Formal privacy protection for data products combining individual and employer frames

Samuel Haney

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Joint work with Ashwin Machanavajjhala, Mark Kutzbach, Matthew Graham, John Abowd, and Lars Vilhuber
Disclaimer & Acknowledgements

- Any opinions and conclusions expressed herein are those of the authors and do not necessarily represent the views of the U.S. Census Bureau. All results have been reviewed to ensure that no confidential information is disclosed.

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Background

- LEHD Origin-Destination Employment Statistics (LODES) are a public-use database of jobs (Worker-Firm connection) released by the U.S. Census Bureau.
- In the most recent data year, LODES constitutes:
  - 128 million jobs for 119 million workers at 6.2 million employer firms with 7.6 million establishments in the U.S.
  - 2 million census blocks with employment
  - 5.5 million census blocks with workers residing in them
- Firm characteristics: Location ($2 \times 10^6$), industry (20), ownership (2)
- Person characteristics: Home location ($5.5 \times 10^6$), age (3), sex (2), race (6), ethnicity (2), educational attainment (4), and job earnings (3)
Existing Protections

- Under existing U.S. law, some characteristics are public and some are private.
  - LODES must protect the size and characteristics of a firm’s workforce.
  - LODES must protect the existence of any particular job and its characteristics.
  - Not protected are the existence of an employer in a location, an industry, and an ownership class.

- LODES uses a permanent multiplicative noise distortion factor at the employer and establishment levels (plus synthetic methods for small cells) to protect employment counts. (Abowd et al, 2006)

- Residence location is protected by synthetic data methods using probabilistic differential privacy. (Machanavajjhala et al, 2008)
Existing LODES data in OnTheMap application

Employment in Lower Manhattan

Residences of Workers Employed in Lower Manhattan

Available at http://onthemap.ces.census.gov/.
Goals

- Answer marginal queries over individual characteristics (e.g. sex, age, salary), and public workplace characteristics (e.g. geographic location).

Give algorithms with a provable privacy guarantee for both individuals and employer businesses.
Algorithms should perform comparably to the current protection system.
(For the purposes of this talk, assume queries are just total employment over some geographic region.)
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Differential Privacy Guarantee

The output of an algorithm should be insensitive to the addition or removal of a single individual (or establishment).
Neighbors

Neighboring datasets differ in one entry.
Definition ($\epsilon$-Differential Privacy)

A mechanism $\mathcal{M}$ satisfies $\epsilon$-differential privacy if for all outputs $S \subseteq \text{range}(\mathcal{M})$, and for all neighbors $D_1$ and $D_2$,

$$\Pr[\mathcal{M}(D_1) \in S] \leq e^\epsilon \cdot \Pr[\mathcal{M}(D_2) \in S]$$
Suppose an adversary believes that record $r$ being in the dataset is $c$ times as likely as $r$ not in the dataset.

After seeing the output, the adversary’s new belief $c'$ is bounded by $e^{-\epsilon}c \leq c' \leq e^{\epsilon}c$. 
Sensitivity

Definition

Let $N$ denote the set of pairs of neighboring datasets. The $L_1$ sensitivity of a query $q$ is:

$$\Delta_q = \max_{(x, x') \in N} |q(x) - q(x')|$$

Ensuring differential privacy generally requires adding noise proportional to the sensitivity.
Sensitivity

**Example:** The query that returns the total size (number of records) has sensitivity 1.
Laplace Mechanism

The Laplace mechanism is $\epsilon$-differentially private.

\[ \mathcal{L}(q, x) = q(x) + \text{Lap}(\sigma) \]

where $\sigma = \Delta q / \epsilon$. 
The Laplace mechanism is $\epsilon$-differentially private.

$$\mathcal{L}(q, x) = q(x) + \text{Lap}(\sigma)$$

where $\sigma = \Delta_q / \epsilon$.

Is this approach any good?
We can judge a mechanism $\mathcal{M}$ by the error it produces.

The per query $L_1$ error is

$$\mathbb{E}[|\text{true answer} - \text{noisy answer}|]$$
For Laplace mechanism, error is $\Delta_q/\epsilon$. 
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For our queries, $\Delta_q$ is the maximum allowable employment size!
Problem & Solution

Problem:

- The sensitivity is the maximum allowable employment.
- The error incurred will almost always dominate the count.

Solution:

1. Provide a weaker (but still provable) privacy guarantee by re-defining neighboring databases.
2. Use the local sensitivity rather than the standard sensitivity (called global sensitivity).
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2. Use the *local sensitivity* rather than the standard sensitivity (called global sensitivity).
Employer protection under differential privacy is too strong:

- Existence of establishment need not be protected.
- We can assume it is common knowledge whether the employment is very large or very small.
Privacy Guarantee Relaxation

The output of a mechanism is not significantly changed due to the presence/absence of a single establishment.

\[ \text{The output of a mechanism is not significantly changed due to a change in employment (of a single establishment) from } C \text{ to } C' \in [C - \alpha C, C + \alpha C]. \]
Semantics

Suppose $C' \in [C - \alpha C, C + \alpha C]$ where $C$ is the true employment of an establishment.

- Suppose an adversary believes that the employment of the establishment being $C$ is $p$ times as likely as $C'$.
- After seeing the output, the adversary’s new belief $p'$ is bounded by $e^{-\epsilon} p \leq p' \leq e^{\epsilon} p$. 
Definition (simplified)

\( \mathbf{x} \) and \( \mathbf{y} \) are neighbors if they satisfying the following:

- \( \mathbf{x} \) and \( \mathbf{y} \) differ in the employment of one establishment (let \( C_x, C_y \) be those employments).
- \( C_x - \alpha C_x \leq C_y \leq C_x + \alpha C_x \).
Problem & Solution

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1. Provide a weaker (but still provable) privacy guarantee by re-defining neighboring databases.
2. Use the local sensitivity rather than the standard sensitivity (called global sensitivity).
Local vs. Global sensitivity

Local sensitivity depends on the input database:

Definition

Let $N(x)$ denote neighbors of $x$. The $L_1$ local sensitivity of a query $q$ with respect to $x$ is:

$$\Delta_q(x) = \max_{x' \in N(x)} |q(x) - q(x')|$$
Local vs. Global sensitivity

- Local sensitivity can vary greatly depending on database.
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- Local sensitivity can vary greatly depending on database.
- Consider $\text{median}(0, 50, 100)$ versus $\text{median}(1, 2, 3)$.
- Local sensitivity is related to the largest employment in the query region, rather than the largest total employment.
Local vs. Global sensitivity

We add noise according to a smoothed upper bound on this sensitivity (Nissim et al).
Extensions (see paper)

- Allow for queries on more attributes.
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- Protect individuals under conventional differential privacy.
Summary

We answer marginal queries over establishment and individual attributes, while providing provable protection to both establishments and individuals. Our algorithms have comparable error to the current protection system.

Questions?