FATE P01, P02

Data Anonymization

Ashwin S they/them

Universitat Pompeu Fabra Barcelona

Programming Sessions

1. **6 Labs =** 3 Modules x 2 Sessions
2. **Grading Policy**

M1: Data Anonymization	**(40%)**	Submit by 11:59 PM, Feb 03, 2025
M2: Algorithmic Fairness I	**(20%)**	Submit by 11:59 PM, Feb 20, 2025
M3: Algorithmic Fairness II	**(40%)**	Submit by 11:59 PM, Mar 07, 2025

3. **Queries / Discussion**

   Please post on the Aula Global Forum for everyone's benefit.

4. **Email**: ashwin.singh01@estudiant.upf.edu

Overview

1. Attributes in Microdata
2. *k*-Anonymity
3. Methods for *k*-Anonymity
    a. Global Recoding (Generalization)
    b. Micro-Aggregation
4. ℓ-Diversity [New!]
5. Local Suppression for ℓ-Diversity

Attributes In Microdata

1. **Identifiers**

   Can unambiguously identify a person (passport, DNI/NIE, email address, etc.)

2. **Quasi-Identifiers**

   Can sometimes identify the person when combined with other quasi-identifiers.

   (gender <-> zip-code <-> age)

3. **Confidential Attributes**

   Sensitive information about a person (salary, ethnicity, gender, etc.)

4. **Non-Confidential Attributes**

   Whatever remains...

k-Anonymity

D1: x_1 , $x_2 \in X$ belong to the same **equivalence class** if $\forall$ quasi-identifiers $q \in Q$, $x_1(q) = x_2(q)$.

D2: X satisfies ***k*-anonymity** when there exist at least ***k*** elements in each **equivalence class**.

Gender	Zip-Code	Salary	Equivalence Class
man	08010	<5000€	C1
man	08010	<5000€	C1
woman	08022	>5000€	C2
woman	08022	>5000€	C2

Sweeney, L. (2002). k-ANONYMITY: A MODEL FOR PROTECTING PRIVACY. International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems, 10(05), 557–570. https://doi.org/10.1142/S0218488502001648

Global Recoding (Generalization)

Gender	Zip-Code	Generalized Zip-Code	Salary	Equivalence Class
man	08011	0801*	<5000€	C1
man	08012	0801*	<5000€	C1
woman	08020	0802*	>5000€	C2
woman	08022	0802*	>5000€	C2

Quasi-Identifiers	Confidential Attribute

Remember

All instances in the database are modified during generalization.

(which is why it is **global**)

It is **non-perturbative.** Why ?

Micro-Aggregation

Company	Workers	Aggregated Workers	Profit	Equivalence Class
A	44	41	+1000€	C1
B	25	27	+500€	C2
C	39	41	+750€	C1
D	30	27	+300€	C2

Identifier	Quasi-Identifiers	Confidential Attribute

Discuss

Why do we take the **mean**?

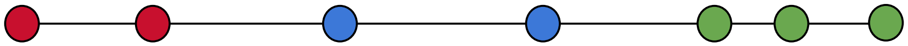
Is it **perturbative** OR **non-perturbative**?

Micro-Aggregation ▶ Intuition

Univariate Case

Sort data by the continuous quasi-identifier

Assign first k items class 1, next k items class 2, and so on… (*not always optimal)

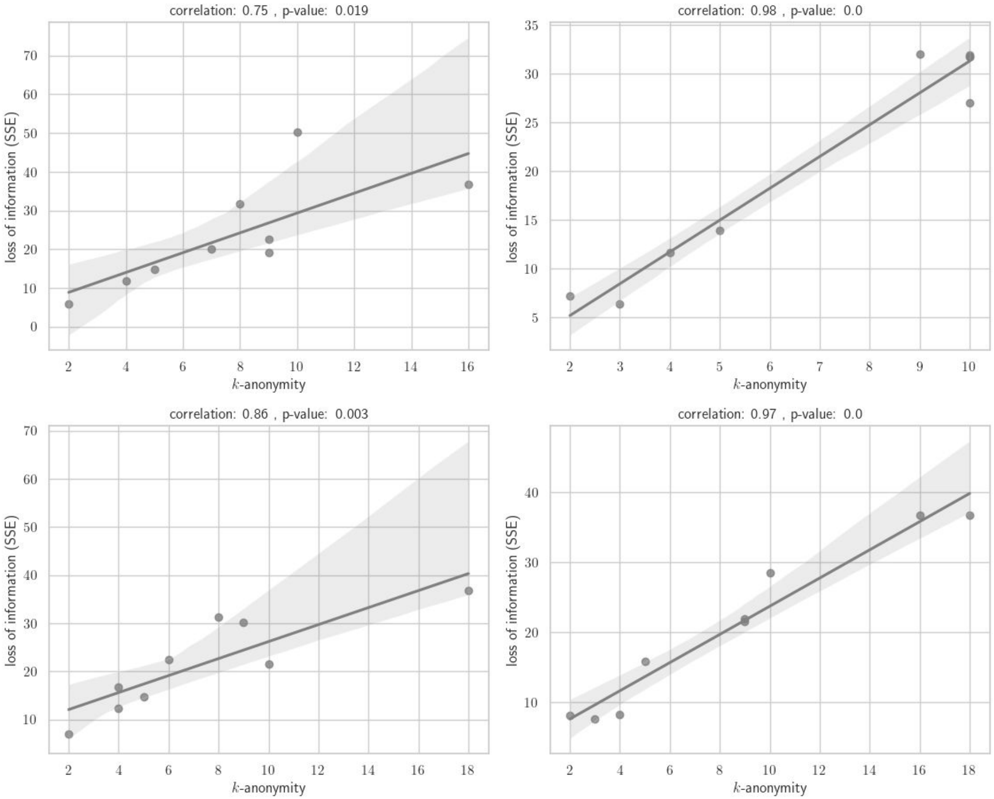


Multivariate Case

k-Partition Problem with Minimal Information Loss [NP-Hard]

J. Domingo-Ferrer and J. M. Mateo-Sanz, "Practical data-oriented microaggregation for statistical disclosure control," in IEEE Transactions on Knowledge and Data Engineering, vol. 14, no. 1, pp. 189-201, Jan.-Feb. 2002, doi: 10.1109/69.979982.

Micro-Aggregation ▶ Loss of Information



Plots generated across different runs of Gaussian Mixture Model to cluster and micro-aggregate data to achieve *k*-anonymity.

Loss of Information

$$SSE = \sum_{c \in C} \sum_{q \in Q_c} (q - \overline{q}_c)'(q - \overline{q}_c)$$

C is the set of equivalence classes

Q_c is the set of quasi-identifier vectors in equivalence class c

ℓ-Diversity

A dataset X satisfies **ℓ-diversity** when there exist at least **ℓ** distinct values of the **confidential attribute** in each **equivalence class**.

Zip-Code	Profession	Equivalence Class
0801*	Software Engineer	C1
0801*	Software Engineer	C1
0802*	Architect	C2
0802*	Doctor	C2

What is the problem here?

Machanavajjhala, A., Kifer, D., Gehrke, J., & Venkitasubramaniam, M. (2007). L -diversity: Privacy beyond k -anonymity. ACM Transactions on Knowledge Discovery from Data, 1(1), 3. https://doi.org/10.1145/1217299.1217302

ℓ-Diversity ▶ Local Suppression

A dataset X satisfies **ℓ-diversity** when there exist at least **ℓ** distinct values of the **confidential attribute** in each **equivalence class**.

Zip-Code	Profession	Equivalence Class
0801*	Software Engineer	C1
0801*	Engineer	C1
0802*	Architect	C2
0802*	Doctor	C2

What is the problem now?

Machanavajjhala, A., Kifer, D., Gehrke, J., & Venkitasubramaniam, M. (2007). L -diversity: Privacy beyond k -anonymity. ACM Transactions on Knowledge Discovery from Data, 1(1), 3. https://doi.org/10.1145/1217299.1217302