PRIVACY-PRESERVING ACCESS CONTROL IN ELECTRONIC HEALTH RECORD LINKAGE

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Outline

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- Background
- Method
- Experiment
- Conclusion

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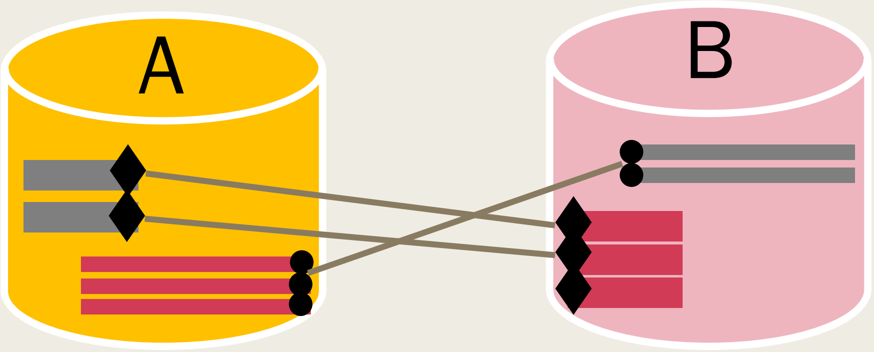
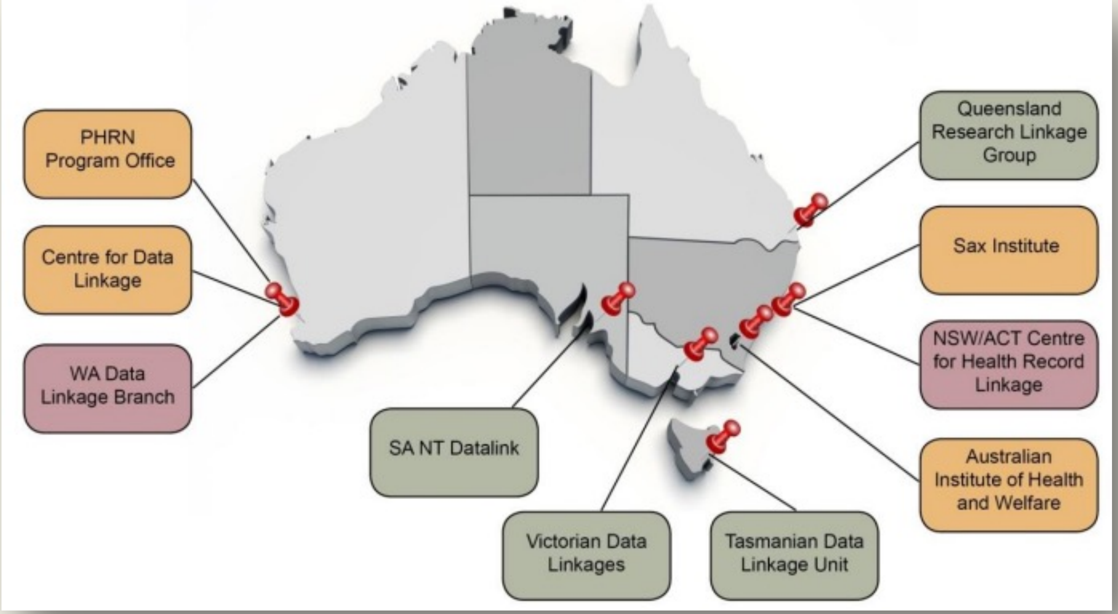
BACKGROUND

Health Record Linkage

Record linkage refers to the technique matching records about same entities across sources (e.g. data files, books, websites, and databases).





Fellegi, I. P., & Sunter, A. B. (1969). A theory for record linkage. Journal of the American Statistical Association, 64(328), 1183-1210.

Protected Personal Information

HIPAA
Health Insurance Portability and Accountability Act

Eliminating *18 identifiers* from personal health information to ensure no one can be identified

Australian Government
National Health and Medical Research Council
NHMRC

Patient identifiers are categorised into *individually identifiable*, *re-identifiable* and *non-identifiable*.

General Data Protection Regulation

GDPR applies to any information relating to an identified or identifiable natural person

	HIPAA protected health information
1	Names
2	Zip Code
3	Dates MM/DD/YYYY
4	Phone numbers
5	Fax numbers
6	E-mail address
7	SSNs
8	MRN numbers
9	Insurance ID #s
10	Account #s
11	Certificate / License
12	Serial #s
13	Device #s
14	URL
15	IP address
16	Biometrics
17	Photos
18	Other

Statistical Disclosure Control

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- “Individuals should not be uniquely identified”
- 87% of the US population could be re-identified by combining de-identified data sets (Sweeney, 2000)
- *Statistical Disclosure Control* (SDC) refers to a family of statistic-based technique are studied to ensure no individual can be re-identified.
  - *K-anonymity and its variants*
  - *Differential privacy*

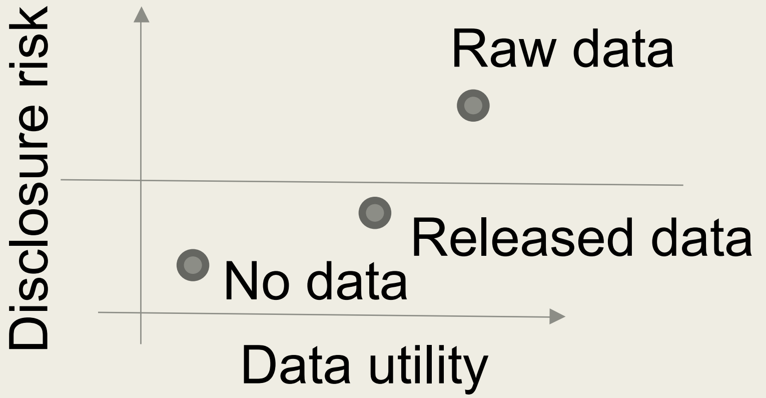
Sweeney, L. (2000). Simple demographics often identify people uniquely. *Health (San Francisco)*, *671*, 1-34.

Challenges

- Delay
  - *Decentralisation?*
- Opaque
  - *Transparent, verifiable, quantifiable?*
- Priori knowledge
  - *(non-malicious) Disclosure risk detection*
  - *Minimizing utility loss*

Privacy Preservation with *K-Anonymity*

R-U confidential map:



Quasi-identifiers (QIs)

	Zip code	Age	Nationality
1	13053	28	Russian
2	13068	29	American
3	13068	21	Japanese
4	13053	23	American
5	14853	50	Indian
6	14853	55	American
7	14850	47	American
8	14850	49	American

4-anonymity

	Zip code	Age	Nationality
1	130**	<30	*
2	130**	<30	*
3	130**	<30	*
4	130**	<30	*
5	1485*	≥40	*
6	1485*	≥40	*
7	1485*	≥40	*
8	1485*	≥40	*

Sweeney, L. (2002). k-anonymity: A model for protecting privacy. *International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems*, *10*(05), 557-570.

Raw records

	Zip code	Age	Nationality
1	13053	28	Russian
2	13068	29	American
3	13068	21	Japanese
4	13053	23	American
5	14853	50	Indian
6	14853	55	American
7	14850	47	American
8	14850	49	American

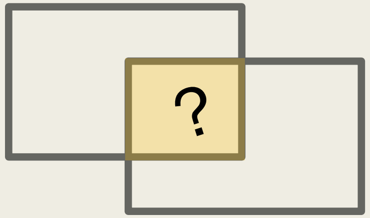
4-anonymity

Released records

	Zip code	Age	Nationality
1	130**	<30	*
2	130**	<30	*
3	130**	<30	*
4	130**	<30	*
5	1485*	≥40	*
6	1485*	≥40	*
7	1485*	≥40	*
8	1485*	≥40	*

The "presence" of individuals is known in k-anonymity case

Linkage disclosure - "presence" is unknow



Weak k-anonymity (Atzori, 2006)

"having the same goal as k-anonymity: released tuples need to match at least *k* individuals back to original dataset."

Atzori, M. (2006, August). Weak k-anonymity: A low-distortion model for protecting privacy. In *International Conference on Information Security* (pp. 60-71). Springer, Berlin, Heidelberg.

Linkage 3-Anonymity (*Time n*)

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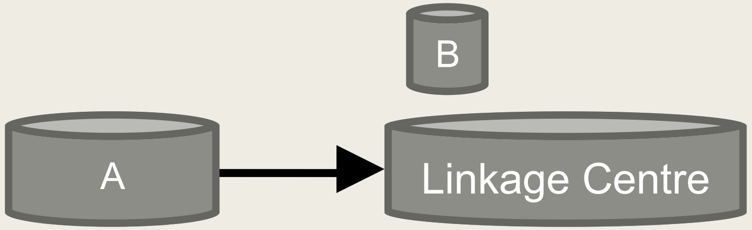

(Linkage) QIs *Non-QI*

	YoB	Sex	Ethnicity	Language
1	1974	F	Chinese	Mandarin
2	1980	F	Chinese	Mandarin
4	1968	M	Malaysian	English

	YoB	Sex	Ethnicity
1	1970-1980	F	Chinese
2	1960-1980	F	Chinese
3	1960-1980	*	Malaysian
4	1970-1980	*	Malaysian
5	1970-1980	F	Chinese
6	1960-1980	*	Malaysian

	YoB	Sex	Ethnicity	Language
1	1970-1980	F	Chinese	Mandarin
2	1960-1980	F	Chinese	Mandarin
3	1960-1980	*	Malaysian	English

“Mandarin → Chinese”

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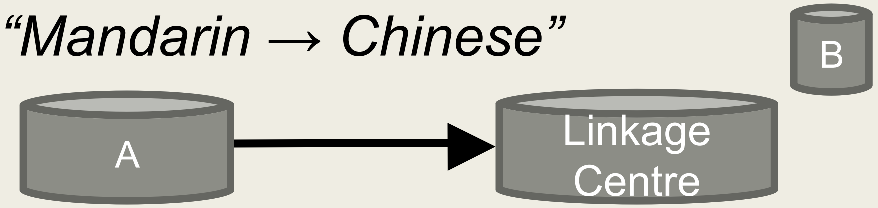
Linkage 3-Anonymity (*Time n+1*)

"Mandarin → Chinese"



(Linkage) QIs

	YoB	Sex	Ethnicity	Language
1	1974	F	Chinese	Mandarin
2	1980	F	Chinese	Mandarin
4	1968	M	Malaysian	English

	YoB	Sex	Ethnicity	Language
1	1960-1980	*	Asian	Mandarin
2	1960-1980	*	Asian	Mandarin
3	1960-1980	*	Asian	Mandarin
4	1960-1980	*	Asian	English
5	1960-1980	*	Asian	English
6	1960-1980	*	Asian	English

	YoB	Sex	Ethnicity	Language
1	1960-1980	*	Chinese	Mandarin
2	1960-1980	*	Chinese	Mandarin
4	1960-1980	*	Asian	English

Design Process - SLKA

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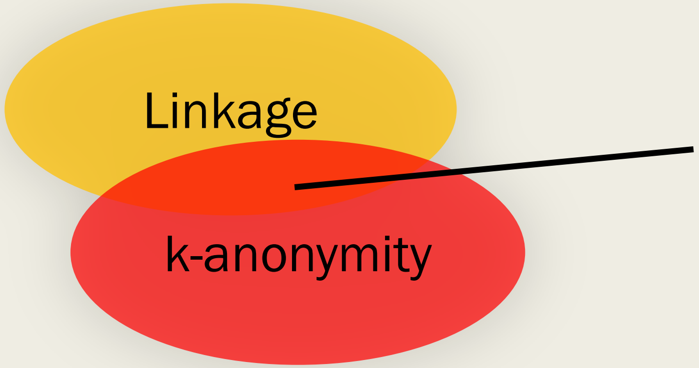
Baseline k-anonymity

$$Anonymity\ Scheme = \{QI, k\}$$

Linkage k-anonymity

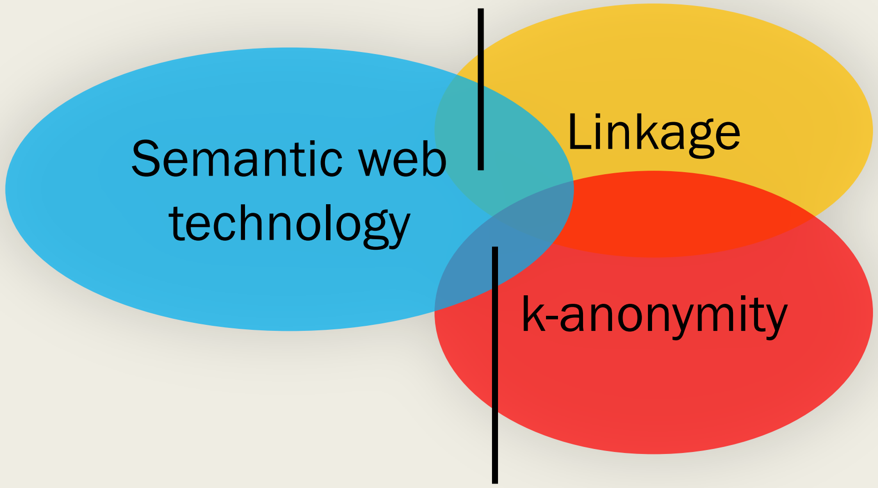


Less information loss

$$Anonymity\ Scheme = \{LQI, k_{max}\}$$

Semantic-based linkage k-anonymity (SLKA)

Privacy verification in dynamic datasets



Policy/Rule composition to arbitrary linkage

$$Anonymity\ Scheme = \{LQI, k_{max}, Associations\}$$

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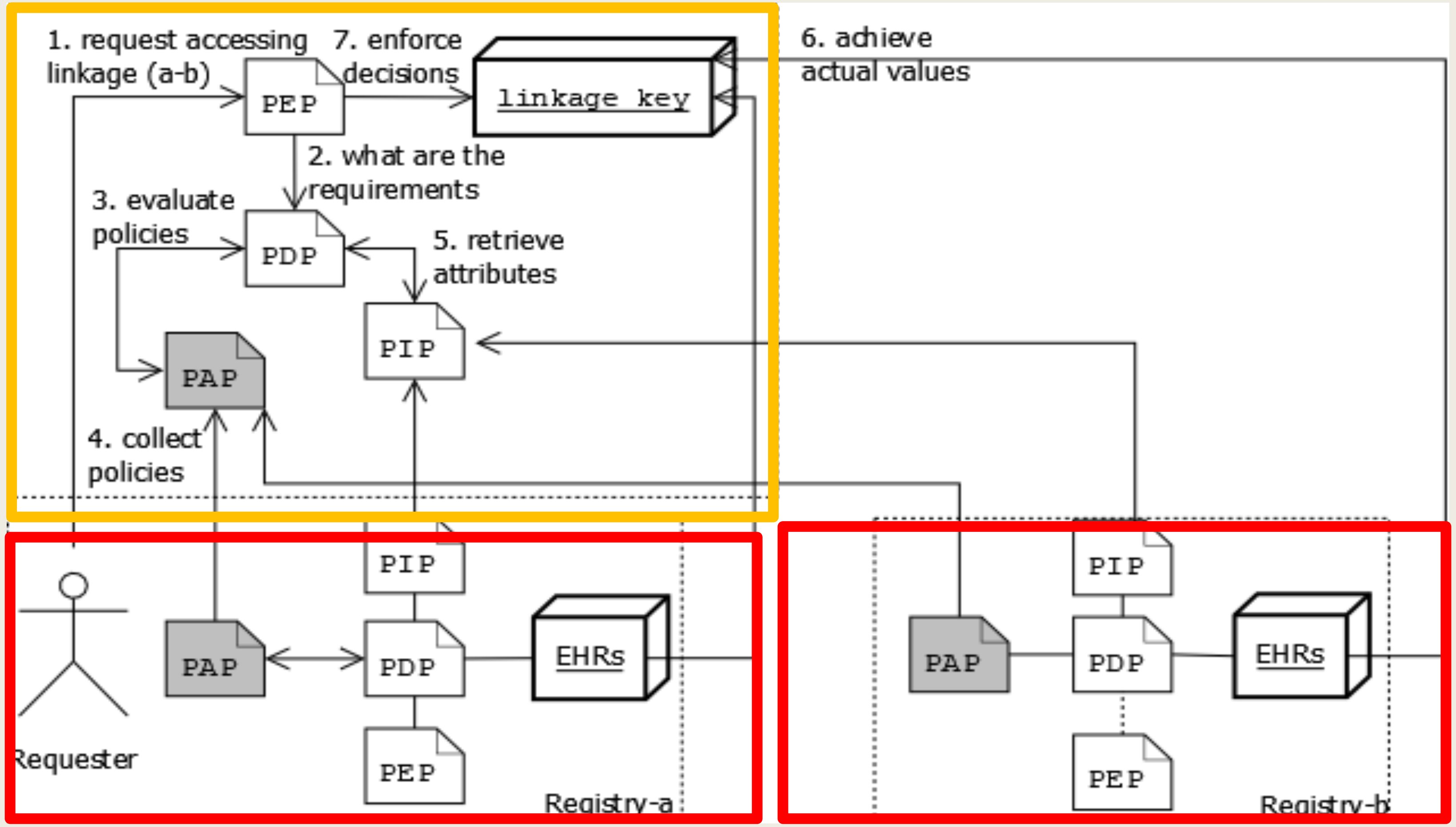
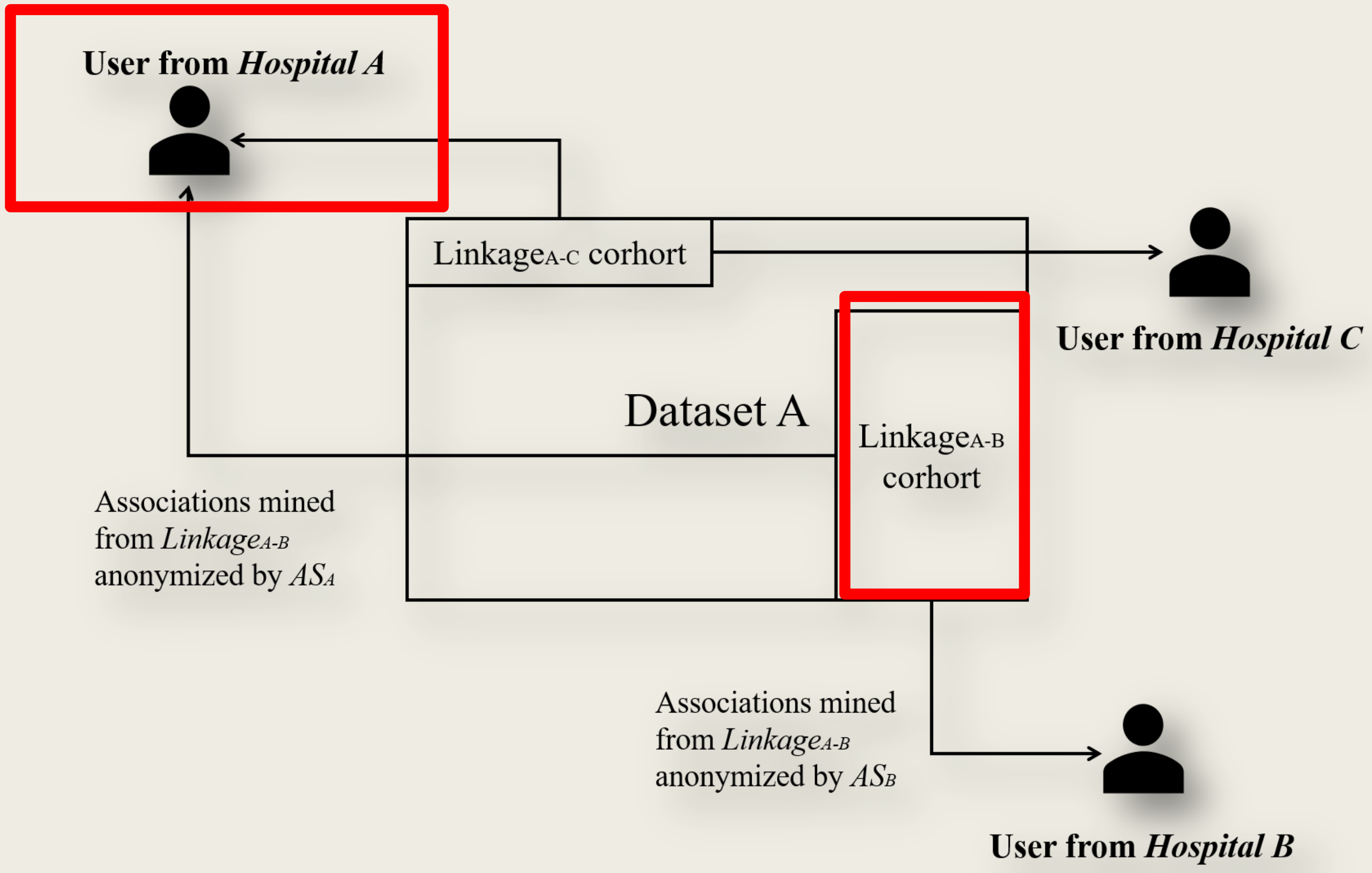
METHOD

Extending XACML Framework

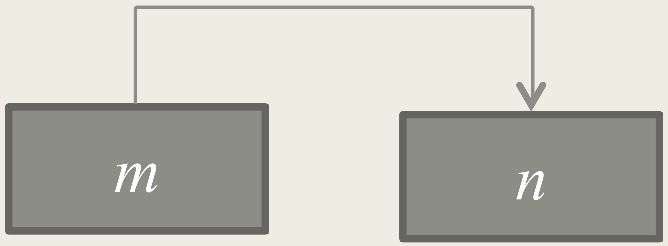


Role-based Knowledge Management

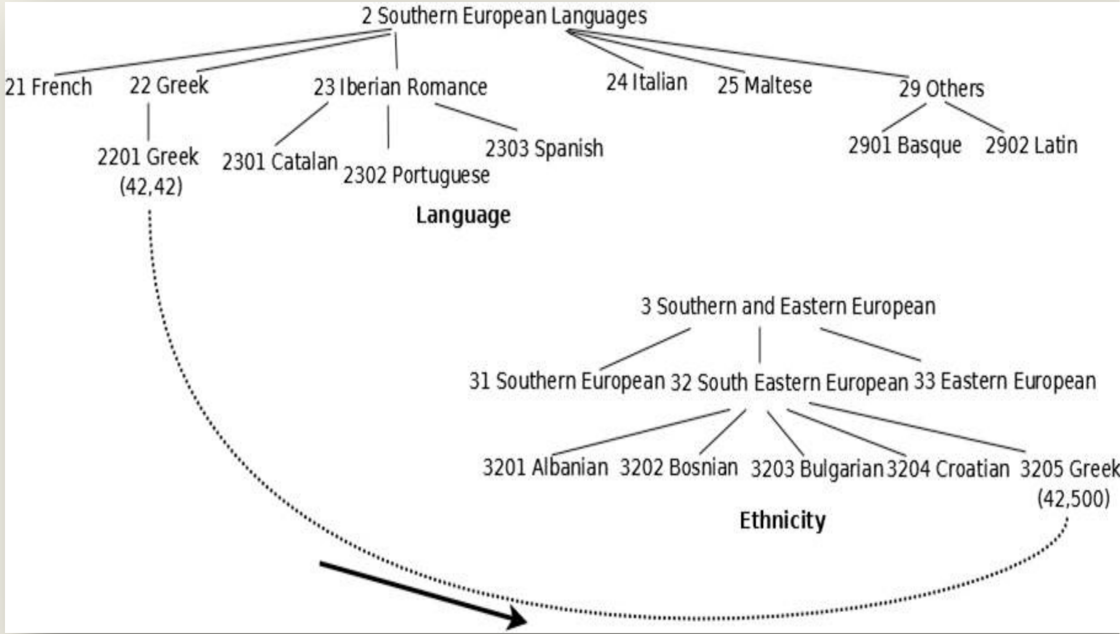


Semantic-based Inference Control

- *Mining associations - Apriori*
- *Minimum Support (ms) and Confidence (mc)*
- *Conditionals – NQI (m); Consequence – LQI (n);*



$$C_1^m \cdot C_1^n$$



Agrawal, R., & Srikant, R. (1994, September). Fast algorithms for mining association rules. In *Proc. 20th int. conf. very large data bases, VLDB* (Vol. 1215, pp. 487-499).

Formalisation and Evaluation (1/2)

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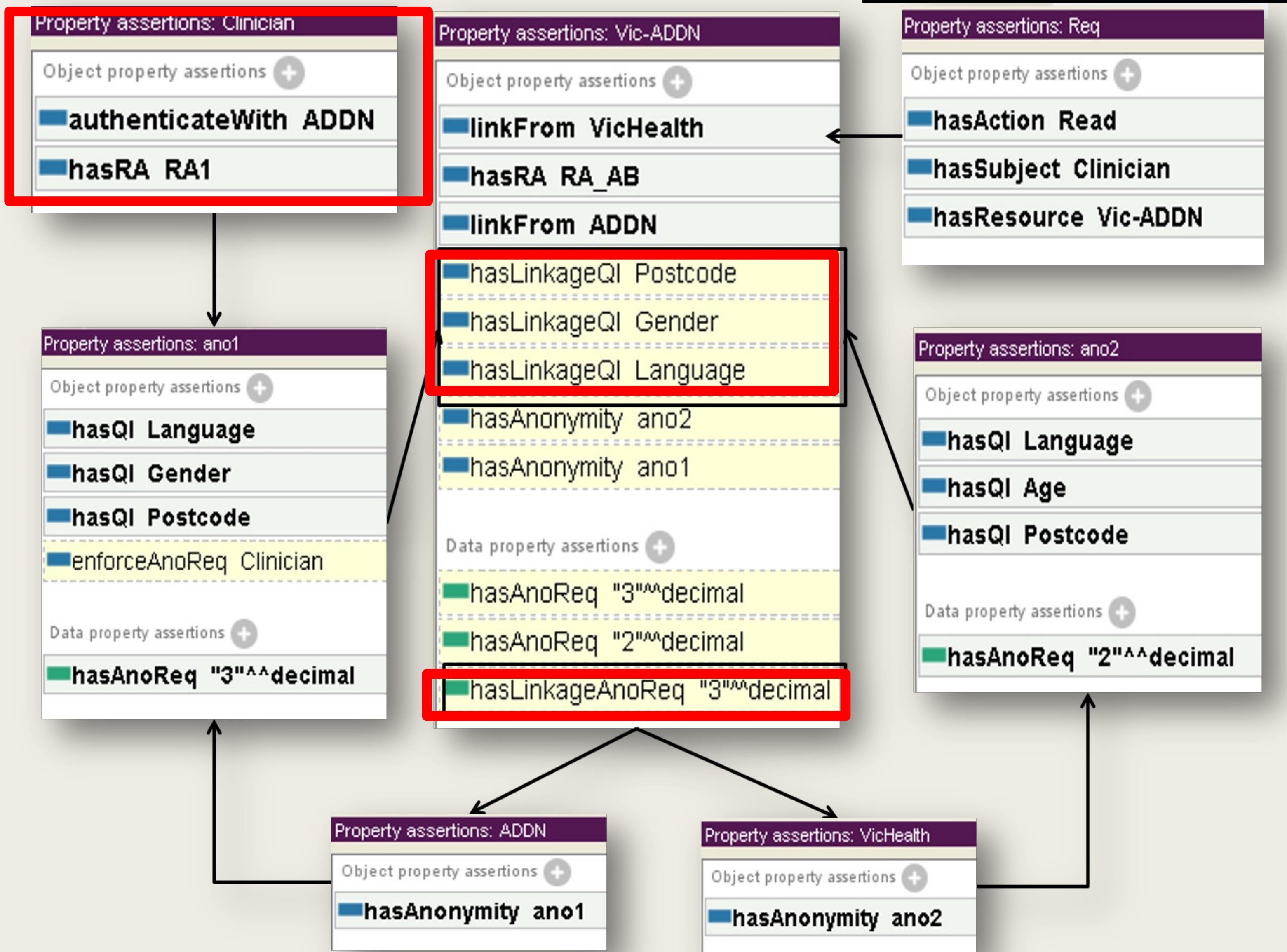
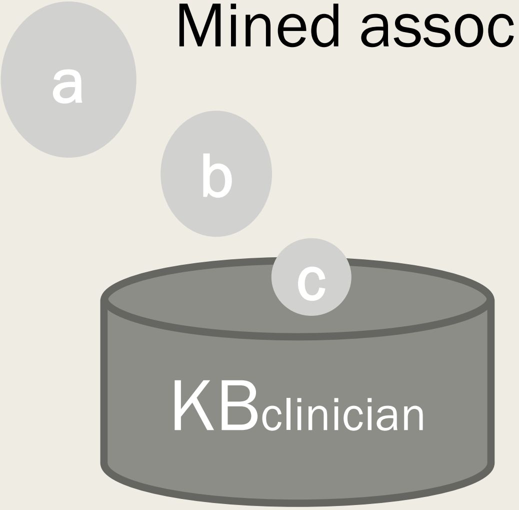
Requestor (role) → Policy scheming

→ Privacy verification



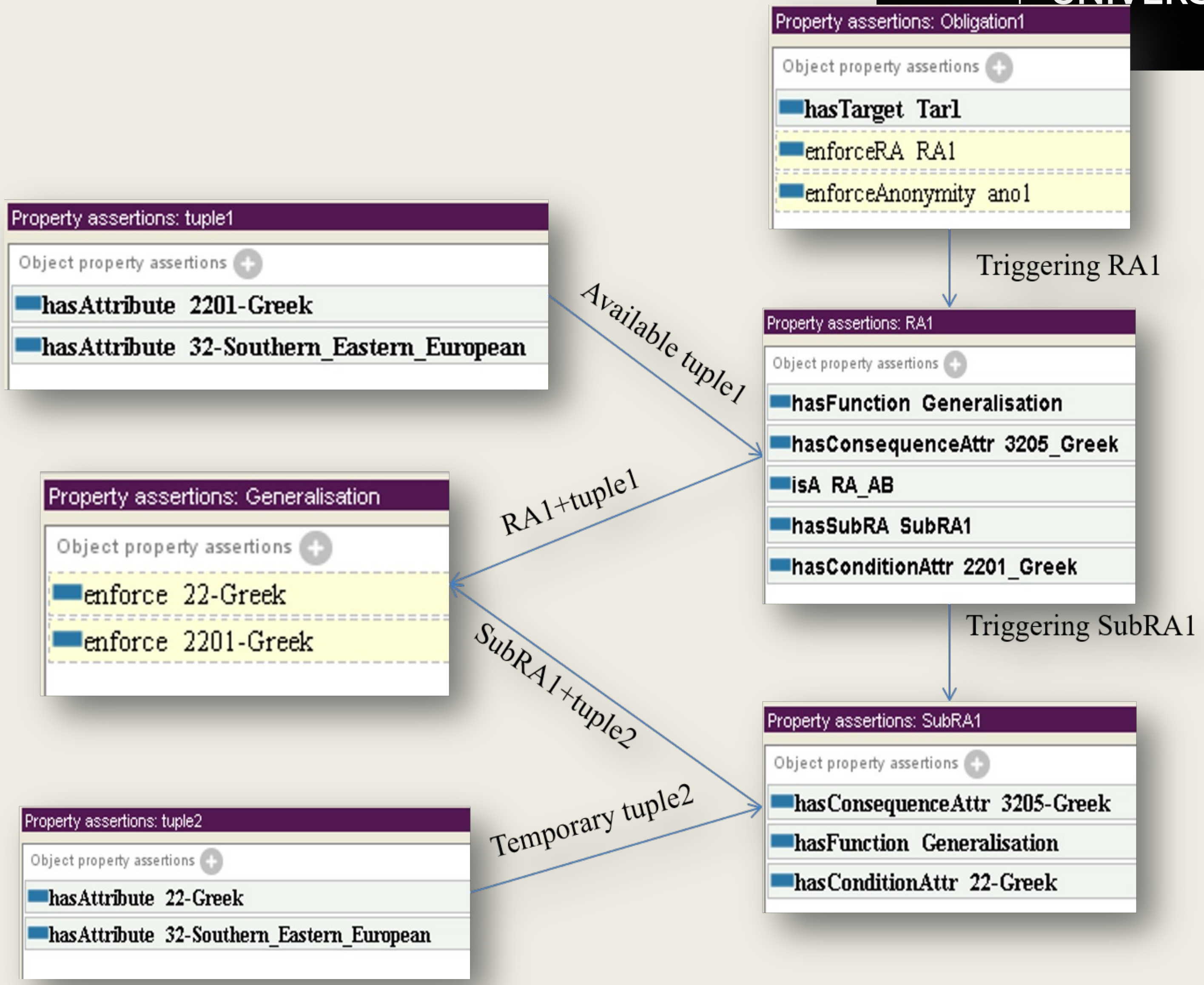
Formalisation and Evaluation (2/2)

Mined associations



NQI -> LQI

e.g. “2201 Greek” -> “3205 Greek”



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EXPERIMENT

Simulation

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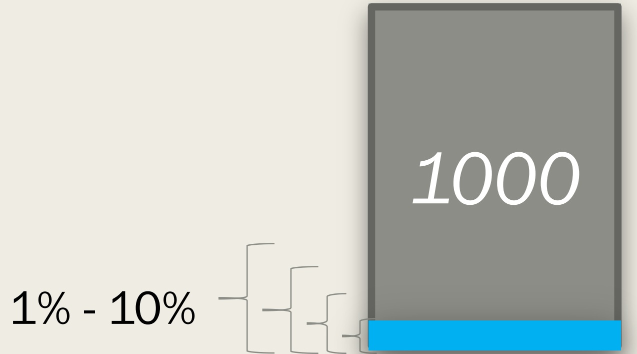
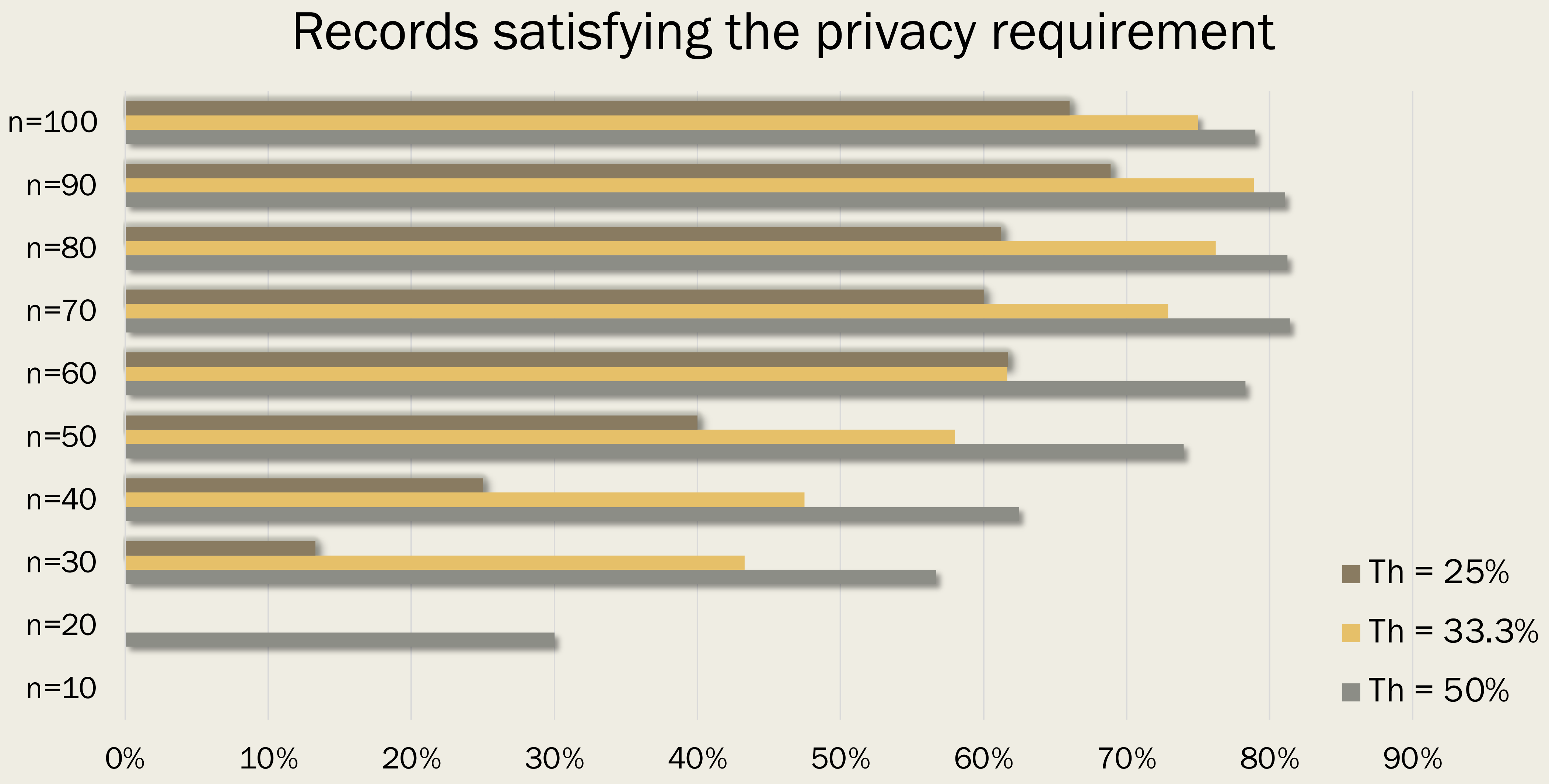
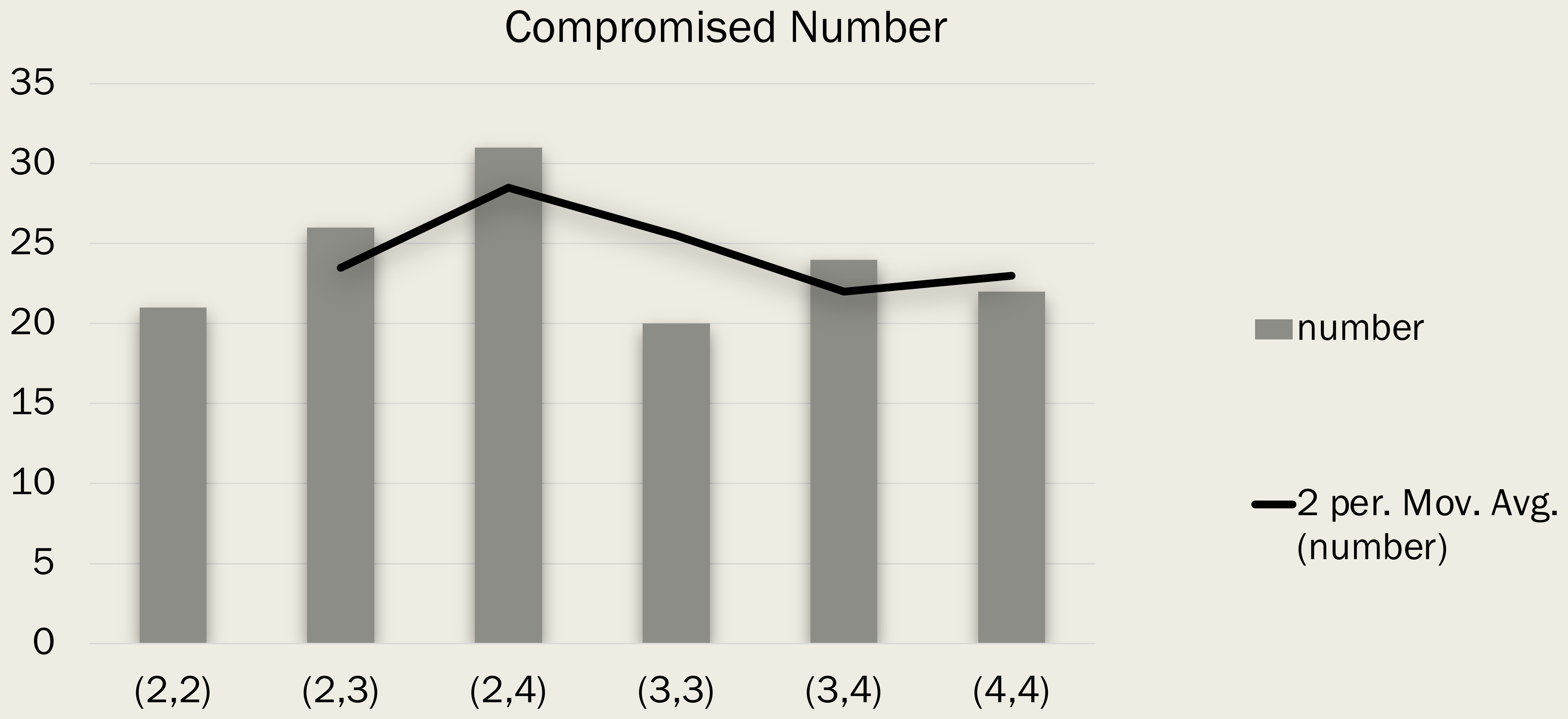
- *1000* (*996* after cleaning) synthetic records about VicHealth survey respondents
- Label records as the "linked" (10 linkage datasets)
- Simulating ***repeated linkage*** requests (Time1 & Time 2)
  - *Same: VicHealth user (role), candidate datasets, cohort, identifiers*
  - *Different: policies (Anonymity schemes)*
    - Time1 {*age*, *ethnicity*, *postcode*} and Time2 {*age*, *ethnicity*, *postcode*, *language*}
- k= *2, 3, 4*



Security Condition



Privacy Violation – Weak k-anonymity



Information Loss (1/2)

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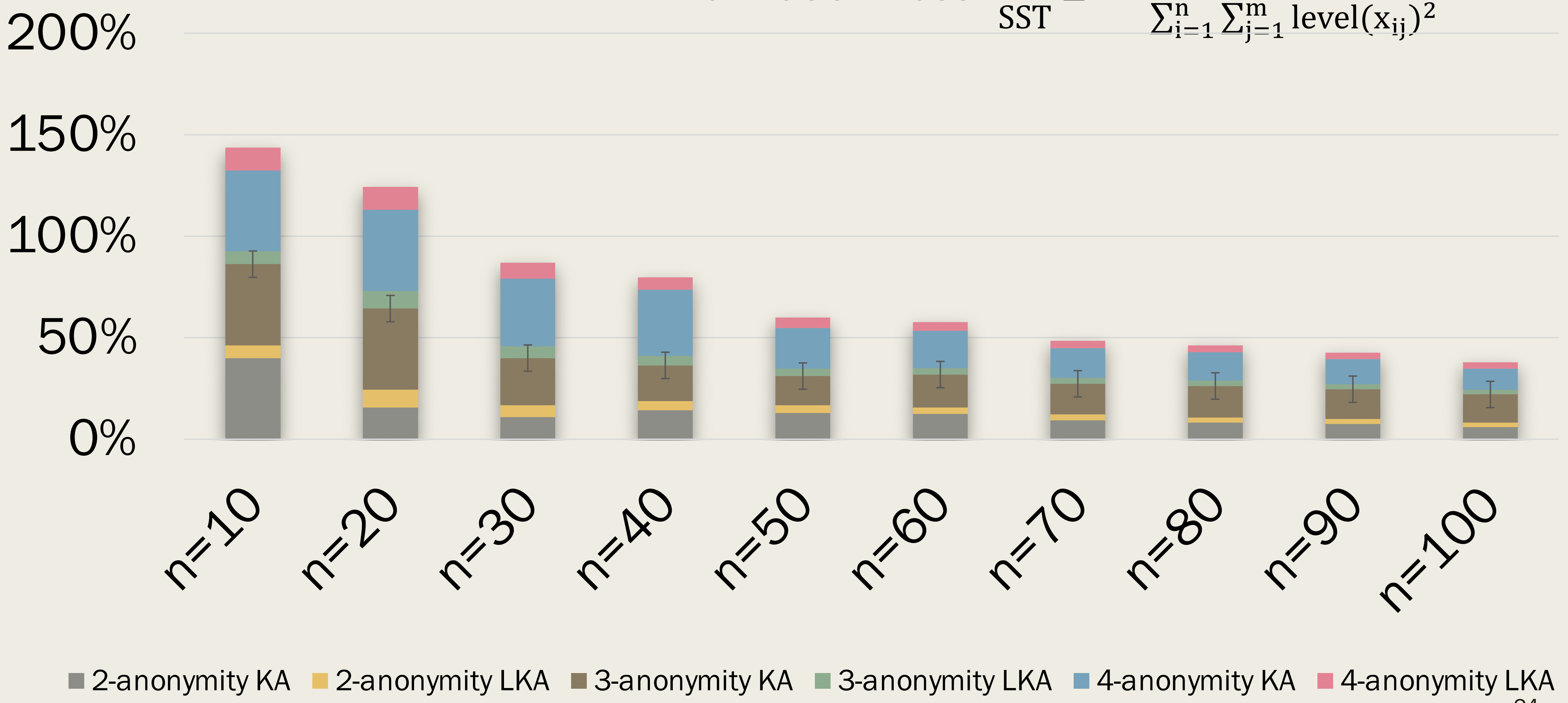
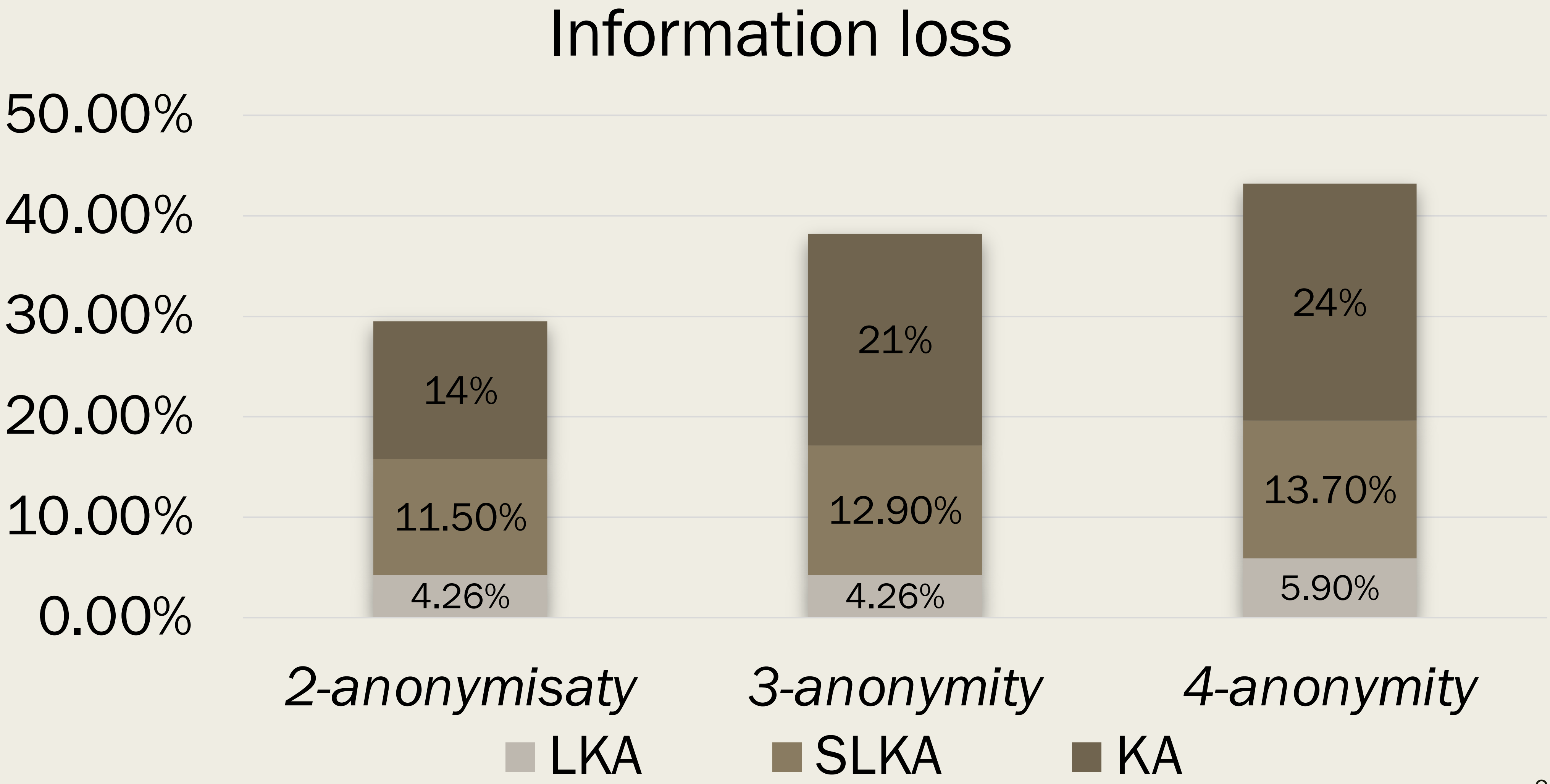
Information Loss $\frac{SSE}{SST} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{m} \mathrm{level\_Dis}(x_{ij}, x'_{ij})^2}{\sum_{i=1}^{n}\sum_{j=1}^{m} \mathrm{level}(x_{ij})^2}$



Information Loss (2/2)



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CONCLUSION

Conclusion

- We adopt semantic web technology to tackle privacy issues…
  - *Providing SLKA according to the characteristics of record linkage*
  - *Striking the balance between* ***Privacy*** *and* ***Utility***
  - *Supporting arbitrary policy (k-anonymity) composition*
  - *Improved effectiveness of security policy*

Lu, Y., Sinnott, R. O., Verspoor, K., & Parampalli, U. (2018, August). Privacy-preserving access control in electronic health record linkage. In *2018 17th IEEE International Conference On Trust, Security And Privacy In Computing And Communications/12th IEEE International Conference On Big Data Science And Engineering (TrustCom/BigDataSE)* (pp. 1079-1090). IEEE.

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THANK YOU