The Complexity of Verifying Boolean Programs as Differentially Private

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Joint work with Mark Bun and Marco Gaboardi

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Plan of the talk

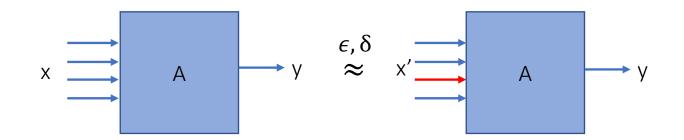
1. Prior work

- How hard is it to verify whether a program is DP for
 - Turing-complete languages
 - Boolean languages with bounded memory without loops

2. Our results and proof ideas

- BPWhile: Boolean language with loops and finite memory
- PSPACE-completeness of verifying DP for BPWhile
- PSPACE-hardness: reduction from TQBF
- PSPACE algorithm based on computing hitting probabilities in a Markov chain

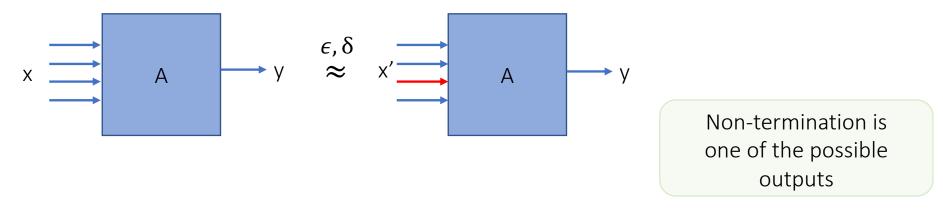
Differential Privacy



C is (ϵ, δ) -differentially private if for every set of possible outputs O, and for every neighboring x, x':

$$P[C(x) \in O] \le e^{\epsilon} \cdot P[C(x') \in O] + \delta$$

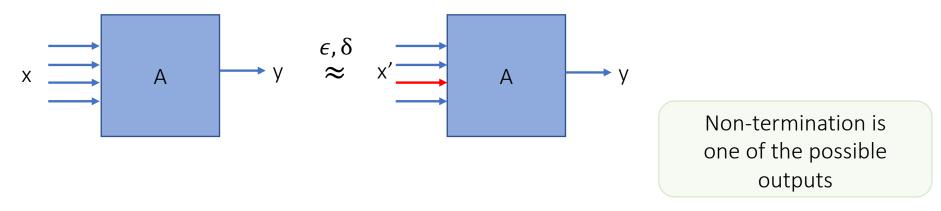
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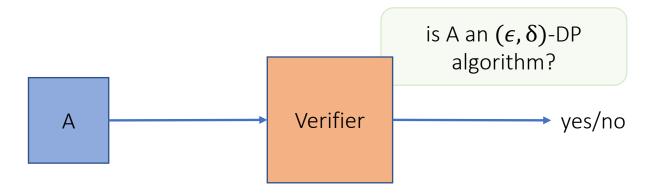


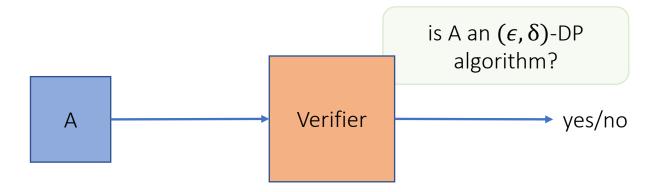
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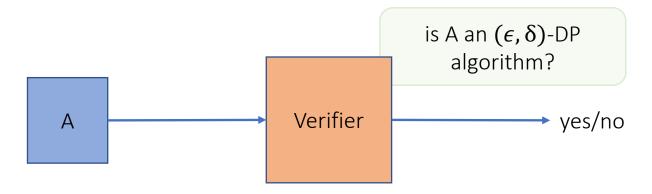
Neighboring relation we consider:

- Inputs are bit strings which differ in one bit
- Can be extended to any bounded polyspace computable relation





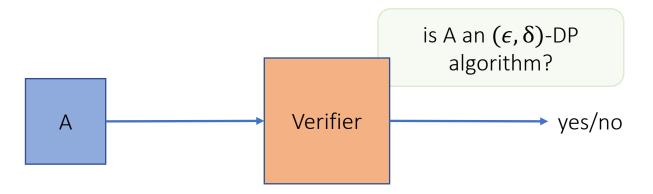
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 - Undecidable for Turing-complete languages

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[Barthe, Chadha, Jagannath, Sistla, Viswanathan'20]

- For a simple Boolean language with bounded memory, if statements and random assignments, but without loops
 - $coNP^{\#P}$ -completeness for $(\epsilon,0)$ -DP
 - Reduction from All-Min-SAT
 - $coNP^{\#P}$ -hard and in $coNP^{\#P^{\#P}}$ for (ϵ, δ) -DP

[Gaboardi, Nissim, Purser'20]

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In this work: white-box model, full access to the code

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- Simple to analyze

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 Variable identifiers

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 Variable identifiers
b ::= true | false | random | x | b \land b | b \lor b | !b

Boolean expressions

- Captures classical computations on real computers
- Simple to analyze

```
x := [a - z]^+ Variable identifiers
b := true \mid false \mid random \mid x \mid b \land b \mid b \lor b \mid !b
c := skip \mid x := b \mid c; c \mid if b then c else c \mid while b then c Commands
```

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b ::= x \mid t, x

List of Boolean variables
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Numbers of variables and input bits are fixed in the definition of the program

⇒ Length of the program is an upper bound on the size of the memory that the program uses

Example of a BPWhile program:

```
\mathtt{input}(\vec{c},\,\epsilon);
0.
1. \vec{k} := \lceil \log(2/\epsilon) \rceil;
                                                            Implementation of the Bounded
2. \vec{d} := (2^{\vec{k}+1} + 1)(2^{\vec{k}} + 1)^{n-1};
                                                            Geometric Mechanism in finite
3. \vec{u} := uniform(0, \vec{d}];
                                                            precision arithmetic
4. \vec{z} := 0;
5. \vec{r} := n;
      while \vec{z} < \vec{n} \wedge \vec{r} = n then
           if ec{z} < ec{c} then
               if \vec{u} \le 2^{\vec{k}(\vec{c}-\vec{z})}(2^{\vec{k}}+1)^{n-(\vec{c}-\vec{z})}
         then ec{r}:=ec{z}
9.
10.
               else skip
11.
            else
               if \vec{u} \le d - 2^{\vec{k}(\vec{z} - \vec{c} + 1)} (2^{\vec{k}} + 1)^{n - 1 - (\vec{z} - \vec{c})}
12.
              then ec{r}:=ec{z}
13.
14.
               else skip
15. \vec{z} = \vec{z} + 1;
        return(\vec{z});
16.
```

[Ghosh, Roughgarden, Sundararajan'09]

[Balcer, Vadhan'17]

Our results

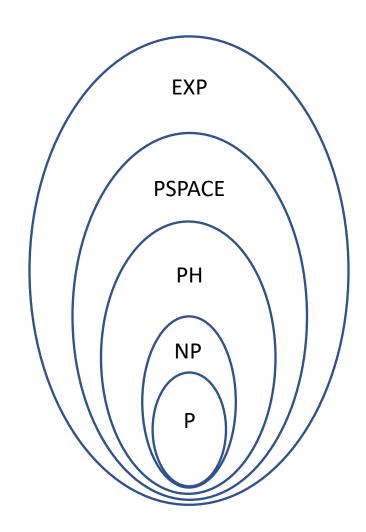
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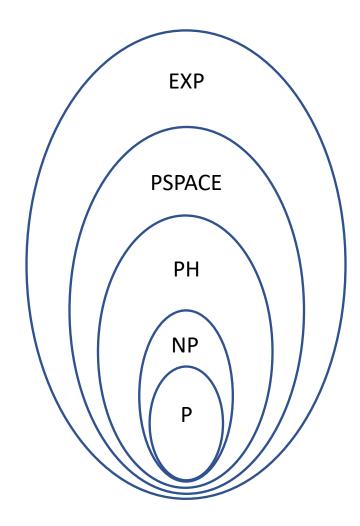
It holds for the following notions of differential privacy:

- $(\epsilon,0)$ -DP
- (ϵ, δ) -DP
- (ϵ, δ) -DP parameters approximation
- Renyi-DP
- Zero-Concentrated-DP
- Truncated Concentrated-DP

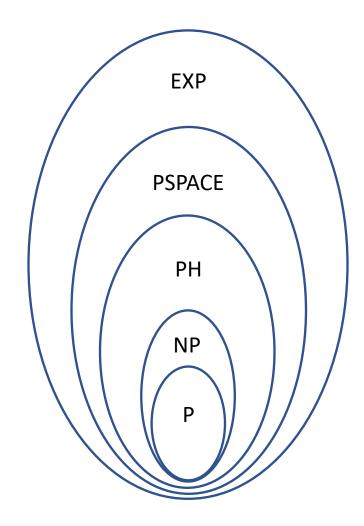


PSPACE-completeness of a problem A implies:

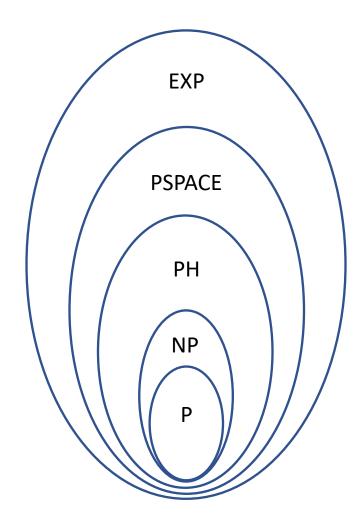
• A is solvable by a TM that uses polynomial space



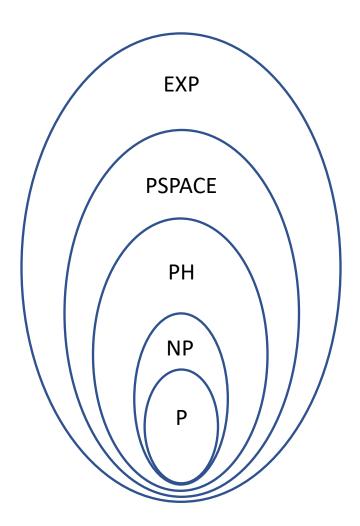
- A is solvable by a TM that uses polynomial space
- A is solvable in exponential time



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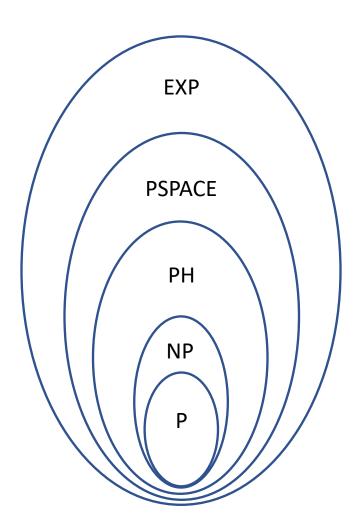
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- No polytime algorithm for A, unless P = PSPACE
 - That is widely believed not to be true



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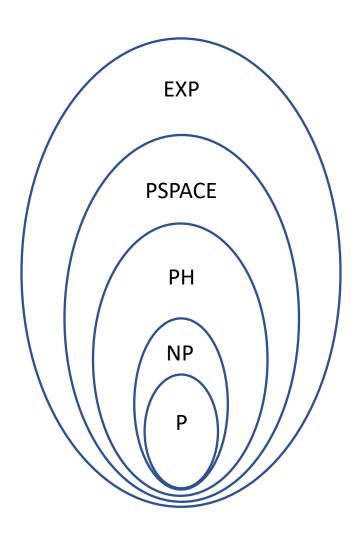


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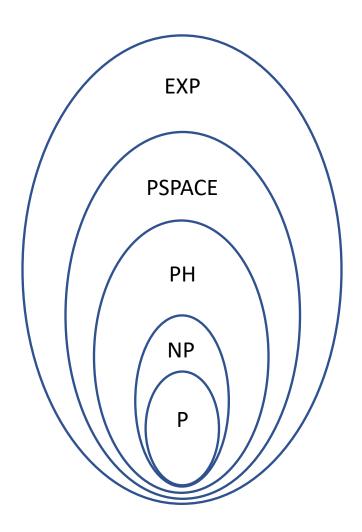


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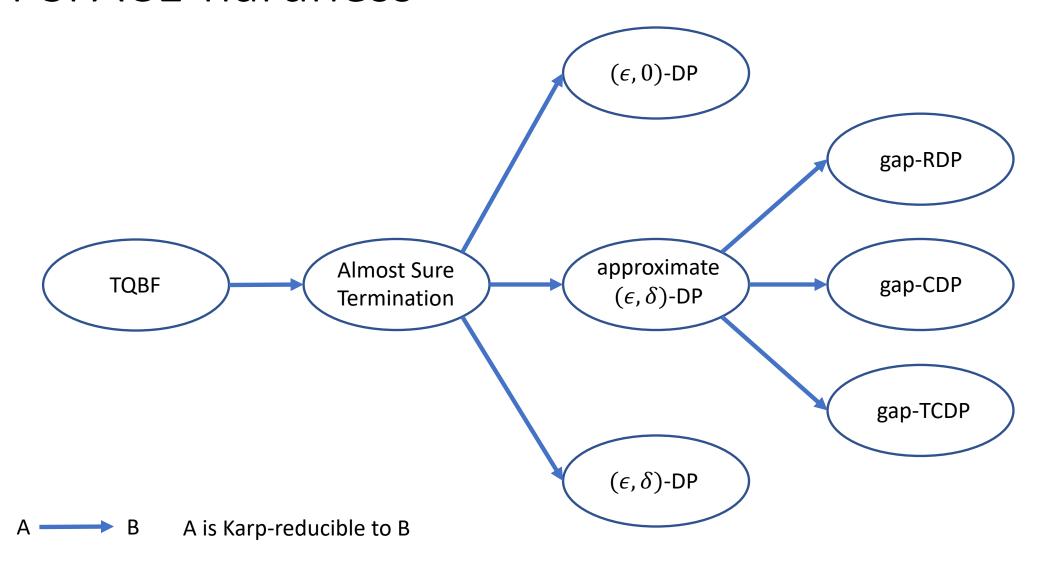
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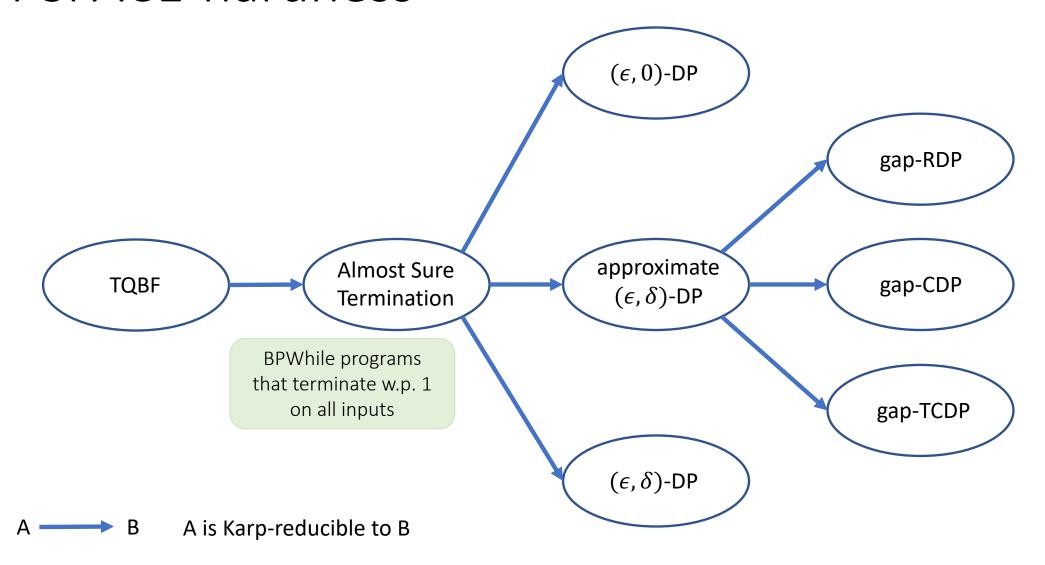
- Show hardness: construct sequence of reductions from TQBF
- 2. Construct polynomial-space algorithm: analyze Markov chain based on the state graph of the program

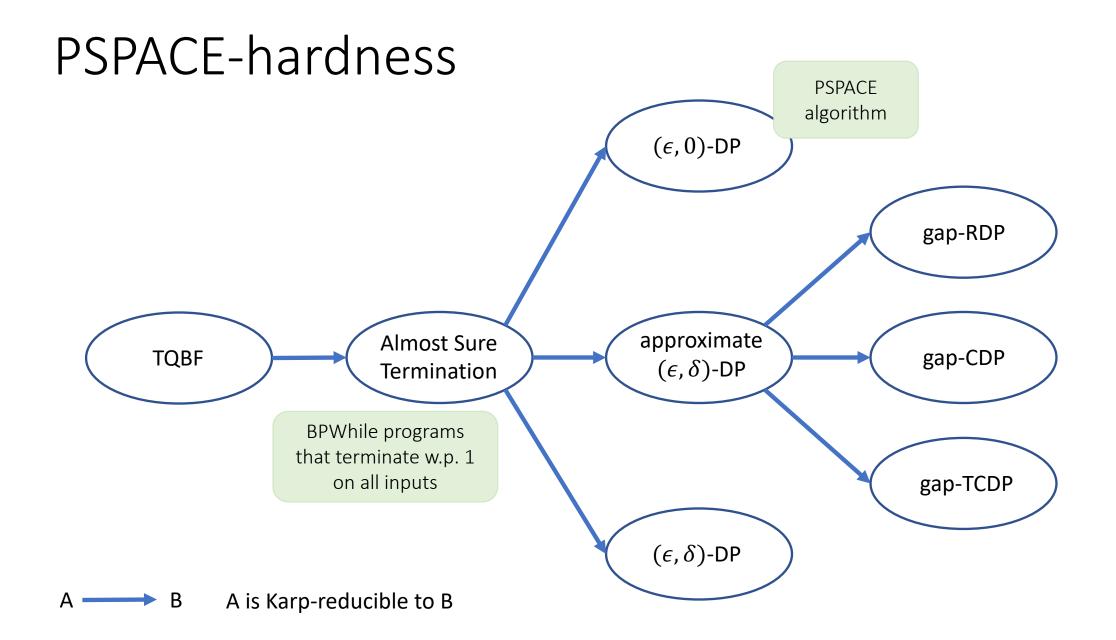


PSPACE-hardness

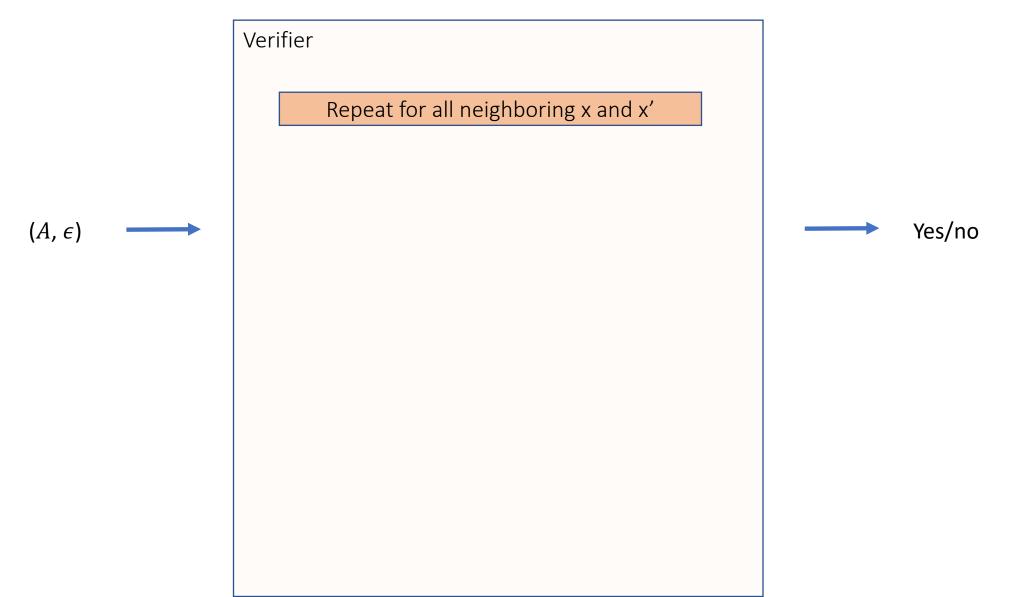


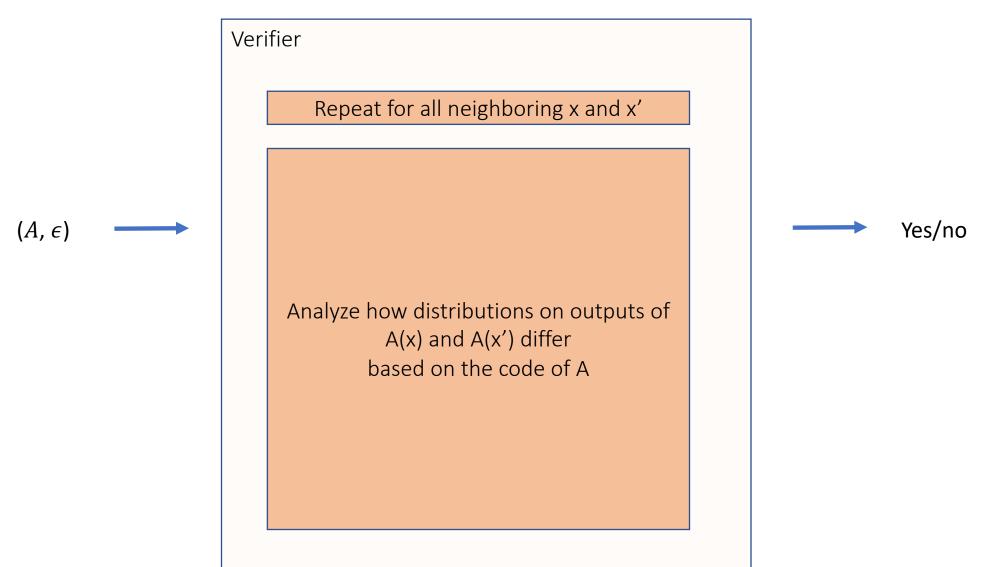
PSPACE-hardness





Polyspace membership: algorithm for $(\epsilon,0)$ -DP





State graph depends on the input values

D(b=1):

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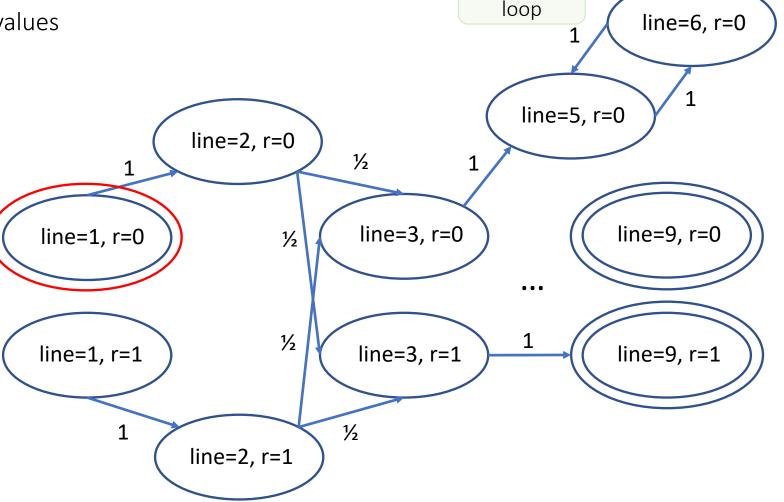
5. while true

6. skip;

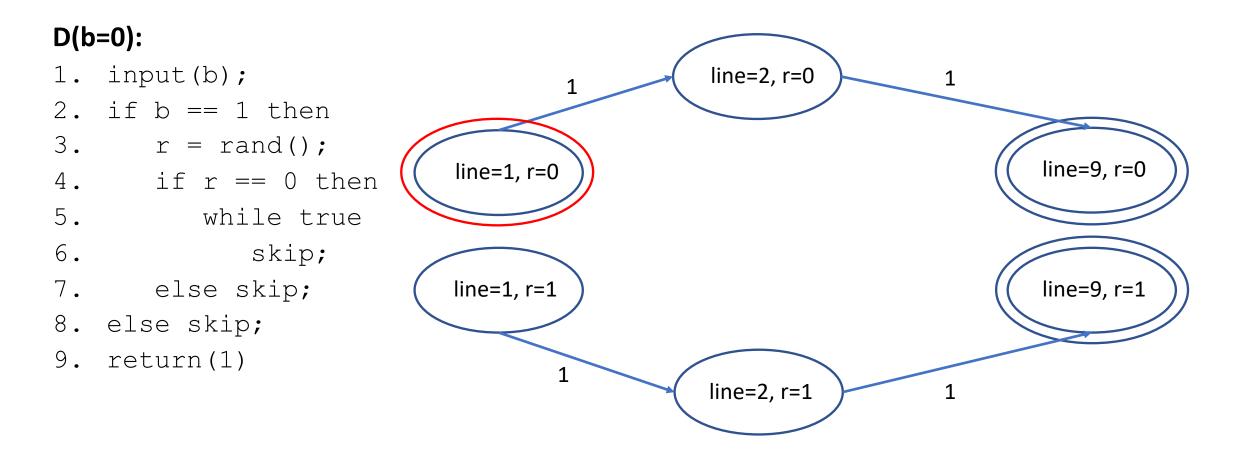
7. else skip;

8. else skip;

9. return(1)



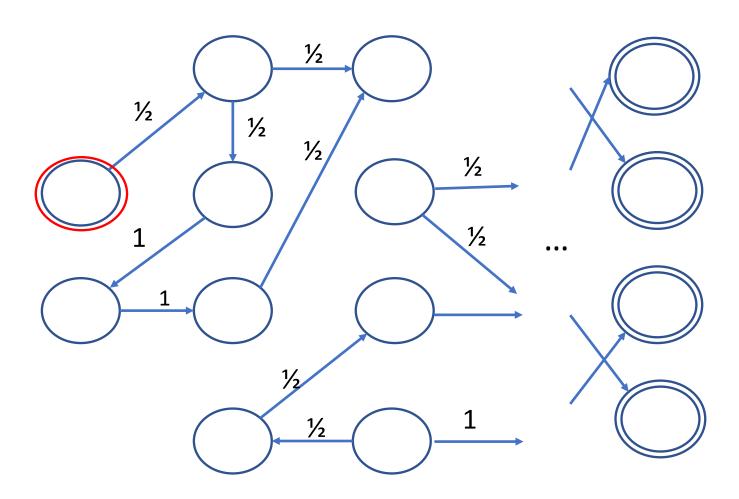
Infinite



PSPACE membership: algorithm for $(\epsilon,0)$ -DP

For a program D and all neighboring inputs x, x':

- Construct the Markov chain for D(x) and D(x')
- Compute and compare hitting probabilities

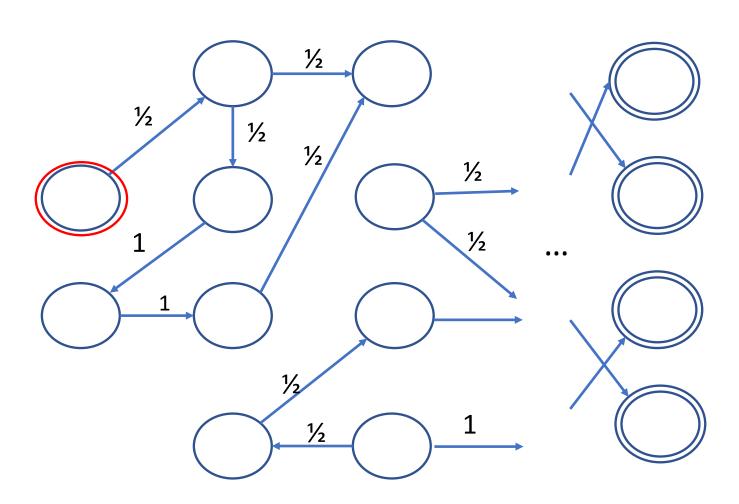


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Problem: Markov chain has exp-many states ⇒ cannot store it explicitly



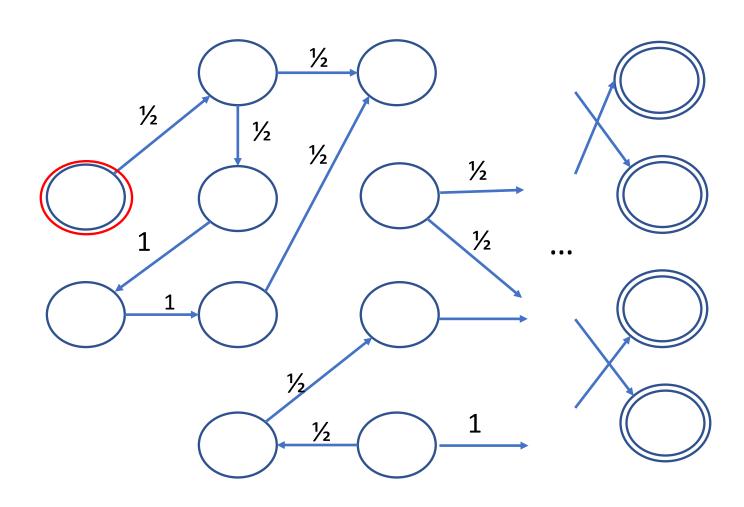
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Need **space-efficient** algorithm for computing hitting probabilities with **implicit access** to the Markov chain



Polyspace algorithm for computing hitting probabilities in a Markov chain

Lemma [Simon'81]: If M is a Markov chain with at most 2^L states

- the initial distribution places all mass on one state,
- there is a set F of final states each with only one self-transition,
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Then there is an $O(L^6)$ -space deterministic algorithm that computes the hitting probability of every state in F.

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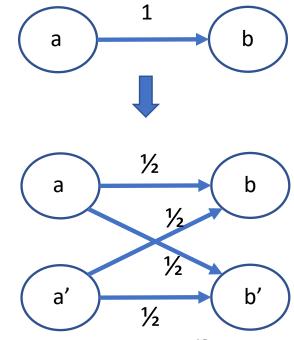
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Note: to use the algorithm, we need to replace all transitions labelled by 1 in the state graph of the BPWhile program:

- Clone all states
- For each state a with outgoing edge w.p. 1 replace it by two edges:
 - Edge (a,b) with weight ½ to original state
 - Edge (a,b') with weight ½ to the clone-state b' of b



PSPACE membership: exponentially long numbers

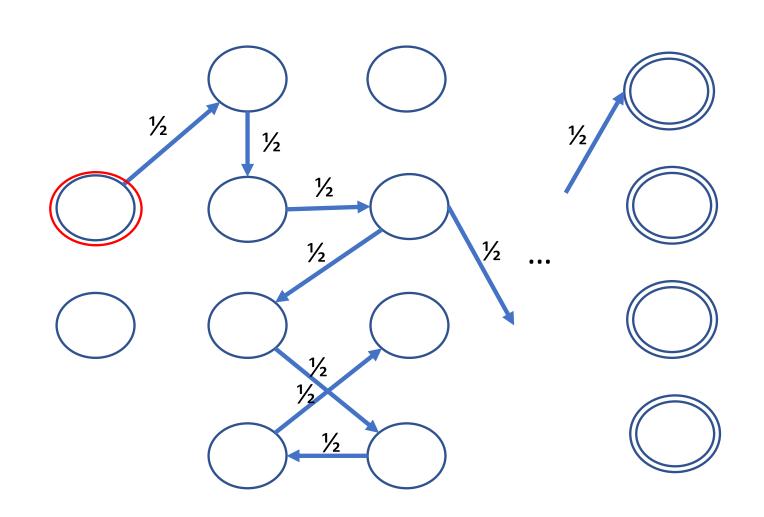
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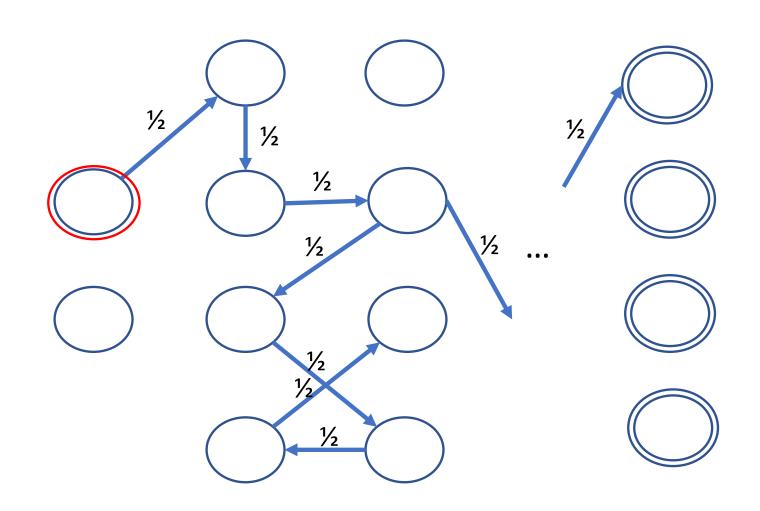
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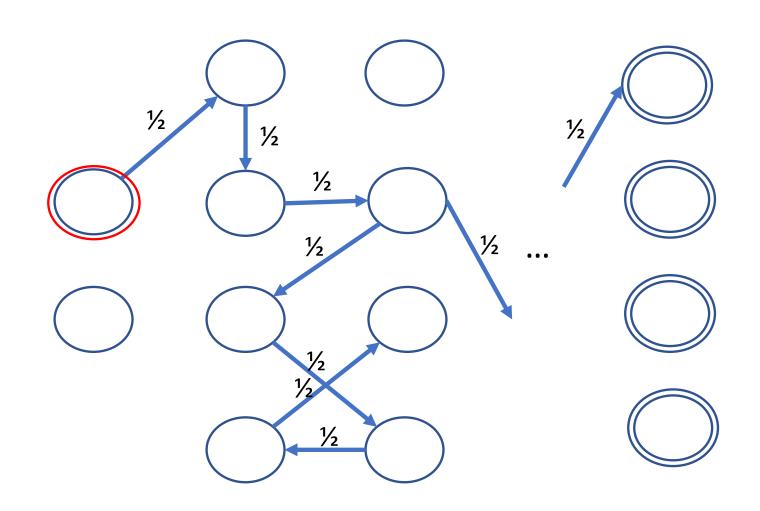
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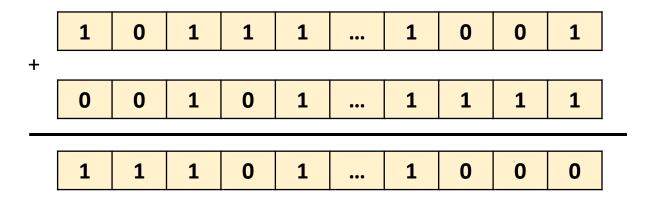
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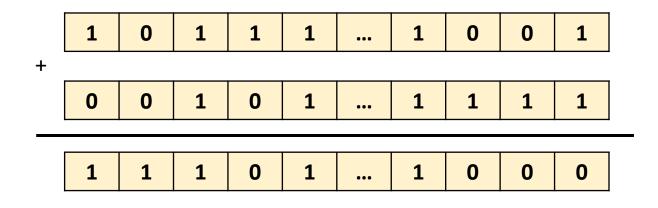
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Operations with exponentially long numbers



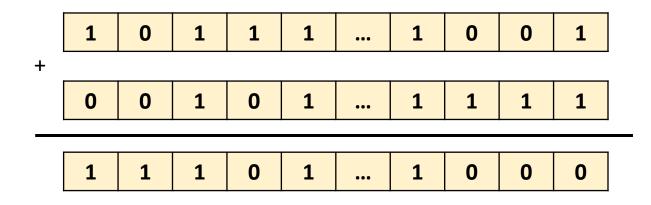
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Lemma:

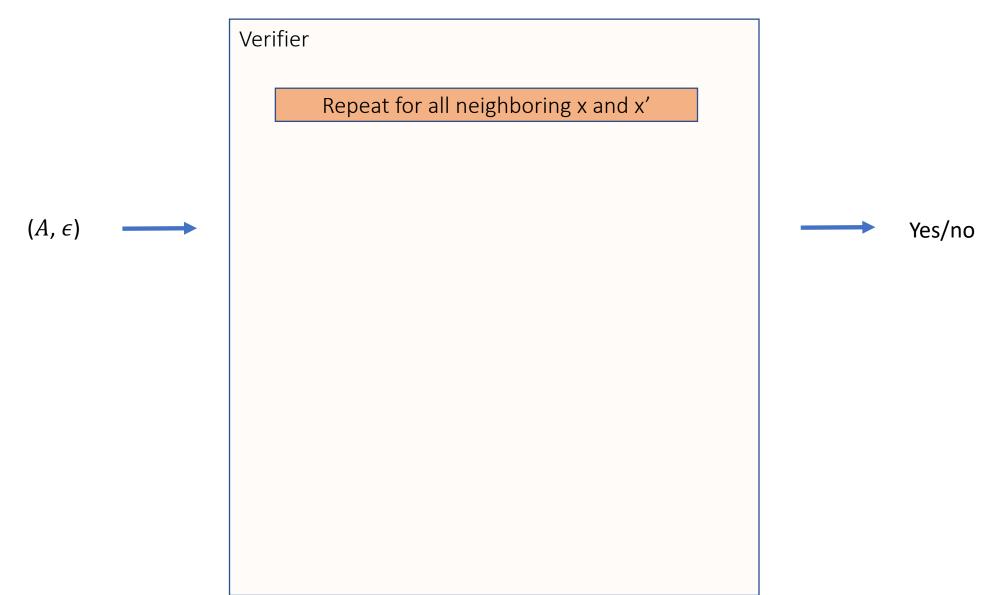
Uniform families of log-depth circuits exist for:

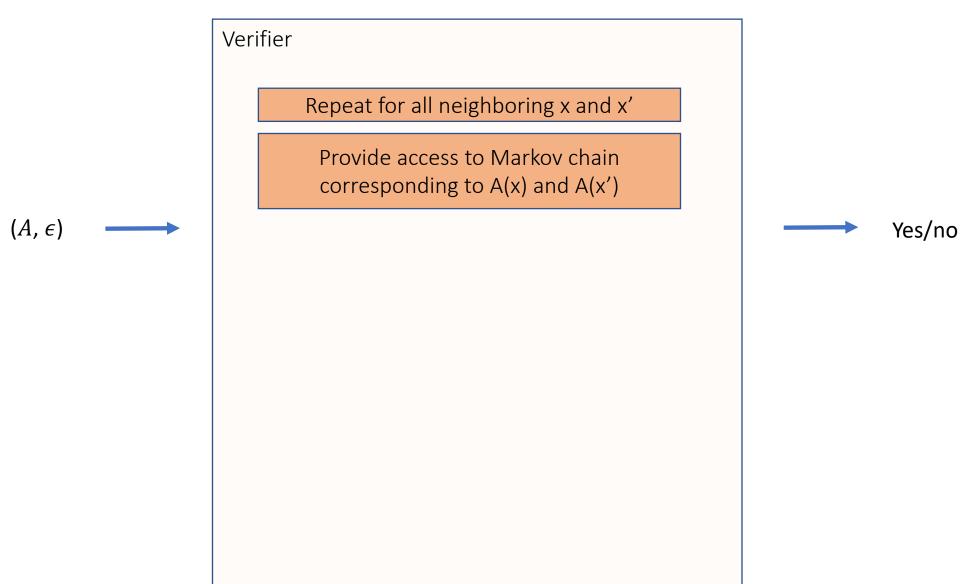
- Comparison
- Addition
- Multiplication by a fixed rational number
- Multiplication

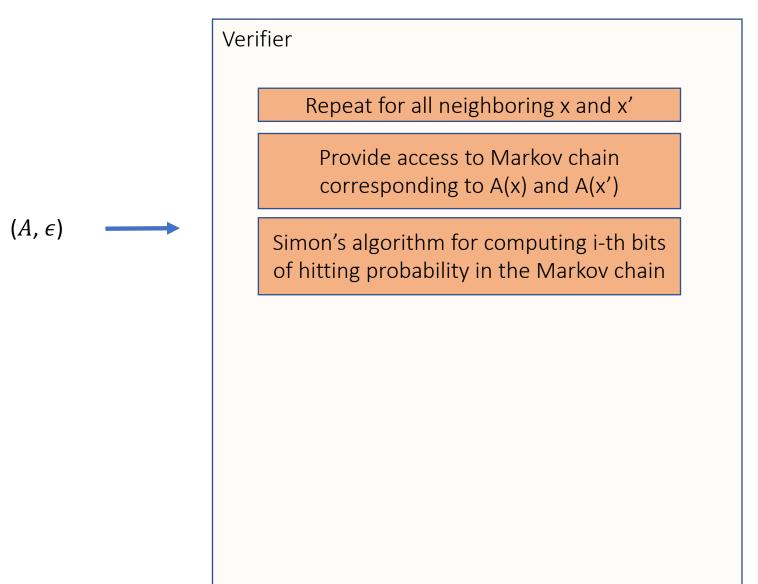
[Reif'86]

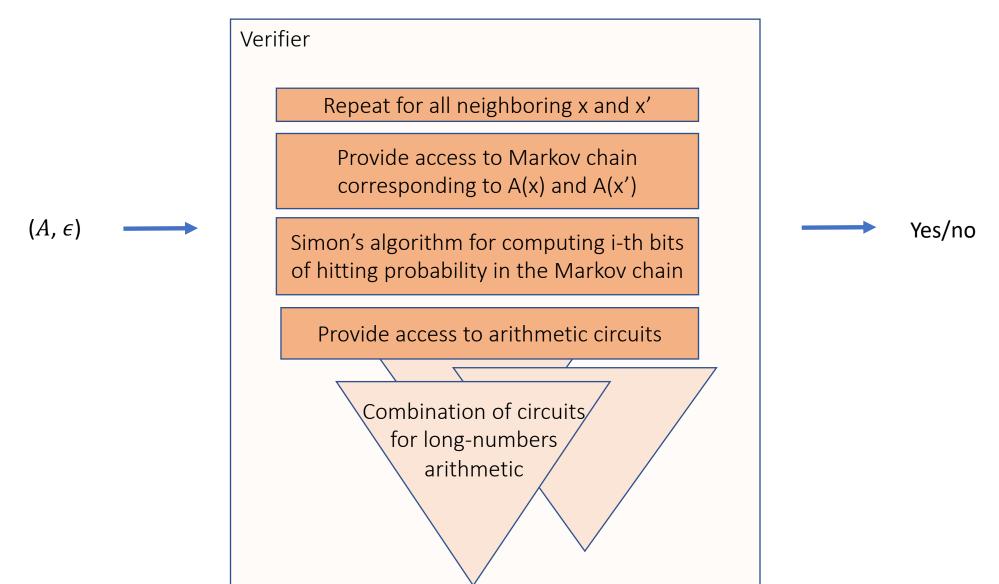
[Ofman'62]

• Square roots









Results and future work

- We showed PSPACE-completeness for the problems of checking:
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 - Approximate-DP
 - Gap-RDP
 - Gap-zCDP
 - Gap-TCDP

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- Possibly can extend the result to show PSPACE-completeness of verifying accuracy
- Improve the exact polynomial in the space complexity of the algorithm
 - Improved analysis and more efficient algorithms for Markov chains analysis and long-numbers arithmetic operations are needed for tighter results