15TH NATIONAL CONVENTION ON STATISTICS
03-05 OCTOBER 2022

Organized by the Philippine Statistical System
Spearheaded by the Philippine Statistics Authority

Mathematically Rigorous Approach to Anonymize the CBMS Micro-data using Differential Privacy

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Crowne Plaza Galleria Manila
08:30-10:00AM, 05 October 2022

Motivation

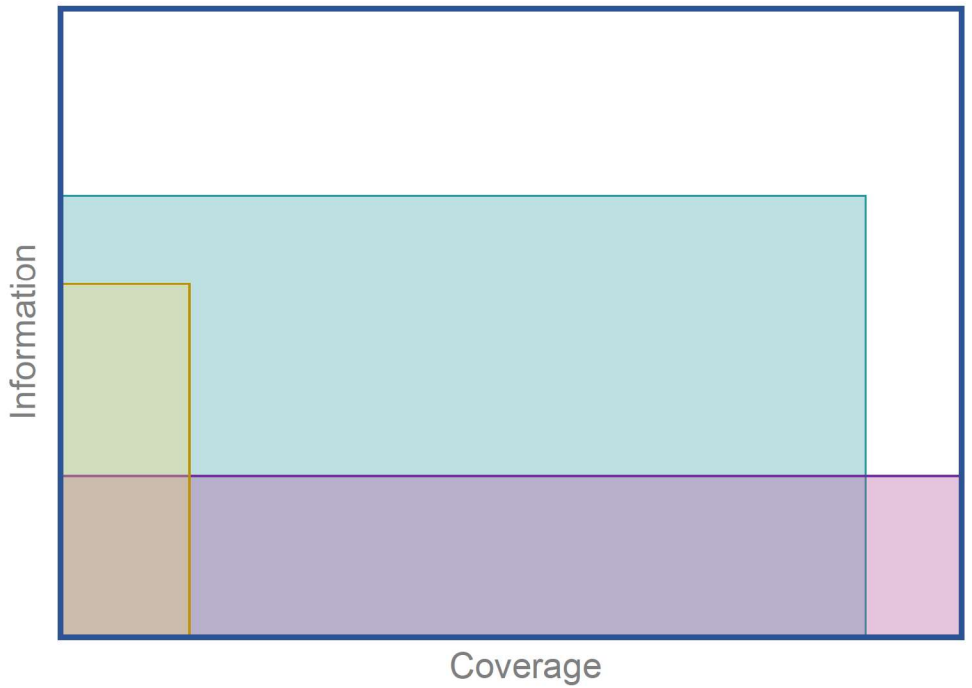
> *Please be informed that all information shared are strictly confidential pursuant to Section 10 (Confidentiality of Information) of Republic Act (RA) No. 11315 or the CBMS Act and Section 8 (Confidentiality) of RA No. 10173 or the Data Privacy Act of 2012 and will not be used against you or to any of your household members for taxation, investigation, or law enforcement purposes.*

Confidentiality guarantee in the 2021 Pilot CBMS Household Profile Questionnaire

Motivation

Why **data privacy** is crucial for **CBMS**?

- Sample surveys
- Census of population
- CBMS



What we usually do to protect the privacy of our respondents

De-identification

Anonymize by removing personally identifiable information

Geo-swapping

Randomly swap the data subject's geographic information

Release only summary or aggregate statistics

Never release the microdata

Privacy guarantee

Aggregate statistics

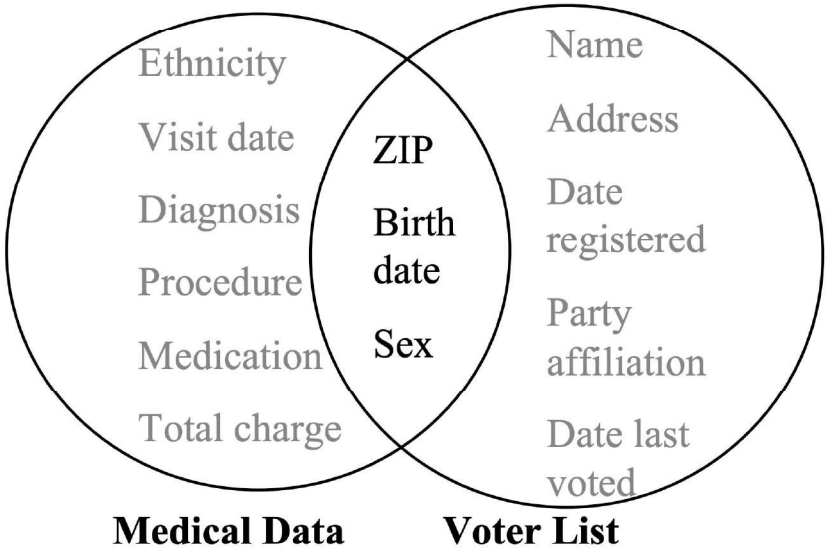
Microdata

Privacy relatively guaranteed

Privacy is at risk

Linkage attack

Re-identification of individuals by directly matching or linking two (2) or more datasets with shared attributes



Linking to re-identify data (Sweeney, 2002)

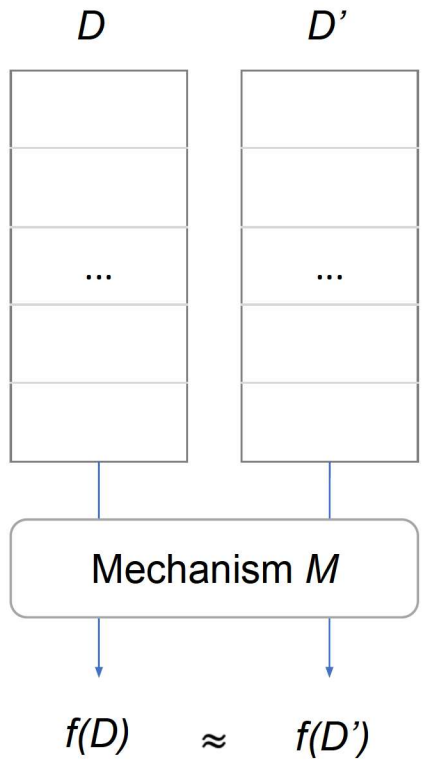
Reconstruction attack

- The U.S. Census Bureau reconstructed 100% of the 2010 Census micro-data records (308,745,538 persons)
- The reconstructed records matched the confidential data (2010 CEF) exactly (every single bit) for 46% of the population (142 million people) and allowing age +/- 1 year for 71% of the population (219 million people).

Reconstruction-abetted re-identification attacks and other traditional vulnerabilities (Abowd, n.d.)

Differential Privacy

- Gives a promise of a quantifiable and provable privacy guarantee at the same time preserve statistical properties of the original data
- Ensures that the same conclusions will be reached, independent of whether any individual opts in or opts out of the dataset.



Differential Privacy

Formal Definition: A randomized mechanism M gives (ϵ, δ)-differential privacy for every set of outputs S, and for any neighbouring datasets of D and D', if M satisfies:

$$P\left[M(D) \in S\right] \leq e^{\epsilon} \cdot P\left[M(D') \in S\right] + \delta\,.$$

Differential Privacy

- The parameter ϵ is defined as the privacy-loss budget which controls the privacy guarantee level of mechanism M.
- For a particular output, the ratio on two probabilities is bounded by e^{ϵ}

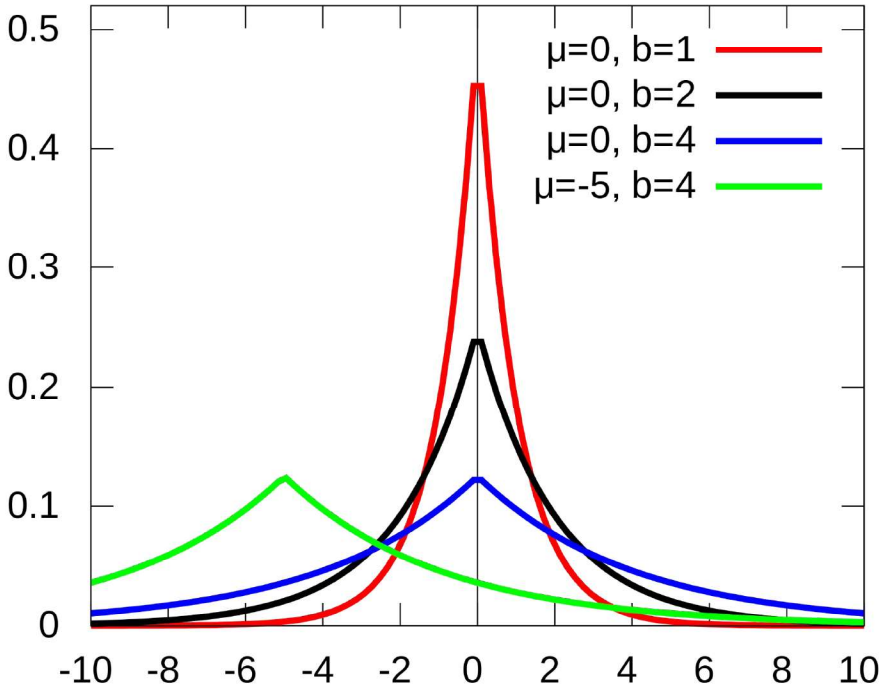
Laplace mechanisms

$$M(D) = f(D) + \text{Lap}\left(\frac{\Delta f}{\varepsilon}\right)$$

$$\Delta f = \max ||f(D) - f(D')||_1$$

Other mechanisms:

- Gaussian
- Exponential



Properties of Differential Privacy

Protection against arbitrary risks

Moving beyond protection against re-identification

Automatic neutralization of linkage attacks

Including all those attempted with all past, present, and future datasets and other forms and sources of auxiliary information

Quantification of privacy loss

Decide the level of privacy and accuracy of the output

Properties of Differential Privacy

Composition

Analysis and control of cumulative privacy loss over multiple computations

Group privacy

Analysis and control of privacy loss incurred by groups, such as families

Closure under post-processing

Data analyst cannot increase privacy loss

Original Dataset *D*

Histogram query using the **Laplace** mechanism

Age Group	Count	ε = 0.01	ε = 0.1	ε = 0.2	ε = 0.3	ε = 0.4	ε = 0.5	ε = 1.0	ε = 5.0
< 5	2,193	2,138	2,198	2,192	2,191	2,189	2,196	2,192	2,193
5-9	2,710	2,796	2,713	2,708	2,713	2,710	2,714	2,708	2,710
10-14	2,739	2,719	2,784	2,733	2,739	2,748	2,739	2,738	2,739
15-19	2,596	2,741	2,600	2,590	2,599	2,600	2,596	2,596	2,596
20-24	2,440	2,653	2,445	2,436	2,443	2,444	2,438	2,440	2,440
25-29	2,153	1,913	2,154	2,153	2,156	2,150	2,157	2,155	2,153
30-34	1,870	1,876	1,872	1,867	1,870	1,867	1,869	1,870	1,870
35-39	1,659	1,813	1,654	1,665	1,661	1,660	1,655	1,660	1,659
40-44	1,344	1,355	1,332	1,332	1,345	1,343	1,349	1,344	1,344
45-49	1,195	1,186	1,221	1,194	1,197	1,196	1,196	1,195	1,195
50-54	1,118	1,363	1,134	1,123	1,096	1,117	1,115	1,119	1,118
55-59	1,045	1,035	1,050	1,038	1,045	1,043	1,045	1,046	1,045
60-64	801	845	810	802	798	803	806	804	801
65-69	665	681	635	661	664	661	665	665	665
70-74	411	253	411	404	412	411	411	411	411
75-79	250	411	257	254	249	250	251	250	250
80-84	130	59	122	138	125	131	129	126	130
85-89	74	0	69	73	72	73	73	73	74
90-94	14	0	6	16	15	14	12	15	14
95-99	1	241	0	0	0	7	0	0	1
100+	1	152	0	0	4	1	8	0	1
Total	25,409	26,230	25,467	25,379	25,394	25,418	25,424	25,407	25,409

Neighboring Dataset *D'*

Histogram query using the **Laplace** mechanism

Age Group	Count	ε = 0.01	ε = 0.1	ε = 0.2	ε = 0.3	ε = 0.4	ε = 0.5	ε = 1.0	ε = 5.0
< 5	2,193	2,174	2,209	2,193	2,192	2,194	2,191	2,194	2,193
5-9	2,710	2,647	2,704	2,707	2,710	2,708	2,712	2,711	2,710
10-14	2,739	2,769	2,735	2,735	2,732	2,739	2,740	2,742	2,739
15-19	2,596	2,496	2,632	2,598	2,594	2,598	2,602	2,594	2,596
20-24	2,440	2,570	2,443	2,428	2,439	2,437	2,440	2,438	2,440
25-29	2,153	2,221	2,174	2,156	2,150	2,152	2,149	2,154	2,153
30-34	1,870	1,911	1,869	1,868	1,874	1,870	1,871	1,871	1,870
35-39	1,659	1,686	1,657	1,658	1,655	1,662	1,660	1,655	1,659
40-44	1,344	1,314	1,348	1,349	1,347	1,349	1,341	1,345	1,344
45-49	1,194	1,200	1,182	1,203	1,194	1,198	1,194	1,195	1,194
50-54	1,118	1,256	1,120	1,115	1,119	1,119	1,116	1,118	1,117
55-59	1,045	1,063	1,038	1,058	1,041	1,051	1,041	1,045	1,046
60-64	801	915	827	804	802	801	801	800	800
65-69	665	618	667	667	663	665	661	661	665
70-74	411	465	411	400	413	410	409	411	411
75-79	250	187	248	249	249	249	246	250	250
80-84	130	151	144	130	139	122	131	130	130
85-89	74	70	71	75	83	74	73	74	74
90-94	14	0	8	17	16	17	11	15	14
95-99	1	15	0	10	0	0	0	0	1
100+	1	176	0	2	0	0	4	1	1
Total	25,408	25,904	25,487	25,422	25,412	25,415	25,393	25,404	25,407

Original Dataset *D*

Histogram query using the **Laplace** mechanism

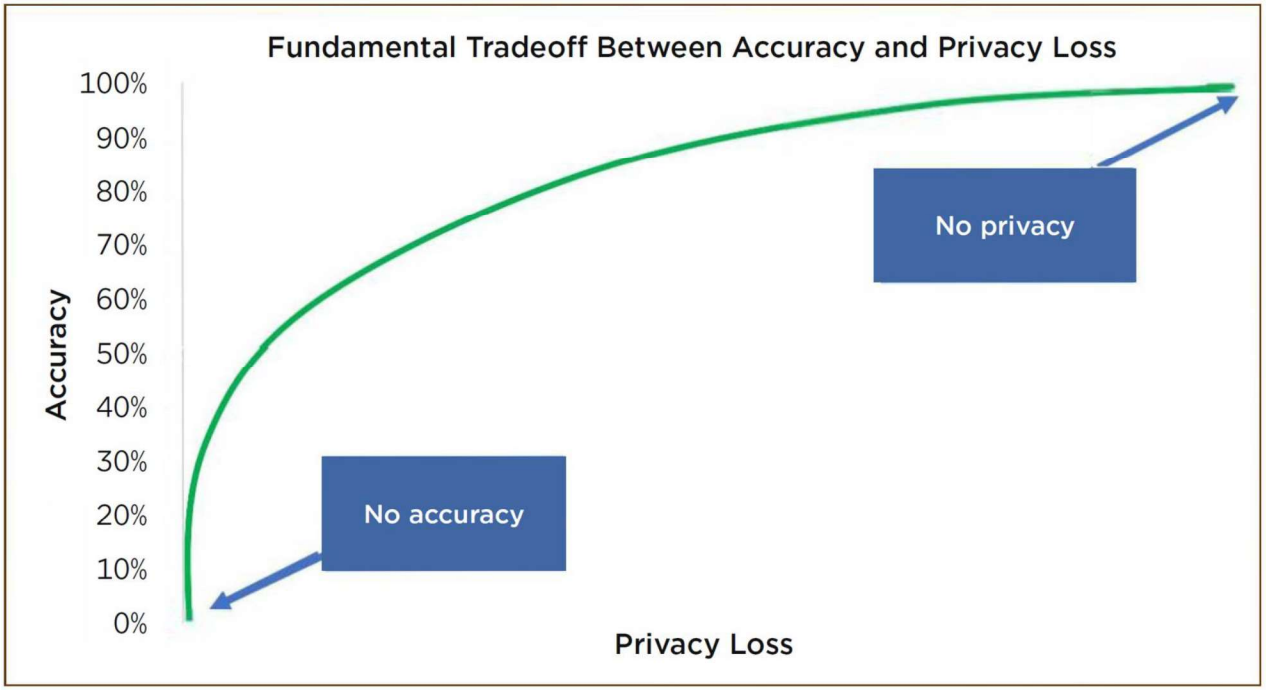
Age Group	ε = 0.01	ε = 0.1	ε = 0.2	ε = 0.3	ε = 0.4	ε = 0.5	ε = 1.0	ε = 5.0
< 5	55	-5	1	2	4	-3	1	0
5-9	-86	-3	2	-3	0	-4	2	0
10-14	20	-45	6	0	-9	0	1	0
15-19	-145	-4	6	-3	-4	0	0	0
20-24	-213	-5	4	-3	-4	2	0	0
25-29	240	-1	0	-3	3	-4	-2	0
30-34	-6	-2	3	0	3	1	0	0
35-39	-154	5	-6	-2	-1	4	-1	0
40-44	-11	12	12	-1	1	-5	0	0
45-49	9	-26	1	-2	-1	-1	0	0
50-54	-245	-16	-5	22	1	3	-1	0
55-59	10	-5	7	0	2	0	-1	0
60-64	-44	-9	-1	3	-2	-5	-3	0
65-69	-16	30	4	1	4	0	0	0
70-74	158	0	7	-1	0	0	0	0
75-79	-161	-7	-4	1	0	-1	0	0
80-84	71	8	-8	5	-1	1	4	0
85-89	74	5	1	2	1	1	1	0
90-94	14	8	-2	-1	0	2	-1	0
95-99	-240	1	1	1	-6	1	1	0
100+	-151	1	1	-3	0	-7	1	0
Total	-821	-58	30	15	-9	-15	2	0

Neighboring Dataset *D'*

Histogram query using the **Laplace** mechanism

Age Group	ε = 0.01	ε = 0.1	ε = 0.2	ε = 0.3	ε = 0.4	ε = 0.5	ε = 1.0	ε = 5.0
< 5	19	-16	0	1	-1	2	-1	0
5-9	63	6	3	0	2	-2	-1	0
10-14	-30	4	4	7	0	-1	-3	0
15-19	100	-36	-2	2	-2	-6	2	0
20-24	-130	-3	12	1	3	0	2	0
25-29	-68	-21	-3	3	1	4	-1	0
30-34	-41	1	2	-4	0	-1	-1	0
35-39	-27	2	1	4	-3	-1	4	0
40-44	30	-4	-5	-3	-5	3	-1	0
45-49	-6	12	-9	0	-4	0	-1	0
50-54	-138	-2	3	-1	-1	2	0	1
55-59	-18	7	-13	4	-6	4	0	-1
60-64	-114	-26	-3	-1	0	0	1	1
65-69	47	-2	-2	2	0	4	4	0
70-74	-54	0	11	-2	1	2	0	0
75-79	63	2	1	1	1	4	0	0
80-84	-21	-14	0	-9	8	-1	0	0
85-89	4	3	-1	-9	0	1	0	0
90-94	14	6	-3	-2	-3	3	-1	0
95-99	-14	1	-9	1	1	1	1	0
100+	-175	1	-1	1	1	-3	0	0
Total	-496	-79	-14	-4	-7	15	4	1

Accuracy-privacy tradeoff



Source: **US Census Bureau**

Discussion

Appropriate algorithm for implementing differential privacy

Design algorithms that fits our need; determination of privacy budget; accuracy specification for pre-determined tabulations

Differentially private microdata

Generate rich synthetic data with differential privacy

Explore interactive data release with differential privacy

References

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