Andreas Holzinger
VO 709.049 Medical Informatics
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Lecture 11 Biomedical Data:
Privacy, Data Protection, Safety, Security
& Privacy Aware Machine Learning

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http://hci-kdd.org/biomedical-informatics-big-data
ML needs a concerted effort fostering integrated research

http://hci-kdd.org/international-expert-network

Interactive

Data Mining

Knowledge Discovery

1. Data Mapping
2. Learning Algorithms
3. Graph-based Data Mining
4. Topological Data Mining
5. Entropy-based Data Mining
6. Data Visualization
7. Privacy, Data Protection, Safety and Security

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- Adverse events
- Anonymization
- Context aware patient safety
- Faults and Human error
- Medical errors
- Privacy
- Pseudonymization
- Privacy aware machine learning
- Safety and Security
- Swiss-Cheese Model of human error
- Technical dependability
Acceptable Risk = the residual risk remaining after identification/reporting of hazards and the acceptance of those risks;

Adverse event = harmful, undesired effect resulting from a medication or other intervention such as surgery;

Anonymization = important method of de-identification to protect the privacy of health information (antonym: re-identification);

Authentication = to verify the identity of a user (or other entity, could also be another device), as a prerequisite to allow access to the system; also: to verify the integrity of the stored data to possible unauthorized modification;

Confidentiality = The rule dates back to at least the Hippocratic Oath: “Whatever, in connection with my professional service, or not in connection with it, I see or hear, in the life of man, which ought not to be spoken of abroad, I will not divulge, as reckoning that all such should be kept secret”;

Data protection = ensuring that personal data is not processed without the knowledge and the consent of the data owner (e.g. patient);

Data security = includes confidentiality, integrity, and availability of data, and helps to ensure privacy;

Hazard = the potential for adverse effects, but not the effect (accident) itself; hazards are just contributory events that might lead to a final adverse outcome;

Human fallibility = addresses the fundamental sensory, cognitive, and motor limitations of humans that predispose them to error;
k-Anonymity = an approach to counter linking attacks using quasi-identifiers, where a table satisfies k-anonymity if every record in the table is indistinguishable from at least \( k - 1 \) other records with respect to every set of quasi-identifier attributes; hence, for every combination of values of the quasi-identifiers in the k-anonymous table, there are at least \( k \) records that share those values, which ensures that individuals cannot be uniquely identified by linking attacks;

Medical error = any kind of adverse effect of care, whether or not harmful to the patient; including inaccurateness, incompleteness of a diagnosis, treatment etc.;

Nomen nescio (N.N) = used to signify an anonymous non-specific person;

Patient safety = in healthcare this is the equivalent of systems safety in industry;

Personally-identifying information = can be used to connect a medical record back to an identified person;

Prevention = any action directed to preventing illness and promoting health to reduce the need for secondary or tertiary health care; including the assessment of disease risk and raising public health awareness;

Privacy = (US pron. “prai ...”; UK pron. “pri ...”); from Latin: privatus “separated from the rest”, is the individual rights of people to protect their personal life and matters from the outside world;

Privacy policy = organizational access rules and obligations on privacy, use and disclosure of data;
- **Protected health information (PHI)** = any info on e.g. health status, treatments or even payment details for health care which may be linked back to a particular person;

- **Pseudonymisation** = procedure where (some) identifying fields within a data record are replaced by artificial identifiers (pseudonyms) in order to render the patient record less identifying;

- **Quasi-Identifiers** = sets of attributes (e.g. gender, date of birth, and zip code) that can be linked with external data so that it is possible to identify individuals out of the population;

- **Safety** = any protection from any harm, injury, or damage;

- **Safety engineering** = is an applied science strongly related to systems engineering / industrial engineering and the subset System Safety Engineering. Safety engineering assures that a life-critical system behaves as needed even when components fail.

- **Safety risk management** = follows the process defined in the ISO 14971 standard (see Lecture 12)

- **Safety-critical systems research** = interdisciplinary field of systems research, software engineering and cognitive psychology to improve safety in high-risk environments; such technologies cannot be studied in isolation from human factors and the contexts and environments in which they are used;

- **Security** = (in terms of computer, data, information security) means protecting from unauthorized access, use, modification, disruption or destruction etc.;

- **Sensitive data** = According to EC definition it encompasses all data concerning health of a person;

- **Swiss-Cheese Model** = used to analyze the causes of systematic failures or accidents in aviation, engineering and healthcare; it describes accident causation as a series of events which must occur in a specific order and manner for an accident to occur;
Learning Goals: At the end of this 11th lecture you ...

- are able to determine between privacy, safety and security;
- know the famous IOM report “Why do accidents happen” and its influence on safety engineering;
- have a basic understanding of human error and are able to determine types of adverse events in medicine and health care;
- have seen some examples on how ubiquitous computing might contribute to enhancing patient safety;
- got an idea of the principles of context-aware patient safety;
- saw a recent approach about pseudonymization for privacy in e-health;
- are aware of the security characteristics of the popular personal health records;
Agenda for today

- 00 Reflection – follow-up from last lecture
- 01 Decision Support Systems (DSS)
- 02 History of DSS = History of AI
- 03 Development of DSS
- 04 Further Practical Examples
- 05 Towards Precision Medicine (P4)
- 06 Case Based Reasoning (CBR)
00 Reflection
Warm-up Quiz

1. [Graph 1]
2. [Mathematical Equation]
3. [Image 1]
4. [Image 2]
5. [Diagram 1]
6. [Diagram 2]
7. [Chart 1]
01 Safety first ...
Key Challenges

- Sensitive, Personal Health Data
- Mobile solutions, Cloud solutions
- Primary use of Data
- Secondary use of Data for Research
- In the medical area ALL aspects require strict

Privacy, Safety, Security and Data Protection!

We start with thinking about safety first ...

http://ngadventure.typepad.com/blog/news-k2-death-trap-is-sec.html
The size of the box represents the range of risk in which a given barrier is active. Reduction of risk beyond the maximum range of a barrier presupposes crossing this barrier. Shaded boxes represent the 5 system barriers. ASA = American Society of Anesthesiologists.

- **Safety** = any protection from harm, injury, or damage;
- Data Protection = all measures to ensure availability and integrity of data
- **Privacy** = (US pron. “prai ...”; UK pron. “pri ...”; from Latin: privatus "separated from the rest", are the individual **rights of people** to protect their personal life and matters Confidentiality = secrecy ("ärztliche Schweigepflicht")

- **Availability** = \( p(x) \) that a system is operational at a given time, i.e. the amount of time a device is actually operating as the percentage of total time it should be operating;

- **Reliability** = the probability that a system will produce correct outputs up to some given time;

- **Security** = (in terms of computer, data, information security) means protecting from unauthorized access, use, modification, disruption or destruction etc.;

- **Dependability** = the system property that integrates such attributes as reliability, availability, safety, security, survivability, maintainability (see slide 11-22);
To err is human: building a safer health system.
Washington (DC), National Academy Press.
Patient safety publications before and after publication of the IOM report “To Err is Human”.

Patient safety research before and after publication of the IOM report "To Err is Human". Number of patient safety research publications and research awards per 100,000 MEDLINE publications and 100,000 federally funded biomedical research awards.

Deaths from avoidable medical error more than double in past decade, investigation shows

By Katherine Harmon | Aug 10, 2009 06:45 PM | 28

Preventable medical mistakes and infections are responsible for about 200,000 deaths in the U.S. each year, according to an investigation by the Hearst media corporation. The report comes 10 years after the Institute of Medicine’s "To Err Is Human" analysis, which found that 44,000 to 98,000 people were dying annually due to these errors and called for the medical community and government to cut that number in half by 2004.

The precise number of these deaths is still unknown because many states lack a standard or mandatory reporting system for injuries due to medical mistakes. The investigative team gathered disparate medical records, legal documents, personnel files and reports and analyzed databases to arrive at its estimate.
What do you see in this picture?
Integration of a correct surgery site protocol into a daily patient care model is a useful step in preventing occurrences of wrong site dermatologic surgery.


3 Modules:
AERFMI = Adverse Events Reporting Forms in Medical Imaging
AERMMI = Adverse Events Manager Reports in Medical Imaging
AEKMMI = Adverse Events Knowledge Manager in Medical Imaging
Rodrigues et al. (2010)
Note: Now just definitions, refer to risk management in Lecture 12

- **Total risk** = identified + unidentified risks.
- **Identified risk** = determined through various analysis techniques. The first task of system safety is to identify, within practical limitations, all possible risks. This step precedes determine the significance of the risk (severity) and the likelihood of its occurrence (hazard probability). The time and costs of analysis efforts, the quality of the safety program, and the state of technology impact the number of risks identified.
- **Unidentified risk** is the risk not yet identified. Some unidentified risks are subsequently identified when a mishap occurs. Some risk is never known.
- **Unacceptable risk** is that risk which cannot be tolerated by the managing activity. It is a subset of identified risk that must be eliminated or controlled.
- **Acceptable risk** is the part of identified risk that is allowed to persist without further engineering or management action. Making this decision is a difficult yet necessary responsibility of the managing activity. This decision is made with full knowledge that it is the user who is exposed to this risk.
- **Residual risk** is the risk left over after system safety efforts have been fully employed. It is not necessarily the same as acceptable risk. Residual risk is the sum of acceptable risk and unidentified risk. This is the total risk passed on to the user.
Improving Safety with Information Technology.
Slide 11-16: Enhancing Patient Safety with ubiquitous devices

1) **Protection precautions:**
   1) vulnerability to eavesdropping,
   2) traffic analysis,
   3) spoofing and denial of service.
   4) Security objectives, such as confidentiality, integrity, availability, authentication, authorization, nonrepudiation and anonymity are *not* achieved unless special security mechanisms are integrated into the system.

2) **Confidentiality:** the communication between reader and tag is unprotected, except of high-end systems (ISO 14443). Consequently, eavesdroppers can listen in if they are in immediate vicinity.

3) **Integrity:** With the exception of high-end systems which use message authentication codes (MACs), the integrity of transmitted information cannot be assured. Checksums (cyclic redundancy checks, CRCs) are used, but protect only against random failures. The writable tag memory can be manipulated if access control is not implemented.

Clinical Example: Context-aware patient safety

Bardram & Norskov (2008)
(1) measuring risk and planning the ideal defense model,

(2) assessing the model against the real behavior of professionals, and modifying the model or inducing a change in behavior when there are gaps,

(3) adopting a better micro- and macro-organization,

(4) gradually re-introducing within the rather rigid, prescriptive system built in steps 1–3 some level of resilience enabling it to adapt to crises and exceptional situations

### Types of adverse events in medicine and care

<table>
<thead>
<tr>
<th>Number</th>
<th>Events</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Sentinel event</td>
<td>The case is not anticipative death, lose any abilities in normal processing, or such that the patient kills himself, the thief takes baby, blood transfusion or blood type incompatible cause hemolysis, or person or operation position identify wrong et al.</td>
</tr>
<tr>
<td>2</td>
<td>Accident</td>
<td>The person is not intentionally, indiscriminately, or unsuitable behavior that forms un-expect or unfortunate events.</td>
</tr>
<tr>
<td>3</td>
<td>Incident</td>
<td>Manual error or equipment shutdown causes fault of processing sporadically. No matter what, operation of the system was broken.</td>
</tr>
<tr>
<td>4</td>
<td>Critical incident</td>
<td>If the event, that was manual error or equipment shutdown, does not timely discovery or correction. The event maybe causes serious result such as extension</td>
</tr>
<tr>
<td>5</td>
<td>Incident reporting</td>
<td>To record all un-normal processing and treatment different with normal processing in hospital.</td>
</tr>
<tr>
<td>6</td>
<td>Near miss</td>
<td>Due to un-expect or immediately action makes who has not happen accident, harm, or disease about the patient.</td>
</tr>
<tr>
<td>7</td>
<td>Medical adverse event</td>
<td>The event causes harm on body of patient, extends hospital day, loses any abilities, or death. But causing the event not come from original disease.</td>
</tr>
<tr>
<td>8</td>
<td>No harm event</td>
<td>The event had happen on patient, but has not caused anything or a bit harm.</td>
</tr>
<tr>
<td>9</td>
<td>Preventable - avoidable adverse event</td>
<td>The related employee had done use specify processing that can avoid harm for patients, but related employee still mistake to cause adverse event.</td>
</tr>
<tr>
<td>10</td>
<td>High-alert drugs</td>
<td>The event maybe cause critical harm to patient result from un-normal use or manage drugs.</td>
</tr>
</tbody>
</table>
| 11     | Adverse drug reaction, ADR | Patients usually not expect serious reaction for using drugs or one of list below entry (notice: about ADR announce that was when patient takes medicine cause expect response, were the ability of encouraged):  
- Do not using any drugs (drugs were either therapy nor diagnosis)  
- To change medicine therapy  
- To adjust dosage (to adjust a bit dosage)  
- Go to hospital over night  
- Extension in hospital day  
- Assisted therapy  
- Causing diagnosis complicated  
- Producing negative effect  
Result in temporary or permanent harm(disabled or death) |
| 12     | Adverse drug event, ADE | Because the patient take medicine or medical employee has not get medicine result in the event. |

<table>
<thead>
<tr>
<th>Category</th>
<th>Ultrasafe System</th>
<th>Type of System</th>
<th>Amalberti et al. (2005)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Example of industry</strong></td>
<td>Nuclear power</td>
<td>High-Reliability Organization</td>
<td>Military systems</td>
</tr>
<tr>
<td></td>
<td>Commercial aviation</td>
<td></td>
<td>Chemical production</td>
</tr>
<tr>
<td></td>
<td>Blood transfusion</td>
<td>Intensive care unit</td>
<td>Surgical ward</td>
</tr>
<tr>
<td></td>
<td>Anesthesiology*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Radiotherapy</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Safety goals</strong></td>
<td>Safety first</td>
<td>Production first (imposed)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Quality of work preserved against unacceptable pressure</td>
<td>Degree of safety as high as possible for the imposed level of performance</td>
<td></td>
</tr>
<tr>
<td><strong>Safety level (in terms of risk per exposure)</strong></td>
<td>Better than $1 \times 10^{-5}$, possibly $1 \times 10^{-6}$</td>
<td>Better than $1 \times 10^{-4}$</td>
<td></td>
</tr>
<tr>
<td><strong>Stability of the process</strong></td>
<td>Well-codified and delineated area of expertise</td>
<td>Broad area of expertise</td>
<td></td>
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<tr>
<td></td>
<td>Ultradominant, rule-based behavior</td>
<td>Frequent knowledge-based behavior</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Consistent recruitment of patients (flow and quality)</td>
<td>Unstable recruitment of patients (flow and quality)</td>
<td></td>
</tr>
<tr>
<td><strong>Complexity of expertise required</strong></td>
<td>Limited complexity</td>
<td>Potential complexity; severe and abnormal cases are challenging</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Actors are requested to follow procedure</td>
<td>Reluctance to simplify</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Equivalent actors</td>
<td>Defere to expertise of individual experts</td>
<td></td>
</tr>
<tr>
<td><strong>Situational awareness</strong></td>
<td>Good at the managerial level</td>
<td>Good among all actors, whatever their role and status</td>
<td></td>
</tr>
<tr>
<td><strong>Supervision</strong></td>
<td>Inside (team) and outside supervision and control (black boxes)</td>
<td>Inside supervision and mutual control (team supervision)</td>
<td></td>
</tr>
<tr>
<td><strong>Teamwork</strong></td>
<td>Effective teamwork and communication, resulting in good task sharing, controls, and collective routines</td>
<td>Effective teamwork and communication, with special attention to safe adaptation to the range of individual experts</td>
<td></td>
</tr>
</tbody>
</table>

Distinction between a limited number of clinical domains that can achieve ultrasafety and sectors in which a certain level of risk is inherent – and cannot be reduced!
02 Privacy Awareness
Data Privacy Training Video

Data Protection Act training video - The Lights Are On

https://www.youtube.com/watch?v=wAe4358amJc
- Do you like Justin Bieber?
- How many albums do you own?
- What is your gender?
- What is your age?
- Is your music taste sensitive information?
- What makes you feel safe?
- Anonymous survey?
Population of interest

\[ \text{Pop} \quad I \subseteq \text{Pop} \]

\[ D_i = \{d_i | i \in I\} \]

\[ R = Q(D_i) \]
What do you want?

- Would you feel safer submitting a survey if you knew that your answer would have no impact on the released results?

\[ R = Q(D_{i-me}) = Q(D_i) \]

- Would you feel safer if you knew that any attacker looking at the published results \( R \) could not learn any new information about my person?

\[ p(\text{secret}(\text{me})|R) = p(\text{secret}(\text{me})) \]
- If individual answers would have no impact on the released results, then the results $R$ would have no utility at all!

$$Q(D_{i-m}) = Q(D_i) \implies Q(D_i) = Q(D_{\emptyset})$$

- If $R$ reveals that there is a strong trend in your population – everyone is age 18-22 and loves Justin Bieber – with high $p(x)$ the trend is true for you as well (even if you do not submit your survey)!

$$p(secret(me))|(secret(Pop) > p(secret(me)))$$
If an attacker knows a function about me which is dependent on general facts about the Pop, e.g. You are twice the average age or you are in the minority gender -> releasing just those general facts provides the attacker with specific information about you!

\[(age(me) = 2 \times mean_{age}) \land (gender(me) \neq mode_{gender}) \land (mean_{age} = 14) \land (mode_{gender} = F) \implies (age(me) = 28) \land (gender(me) = M)\]

Disappointed?
Data can not be fully anonymized and remain the same useful as non-anonymized.

One solution: Differential Privacy (Dwork, 2006)

\[
\frac{\Pr(M(D) = C)}{\Pr(M(D_{\pm i}) = C)} < e^\varepsilon
\]

For any \( |D_{\pm i} - D| \leq 1 \) and any \( C \in \text{Range}(M) \).

\[
\frac{\Pr(R \mid \text{true world} = D_1)}{\Pr(R \mid \text{true world} = D_{i \pm 1})} \leq e^\varepsilon, \quad \text{for all } i, R \text{ and small } \varepsilon > 0
\]

03 Privacy of Medical Data
Anonymization: Personal data cannot be re-identified (e.g. k-Anonymization)
Pseudonymization: The personal data is replaced by a "pseudonym", which allows later tracking back to the source data (re-identification)

HSM = Hardware Security Module
Note: Similar to authorization, a user affiliation requires that both the patient as data owner and the trusted relative as affiliated user are authenticated at the same workstation. Consequently, both user identifiers are transferred to the pseudonymization server where they are encrypted with both the users’ inner symmetric keys. The patient’s inner private key is also encrypted with the relative’s inner symmetric key, and all elements are stored in the pseudonymization metadata storage as affiliation relation.

Example: private personal health record

http://healthbutler.com/

https://www.healthcompanion.com
Example: Concept of a Personal Health Record System 1/4

Slide 11-36

Fox et al. (2011)
Fox et al. (2011)
Collaborating application

- Sqwelch: Default.html: pollsocialsubscriptions()
- Sqwelch.com
- Subscribing widget: receiver()

Loop
  [every 10 seconds]
  getsocialsubscription(user, view)
  Trusts, payloads

Loop
  [for each payload]
  [widgettrust=false]
  Alert("No Widget Trust")
  [usertrust=false]
  Alert("No user trust")
  postMessage(payload, DOM/widgetid)

Fox et al. (2011)

We checked your confidential medical records on the internet. Cheese and anchovies would be bad for you, so we left them off.
General Privacy Principles

- Lawfulness, **fairness** and transparency
- **Necessity** of data collection and processing
- **Purpose** specification and purpose binding
- There are no "non-sensitive" data
- The right to information **correction**
- Deleting or blocking of incorrect/ illegally stored data
- Supervision by independent data protection authority with sanctions
- Adequate organizational and technical safeguards

Privacy protection can be undertaken by...

- Privacy and data protection **laws** promoted by government
- **Supervision** by independent data protection authority (Datenschutzbeauftragte(r))
- Self-regulation for fair information practices by **codes of conducts** promoted by businesses
- **Privacy-enhancing technologies (PETs)** adopted by individuals
- Privacy education of consumers and IT professionals
With 2018 EU law: The right to be forgotten

- Basically: A user has the right to have their data deleted from a database upon request
- In some past cases, the requirement only meant deletion from a search index (due to EU tech ignorance)
- From 2018 onwards, the “right to be forgotten” will be part of the new EU data protection & privacy act (look up exact wording)
- Since one cannot foresee which (non-existing) laws will be enforced by the European bureaucracy in the future (see Apple..), it would be wise to be prepared...

This poses a big privacy problem

87 % of the population in the USA can be uniquely re-identified by Zip-Code, Gender and date of birth.


- **K-Anonymity** ... a release of data is said to have the \textit{k-anonymity property} if the information for each person contained in the release cannot be distinguished from at least $k - 1$ individuals whose information also appear in the release.

- **L-Diversity** ... extension requiring that the values of all confidential attributes within a group of $k$ sets contain at least $L$ clearly distinct values.

- **t-Closeness** ... extension requiring that the distribution of the confidential attribute within a group of $k$ records is similar to the confidential attribute’s distribution in the whole data set (local distribution must resemble the global distribution).
The Right to Be Forgotten: Towards Machine Learning on Perturbed Knowledge Bases

Bernd Malle¹,², Peter Kieseberg¹,², Edgar Weippl², and Andreas Holzinger¹(✉)

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Abstract. Today’s increasingly complex information infrastructures represent the basis of any data-driven industries which are rapidly becoming the 21st century’s economic backbone. The sensitivity of those infrastructures to disturbances in their knowledge bases is therefore of crucial interest for companies, organizations, customers and regulating bodies. This holds true with respect to the direct provisioning of such information in crucial applications like clinical settings or the energy industry, but also when considering additional insights, predictions and personalized services that are enabled by the automatic processing of those data. In the light of new EU Data Protection regulations applying from 2018 onwards which give customers the right to have their data deleted on request, information processing bodies will have to react to these changing jurisdictional (and therefore economic) conditions. Their choices include a re-design of their data infrastructure as well as preventive actions like anonymization of databases per default. Therefore, insights into the effects of perturbed/anonymized knowledge bases on


Keywords: Machine learning · Knowledge bases · Right to be forgotten · Perturbation · Anonymization · k-anonymity · SaNGreeA ·
Data properties => Reduce granularity

<table>
<thead>
<tr>
<th>Name</th>
<th>Age</th>
<th>Zip</th>
<th>Gender</th>
<th>Disease</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alex</td>
<td>25</td>
<td>41076</td>
<td>Male</td>
<td>Allergies</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
</tbody>
</table>

- **Identifiers**: immediately reveal identity
  - name, email, phone nr., SSN
  => DELETE

- **Sensitive data**
  - medical diagnosis, symptoms, drug intake, income
  => NECESSARY, KEEP

- **Quasi-Identifiers**: used in combination to retrieve identity
  - Age, zip, gender, race, profession, education
  => MAYBE USEFUL
  => MANIPULATE / GENERALIZE
**k-anonymity:** for every entry in the DS, there must be at least k-1 identical entries (w.r.t. QI's) => this is 3-anon:

<table>
<thead>
<tr>
<th>Node</th>
<th>Name</th>
<th>Age</th>
<th>Zip</th>
<th>Gender</th>
<th>Disease</th>
</tr>
</thead>
<tbody>
<tr>
<td>X1</td>
<td>Alex</td>
<td>25</td>
<td>41076</td>
<td>Male</td>
<td>Allergies</td>
</tr>
<tr>
<td>X2</td>
<td>Bob</td>
<td>25</td>
<td>41075</td>
<td>Male</td>
<td>Allergies</td>
</tr>
<tr>
<td>X3</td>
<td>Charlie</td>
<td>27</td>
<td>41076</td>
<td>Male</td>
<td>Allergies</td>
</tr>
<tr>
<td>X4</td>
<td>Dave</td>
<td>32</td>
<td>41099</td>
<td>Male</td>
<td>Diabetes</td>
</tr>
<tr>
<td>X5</td>
<td>Eva</td>
<td>27</td>
<td>41074</td>
<td>Female</td>
<td>Flu</td>
</tr>
<tr>
<td>X6</td>
<td>Dana</td>
<td>36</td>
<td>41099</td>
<td>Female</td>
<td>Gastritis</td>
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<tr>
<td>X7</td>
<td>George</td>
<td>30</td>
<td>41099</td>
<td>Male</td>
<td>Brain Tumor</td>
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<tr>
<td>X8</td>
<td>Lucas</td>
<td>28</td>
<td>41099</td>
<td>Male</td>
<td>Lung Cancer</td>
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<tr>
<td>X9</td>
<td>Laura</td>
<td>33</td>
<td>41075</td>
<td>Female</td>
<td>Alzheimer</td>
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</table>

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<tr>
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</tr>
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<td>X9</td>
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<td>410**</td>
<td>*</td>
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Limits of anonymization

Trade-off between:

- Data utility => min. information loss
- Privacy => max. information loss

Both can be easily achieved (but not together 😊)

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<tr>
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<td>X9</td>
<td>*</td>
<td>*</td>
<td>*</td>
<td>Alzheimer</td>
</tr>
</tbody>
</table>
Generalization hierarchies

• Generalization (hierarchies)
  • fixed ruleset
  • range partitioning (numerical values...)

![Diagram of a generalization hierarchy]

• Suppression
  • Special case of generalization (with one level)

“Social Network Greedy Anonymization” (SaNGreeA)

• Anonymizes a dataset w.r.t 2 information categories:
  • Feature vector values => traditional, tabular
  • Graph structure => edge configuration

• Based on the concept of ‘greedy’ clustering

• Which poses the question:
  • How do we choose the next node to add to a cluster w.r.t the above two criteria?

! We need some (good) cost functions !
• Generalization Information loss (GIL)
  • Based on content of nodes

• We assume
  • Continuous properties (age, body height, ...)
    • Candidate Nodes hold a particular value
    • Clusters have either particular value (at the start) or a generalized range
    • In order to incorporate the node into the cluster, we may have to generalize this range further, increasing the cost.

• Categorical properties (work class, native-country, ...)
  • Same preconditions as above
  • We use generalization hierarchies to determine the cost of clustering
• Generalization information loss function:

\[
GIL(cl) = |cl| \cdot \left( \sum_{j=1}^{s} \frac{\text{size}(\text{gen}(cl)[N_j])}{\text{size}(\min_{X \in \mathcal{N}}(X[N_j]), \max_{X \in \mathcal{N}}(X[N_j]))} + \sum_{j=1}^{t} \frac{\text{height}(\Lambda(\text{gen}(cl)[C_j]))}{\text{height}(\mathcal{H}_{C_j})}\right)
\]

where:
- \(|cl|\) denotes the cluster \(cl\)'s cardinality;
- \(\text{size}([i_1, i_2])\) is the size of the interval \([i_1, i_2]\), i.e., \((i_2 - i_1)\);
- \(\Lambda(w), w \in \mathcal{H}_{C_j}\) is the subhierarchy of \(\mathcal{H}_{C_j}\) rooted in \(w\);
- \(\text{height}(\mathcal{H}_{C_j})\) denotes the height of the tree hierarchy \(\mathcal{H}_{C_j}\).

• Example GIL:

  • age_range overall = [11 – 91]
  • In order to cluster some nodes, we need to generalize 27 to [20 - 30]
  • Cost = (30-20)/(91-11) = 1/8

• Given a generalization hierarchy ‘native-country’ with 4 levels
  • In order to cluster, we need to generalize ‘Austria’, ‘France’, or ‘Portugal’ to ‘Western Europe’, which is 1 level higher
  • Cost = 1/4
```python
## MAIN LOOP
for node in adults:
    if node in added and added[node] == True:
        continue
# Initialize new cluster with given node
cluster = CL.NodeCluster(node, adults, adj_list, gen_hierarchies)
# Mark node as added
added[node] = True
# SaNGreeA inner loop - Find nodes that minimize costs and
# add them to the cluster since cluster_size reaches k
while len(cluster.getNodes()) < GLOB.K_FACTOR:
    best_cost = float('inf')
    for candidate, v in ((k, v) for (k, v) in adults.items() if k > node):
        if candidate in added and added[candidate] == True:
            continue
        cost = cluster.computeNodeCost(candidate)
        if cost < best_cost:
            best_cost = cost
            best_candidate = candidate
            cluster.addNode(best_candidate)
            added[best_candidate] = True
# We have filled our cluster with k entries, push it to clusters
clusters.append(cluster)
```
<table>
<thead>
<tr>
<th>Weight Vectors 1/2</th>
</tr>
</thead>
<tbody>
<tr>
<td>[51 - 76]</td>
</tr>
<tr>
<td>[51 - 76]</td>
</tr>
<tr>
<td>[51 - 76]</td>
</tr>
</tbody>
</table>

57 | Private | United-States | Male | White | Married-civ-spouse |

<table>
<thead>
<tr>
<th>Weight Vectors 1/2</th>
</tr>
</thead>
<tbody>
<tr>
<td>[48 - 70]</td>
</tr>
<tr>
<td>[48 - 70]</td>
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<td>[48 - 70]</td>
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</table>
Applying a weight vector to our desired columns will change our cost function and thereby produce different anonymization results:

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<th>workclass</th>
<th>native-country</th>
<th>sex</th>
<th>race</th>
<th>marital-status</th>
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<tbody>
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<tr>
<td>new values</td>
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</tbody>
</table>
Experiments – original dataset
Experiments – example anonymized dataset

- **capital-gain**: A histogram showing the distribution of capital gain values.
- **education-num**: A histogram showing the distribution of education-num values.
- **marital-status**: A histogram showing the distribution of marital-status values.
- **relationship**: A histogram showing the distribution of relationship values.
- **occupation**: A histogram showing the distribution of occupation values.
- **hours-per-week**: A histogram showing the distribution of hours-per-week values.
• We used k-factors of:

• 3, 7, 11, 15 and 19

• Each combined with three different weight vectors

  ➢ Equal weights for all columns
  ➢ Age preferred (0.88 vs 0.01 rest)
  ➢ Race preferred (0.88 vs. 0.01 rest)

• Resulting in 15 differently anonymized data sets
Experiments - ML on Anonymization - Results

F1 score dependent on perturbation, gradient boosting

F1 score dependent on perturbation, linear SVC

F1 score dependent on perturbation, logistic regression

F1 score dependent on perturbation, random forest
1. Succumbing to the “right-to-be-forgotten” still seems better than performing ML on anonymized DBs

2. A whole lot of future research is needed in order to corroborate and expand on those results

- Extension to other datasets
- Extension to other ML approaches
  => Prediction, Clustering, Dim. Reduction
- Other perturbation techniques
- Graph-based datasets
Other Perturbation techniques (tab)

• Adding noise (only distribution counts)
  • Value perturbation => numerical attributes
    • Idea: alter individual data points, keep distribution

• Microaggregation / Clustering
  • Replace node data by centroid data
  • good for numerical data, but possible also for others given respective rules
  • Ensures k-anonymity only when computed over all attributes at the same time
  • Exact optimal only in P when computed over just 1 attribute (else heuristic)
Graph based data sets

- Graph data / social network data, in which
  - nodes represent microdata
  - edges represent their structural context
  - graph data are harder to anonymize
    - It's harder to model the background knowledge of an attacker.
    - It is harder to quantify the information loss of modifications.

- Graph perturbation
  - (randomly) adding / deleting nodes / edges
  - very efficient
  - hard to reconstruct - (sub)graph iso-, homomorphism problem
05 Conclusion and Future Outlook
Privacy, Security, Safety and Data Protection are of enormous increasing importance in the future ...

due to the trend to mobile and cloud computing

EHR are the fastest growing application which concern data privacy and informed patient consent.

Personal health data are being stored for the purpose of maintaining a life-long health record.

Secondary use of data, providing patient data for research.

Production of Open Data to support international research efforts (e.g. cancer) without boundaries.

Data citation approaches are needed for full transparency and replicability of research ...
Thank you!
Questions
Sample Questions (1)

- What is the core essence of the famous IOM report “Why do accidents happen”?
- What is a typical ultrasafe system – what is an example for a high risk activity?
- Which influence had the IOM report on safety engineering?
- What are the differences between the concepts of Privacy, Security and Safety?
- Why is privacy important in the health care domain?
- How do you classify errors when following the Eindhoven Classification Model?
- Please describe the basic architecture of a adverse event reporting and learning system?
- What is a typical example for medical errors?
- Please, explain the Swiss-Cheese Model of Human Error!
Sample Questions (2)

- What factors does the framework for understanding human error include?
- Which possibilities does ubiquitous computing offer to contribute towards enhancing patient safety?
- What different types of risk does the FAA System Safety Guideline explain?
- Ubiquitous computing offers benefits for health care, but which genuine security problems does ubiquitous computing bring?
- How can mobile computing device help in terms of patient safety?
- What is a context-aware patient safety approach?
- How can we describe patient safety both quantitatively and qualitatively?
- What is technical dependability?
- Which types of technical faults can be determined?
Sample Questions (3)

- What types of adverse events can be discriminated in medicine and health care?
- How is the safety level (measurement) defined?
- Which factors contribute to ultrasafe healthcare?
- What are the typical requirements of any electronic patient record?
- Why is Pseudonymization important?
- What is the basic idea of k-Anonymization?
- What is a potential threat of private personal health records?
- Please describe the concept of a personal health record system!
- How would you analyze personal health record systems?
- What does a privacy policy describe?
- Which ethical issues are related to quality improvement?
Appendix
Medical Action = Decision Making
Search Task in $H$
Problem: Time ($t$)
Some Useful Links

- http://www.ico.gov.uk (Information Commissioner’s Office in the UK)
- http://www.dsk.gv.at/ (Österreichische Datenschutz Kommission)
- http://videolectures.net/kdd09_mohammed_ahdcsbts (Anonymizing Healthcare Data: A Case Study on the Blood Transfusion Service)
Appendix: Advances in patient safety are hampered by ...

... the silo and insurance-driven approaches, and by the narrow timeframe used in AE detection and analysis. Many AEs occurring at strategic points escape scrutiny, and the impact of widely publicized insurance claims on public health is often greater than that of the immediate consequences of obvious errors.

Appendix: Example for a simple warning message

Appendix: Example for trust policies in HIS networks

Appendix: Example of new threats to health data privacy

A real-world example of cross-site information aggregation: The target patient “Jean” has profiles on two online medical social networking sites (1) and (2). By comparing the attributes from both profiles, the adversary can link the two with high confidence. The attacker can use the attribute values to get more profiles of the target through searching the Web (3) and other online public data sets (4 and 5). By aggregating and associating the five profiles, Jean’s full name, date of birth, husband’s name, home address, home phone and cell phone number, two email addresses, occupation, medical information including lab test results are disclosed!

1) Privacy Policy
   - 0. The Privacy Policy is not visible or not accessible.
   - 1. The Privacy Policy is accessed by clicking one link.
   - 2. The Privacy Policy is accessed by clicking two or more links.

2) Data Source
   - 0. Not indicated.
   - 1. User.
   - 2. User healthcare provider.
   - 3. User and his/her healthcare providers.
   - 4. User, other authorized users and other services/programs.
   - 5. Self-monitoring devices connected with the user.

3) Data Management
   - 0. Not indicated.
   - 1. Data user.
   - 2. Data user and his/her family data.

4) Access Management
   - 0. Not indicated.
   - 1. Other users and services/programs.
   - 3. Other users.
   - 4. Other users, healthcare professionals and services/programs.
5) Access audit
   - 0. No.
   - 1. Yes.

6) Data access without the end user's permission
   - 0. Not indicated.
   - 1. Information related to the accesses.
   - 2. De-identified user information.
   - 3. Information related to the accesses and de-identified user information.
   - 4. Information related to the accesses and identified user information.

7) Security measures
   - 0. Not indicated.
   - 1. Physical security measures.
   - 2. Electronic security measures.
   - 3. Physical security measures and electronic security measures.

8) Changes in Privacy Policy
   - 0. Not indicated.
   - 1. Changes are notified to users.
   - 2. Changes are announced on home page.
   - 3. Changes are notified to users and changes are announced on home page.
   - 4. Changes may not be notified.

9) Standards
   - 0. Not indicated.
   - 1. HIPAA is mentioned.
   - 2. System is covered by HONcode (HON = Health on the Net).
   - 3. HIPAA is mentioned and system is covered by HONcode.
### Overview Personal Health Records (PHR)

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<th>Tool</th>
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</table>

**Legend:**
- **PL** = Privacy policy location; **DS** = Data source; **DM** = Data managed; **AM** = Access management; **AA** = Access audit; **DA** = Data accessed without the user's permission; **SM** = Security measures; **CP** = Changes in privacy policy; **S** = Standards

Carrió et al. (2011)
Example: Differentially Private Kernel Learning

(a) Interactive Model

(b) Semi-interactive model

(c) Non-interactive Model
The larger the set of indistinguishable entities, the lower probability of identifying any one of them

"Hiding in a crowd"

Less anonymous (1/4)

More anonymous (1/n)

Anonymity set $A$

$A = \{(s_1, p_1), (s_2, p_2), ..., (s_n, p_n)\}$

$s_i$: subject $i$ who might access private data

$p_i$: probability that $s_i$ accessed private data

More details see: Bharat K. Bharava (2003), Purdue University
Effective anonymity set size is calculated by

\[ L = |A| \sum_{i=1}^{\frac{|A|}{\min p_i}} \frac{1}{|A|} \]

Maximum value of \( L \) is \( |A| \) iff all \( p_i = 1/|A| \)

\( L \) below maximum when distribution is skewed

skewed when \( p_i \) have different values

Deficiency:

\( L \) does not consider violator’s *learning* behavior

More details see: Bharat K. Bharava (2003), Purdue University
• Remember: Entropy measures the randomness (uncertainty) – here private data
• The attacker gains more information -> entropy decreases!
• Metric: Compare the current entropy value with its maximum value and the difference shows how much information has been leaked
• Privacy loss $D(A,t)$ at time $t$, when a subset of attribute values $A$ might have been disclosed:

$$D(A,t) = H^*(A) - H(A,t)$$

$H^*(A)$ – the maximum entropy
Computed when probability distribution of $p_i$’s is uniform

$H(A,t)$ is entropy at time $t$
$w_j$ – weights capturing relative privacy “value” of attributes
- Production of Open Data Sets
- Design of Synthetic data sets
- Privacy preserving ML, DM & KDD
- Data leak detection
- Data citation
- Differential privacy
- Anonymization and pseudonymization
- Securing expert-in-the-loop machine learning systems
- Evaluation and benchmarking
