Differential Privacy and Verification

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Given a program P, is it differentially private?

Given a differentially private program P, does it maintain its accuracy promises?

Given a differentially private program P that maintains its accuracy promises, can we guarantee that it is also efficient?

An algorithm

Algorithm 2 DualQuery

Input: Database $D \in \mathbb{R}^{|\mathcal{X}|}$ (normalized) and linear queries $q_1, \ldots, q_k \in \{0, 1\}^{|\mathcal{X}|}$. **Initialize:** Let $\mathcal{Q} = \bigcup_{j=1}^{k} q_j \cup \overline{q_j}$, Q^1 uniform distribution on \mathcal{Q} ,

$$
T = \frac{16 \log |\mathcal{Q}|}{\alpha^2}, \qquad \eta = \frac{\alpha}{4}, \qquad s = \frac{48 \log \left(\frac{2|\mathcal{X}|T}{\beta}\right)}{\alpha^2}.
$$

For $t = 1, ..., T$: Sample *s* queries $\{q_i\}$ from Q according to Q^t . Let $\overline{q}:=\frac{1}{s}$ $\sum_i q_i$. Find x^t with $\langle \overline{q}, x^t \rangle \ge \max_x \langle \overline{q}, x \rangle - \alpha/4$. **Update:** For each $q \in \mathcal{Q}$: $Q_q^{t+1} := \exp(-\eta \langle q, x^t - D \rangle) \cdot Q_q^t.$ Normalize Q^{t+1} . Output synthetic database $\widehat{D} := \bigcup_{t=1}^{T} x^t$.

https://github.com/ejgallego/dualquery/

Some issues

- Are the algorithms bug-free?
- Do the implementations respect their specifications?
- Is the system architecture bug-free?
- Is the code efficient?
- Do the optimization preserve privacy and accuracy?
- Is the actual machine code correct?
- Is the full stack attack-resistant?

Outline

- Few more words on program verification,
- Challenges in the verification of differential privacy,
- Few verification methods developed so far,
- Looking forward.

Knight Capital Group

Some successful stories - I

- CompCert a fully verified C compiler,
- Sel4, CertiKOS formal verification of OS kernel
- A formal proof of the Odd order theorem,
- A formal proof of Kepler conjecture (lead by T. Hales).

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Years of work from very specialized researchers!

Some successful stories - II

- Automated verification for Integrated Circuit Design.
- Automated verification for Floating point computations,
- Automated verification of Boeing flight control Astree,
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The years of work go in the design of the techniques!

Verification trade-offs

What program verification isn't...

- Algorithm design,
- Trial and error,
- Program testing,
- System engineering,
- A certification process.

What program verification can help with…

- Designing languages for non-experts,
- Guaranteeing the correctness of algorithms,
- Guaranteeing the correctness of code,
- Designing automated techniques for guaranteeing differential privacy,
- Help providing tools for certification process.

The challenges of differential privacy

Given ε, δ ≥ 0, a mechanism M: db → O is (ε,δ)-differentially private iff ∀b1, b2 :db at distance one and for every S⊆O: $Pr[M(b_1) \in S] \leq exp(\mathcal{E}) \cdot Pr[M(b_2) \in S] + \delta$

- Relational reasoning,
- Probabilistic reasoning,
- Quantitative reasoning

A 10 thousand ft view on program verification

Work-flow

VCs = Verification Conditions

Semi-decision procedures

- Require a good decomposition of the problem,
- Handle well logical formulas, numerical formulas and their combination,
- Limited support for probabilistic reasoning (usually through decision procedures for counting).

Compositional Reasoning about the privacy budget

Sequential Composition Let M_i be ϵ_i -differentially private $(1 \leq i \leq k)$. Then $M(x) = (M_1(x), ..., M_k(x))$ is $\sum_{i=0}^{k} \epsilon_i$.

- We can reason about DP programs by monitoring the privacy budget,
- If we have basic components for privacy we can just focus on counting,
- It requires a limited reasoning about probabilities,
- This way of reasoning adapt to other compositions.

Iterated - CDF

 $CDF(X)$ = number of records with value $\leq X$.

buckets

it-CDF (raw : data) (budget : R) (buckets : list) (ϵ : R) : list

{

}

 var agent = new PINQAgentBudget(budget); var db = new PINQueryable<data>(rawdata, agent); foreach (var b in buckets)

 $b = db$.where(y => y.val $\leq b$).noisyCount(ϵ); yield return b;

it-CDF (raw : data) (budget : R) (buckets : list) $(E: R)$: list

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{

}

agent is responsible for the budget

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{

}

raw data are accessed through a PINQueryable

it-CDF (raw : data) (budget : R) (buckets : list) $(E: R)$: list

{ var agent = new PINQAgentBudget(budget); var db = new PINQueryable<data>(rawdata, agent); foreach (var b in buckets)

$$
b = db \cdot \text{where}(y \implies y \cdot val \leq b) \cdot \text{noisyCount}(\epsilon);
$$

yield return b;

}

we have transformations (scaling factor)

it-CDF (raw : data) (budget : R) (buckets : list) (ϵ : R) : list

{ var agent = new PINQAgentBudget(budget); var db = new PINQueryable<data>(rawdata, agent); foreach (var b in buckets)

$$
b = db \cdot \text{where}(y \implies y \cdot val \leq b) \cdot \text{noisyCount}(\mathcal{E});
$$

yield return b;

} we have transformations (scaling factor)

aggregate operations (actual budget consumption)

Enough budget?

it-CDF (raw : data) (budget : R) (buckets : list) $(E: R)$: list

var agent = new PINQAgentBudget(budget); var db = new PINQueryable<data>(rawdata, agent); foreach (var b in buckets)

{

}

 $b = db$.where(y => y.val $\leq b$).noisyCount(ϵ); yield return b;

We can check local vs global budget

Compositional reasoning about sensitivity

$$
GS(f) = \max_{v \sim v'} |f(v) - f(v')|
$$

- It allows to decompose the analysis/construction of a DP program,
- A metric property of the function (DMNS06),
- It requires a limited reasoning about probabilities,
- Similar worst case reasoning as basic composition.

```
it-CDF (b : data) (buckets : list) : list 
{
 case buckets of
    |nil \Rightarrow nil
    |x::xs \Rightarrow size (filter (fun y \Rightarrow y \leq x) b))):: it-CDF xs b
}
```


```
it-CDF (b :[??] data) (buckets : list) : list 
{
 case buckets of
   \vertnil \Rightarrow nil
   |x::xs = (size)(filter (fun y =& y ≤ x) b))): Wit-CDF xs b
}
       Let's assume |- size : [1]data --o R
```


Reasoning about DP via probabilistic coupling - BGGHS

For two (sub)-distributions $\mu_1, \mu_2 \in \text{Dist}(A)$ we have an approximate coupling $\mu_1 C_{\epsilon,\delta}(R) \mu_2$ iff there exists $\mu \in \text{Dist}(A \times A)$ s.t.

• supp $\mu \subseteq R$

$$
\bullet\ \pi_i\mu\leq\mu_i
$$

•
$$
\max_A (\pi_i \mu - e^{\epsilon} \mu_i, \mu_i - e^{\epsilon} \pi_i \mu) \le \delta
$$

- Generalize indistinguishability to other relations allowing more general relational reasoning,
- More involved reasoning about probability distances and divergences,
- Preserving the ability to use semi-decision logical and numerical procedures.

pRHL-like languages

CDF example similar to the previous ones

 $b \sim b' \Rightarrow$ (itcdf *b l e*) $C_{\epsilon,0} (=)$ (itcdf *b' l e*)

pRHL-like languages

CDF example similar to the previous ones

$$
b \sim b' \Rightarrow (\underleftarrow{\text{itcdf}}{b} \, l \, \epsilon) \, \mathcal{C}_{\epsilon,0} (=) \, (\underleftarrow{\text{itcdf}}{b} \, l \, \epsilon) \, \text{if}
$$
\nHaving two copies of the program allows to compare different parts of the same

program.

It allows to internalize better the properties of Laplace

$$
(\underline{\mathrm{Lap}}\,(1/\epsilon)\,v_1)\;\mathcal{C}_{|k+v_1-v_2|\epsilon,0}(x_1+k=x_2)\;(\underline{\mathrm{Lap}}\,(1/\epsilon)\,v_2)
$$

can be used to assert symbolically several facts about probabilities.

$$
(\underline{\mathsf{Lap}}(1/\epsilon)v_1) \mathcal{C}_{|v_1-v_2|\epsilon,0}(x_1=x_2) (\underline{\mathsf{Lap}}(1/\epsilon)v_2)
$$

expresses

$$
\left| \log \left(\frac{\Pr(\text{Lap}(1/\epsilon) v_1 = r)}{\Pr(\text{Lap}(1/\epsilon) v_2 = r)} \right) \right| \leq |v_1 - v_2|\epsilon
$$

 $|v_1 - v_2| \leq k \Rightarrow (\textsf{Lap}(1/\epsilon) v_1) C_{2k\epsilon,0}(x_1 + k = x_2) (\textsf{Lap}(1/\epsilon) v_2)$

expresses

$$
|v_1 - v_2| \le k \Rightarrow \left| \log \left(\frac{\Pr(\text{Lap}(1/\epsilon) v_1 = r + k)}{\Pr(\text{Lap}(1/\epsilon) v_2 = r)} \right) \right| \le 2k\epsilon
$$

 $(\textsf{Lap}(1/\epsilon) v_1) C_{0,0}(x_1 - x_2 = v_1 - v_2) (\textsf{Lap}(1/\epsilon) v_2)$

expresses

$$
\left| \log \left(\frac{\Pr(\text{Lap}(1/\epsilon) v_2 + k = r + k)}{\Pr(\text{Lap}(1/\epsilon) v_2 = r)} \right) \right| \leq 0
$$

Other works

- Bisimulation based methods (Tschantz&al Xu&al)
- Fuzz with distributed code (Eigner&Maffei)
- Satisfiability modulo counting (Friedrikson&Jha)
- Bayesian Inference (BFGGHS)
- Adaptive Fuzz (Penn)
- Accuracy bounds (BGGHS)
- Continuous models (Sato)
- Lightweight verification injective function argument (Zhang&Kifer)
- Relational symbolic execution for R generating DP counterexamples (Chong&Farina&Gaboardi)
- Formalizing the local model (Ebadi&Sands)
- zCDP (BGHS)

Challenges

• All of these tools are research projects and most of them are usable only by experts.

Can we use them to certify correct a library of basic mechanism?

Which non-expert we should aim for?

Other Challenges

- Are there other fundamental principles that we can use?
- How can we extend them to verify accuracy and efficiency?
- There are several works on the verification of randomness, floating points, SMC, etc. Can we combine the different approaches?
- How can we internalize more involved data models assumptions?
- From benchmarks to certification?