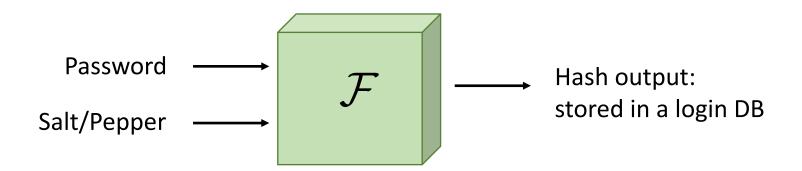
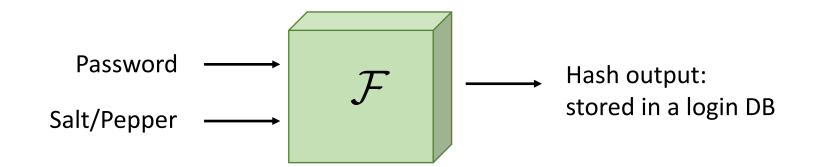
# Static-Memory-Hard Functions, and Modeling the Cost of Space vs. Time

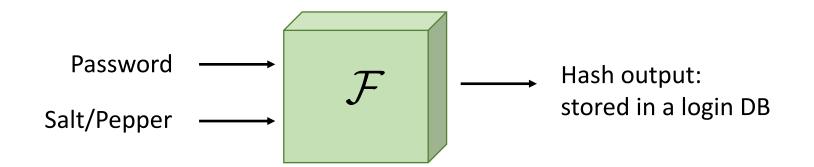
Thaddeus Dryja, Quanquan C. Liu, Sunoo Park

MIT



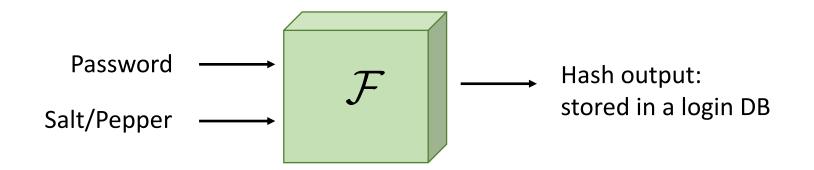


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Adversaries may run  $\mathcal{F}$  many times (e.g. large-scale server attacks).

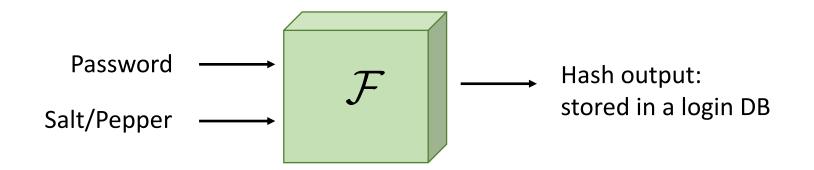


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#### Desirable goal:

Make brute-force attacks hard by making  $\mathcal{F}$  hard to compute over many hashes.



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(Not implied by traditional hash function guarantees like collision-resistance.)

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- Few evaluations
  - Total cost ≈ cost per evaluation

#### **Adversary**

- Many evaluations
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#### Desirable goal:

Make brute-force attacks hard by making  $\mathcal{F}$  hard to compute over many hashes even against adversaries with the advantages of hardware and scale.

### Memory Complexity Measures

- Several have been proposed
  - 1. ST-Complexity
  - 2. Cumulative Complexity
  - 3. Sustained Space Complexity
- Each has their strengths and weaknesses

Memory doesn't just mean buying a disk, it could mean renting storage space from AWS, etc.

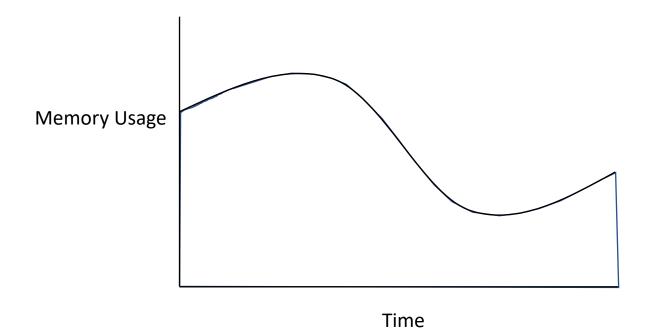
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- Next: a quick overview of prior proposed measures
  - Then we'll get into our contributions

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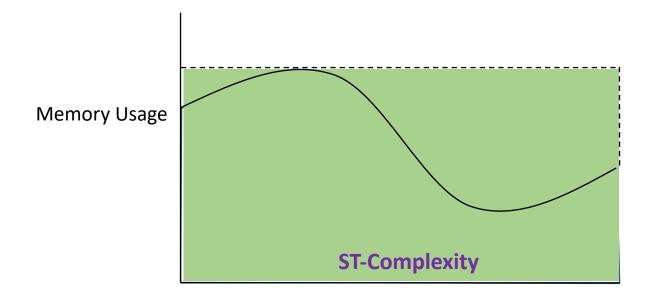
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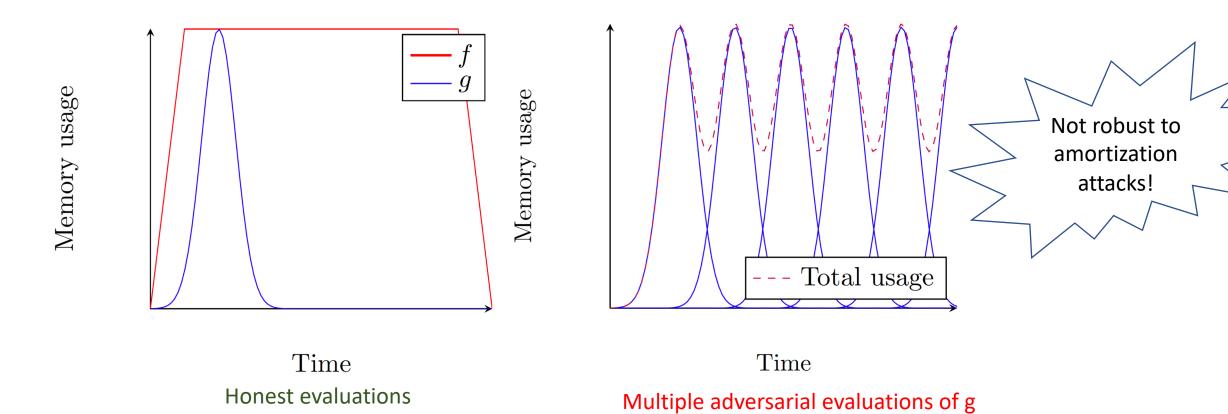


Time

### ST-Complexity

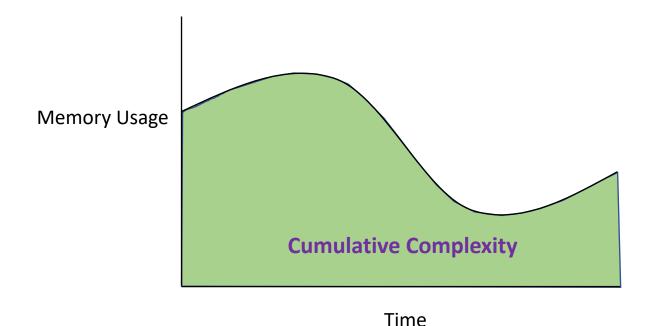
• Limitation: does not capture amortization

(f & g have same ST-complexity)



### Cumulative Memory Complexity (CC) [AS15]

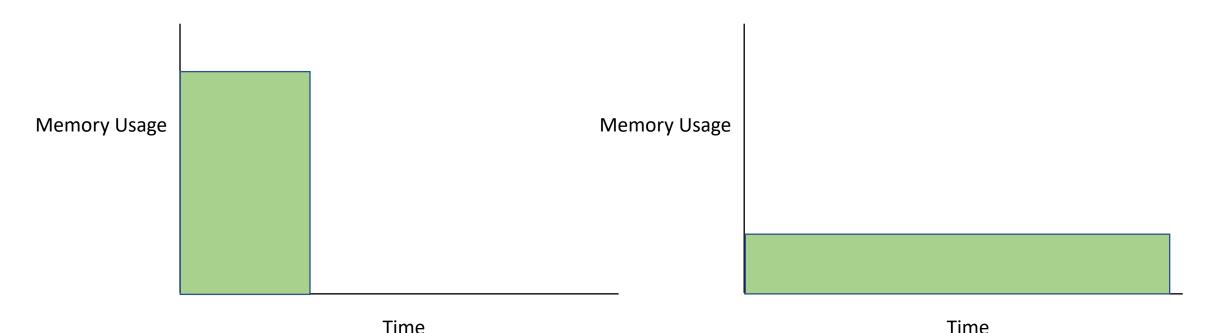
- Goal: Solves amortization of cost issue for ST-complexity
- CC: Sum of the memory used over time



### Cumulative Memory Complexity (CC) [AS15]

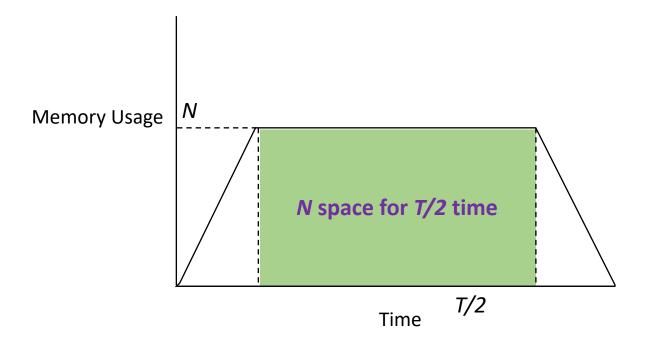
• <u>Caveat</u>: Could still result in different hardware costs (e.g. one time cost or cost varies with time)

Same CC but different cost i.e. cost is not uniform w.r.t. time



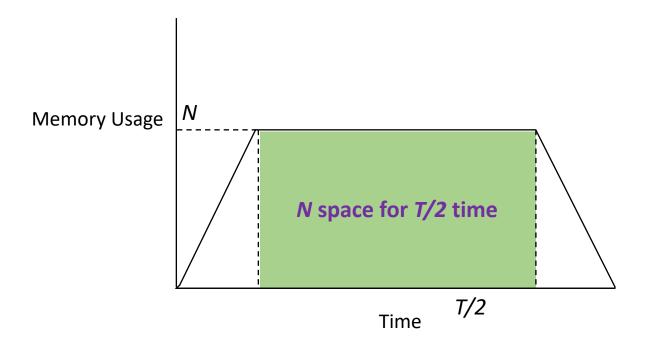
### Sustained-Space Complexity (SSC) [ABP17]

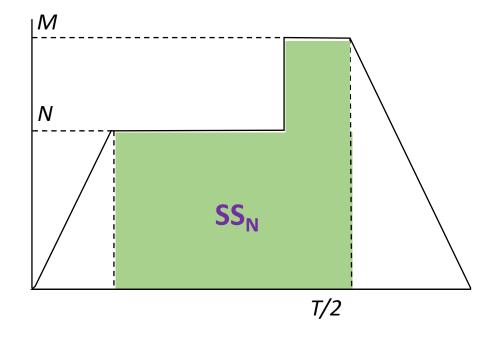
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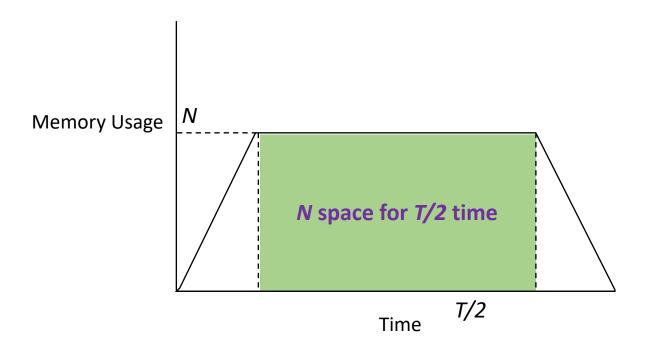


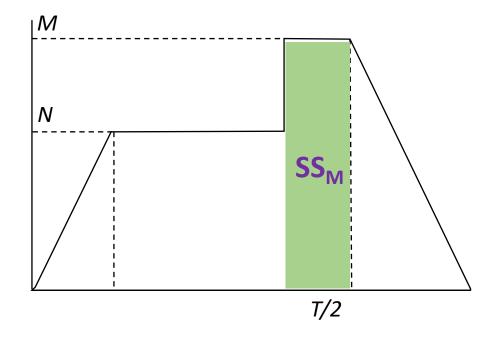


Inherently parameterized notion

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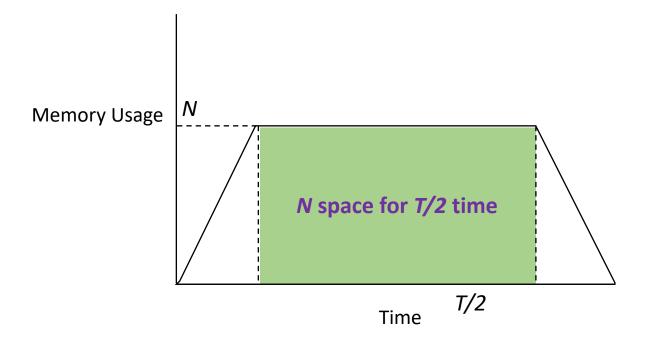


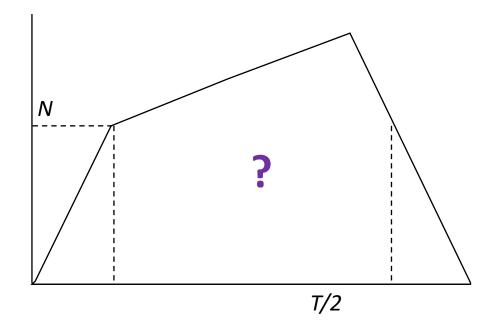


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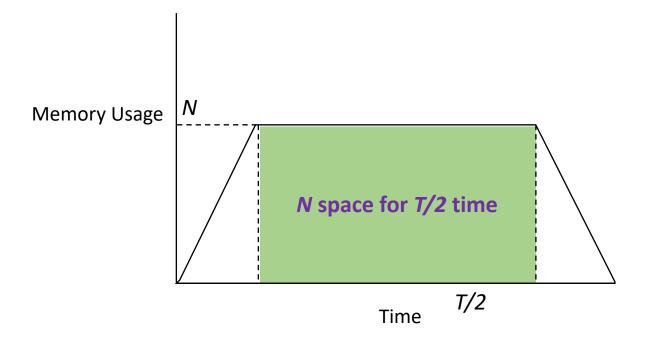
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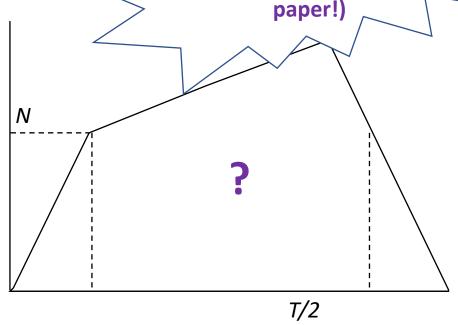
# Sustained Space Complexity (SSC) [ABP]/

SSC<sub>N</sub>: Space usage ≥ N is sustained for a period of

Sum of all memory (to some power) over total eval time:

CC-alpha (look in paper!)





#### Inherently parameterized notion

#### Memory-Hard Functions [AS15]

- **Goal**: Protection against large-scale password-cracking attacks
  - **Resilient against**: special circuitry, parallel evaluation, amortization of cost over multiple evaluations

- Using memory instead of time [Percival 2009, ACPRT16]: A (data-dependent) function scrypt that needs a lot of memory to compute (not time)

  - Complexity measure (CC-complexity) 

    √ Amortization

#### Memory-Hard Functions (MHFs)

- MHFs [AS15, AB16, AB17, ABP17, RD16]: Memory is generated dynamically at runtime given the input to the hash function (i.e. in RAM, not on disk)
  - Existing constructions rely on combinatorial concept of pebbling a hard-topebble graph "via" random oracle queries
- <u>Caveats</u>: Size of memory requirement is <u>bounded by runtime needed by honest</u> evaluator
  - Honest evaluator needs to pebble the graph at runtime provided input to the function

#### **Our Contributions**

- Static-Memory-Hard Functions (SHFs)
  - Definition
  - Preliminaries for construction:
     graph pebbling & parallel random oracle model (PROM)
    - New pebbling game useful for our constructions: black-magic pebble game
  - Constructions
- CC-alpha
   (new complexity measure capturing non-linear space/time tradeoffs)
- Optimal-CC construction in sequential setting (up to polylog factors)

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- **Goal**: Account for **static** memory requirements
  - Static (read-only, on-disk) memory requirements can serve as deterrent to large-scale attacks, but are not captured at all by existing MHF definitions.
  - Static memory requirements may be much greater than *dynamic* memory requirements captured by MHF notions, because they could be >> runtime.
- Two-part hash function:
  - Part 1 (setup phase):
     One-time generation of value table (static generation of memory)
  - Part 2 (online phase):

     Quick online lookups, given oracle access to the output of Part 1
     (Low time complexity hash evaluation given input, for honest evaluator)
  - Note: Part 1 is input-independent.
- Complementary & incomparable to standard MHF guarantee
  - Ideally, want both! ("Dynamic-SHF" will mention briefly later.)

- (Parallel) random oracle model
- Syntax:
  - A static-memory hash function family

$$\mathcal{H}^{\mathcal{O}} = \{ h_{\kappa}^{\mathcal{O}} : \{0, 1\}^{w'} \to \{0, 1\}^{w} \}_{\kappa \in \mathbb{N}}$$

is described by deterministic oracle algorithms  $(\mathcal{H}_1,\mathcal{H}_2)$ :

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One-time setup: 
$$\mathcal{H}_1(1^\kappa)=R$$

(R is a "big string" or "lookup table" and H<sub>1</sub> is a succinct description of how to generate R)

Online computation: 
$$\mathcal{H}_2^R(1^\kappa,x)=h_\kappa(x)$$

( $H_2$  computes the correct hash output **on input x**, and has oracle access to the output of  $H_1$ )

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models **static** (disk) memory access

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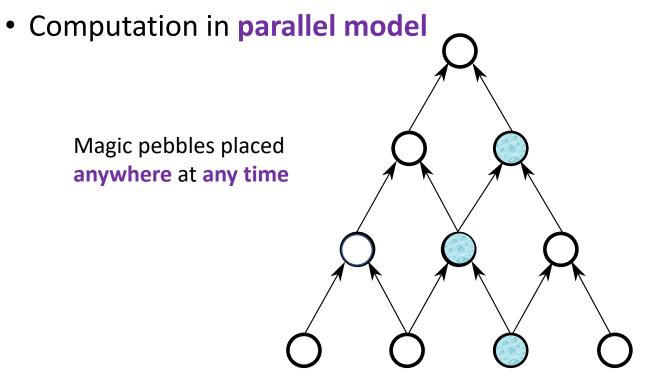
- Adversary model: 2-part adversary  $(A_1, A_2)$ 
  - A<sub>1</sub> outputs a "big string" R' (think of this as the adversary's static memory)
  - A<sub>2</sub> tries to output correct pairs (x,h(x)) given oracle access to R'
     <u>Intuition:</u> A<sub>2</sub> shouldn't be able to correctly guess more pairs than fit in R'

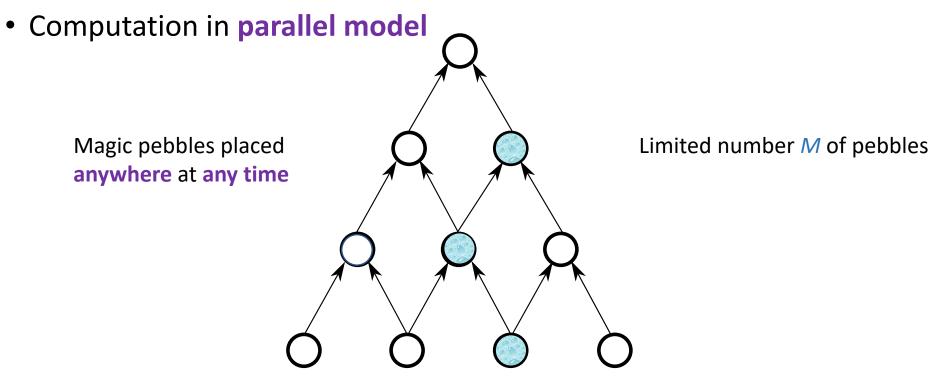
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- Security guarantee (informal):  $(\Lambda, \Delta, \tau, q)$ -hardness Any adversary  $(A_1, A_2)$  that produces  $\geq q$  correct input-output pairs of the hash function must **either** 
  - have  $A_1$  produce  $\Lambda$ - $\Delta$  static memory (i.e.,  $|R'| \ge \Lambda$ - $\Delta$ ) or
  - have  $A_2$  use  $\Lambda$  dynamic memory sustained over  $\tau$  time-steps

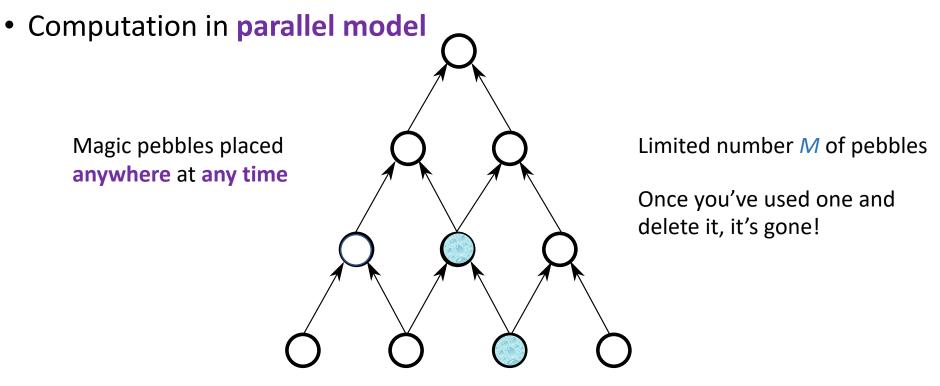
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  - have  $A_2$  use  $\Lambda$  dynamic memory sustained over  $\tau$  time-steps  $\Rightarrow$  requires runtime at least  $\Lambda$ .
    - Recall:  $\Lambda$  may be gigabytes & honest evaluator only requires a few oracle accesses to their "big string", so this adversary's runtime >> honest runtime of  $H_2$ !

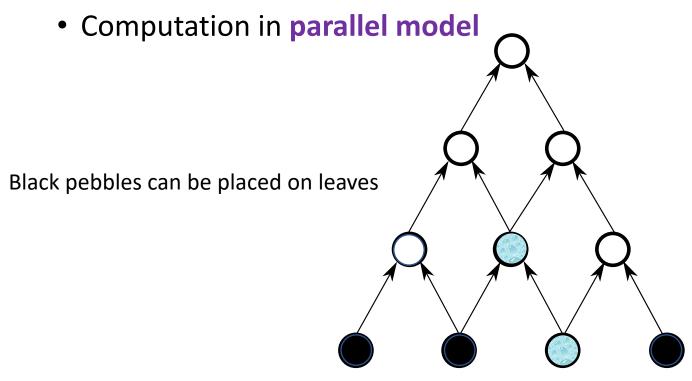
#### Graph Pebbling and PROM

 Given a DAG, computation of the hash result follows from rules of our black-magic pebble game

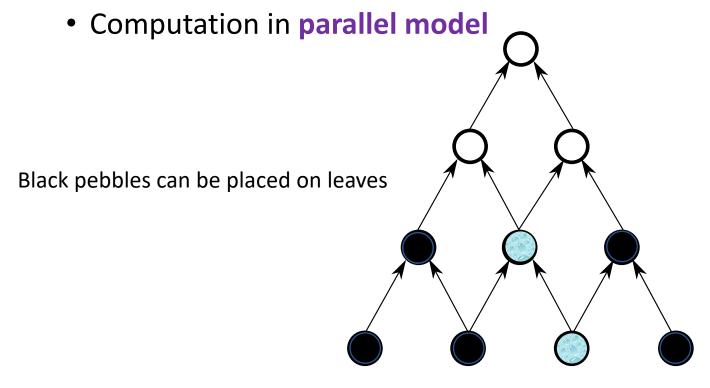




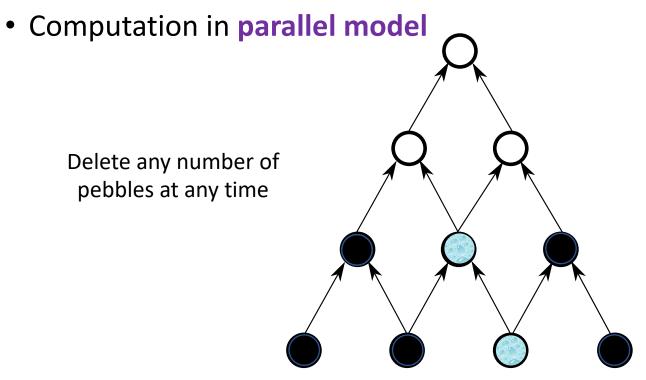


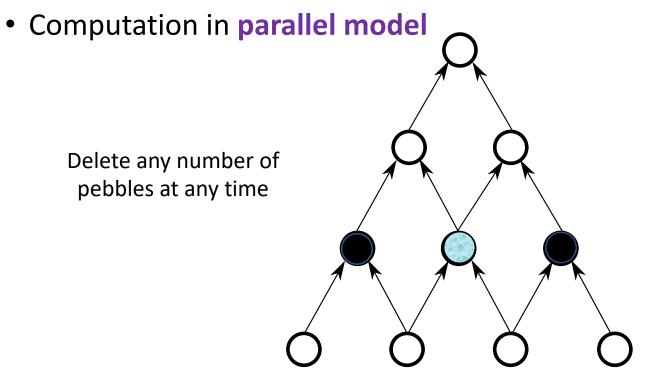


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Black pebbles can be placed on nodes where all predecessors are pebbled

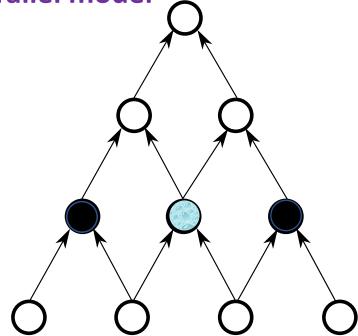




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Computation in parallel model

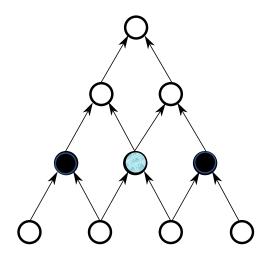
Similar to the pebble game presented in [DFKP15].



Complexity of Strategy = maximum number of pebbles on the graph at any time and total number of magic pebbles

- Function defined by DAG:
  - Magic pebbles represent stored labels
  - Label each node via recursive function where a black pebble represents computing a label:

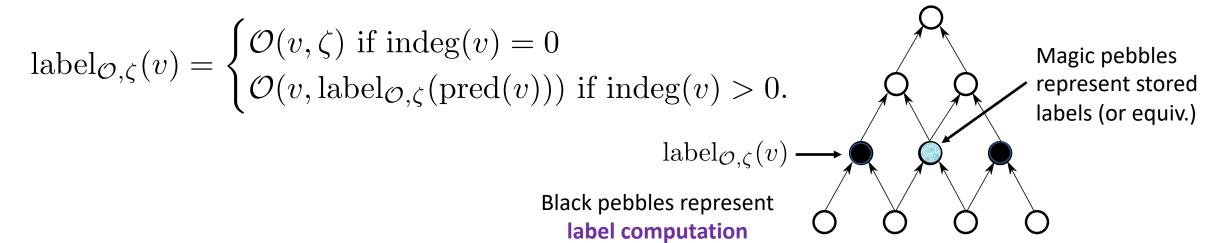
$$label_{\mathcal{O},\zeta}(v) = \begin{cases} \mathcal{O}(v,\zeta) \text{ if } indeg(v) = 0\\ \mathcal{O}(v,label_{\mathcal{O},\zeta}(\operatorname{pred}(v))) \text{ if } indeg(v) > 0. \end{cases}$$



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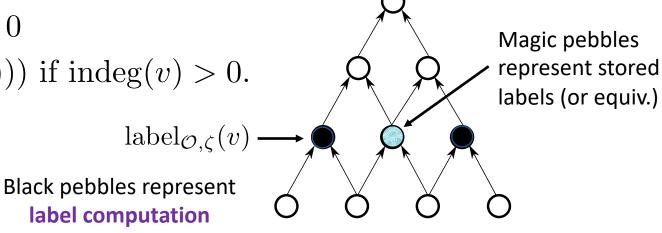
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    Target nodes -> R

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#### Static-Memory-Hard Function Definition

- $(\mathcal{H}_1,\mathcal{H}_2)$ :  $\mathcal{H}_1$  computes static table of values via black-magic pebble game
  - One-time set-up computation
- $\mathcal{H}_2$  queries for values in table provided hash function input
  - Many queries over entire period of use
- $\mathcal{H}_2$  construction:
  - On input x and given oracle access to  $\mathrm{Seek}_R$  where R is the string output from  $\mathcal{H}_1$

#### **Random Oracle**

Input: 
$$x \longrightarrow \mathcal{O} \longrightarrow p_0 = \mathcal{O}(x)$$
  
 $x+1 \longrightarrow \mathcal{O} \longrightarrow p_1 = \mathcal{O}(x+1)$ 

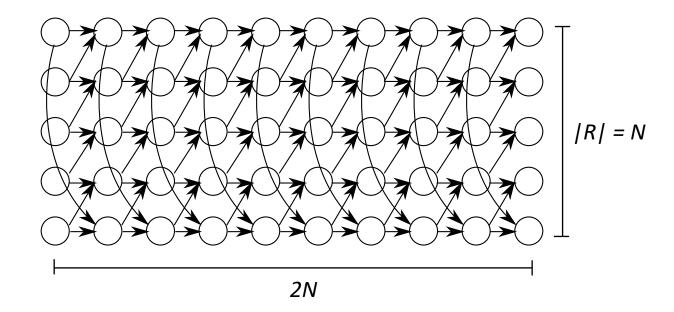
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Random Oracle 
$$x \longrightarrow p_0 = \mathcal{O}(x) \longrightarrow \iota \in [|R|] \xrightarrow{R} 0$$
 Output: 
$$x + 1 \longrightarrow p_1 = \mathcal{O}(x+1) \longrightarrow \iota \in [|R|]$$

#### Candidate Constructions of $\mathcal{H}_1$

- Any graph with one target node doesn't work
- Need at least enough target nodes so that R is reasonably large
- Simple construction cylinder graph we implemented (n = N^2)



#### Our Constructions & Security Guarantees

• <u>Cylinder Graph SHF</u>: For  $\Lambda \in \Theta\left(\sqrt{n}/\kappa - \xi \log(\kappa)\right)$  where n is the number of nodes in the graph,  $\kappa$  is the security parameter, and  $\xi \in \omega(1)$ , an adversary attempting to query  $Q = \omega(S)$  non-trivially more hashes than she stored must incur at least  $\Lambda$  dynamic memory usage for at least  $\Theta(\sqrt{n})$  steps.

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• "Shortcut-Free" SHF: For  $\Lambda \in \Theta\left(\sqrt{n}/\kappa - \xi \log(\kappa)\right)$  where definitions as above, an adversary attempting to query non-trivially more hashes than she stored must incur at least  $\Lambda$  dynamic memory usage for at least  $\Theta(n)$  steps.

#### Dynamic-SHFs: Best of Both Worlds

 Combine with MHFs [AS15, AB16, AB17, ABP17, RD16] from previous works via simple concatenation scheme

#### • Benefits:

- Inherits both the properties of SHFs and MHFs
- Dynamic memory requirement upon input from MHF
- Adversaries incur large static memory requirement from SHF

#### Open Questions

#### • SHFs:

- Can we improve the security guarantee to have a smaller loss from the security parameter?
- Can we have better space guarantees for SHFs in general graphs?
- CC-alpha (from paper)
  - Does there exist an example where CC-alpha differs between linear and quadratic trade-off?
- Optimal CC construction (from paper)
  - Can our optimal sequential construction be modified to obtain optimal bounds in the parallel case?

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#### $CC^{\alpha}$

- <u>Goal</u>: Another complexity measure for non-linear space-time cost tradeoffs
- Based on the cumulative complexity measure [AS15]
- <u>Definition</u>: Given a graph G=(V,E) , the  $CC^{\alpha}(G)$  is  $\min_{\mathcal{P}\in\mathbb{P}}\left(\sum_{P_i\in\mathcal{P}}|P_i|^{\alpha}\right)$

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- Based on the cumulative complexity measure [AS15]
- <u>Definition</u>: Given a graph G=(V,E) , the  $CC^{lpha}(G)$  is  $\min_{\mathcal{P}\in\mathbb{P}}\left(\sum_{P_i\in\mathcal{P}}|P_i|^{lpha}\right)$

Main Theorem: There exist graphs for which an adversary facing a *linear space-time* trade-off would **employ a different pebbling strategy** from one facing a *cubic trade-off*.

#### Talk Outline

- Static-Memory-Hard Functions
  - Definition
  - Preliminaries for our constructions
    - Graph pebbling & parallel random oracle model (PROM)
      - New pebbling game useful for our constructions: black-magic pebble game
    - Functions defined by DAGs
  - Constructions
- CC-alpha

   (new complexity measure capturing non-linear space/time tradeoffs)
- Optimal-CC construction in sequential setting (up to polylog factors)

#### Optimal CC Construction for Sequential Case

- Asymptotically tight sequential lower bound for lpha=1
- Using stacked superconcentrator construction of [LT82] (with slight modification)
  - Gives CC of  $\Theta\left(\frac{n^2 \log \log n}{\log n}\right)$
  - Meets upper bound [AB16, ABP17] up to polylog factors