Privacy Research at Carnegie Mellon (A Sampling)

Jeannette M. Wing

President's Professor of Computer Science Department Head Computer Science Department

Information Security and Privacy Advisory Board NIST 30 May 2012

Breadth of Approaches from Across CMU

- Science
 - Algorithms
 - Game Theory
 - **Formal Methods**
 - Machine Learning
 - **Programming Languages**
 - **Statistics**
- Engineering
 - **Distributed Systems**
 - **Human-Computer Interaction**
 - Mobile and Pervasive Computing
 - Networking
 - Security
 - Software Engineering
- Societal
 - **Behavioral and Social Science**
 - **Economics**
 - **Ethics and Philosophy**
 - **Public Policy**

Alessandro Acquisti Peter Madsen Avrim Blum Travis Breaux Lorrie Cranor Anupam Datta Stephen Fienberg Virgil Gligor Anupam Gupta **Bob Harper** Jason Hong Jiashun Jin Ramayya Krishnan

Rema Padman Frank Pfenning Bhiksha Raj Alessandro Rinaldo Norm Sadeh M. Satyanarayanan **Tuomas Sandholm** Srini Seshan Larry Wasserman Jeannette Wing Eric Xing

24 faculty, 6 Schools/Centers, 10 Departments

Sampling of Three Foci

- Auditing, Accountability, Compliance
 - Formal Methods: Anupam Datta, Jeannette Wing
 - Software Engineering: Travis Breaux
 - Applications to Healthcare: Travis Breaux, Rema Padman, Jeannette Wing
- Public (Government) Databases
 - Statistical, e.g., Differential Privacy
 - Sanitized Databases: Avrim Blum
 - Practical Limits: Steve Fienberg, Alessandro Rinaldo, Larry Wasserman
 - Vulnerabilities: Alessandro Acquisti
- Consumer-centric
 - Usability: Lorrie Cranor
 - Location privacy: Jason Hong, Norm Sadeh
 - Behavioral Economics: Alessandro Acquisti



Auditing, Accountability, Compliance Checking

Formal Methods: Semantics of Use and Purpose [IEEE Security and Privacy 2012]

Michael Tschantz, Anupam Datta, Jeannette Wing

Computer Science Department, CyLab

Purpose in EU Law

 Member States shall provide that personal data must be [...] collected for specified, explicit and legitimate purposes and not further processed in a way incompatible with those purposes

Purpose in Yahoo's Policy

- Yahoo!'s practice is not to use the content of messages [...] for marketing purposes.¹
- This information is transmitted [...] for the **purpose** of registering your web address [...].¹
- Yahoo! uses information for the following general **purposes**: to customize the advertising [...].²
- Yahoo! does not contact children [...] for marketing purposes [...].²
- [...] companies who may use this information for their own **purposes**.²

Purpose in HIPAA

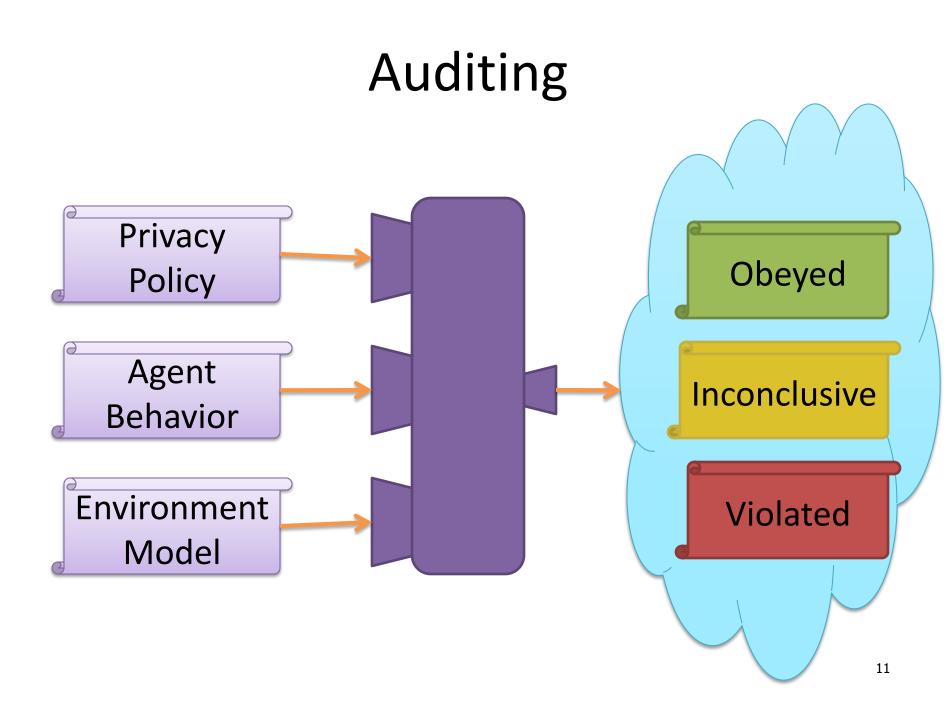
- [...] use and disclose protected health information
 [...] for the following purposes or situations:
 - To the Individual (unless required for access or accounting of disclosures);
 - (2) Treatment, Payment, and Health Care Operations;

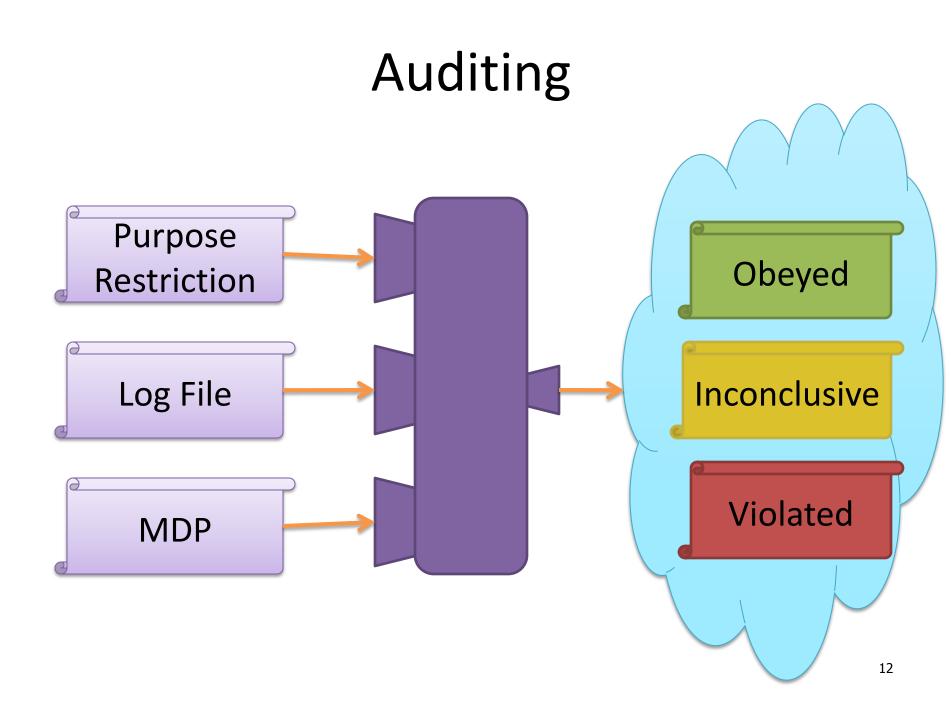
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Purpose in Government Agency Policies

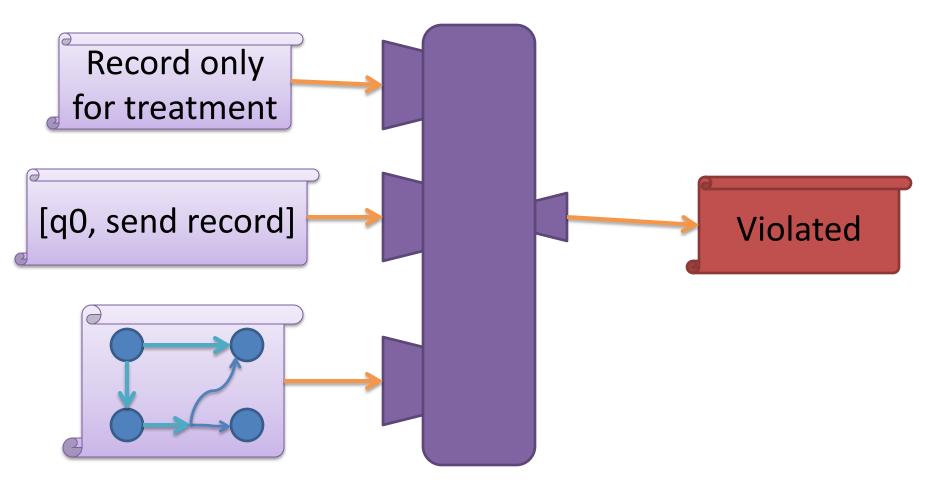
• By providing your personal information, you give [SSA] consent to use the information only for the **purpose** for which it was collected. We describe those **purposes** when we collect information.

http://www.ssa.gov/privacy.html





Auditing



Languages and Software Architecture: Exceptions in Law and Patterns of Compliance

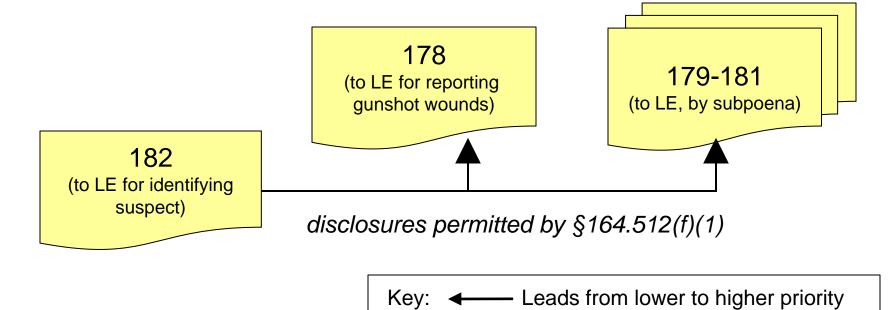
Travis Breaux

Institute for Software Research School of Computer Science

Handling Legal Exceptions

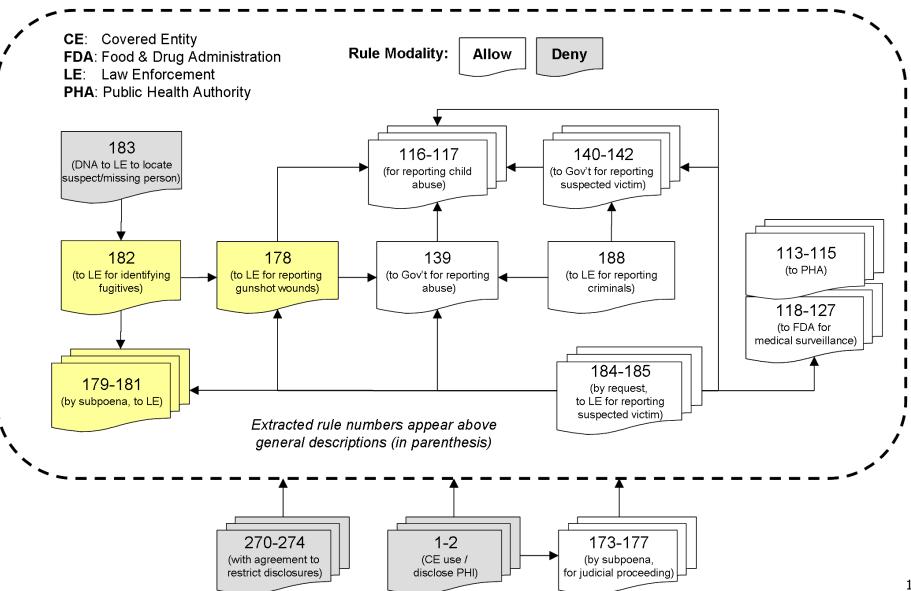
[IEEE TSE, January 2008]

HIPAA §164.512(f)(2): Except for disclosures required by law as permitted by paragraph 164.512(f)(1), a CE may disclose PHI in response to a law enforcement (LE) official's request for the purpose of identifying or locating a suspect

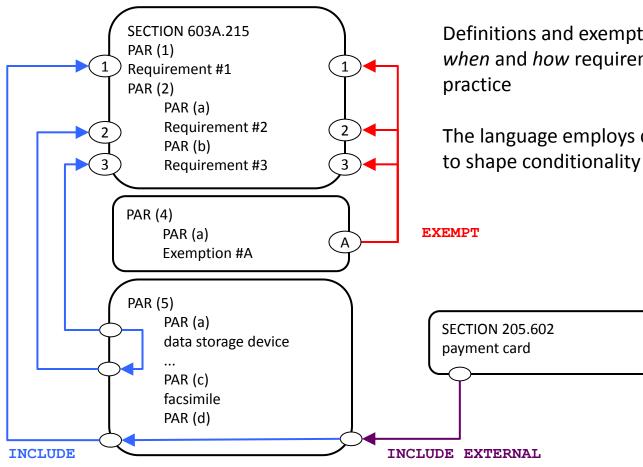


Requirements Exception Hierarchy

[IEEE TSE, January 2008]



Shaping Policy via Distributed Conditionality



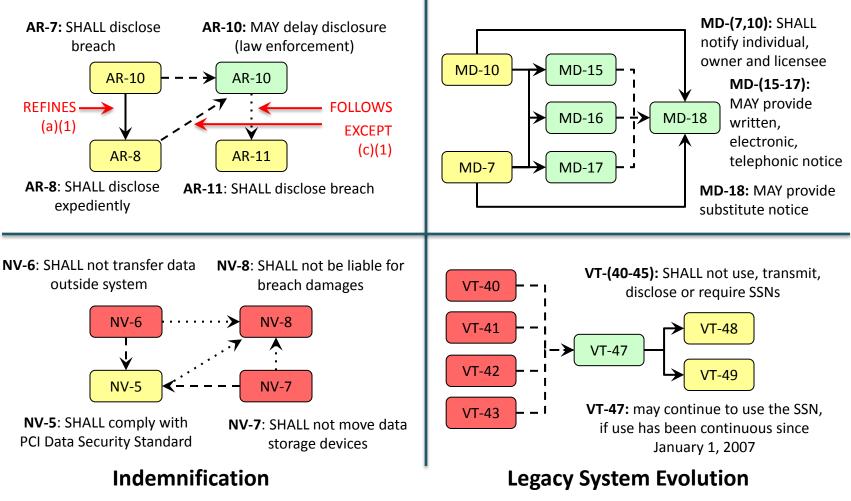
Definitions and exemptions shape who, when and how requirements are applied in

The language employs distributed controls

Language-supported Compliance Patterns

Design Alternatives

Process Suspension

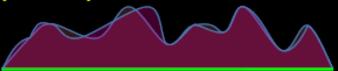


Statistics: Release of Public (Government) Data

In this section, all slides with a black background are from Avirm Blum.

The science of privacy

 Fundamental breakthrough came from MSR in work of [Dwork-McSherry-Nissim-Smith] building on earlier work of Dwork et al, in definition of differential privacy.

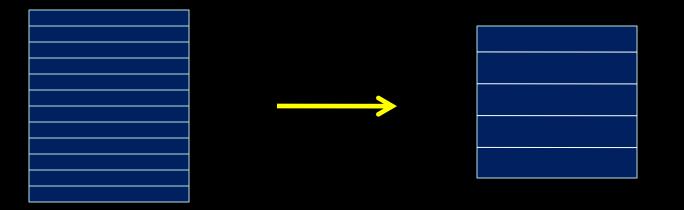


Any participant should be able to plausibly deny any fact claimed about them (the probability of any given output of mechanism would change by only $1 \pm \epsilon$)

Outputting Sanitized Databases Using Differential Privacy

Avrim Blum Computer Science Dept

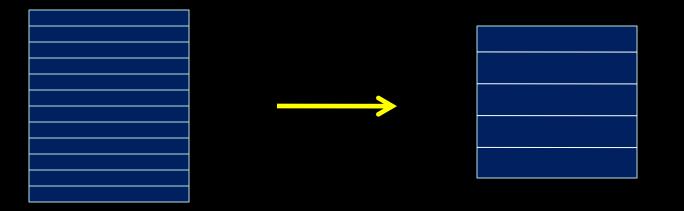
What about outputting sanitized databases?



- So far, just question-answering. Each answer leaks some privacy – at some point, have to shut down.
- What about outputting a sanitized database that people could then examine as they wish?

And is related to the original database...

What about outputting sanitized databases?



- Could ask a few guestions (using previous mechs) and then engineer a database that roughly agrees on these answers.
- But really, we want a database that matches on questions we haven't asked yet.
- Do you need to leak privacy in proportion to number of questions asked?

What about outputting sanitized databases?

(At least not for Actually, no you don't [Blum-Ligett-Roth] count-queries)

- Fix a class C of quantities to preserve. E.g., fraction of entries with x[i₁]=1, x[i₂]=0...x[i_k]=1.
- Want ε -privacy and preserve all $q \in C$ up to $\pm \alpha$.
- [BLR] show: in principle, can do with database of size only $n = O(d \log |C|)$. Allowing exponentially-

many questions!

Statistical Disclosure Limitation & the Challenge of Societal-Scale Data

Stephen E. Fienberg Department of Statistics, Heinz College, Machine Learning Department, and Cylab Carnegie Mellon University Pittsburgh, PA 15213-3890 USA fienberg@stat.cmu.edu Differential Privacy for Protecting Multi-dimensional Contingency Table Data: Extensions and Applications, *Journal of Privacy and Confidentiality*, 2011.

Yang, Fienberg, & Rinaldo: Examined DP Approach

Robustness of approach for RU tradeoff

- Edwards 2⁶ genetics table, with *n*=70.
- Czech auto workers 2⁶ heart attack risk table, with n=1,841.
- Rochdale 28 survey data on women's work, with n=665;very sparse structure.
- American Community Survey 4 × 4 × 16 travel to work table.
- National Long Term Care Survey
 - 2^{16} disability table with *n*=21,574.
 - 2^{96+5} version based on 6 waves (plus mortality), *n*~45,000. Our models have no MSSs!

Lessons Learned

- As ε increases, amount of noise added decreases
 - Deviance between DP generated tables and real MLEs gets smaller.
 - If we add a lot of noise, it has strong privacy guarantees but the statistical inference becomes infeasible.
 - When we add little noise, the statistical inference is better but no privacy guarantees.
- DP struggles with releasing useful information associated with large sparse contingency tables.



Differential Privacy summary

Positives:

- Clear semantic definition. Any event (anything an adversary might do to you) has nearly same prob if you join or don't join, lie or tell the truth.
- Nice composability properties.
- Variety of mechanisms developed for question answering in this framework.
- *Some* work on sanitized database release.

Differential Privacy summary Negatives / open issues

- It's a pessimistic/paranoid quantity, so may be more restrictive than needed.
- " ϵ " is not zero. Privacy losses add up with most mechanisms (but see, e.g., [RR10],[HR10])
- Doesn't address group information.
- Notion of "neighboring database" might need to be different in network settings.

Consumer-Centric: Usability, Location Privacy, Behavioral Economics

CUPS Lab Privacy Research Overview

Lorrie Faith Cranor May 2012 **Carnegie** Mellon University CyLab



Engineering & Public Policy



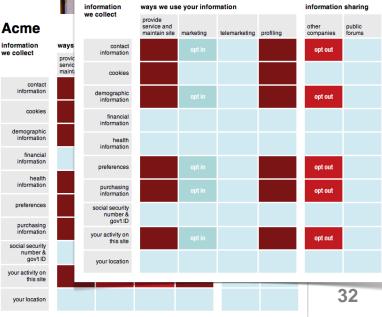
Towards a privacy "nutrition label"

- Standardized format
 - People learn where to find answers
 - Facilitates policy comparisons
- Standardized language
 - People learn terminology
- Brief
 - People find info quickly
- Linked to extended view
 - Get more details if needed

Standardizing Privacy Notices: An Online Study of the Nutrition Label Approach [Kelley, Cesca, Bresee, and Cranor, CHI 2010]

Shredded Oats				TRADER JOE'S Organic HIGH FIBER		
Nutrition Serving Size 1-1/4 C Servings Per Contai	up (2 oz ner Abo	z/55g) out 12 th 1/2 Cup Vit. A & D Fortified	Nutrition Fa Serving Size 1 1/4 cup (55 Servings per Container 8			
Amount Per Serving		Skim Milk	Amount per Serving			
Calories Calories from Fat	220	260	Calories 190 Calories from			
Calones nom Fat	% Daily		% Daily			
Total Fat 2.5g*	% Daily	4%	Total Fat 1g	2%		
Saturated Fat 0.5g	2%	2%	Saturated Fat 0g	0%		
Trans Fat 0g	2/0	470	Trans Fat 0g			
cholesterol Omg	0%	1%	Cholesterol Omg	0%		
Sodium 250mg	10%	12%	Sodium 115mg	5%		
Potassium 180mg	5%	11%	Total Carbohydrate 44	g 15%		
fotal			Dietary Fiber 9g	36%		
Carbohydrate 42g	14%	16%	Soluble Fiber less than	1g		
Dietary Fiber 5g	20%	20%	Insoluble Fiber 8g			
Soluble Fiber 2g			Sugars 9g			
Insoluble Fiber 3g			Protein 6g	12%		
Sugars 11g			Vitamin A 0% • Vitamin C	1200/		
Protein 6g			Calcium 4% • Iron 30%	130%		
			Thiamin 25% • Biboflavin	050/		
/itamin A	0%	6%	Niacin 25% • Vitamin B			
litamin C	35%	35%	Folate 25% • Vitamin B			
alcium	2%	15%	Zinc 15%	2 25%		
on	10%	10%				
/itamin E	8%	8%	* Percent Daily Values are based or	a 2,000		

Bell Group



Online behavioral advertising notice and choice

- Tools that facilitate notice and choice about OBA are part of self-regulatory privacy efforts
 - Browsers can block cookies
 - Opt-out cookies, AdChoices icon
 - Browser plugins



- Series of studies to investigate user understanding of OBA and usability of tools
 - Users understand little about OBA, unaware of tools
 - Tools are difficult to configure properly
 - Users don't know enough about ad companies to choose between them
 - Users unfamiliar with Adchoices icon and afraid to click on it

CMU privacy nudges project

- Goal: Study, design, and test systems that anticipate and sometimes exploit cognitive and behavioral biases that hamper users' privacy and security decision making
- Multidisciplinary project: behavioral economics + decision sciences
 + machine learning + human computer interaction +
- Social network regrets Surveyed 1000+ users about things they regret doing on Facebook and Twitter, identified categories of regrets and underlying causes
- Nudge prototypes Testing software that will nudge FB and Twitter users before they post, e.g., with photos of random friends or a countdown timer

I Regretted the Minute I Pressed Share: A Qualitative Study of Regrets on Facebook. [Wang, Komanduri, Leon, Norcie, Acquisti, Cranor 2011]

Location Privacy

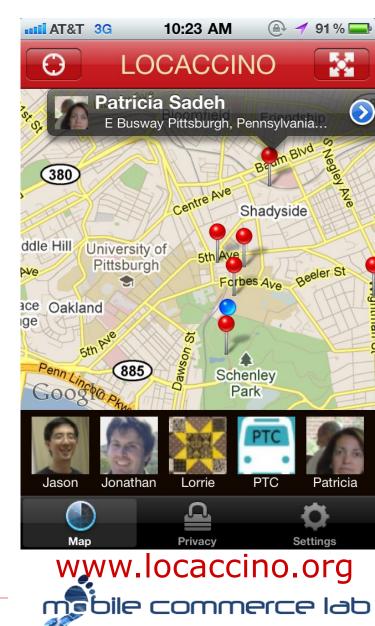
Norman M. Sadeh

Professor, ISR - School of Computer Science Director, Mobile Commerce Lab. Co-Director, COS PhD Program Carnegie Mellon University <u>www.cs.cmu.edu/~sadeh</u>



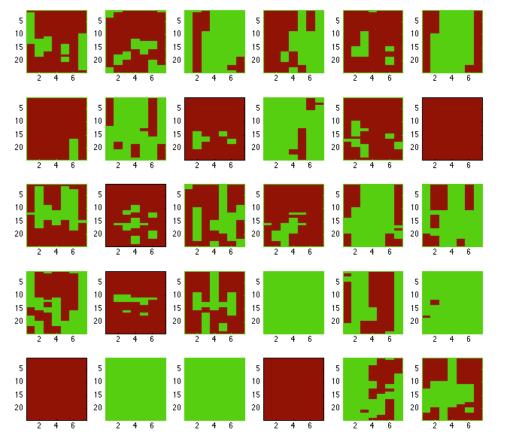
Empowering Users to Regain Control of their Privacy

- Mobile Apps collect a wide range of information about their users
- Research combining:
 - Understanding people's privacy preferences?
 - How diverse? How complex? Do they change?
 - User-Oriented Machine Learning/AI: Can we learn people's preferences through selective dialogues?
 - Better Uis
- Informed by Large-Scale Deployments (e.g. location sharing app)



Diverse and Complex Privacy Preferences

Each square represents **a different individual** and displays her willingness to share her location with members of the CMU campus community



Green: Share **Red:** Don't

In each square:

Horizontal axis: 7 days of the week

Vertical axis: 24 hours of the day



Copyright © 2007-2011 Norman M. Sadeh

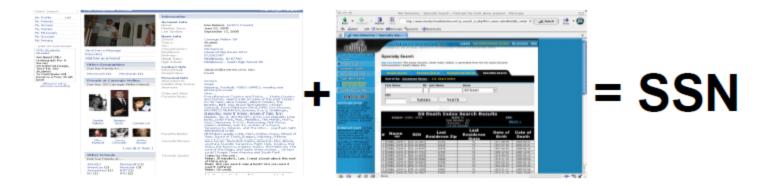
The Economics and Behavioral Economics of Privacy

Alessandro Acquisti

Heinz College/CyLab Carnegie Mellon University

Predicting SSNs from public data

- We reverse-engineered SSN issuance patterns, showing that they were significantly less random than previously predicted
- We found that mere knowledge of an individual's DOB and State of birth is sufficient to predict that individual's SSN



Experimental studies over ~8 years on behavioral economics of privacy

A sampling of results:

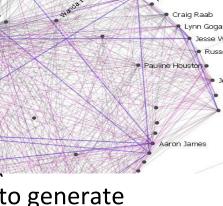
- Individuals more likely to disclose sensitive information to unprofessional sites than professional sites.
- People assign different values to their personal information depending on whether they are focusing on protecting it or revealing it
- People may make disclosure decisions that they stand to later regret.
- Risks greatly magnified in online information revelation

Overall implications of these privacy studies

- "Choice & notification" privacy model may be outdated
- Implications for policy-making & the debate on privacy regulation
 - Consider: Chicago School approach vs. privacy advocates
 - "Nudging" privacy?

Privacy in Social Networks

- Behavioral Economics: Alessandro Acquisti
 - Control vs. Access/Use: Giving more control to use social networks) over information publication seems to generate higher willingness to disclose sensitive information
- Statistical: Avrim Blum and Anupam Datta
 - Given a sensitive social network, can we release a sanitized version of it that preserves privacy and is still useful? Inspired by differential privacy work.
- Formal Methods: Bob Harper and Jeannette Wing
 - What is a formal logic for reasoning about privacy properties in a
 social network? Uses a linear, epistemic logic.



facebook

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Thank you!