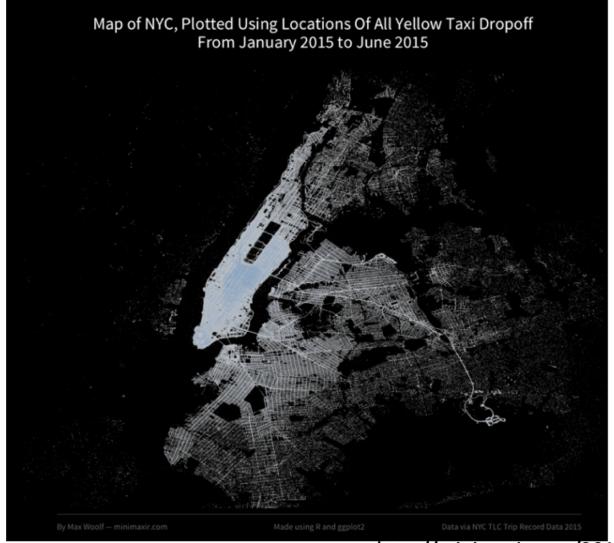
	A	В	С	D	Е	F	G	Н	1	J	K
1	medallion ,	hack_license	vendor_id	pickup_datetime	payment_type	fare_amoun	surcharge	mta_tax	tip_amount	tolls_amoun	total_amount
2	89D227B655E5C82AECF13C3	BA96DE419E711691B944	CMT	1/1/13 15:11	CSH	6.5	0	0.5	0	0	7
3	0BD7C8F5BA12B88E0B67BED	9FD8F69F0804BDB5549F	CMT	1/6/13 0:18	CSH	6	0.5	0.5	0	0	7
4	0BD7C8F5BA12B88E0B67BED	9FD8F69F0804BDB5549F	CMT	1/5/13 18:49	CSH	5.5	1	0.5	0	0	7
5	DFD2202EE08F7A8DC9A57B0	51EE87E3205C985EF843	CMT	1/7/13 23:54	CSH	5	0.5	0.5	0	0	6
6	DFD2202EE08F7A8DC9A57B0	51EE87E3205C985EF843	CMT	1/7/13 23:25	CSH	9.5	0.5	0.5	0	0	10.5
7	20D9ECB2CA0767CF7A01564	598CCE5B9C1918568DEE	CMT	1/7/13 15:27	CSH	9.5	0	0.5	0	0	10
8	496644932DF3932605C22C79	513189AD756FF14FE670	CMT	1/8/13 11:01	CSH	6	0	0.5	0	0	6.5
9	0B57B9633A2FECD3D3B1944	CCD4367B417ED6634D9	CMT	1/7/13 12:39	CSH	34	0	0.5	0	4.8	39.3
10	2C0E91FF20A856C891483ED6	1DA2F6543A62B8ED934	CMT	1/7/13 18:15	CSH	5.5	1	0.5	0	0	7

Every trip:

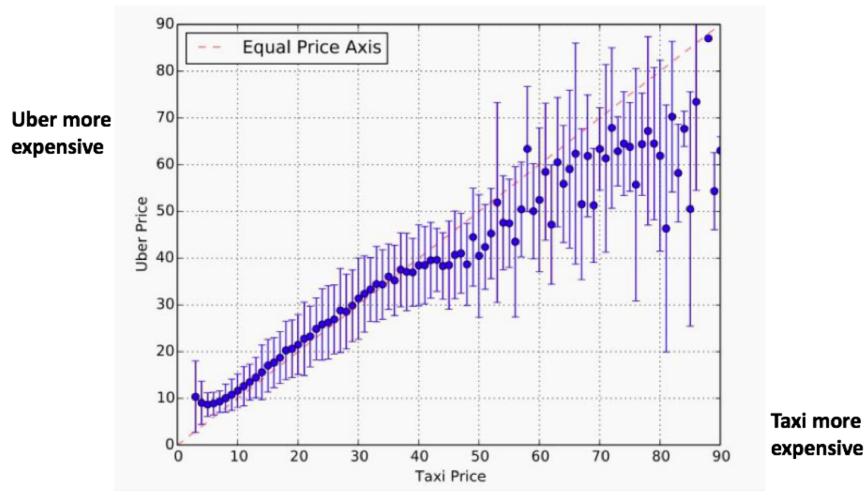
- Pickup date, time & GPS
- Drop-off date, time & GPS
- Fare & tip
- Encoded medallion number

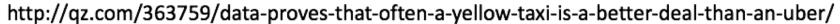


With this data, you can make a map of NYC Taxi Service



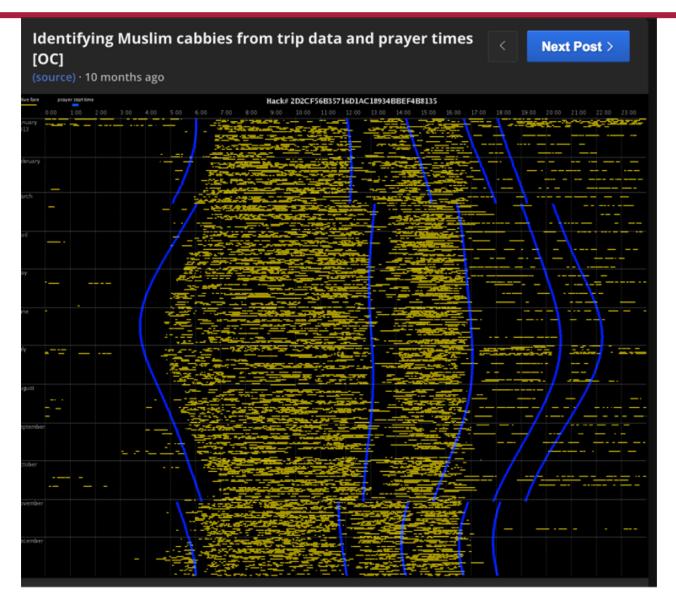
Compare taxi prices and Uber prices:







Each taxi has a pseudonym, which allows taxi rides to be linked.



Oops. The taxi medallion numbers were not properly de-identified.

Pseudonym	Taxi Medallion
0f76c35d4a069e0fe76b21d28f009639	5C27
be9f314926dd314b36496d926e42f4db	5C28
9ee993809f648d39d24f5ba8f862d7f1	5C29
23f7e8636fb9099822aa381054d215d4	5C30

The pseudonyms looked suspicious to Anthony Tockar, an intern at Neustar Research.

Tockar realized that the pseudonyms were MD5 hashes MD5("5C28") = be9f314926dd314b36496d926e42f4db

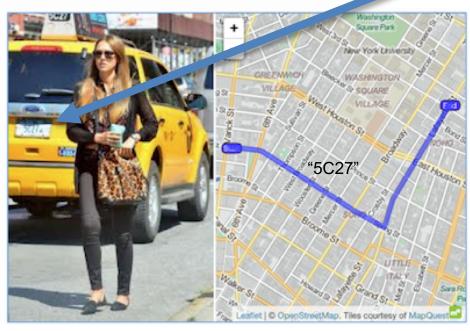
MD5 can't be reversed, but it's possible to do a "brute force search" on all possible values.

Anthony Tockar identified the medallion number the records.

He searched for photos in flickr that showed movie stars at

taxis ^V Riding with the Stars: Passenger Privacy in the NYC Taxicab Dataset





May 18, 1996: Massachusetts Governor William Weld Collapses at Bentley College Commencement



Massachusetts Governor Doing Well After Collapse

WALTHAM, Massachusetts (CNN, May 18) -- Gov. William Weld collapsed during a graduation ceremony at Bentley College, but doctors said he was doing well.

The governor was taken to Deaconess-Waltham Hospital, where he was undergoing a battery of tests, according to Bentley College spokeswoman Katherine Blake. Weld will remain in the hospital overnight for observation, she said.

Doctors said they performed an electrocardiogram, chest X-ray and blood tests, but found no immediate cause for concern.

"With all this testing we have done, nothing acute is showing," said Dr. Rifat Dweik.

"Right now, it looks like maybe the flu," said Pam Jonah, one of Weld's press aides.

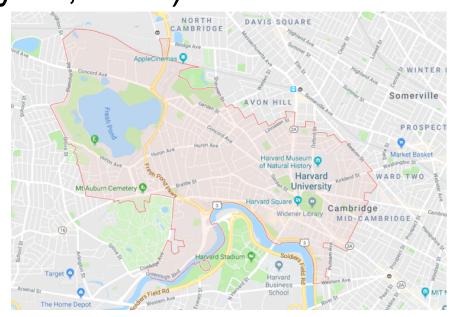
Weld was receiving an honorary doctorate of law at 11 a.m. EDT when he was stricken, according to Blake.



In 1997, MIT Graduate Student Latanya Sweeney decided to search for William Weld's medical records in the GIC data.

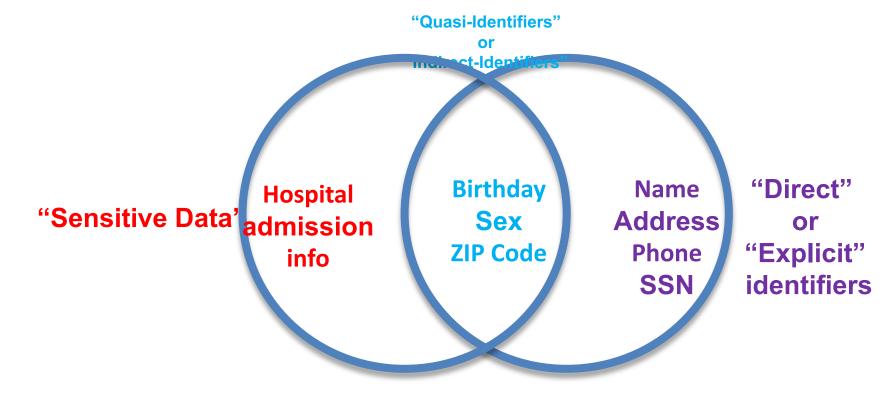
Sweeney obtains GIC dataset and looks for Weld's data.

- She knew that Weld lived in Cambridge, MA.
- Sweeney purchased Cambridge voter rolls for \$20.
- Six people had the same birthday (July 31, 1945)
- Three were men
- One person had the same ZIP code.



"Linkage Attack" Matching records using quasi-identifiers

- Weld's records were uniquely identified.
- Sweeney estimated 87% of US population were uniquely identified by birthday, sex & ZIP



Sweeney invented K-Anonymity A model for de-identifying structured data.

A dataset that you would like to release:

Name	Race	Birthdate	Sex	Zip	Medication	Diagnosis
Alice	Black	9/20/65	M	37203	M1	Gastric Ulcer
Bob	Black	2/14/65	M	37203	M1	Gastric Ulcer
Candice	Black	10/23/65	F	37215	M1	Gastritis
Dan	Black	8/24/65	F	37215	M2	Gastritis
Eliza	Black	11/7/64	F	37215	M2	Gastritis
Felix	Black	12/1/64	F	37215	M2	Stomach Cancer
Gazelle	White	10/23/64	М	37215	M3	Flu
Harry	White	3/15/64	F	37217	M3	Flu
Irene	White	8/13/64	М	37217	M3	Flu
Jack	White	5/5/64	М	37217	M4	Pneumonia
Kelly	White	2/13/67	M	37215	M4	Pneumonia
Lenny Department of Commerce	White	3/21/67	M	37215	M4	Flu



First the identifiers are removed

	Name		Quasi Identifiers			Medication	Diagnosis
		Black	9/20/65	М	37203	M1	Gastric Ulcer
		Black	2/14/65	М	37203	M1	Gastric Ulcer
		Black	10/23/65	F	37215	M1	Gastritis
		Black	8/24/65	F	37215	M2	Gastritis
		Black	11/7/64	F	37215	M2	Gastritis
		Black	12/1/64	F	37215	M2	Stomach Cancer
		White	10/23/64	M	37215	M3	Flu
		White	3/15/64	F	37217	M3	Flu
		White	8/13/64	M	37217	M3	Flu
		White	5/5/64	M	37217	M4	Pneumonia
		White	2/13/67	M	37215	M4	Pneumonia
S.		White erce	3/21/67	М	37215	M4	Flu



A dataset is "k-anonymous" if every record is in a set of at least k indistinguishable individuals

Race	Birthdate	Sex	Zip	Medication	Diagnosis	
Black	65	M	37203	M1	Gastric Ulcer	
Black	65	M	37203	M1	Gastric Ulcer	
Black	65	F	37215	M1	Gastritis	
Black	65	F	37215	M2	Gastritis	
Black	64	F	37215	M2	Gastritis	
Black	64	F	37215	M2	Stomach Cancer	
White	64	M	3721-	M3	Flu	
White	64	-	37217	M3	Flu	
White	64	M	3721-	M3	Flu	
White	64	-	37217	M4	Pneumonia	
White	67	M	37215	M4	Pneumonia	
U.S. Department of Commerce Economics and Statistics Advivoring to U.S. CENSUS BUREAU census.gov	67	M	37215	M4 ⁴⁹	Flu	

Attribute disclosure: We know the Black / 65 / M had a Gastric Ulcer.

_					
Black	65	М	37203	M1	Gastric Ulcer
Black	65	M	37203	M1	Gastric Ulcer
Black	65	F	37215	M1	Gastritis
Black	65	F	37215	M2	Gastritis
Black	64	F	37215	M2	Gastritis
Black	64	F	37215	M2	Stomach Cancer
White	64	М	3721-	M3	Flu
White	64	-	37217	M3	Flu
White	64	M	3721-	M3	Flu
White	64	-	37217	M4	Pneumonia
White	67	M	37215	M4	Pneumonia
White	67	M	37215	M4	Flu



De-identification caveats — what can go wrong

Mistakes happen:

- Metadata may contain identifiers.
- Direct identifiers can be missed.
- Hard to determine what's a quasi-identifier.

Even worse:

- k-anonymity and I-diversity can significantly damage data quality.
- There is no mathematical proof that k-anonymity actually protects privacy.

Netflix Awards \$1 Million Prize and Starts a New Contest

BY STEVE LOHR SEPTEMBER 21, 2009 10:15 AM



Jason Kempin/Getty Images Netflix prize winners, from left: Yehuda Koren, Martin Chabbert, Martin Piotte, Michael Jahrer, Andreas Toscher, Chris Volinsky and Robert Bell.

All data are potentially identifying.

The Netflix Challenge (2008-2009)

Netflix published movie data for ~450,000 subscribers:

- Pseudonymized username
- Information on movies watched:

Movie Title

Date watched

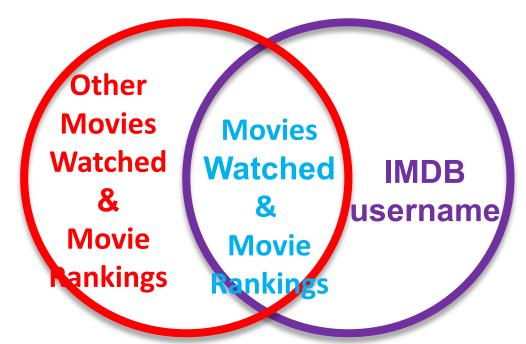
Rating

Challenge: Improve Netflix recommendation algorithm

Unintentional Challenge: Identify Netflix subscribers!

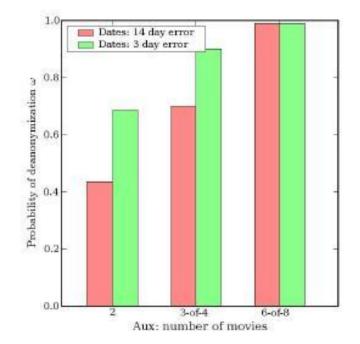
Re-identifying the Netflix Challenge Victims

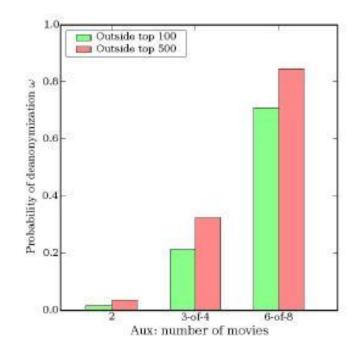
"Sensitive Data"



"Direct" or "Explicit" identifiers

Netflix Provided Data





Aux: 3-of-4 movies Aux: 4-of-5 movies Probability of deanonymization ω Not in top 100 Not in top 500 Aux: popularity of movies

Figure 4. Adversary knows exact ratings Figure 8. Adversary knows exact ratings and approximate dates.

but does not know dates at all.

Figure 9. Effect of knowing less popular movies rated by victim. Adversary knows approximate ratings (± 1) and dates (14day error).

Netflix Settles Privacy Lawsuit, Cancels Prize Sequel

NETFLIX













The Firewall

the world of security FULL BIO >

Opinions expressed by Forbes Contributors are their own

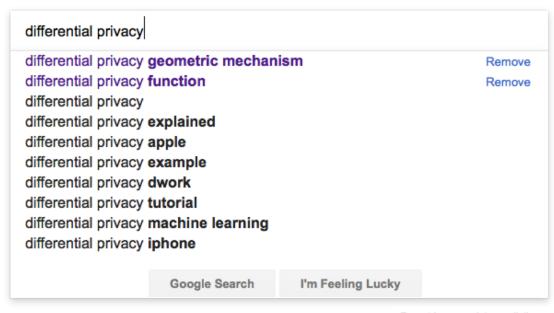


On Friday, Netflix announced on its corporate blog that it has settled a lawsuit related to its Netflix Prize, a \$1 million contest that challenged machine learning experts to use Netflix's data to produce better recommendations than the movie giant could serve up themselves.

The lawsuit called attention to academic research that suggests that Netflix indirectly exposed the movie preferences of its users by publishing anonymized customer data. In the suit, plaintiff Paul Navarro and others sought an injunction preventing Netflix from going through the so-called "Netflix Prize II," a follow-up challenge that Netflix promised would offer up even more personal data such as genders and zipcodes.

"Netflix is not going to pursue a sequel to the Netflix Prize," says spokesman Steve Swasey. "We looked at this, we heard some dissension and so we've settled it, resolved the issues and are moving on."





Report inappropriate predictions

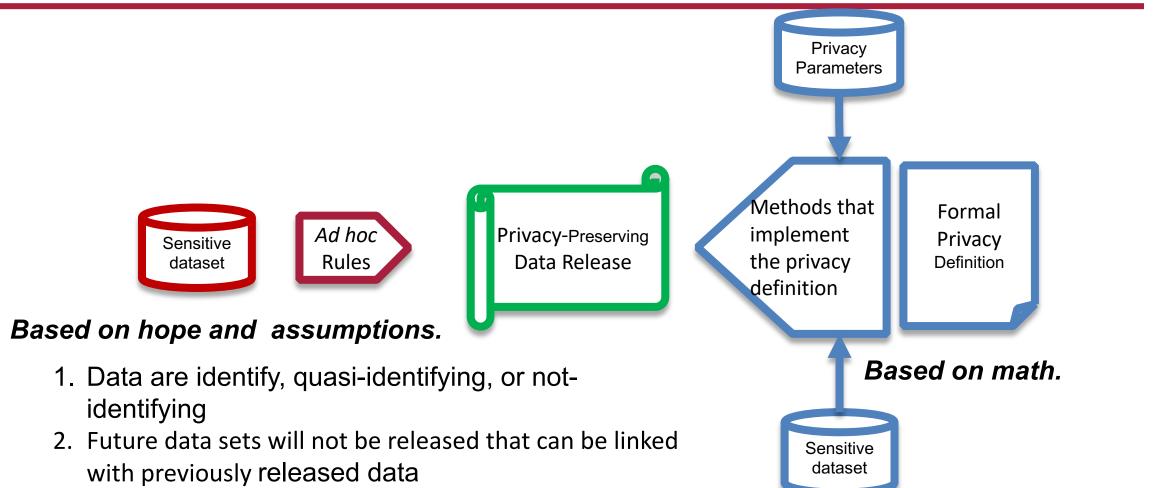
Differential Privacy: The Big Idea



Differential privacy is a new approach for assuring privacy in the release of statistical data.

3. Adversaries have limited resources to pursue re-

identification attacks





In traditional data publications, there are many ways that the contributions of an individual can leak out

January

Name	Affect	Grade
Alex	Sad	30
Bobbie	Sad	50
Casey	Нарру	80
Harper	Нарру	100



Students: 4
Percent Happy: 50%
Average Grade: 65

February

Name	Affect	Grade
Alex	Sad	30
Bobbie	Sad	50
Casey	Нарру	80
Emerson	Sad	90
Harper	Нарру	100

Statistical Tabulation

Students: 5 Percent Happy: 40% Average Grade: 70

It's pretty easy to determine that the new kid is sad and has a 90.

Differential privacy's core idea:

Create uncertainty regarding the presence any person in the dataset.

Noise is added to mask an individual's contribution



January

Name	Affect	Grade
Alex	Sad	30
Bobbie	Sad	50
Casey	Нарру	80
Harper	Нарру	100

Statistical Tabulation + noise

Students: 4 Percent Happy: 45% Average Grade: 50

February

Name	Affect	Grade
Alex	Sad	30
Bobbie	Sad	50
Casey	Нарру	80
Emerson	Sad	90
Harper	Нарру	100



Students: 5 Percent Happy: 60% Average Grade: 75

If we ran the statistics different times, we would get different results

Affect Grade Name Alex Sad 30 Students: 4 Statistical Tabulation Percent Happy: 45% January **Bobbie** Sad 50 + noise Average Grade: 50 80 Casey Нарру Harper Happy 100 Name **Affect** Grade Alex Sad 30 Statistical Students: 4 Tabulation Percent Happy: 55% January Bobbie Sad 50 Average Grade: 75 + noise 80 Casey Happy Harper 100 Happy Name Affect Grade Alex Sad 30 Statistical Students: 4 Percent Happy: 51% Tabulation 50 January **Bobbie** Sad Average Grade: 60 + noise Casey 80 Happy 100 Harper Happy

In this example, a *policy decision* requires that the number of students be accurately reported.

Data users understand that noise has been added.

January

Name	Affect	Grade
Alex	Sad	30
Bobbie	Sad	50
Casey	Нарру	80
Harper	Нарру	100

Statistical
Tabulation
+ noise

Students: 3
Percent Happy: 40%
Average Grade: 50

January

Name	Affect	Grade
Alex	Sad	30
Bobbie	Sad	50
Casey	Нарру	80
Harper	Нарру	100

Statistical
Tabulation
+ noise

Students: 6
Percent Happy: 45%
Average Grade: 45

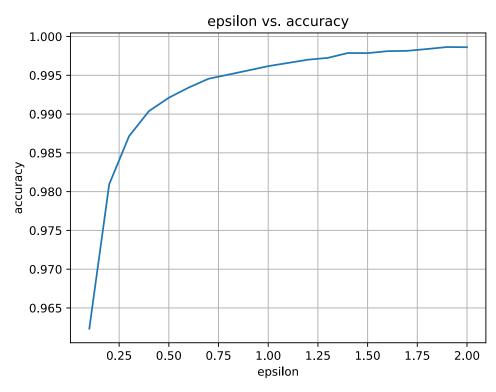
January

Name	Affect	Grade
Alex	Sad	30
Bobbie	Sad	50
Casey	Нарру	80
Harper	Нарру	100



In this example, a *policy decision* requires that the exact number of students in the class be confidential.

How much noise do we add? That is a policy decision



Differential privacy uses the parameter ϵ (epsilon) to describe the privacy/accuracy tradeoff.

 $\varepsilon = 0$ — No accuracy, full privacy $\varepsilon = \infty$ — No privacy, full accuracy

Noise can be added in two places:

1) When data are collected. 2) When statistics are produced.

Input noise infusion:

<u> </u>	_	
Name	Affect	Grade
Alex	Sad + NOISE	30 + NOISE
Bobbie	Sad + NOISE	50 + NOISE
Casey	Happy + NOISE	80 + NOISE
Harper	Happy + NOISE	100 + NOISE



Advantages:

- Tabulator need not be trusted.
- More statistics do not pose additional privacy threats.

Output noise infusion:

Name	Affect	Grade
Alex	Sad	30
Bobbie	Sad	50
Casey	Нарру	80
Harper	Нарру	100



Advantages:

- More accurate for the same level of privacy
- Allows uses of confidential data that do not involve publication.

Other choices for policy makers

Where should the accuracy be spent?

What values should be reported exactly (with no privacy)

What are the possible bounds (sensitivity) of a person's data? e.g. If reporting average student age, can students be 5..18 or 5..115?

How do we convey privacy guarantees to public?

Differential privacy was invented in 2006 by Dwork, McSherry, Nissim and Smith

Differential privacy is just 12 years old.



Today's public key cryptography was invented in 1976-1978

Remember public key cryptography in 1990?

- No standardized implementations. No SSL/TLS. No S/MIME or PGP.
- Very few people knew how to build systems that used crypto.





In Summary

Communications security: Be careful when you get data form your sources.

Storage security: Be careful where you store data; use two-factor security.

Publication security: Be careful when you publish. Remember that data can be reverse-engineered if you do not take appropriate measures.

Questions?

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