

CS208: Applied Privacy for Data Science Programming Frameworks & Query Interfaces

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March 22, 2022

Programming Frameworks for DP

Goal: make it easier for a data custodian or analyst to write programs that are DP, and be confident that they actually are DP.

Common approach (starting with PinQ [McSherry `09]):

- (Small) set of trusted DP subroutines: (Lap, Geo, ExpMech, ...) only channel for info to flow from dataset to rest of program.
- Track privacy budget consumption: using composition of DP, with either a runtime monitor or static analysis.
- Allow "stable" data transformations: (recursively) track impact on privacy consumption.

Dataset Transformations

- Let d(x, x') denote distance between datasets x, x'.
 - Number of rows on which they differ for public n model.
 - $-|x\Delta x'|$ for unknown n model.
- Def: A mapping from datasets to datasets is c-stable (aka c-Lipschitz or c-stable) iff

$$\forall x, x' \ d\big(T(x), T(x')\big) \le c \cdot d(x, x').$$

- Lemmas:
 - If M is ε -DP and T is c-stable, then $M \circ T$ is $c\varepsilon$ -DP.
 - If T_1 is c_1 -stable and T_2 is c_2 -stable, then $T_2 \circ T_1$ is c_1c_2 -stable.

Calculate the Stability Constants

Per-row transforms (SELECT):

$$T((x_1, \dots, x_n)) = (f(x_1), \dots, f(x_n)).$$

- Trimming: T(x) = remove the bottom and top 20 elts (viewing x and T(x) as unordered)
- Subsetting (WHERE): $T(x) = \{r \in x : \pi(r) = \text{true}\}$ (multiset) (use unknown n model)
- GROUP BY: $T(x) = (\{r \in x : r_i = c\})_{c \in \text{dom}_i}$

Partitioning

- "Parallel Composition" Lemma: Let $S_1, ..., S_k$ be disjoint subsets of \mathcal{X} and let $M_1, ..., M_k$ be ε -DP algorithms (for the unknown n model). Then $M(x) = \left(M_1(x|_{S_1}), ..., M_k(x|_{S_k})\right)$ is ε -DP.
- A "1-stable" 1-to-k transformation $T(x) = (x|_{S_1}, ..., x|_{S_k})$.
- Also have 2-to-1 transformations (Union, Intersection, Join).

Tracking Sensitivity

| Transformation | Stability |
|---|-----------|
| Select(T, maper) | (1) |
| Where $(T, predicate)$ | (1) |
| GroupBy $(T_1, keyselector)$ | (2) |
| $Join^*(T_1,T_2, n, m, keyselector_1, keyselector_2)$ | (n,m) |
| $Intersect(T_1,T_2)$ | (1,1) |
| $\mathrm{Union}(T_1,T_2)$ | (1,1) |
| Partition(T, keyselector, keysList) | (1) |

Table 1. Transformation stability

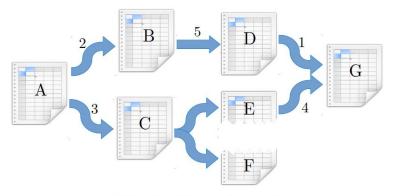


Fig. 2. Transformations

| | | Calculation |
|---|-----|---|
| A | 1 | Input table |
| В | 2 | $s(A) \times 2$ |
| C | 1 | Input table $s(A) \times 2$ $s(A) \times 3$ $s(B) \times 5$ |
| D | 10 | $s(B) \times 5$ |
| E | 3 | s(C) |
| F | 3 | s(C) |
| G | 22 | $s(D) \times 1 + s(E) \times 4$ |
| | . ' | |

Fig. 3. Scaling factors (s)

[from Ebadi & Sands, "Featherweight PinQ", 2017]



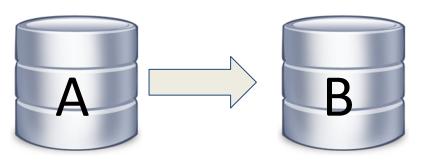
- Generality in privacy definitions & algorithms
 - Pure DP, approximate DP, concentrated DP, f-DP, etc.
 - Node-level privacy in graphs, user-level privacy in streams, etc.
- Generality in privacy calculus
 - Composition, amplification by subsampling, group privacy, etc.
- Safe extensions of framework with vetted contributions
 - Clear spec for each component's privacy-relevant properties
- Interactive DP algorithms as first-class citizens
 - Adaptive composition, sparse vector, etc.
 - Still in implementation!
- Implementation in Rust w/Python bindings



Transformations and Measurements

Transformations:

Function from data(sets) to data(sets).

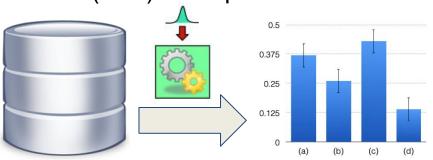


Transformation Attributes

- Input domain
- Input metric
- Output domain
- Output metric
- Function
- Stability relation

Measurements:

Randomized functions from data(sets) to outputs.

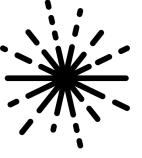


Measurement Attributes

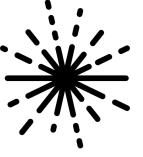
- Input domain
- Input metric
- Output measure
- Function
- Privacy relation



| | Input domain | Input closeness | Output domain | Output closeness |
|--------------|--------------|-----------------|---------------|------------------|
| Clamp | | | | |
| Bounded Sum | | | | |
| Base Laplace | | | | |



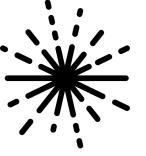
| | Input domain | Input closeness | Output domain | Output closeness |
|-------------------------|--------------|-----------------|---------------|------------------|
| Clamp | | | | |
| Bounded Sum | | | | |
| Base Laplace | | | | |
| c-stable transformation | | | | |



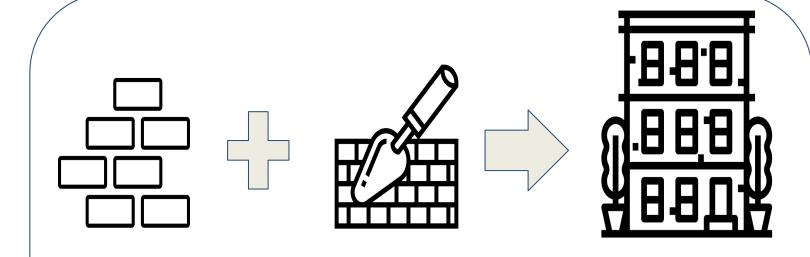
| | Input domain | Input closeness | Output domain | Output closeness |
|----------------------------|--------------|-----------------|---------------|------------------|
| Clamp | | | | |
| Bounded Sum | | | | |
| Base Laplace | | | | |
| c-stable transformation | | | | |
| global sensitivity | | | | |



| | Input domain | Input closeness | Output domain | Output closeness |
|----------------------------|--------------|-----------------|---------------|------------------|
| Clamp | | | | |
| Bounded Sum | | | | |
| Base Laplace | | | | |
| c-stable transformation | | | | |
| global sensitivity | | | | |
| | | | | |
| Base Multidim Gaussian | | | | |
| Restricted Sensitivity | | | | |



Combinators: Chaining, Composition and Post-processing



Measurements

&

Transformations

Combinators, e.g.

Chaining,

Composition,

Post-processing

Complex DP

programs



Privacy calculus: privacy and stability relations

To implement a privacy calculus based on the idea of stability we have:

- privacy relations in measurements to capture several notions of privacy. E.g. DP, approx. DP, Renyi DP, zCDP, f-DP.
- stability relation in transformations to capture general aggregate operations. E.g. bounded joins.
- combination of these relations by means of combinators such as chaining and composition.

relation(d_{in},d_{out}) should imply:
if two inputs are "d_{in}-close",
then the corresponding outputs (or
distributions) are "d_{out}-close".

Measurement attributes

- Input domain
- Input metric
- Output measure
- Function
- Privacy relation

Transformation attributes

- Input domain
- Input metric
- Output domain
- Output metric
- Function
- Stability relation

Other Issues in Programming DP

Multi-relational databases

- Need to define input metric/adjacency carefully
- Standard joins have unbounded stability constant, so need to truncate results or use "local sensitivity" approximations.

Side-channel attacks

- Info can be leaked through timing, approx. of real numbers, global state, exceptions, etc.
- Constrain language & implementation to match model better.

Verifying DP building blocks or more complex DP algs

- Specialized programming languages.
- Annotate programs with types to assist automated verification of DP.
- Tradeoff between usability and expressiveness.
- Now can even synthesize DP algorithms from examples!
- Guidance on Accuracy & Privacy Budgeting
 - Next time!
- Choice of Programming Model (e.g. SQL vs. MapReduce