

Advanced Cryptography

CS 655

Week 5:

- Preprocessing: Bit-Fixing Model to Auxiliary Input
- Compression Arguments
- Memory Hard Functions and Pebbling

Recap: Auxiliary-Input Attacker Model

- **Auxiliary-Input Attacker Model** $A = (A_1, A_2)$
- **Random Oracle Version:**
- Offline attacker A_1 is unbounded and outputs an S -bit hint for online attacker A_2 after viewing entire truth table $H(\cdot)$
- A_2 will try to win security games using this hint
- (S, T, p) -attacker
 - A_1 outputs a S -bit hint
 - A_2 makes at most T random oracle queries
 - A_2 may be constrained in other ways (space/time/signing queries etc...) as specified by parameters p .
- $((S, T, p), \varepsilon)$ -security $\rightarrow$ Any (S, T, p) attacker wins with advantage at most ε

Recap: Bit-Fixing Model

- **Auxiliary-Input Attacker Model** $A = (A_1, A_2)$
- **Random Oracle Version:**
- Offline attacker A_1 fixes output of random oracle $H(\cdot)$ at P locations and then outputs a S -bit hint.
- A_2 initially knows nothing about remaining unfixed values i.e., $H(x)$ picked randomly for $x \notin P$ after A_1 generates hint
- (P, T, p) -attacker
 - A_1 fixes H on at most P locations and outputs S -bit hint
 - A_2 makes at most T random oracle queries
 - A_2 may be constrained in other ways (space/time/signing queries etc...) as specified by parameters p .
- $((S, T, p), \varepsilon)$ -security $\rightarrow$ Any (S, T, p) attacker wins with advantage at most ε

Bit-Fixing Model (Unruh)

- **Pro:** Much easier to prove lower bounds in Bit-Fixing Model
- **Con:** **Bit-Fixing model is not** a compelling model for pre-processing attacks
- **Usage:** Lower bound in bit-fixing model → Lower bound in Auxilliary-Input Model
- This approach yields tight lower-bounds in the Auxilliary-Input Model for some applications 😊
- Other applications require a different approach (e.g., compression)

Typical Relationship: BF-RO and AI-RO

Theorem 5. *For any $P \in \mathbb{N}$ and every $\gamma > 0$, if an application G is $((S, T, p), \varepsilon')$ -secure in the BF-RO(P)-model, then it is $((S, T, p), \varepsilon)$ -secure in the AI-RO-model, for*

$$\varepsilon \leq \varepsilon' + \frac{2(S + \log \gamma^{-1}) \cdot T_G^{\text{comb}}}{P} + 2\gamma ,$$

where T_G^{comb} is the combined query complexity corresponding to G .

Example: Set $\gamma = 2^{-2\lambda}$ and the advantage is $\varepsilon' + \frac{2(S+2\lambda)T}{P} + 2^{-2\lambda}$

Balancing: ε' usually increases with P i.e., as BF-attacker gets to fix more and more points.

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where T_G^{comb} is the combined query complexity corresponding to G .

So far we have used this result (or similar results for Ideal-Ciphers, Permutations etc...) as a black-box.

How is this result proved?

Preliminary Definitions

- **Definition:** A (N, M) -source is a random variable $\mathbf{X}$ with range $[M]^N$
- **Random Oracle H :** $[N] \rightarrow [M]$ can be viewed as a random variable $\mathbf{X}$ with range $[M]^N$ e.g., if $H: \{0, 1\}^n \rightarrow \{0, 1\}^m$ then we set $M = 2^m$ and $N = 2^n$
- Given $I \subseteq [N]$ (inputs) and $x \in [M]^N$ let $x_I \in [M]^{|I|}$ denote the substring specified by I e.g., value of random oracle on all inputs in I
- **Dense-Source:** $\mathbf{X}$ is $(1 - \delta)$ dense if for **every** subset $I \subseteq [N]$ (inputs) we have $H_\infty(X_I) \geq (1 - \delta)|I| \log_2 M = (1 - \delta) \log_2 M^{|I|}$

 **Minimum Entropy:** Equivalent statement is that for all $y \in [M]^{|I|}$ we have $\Pr[X_I = y] \leq |M|^{-|I|(1-\delta)}$

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- **Dense-Source:** X is $(1 - \delta)$ –dense if for **every** subset $I \subseteq [N]$ (inputs) we have $H_\infty(X_I) \geq (1 - \delta)|I| \log_2 M = (1 - \delta) \log_2 M^{|I|}$
- **Example:** Random oracle is $(1 - \delta)$ –dense with $\delta = 0$.

Preliminary Definitions

- **Definition:** A (N, M) -source is a random variable $\mathbf{X}$ with range $[M]^N$
- **Dense-Source:** $\mathbf{X}$ is $(P, 1 - \delta)$ –dense if there is a subset $S \subseteq [N]$ of size $|S| \leq P$ such that for **every** subset $I \subseteq [N \setminus S]$ we have
$$H_\infty(X_I) \geq (1 - \delta)|I| \log_2 M = (1 - \delta) \log_2 M^{|I|}$$
- **Intuition:** Fixed on P coordinates but dense on the rest
- **Bit-Fixing Source:** $\mathbf{X}$ is $(P, 1)$ –dense i.e., fixed on P and uniform on the rest

Preliminary: Leaky Source

- **Leaky-Source (Auxiliary-Input):** Online attacker gets hint $z = f(\mathbf{X})$ for some function $f: [M]^N \rightarrow \{\mathbf{0}, \mathbf{1}\}^S$.

- **Bayesian Update:** Conditional Distribution $\mathbf{X}_z$ for all x in $[M]^N$ we have
$$\Pr[\mathbf{X}_z = x] := \Pr[X = x | f(X) = z]$$

Challenge: It can be difficult to reason about the source $\mathbf{X}_z$

Entropy Deficiency: $S_z = N \log M - H_\infty(\mathbf{X}_z)$

In expectation we have $\mathbf{E}[S_z] \leq S$, but the actual value can vary depending on $z = f(\mathbf{X})$

Proof Strategy

- **Leaky-Source (Auxiliary-Input):** Online attacker gets hint $z = f(X)$ for some function $f: [M]^N \rightarrow \{0, 1\}^S$.

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Entropy Deficiency: $S_z = N \log M - H_\infty(X_z)$ $\mathbb{E}[S_z] \leq S$

- **Step 1:** Show that any leaky source X_z is γ -close to a source Y_z which is a convex combination of $(P', 1 - \delta)$ -dense sources.
 - **Convex Combination:** Let $D_1, \dots, D_k$ each be $(P', 1 - \delta)$ -dense sources. Y_z has the form sample a source $i \leq k$ with probability p_i then sample from $(P', 1 - \delta)$ -dense sources D_i
 - **Number of Fixed Points:** $P' \leq \frac{S_z + \log 1/\gamma}{\delta \log M}$

Proof Strategy

- **Leaky-Source (Auxiliary-Input):** Online attacker gets hint $z = f(\mathbf{X})$ for some function $f: [M]^N \rightarrow \{0, 1\}^S$.

- **Bayesian Update:** Conditional Distribution $\mathbf{X}_z$ for all x in $[M]^N$ we have

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Challenge: It can be difficult to reason about the source $\mathbf{X}_z$

Entropy Deficiency: $S_z = N \log M - H_\infty(\mathbf{X}_z)$ $\mathbb{E}[S_z] \leq S$

- **Step 2:** Show that a $(P', 1 - \delta)$ -dense source X' cannot be distinguished from a P' -bit fixing source Y' by a distinguisher making at most T (adaptive) queries.

$$\Pr[\mathcal{D}^{X'} = 1] \leq \Pr[\mathcal{D}^{Y'} = 1] \times M^{T\delta}$$

And

$$|\Pr[\mathcal{D}^{X'} = 1] - \Pr[\mathcal{D}^{Y'} = 1]| \leq T\delta \log M$$

Proof Strategy

- **Step 1:** Show that any leaky source $\mathbf{X}_Z$ is γ -close to a source $\mathbf{Y}_Z$ which is a convex combination of $(P', 1 - \delta)$ -dense sources.
- Define $\mathbf{Y} = \mathbf{X}_Z$. If $\mathbf{Y}$ is $(1 - \delta)$ -dense then we are done. Otherwise, let I be the largest subset for which there exists a violation i.e., $y_I \in [M]^{|I|}$ s.t.

$$\Pr[\mathbf{Y}_I = y_I] > 2^{-(1-\delta)|I| \log M}$$

- Let $\mathbf{Y}'$ denote distribution of $\mathbf{Y}$ conditioned on $\mathbf{Y}_I = y_I$
- **Claim 1:** $\mathbf{Y}'$ is $(P', 1 - \delta)$ dense with $P' = |I|$
 - **Proof Sketch:** If there is a subset $J \subseteq [N \setminus I]$ and $y_J \in [M]^{|J|}$ s.t.

$$\Pr[\mathbf{Y}'_J = y_J] > 2^{-(1-\delta)|J| \log M}$$

Then we could take $I' = I \cup J$ and

$$\Pr[\mathbf{Y}_{I'} = y_{I'}] = \Pr[\mathbf{Y}_I = y_I] \Pr[\mathbf{Y}_J = y_J | \mathbf{Y}_I = y_I] > 2^{-(1-\delta)|I'| \log M}$$

This contradicts the maximality of I !

Proof Strategy

- **Step 1:** Show that any leaky source $\mathbf{X}_Z$ is γ -close to a source $\mathbf{Y}_Z$ which is a convex combination of $(P', 1 - \delta)$ -dense sources.
- Define $\mathbf{Y} = \mathbf{X}_Z$. If $\mathbf{Y}$ is $(1 - \delta)$ -dense then we are done. Otherwise, let I be the largest subset for which there exists a violation i.e., $y_I \in [M]^{|I|}$ s.t.
$$\Pr[\mathbf{Y}_I = y_I] > 2^{-(1-\delta)|I| \log M}$$
- Let $\mathbf{Y}'$ denote distribution of $\mathbf{Y}$ conditioned on $\mathbf{Y}_I = y_I$
- **Claim 1:** $\mathbf{Y}'$ is $(P', 1 - \delta)$ dense with $P' = |I|$
- **Claim 2:** $|I| \leq \frac{S_Z}{(\delta \log M)}$
 - **Proof Sketch:** On one hand we have $H_\infty(\mathbf{Y}_I) \geq |I| \log M - S_Z$ (def of S_Z)
 - On the other hand $H_\infty(\mathbf{Y}_I) < -\log_2(2^{-(1-\delta)|I| \log M}) = (1 - \delta)|I| \log M$
 - Claim 2 follows immediately by combining the above two inequalities.

Proof Strategy

- **Step 1:** Show that any leaky source $\mathbf{X}_Z$ is γ -close to a source $\mathbf{Y}_Z$ which is a convex combination of $(P', 1 - \delta)$ -dense sources.
- Define $\mathbf{Y} = \mathbf{X}_Z$. If $\mathbf{Y}$ is $(1 - \delta)$ -dense then we are done. Otherwise, let I be the largest subset for which there exists a violation i.e., $y_I \in [M]^{|I|}$ s.t.

$$\Pr[\mathbf{Y}_I = y_I] > 2^{-(1-\delta)|I| \log M}$$
- Let $\mathbf{Y}'$ denote distribution of $\mathbf{Y}$ conditioned on $\mathbf{Y}_I = y_I$
- **Claim:** $\mathbf{Y}'$ is $(P', 1 - \delta)$ dense with $P' = |I|$ with $|I| \leq \frac{S_Z}{(\delta \log M)}$
- **Key Idea (Recursion!):** $\mathbf{Y}_Z$ uses $(P', 1 - \delta)$ dense source $\mathbf{Y}'$ with probability $\Pr[\mathbf{Y}_I = y_I]$ and samples from $\mathbf{Y}_Z'$ with probability $1 - \Pr[\mathbf{Y}_I = y_I]$
- $\mathbf{Y}_Z'$ is also convex combination of finitely many $(P', 1 - \delta)$ -dense sources which is gamma close to $\mathbf{Y}_1$, the distribution of $\mathbf{Y}$ conditioned on $\mathbf{Y}_I \neq y_I$

Proof Strategy

- **Step 1:** Show that any leaky source X_Z is γ -close to a source Y_Z which is a convex combination of $(P', 1 - \delta)$ -dense sources.
- **Key Idea (Recursion!):** Y_Z uses $(P', 1 - \delta)$ dense source Y' with probability $\Pr[Y_I = y_I]$ and samples from Y_Z' with probability $1 - \Pr[Y_I = y_I]$
- Y_Z' is also convex combination of finitely many $(P', 1 - \delta)$ -dense sources which is gamma close to Y_1 , the distribution of Y conditioned on $Y_I \neq y_I$
- Each step of recursion decreases size of support $\rightarrow$ finite termination
- Recurse as long as $\Pr[X \in \text{Supp}(Y_k)] > \gamma$
- **Claim:** Y_k' is $(P', 1 - \delta)$ dense with $P' \leq \frac{S_Z + \log \frac{1}{\gamma}}{(\delta \log M)}$
- Process ends with $\Pr[X \in \text{Supp}(Y_{final})] \leq \gamma \rightarrow$ replace Y_{final} with uniform distribution

Proof Strategy

- **Step 2:** Show that a $(P', 1 - \delta)$ -dense source X' cannot be distinguished from corresponding P' -bit fixing source Y' (uniform on non-fixed coordinates) by a distinguisher making at most T (adaptive) queries to the source.

$$\Pr[\mathcal{D}^{X'} = 1] \leq \Pr[\mathcal{D}^{Y'} = 1] \times M^{T\delta}$$

And

$$|\Pr[\mathcal{D}^{X'} = 1] - \Pr[\mathcal{D}^{Y'} = 1]| \leq T\delta \log M$$

Claim 3. *For any $(P', 1 - \delta)$ -dense source X' and its corresponding P' -bit-fixing source Y' , it holds that for any (adaptive) distinguisher $\mathcal{D}$ that queries at most T coordinates of its oracle,*

$$\left| \mathbb{P}[\mathcal{D}^{X'} = 1] - \mathbb{P}[\mathcal{D}^{Y'} = 1] \right| \leq T\delta \cdot \log M,$$

and

$$\mathbb{P}[\mathcal{D}^{X'} = 1] \leq M^{T\delta} \cdot \mathbb{P}[\mathcal{D}^{Y'} = 1].$$

Proof Strategy

- **Step 2:** Show that a $(P', 1 - \delta)$ -dense source X' cannot be distinguished from a P' -bit fixing source Y' by a distinguisher making at most T (adaptive) queries to the source.

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And

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Proof Intuition:

- WLOG we can assume $\mathcal{D}$ is deterministic (otherwise we can fix the random coins that maximizes the advantage of the distinguisher for $\mathcal{D}$) and only queries on non-fixed points.
- Transcript τ is a list of all of the query/answer pairs that distinguisher $\mathcal{D}$ makes.

Proof Strategy

- **Step 2:** Show that a $(P', 1 - \delta)$ -dense source X' cannot be distinguished from a P' -bit fixing source Y' by a distinguisher making at most T (adaptive) queries to the source.

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Proof Intuition: Transcript τ is a list of all of the query/answer pairs that distinguisher $\mathcal{D}$ makes.

- Let $T_{X'}$ (resp. $T_{Y'}$) denote random variable over transcripts resulting from interaction with source X' (resp. Y').
- Note: The support of $T_{Y'}$ contains the support of $T_{X'}$.
- For every transcript τ in the support of $T_{X'}$, we have

$$\Pr[T_{X'} = \tau] \leq 2^{-(1-\delta)T \log M} \quad \text{and} \quad \Pr[T_{Y'} = \tau] = 2^{-T \log M}$$
$$\Pr[T_{X'} = \tau] \leq M^{T\delta} \Pr[T_{Y'} = \tau]$$

Proof Strategy

- **Step 2:** Show that a $(P', 1 - \delta)$ -dense source X' cannot be distinguished from a P' -bit fixing source Y' by a distinguisher making at most T (adaptive) queries to the source.

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$$\Pr[T_{X'} = \tau] \leq 2^{-(1-\delta)T \log M} \quad \text{and} \quad \Pr[T_{Y'} = \tau] = 2^{-T \log M}$$

$$\Pr[T_{X'} = \tau] \leq M^{T\delta} \Pr[T_{Y'} = \tau]$$

Let $\mathcal{T}_{\mathcal{D}}$ denote the set of all transcripts where $\mathcal{D}$ outputs 1.

$$\Pr[\mathcal{D}^{X'} = 1] = \sum_{\tau \in \mathcal{T}_{\mathcal{D}}} \Pr[T_{X'} = \tau] \leq M^{T\delta} \sum_{\tau \in \mathcal{T}_{\mathcal{D}}} \Pr[T_{Y'} = \tau] = M^{T\delta} \times \Pr[\mathcal{D}^{Y'} = 1]$$

Claim 3. For any $(P', 1 - \delta)$ -dense source X' and its corresponding P' -bit-fixing source Y' , it holds that for any (adaptive) distinguisher $\mathcal{D}$ that queries at most T coordinates of its oracle,

$$\left| \mathbf{P}[\mathcal{D}^{X'} = 1] - \mathbf{P}[\mathcal{D}^{Y'} = 1] \right| \leq T\delta \cdot \log M,$$

and also $\mathbf{P}[T_{Y'} = \tau] = \mathbf{p}_{Y'}(\tau)$. Towards proving the first part of the lemma, observe that

$$\left| \mathbf{P}[\mathcal{D}^{X'} = 1] - \mathbf{P}[\mathcal{D}^{Y'} = 1] \right| \leq \text{SD}(T_{X'}, T_{Y'})$$

and a

$$\begin{aligned} &= \sum_{\tau} \max \{0, \mathbf{P}[T_{X'} = \tau] - \mathbf{P}[T_{Y'} = \tau]\} \\ &= \sum_{\tau \in \mathcal{T}_X} \max \{0, \mathbf{p}_{X'}(\tau) - \mathbf{p}_{Y'}(\tau)\} \\ &= \sum_{\tau \in \mathcal{T}_X} \mathbf{p}_{X'}(\tau) \cdot \max \left\{ 0, 1 - \frac{\mathbf{p}_{Y'}(\tau)}{\mathbf{p}_{X'}(\tau)} \right\} \\ &\leq 1 - M^{-T\delta} \leq T\delta \cdot \log M, \end{aligned}$$

where the first sum is over all possible transcripts and where the last inequality uses $2^{-x} \geq 1 - x$ for $x \geq 0$.

$$\begin{aligned} &= \sum_{\tau \in \mathcal{T}_X} \mathbf{p}_{X'}(\tau) \cdot \max \left\{ 0, 1 - \frac{\mathbf{p}_{Y'}(\tau)}{\mathbf{p}_{X'}(\tau)} \right\} \\ &\leq 1 - M^{-T\delta} \leq T\delta \cdot \log M, \end{aligned}$$

where the first sum is over all possible transcripts and where the last inequality uses $2^{-x} \geq 1 - x$ for $x \geq 0$.

Lemma 1. *Let X be distributed uniformly over $[M]^N$ and $Z := f(X)$, where $f : [M]^N \rightarrow \{0, 1\}^S$ is an arbitrary function. For any $\gamma > 0$ and $P \in \mathbb{N}$, there exists a family $\{Y_z\}_{z \in \{0, 1\}^S}$ of convex combinations Y_z of P -bit-fixing (N, M) -sources such that for any distinguisher D taking an S -bit input and querying at most $T < P$ coordinates of its oracle,*

$$|\mathbb{P}[\mathcal{D}^X(f(X)) = 1] - \mathbb{P}[\mathcal{D}^{Y_{f(X)}}(f(X)) = 1]| \leq \frac{(S + \log 1/\gamma) \cdot T}{P} + \gamma$$

and

$$\mathbb{P}[\mathcal{D}^X(f(X)) = 1] \leq 2^{(S+2 \log 1/\gamma)T/P} \cdot \mathbb{P}[\mathcal{D}^{Y_{f(X)}}(f(X)) = 1] + 2\gamma.$$

Let Y'_z be obtained by replacing every X' by the corresponding Y' in X'_z . Setting $\delta_z = (S_z + \log 1/\gamma)/(P \log M)$, Claims 2 and 3 imply

$$\left| \mathbb{P}[\mathcal{D}^{X_z}(z) = 1] - \mathbb{P}[\mathcal{D}^{Y'_z}(z) = 1] \right| \leq \frac{(S_z + \log 1/\gamma) \cdot T}{P} + \gamma, \quad (2)$$

as well as

$$\mathbb{P}[\mathcal{D}^{X_z}(z) = 1] \leq 2^{(S_z + \log 1/\gamma)T/P} \cdot \mathbb{P}[\mathcal{D}^{Y'_z}(z) = 1] + \gamma. \quad (3)$$

Moreover, note that for the above choice of δ_z , $P' = P$, i.e., the sources Y' are fixed on at most P coordinates, as desired.

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One Missing Link Remains! Prior bounds relied on entropy deficiency $S_Z = N \log M - H_\infty(\mathbf{X}_Z)$ instead of S .

Claim: $E[S_Z] \leq S$ and $\Pr \left[S_{f(X)} > S + \log \frac{1}{\gamma} \right] \leq \gamma$

Key Fact: $\Pr[f(X) = z] \leq 2^{-S_Z}$

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Claim: $E[S_Z] \leq S$ and $\Pr\left[S_{f(X)} > S + \log \frac{1}{\gamma}\right] \leq \gamma$

Key Fact: $\Pr[f(X) = z] \leq 2^{-S_z}$

Proof: By definition of S_z (min-entropy deficiency) there exists $x \in [M]^N$ with $f(X) = z$ such that $\Pr[X = x | f(X) = z] = \frac{2^{S_z}}{M^N}$. We have

$$\frac{1}{M^N} = \Pr[X = x] = \Pr[X = x | f(X) = z] \Pr[f(X) = z] = \frac{2^{S_z}}{M^N} \Pr[f(X) = z]$$

Lemma 1. *Let X be distributed uniformly over $[M]^N$ and $Z := f(X)$, where $f : [M]^N \rightarrow \{0, 1\}^S$ is an arbitrary function. For any $\gamma > 0$ and $P \in \mathbb{N}$, there exists a family $\{Y_z\}_{z \in \{0, 1\}^S}$ of convex combinations Y_z of P -bit-fixing (N, M) -sources such that for any distinguisher D taking an S -bit input and querying at most $T < P$ coordinates of its oracle,*

$$|\mathbb{P}[\mathcal{D}^X(f(X)) = 1] - \mathbb{P}[\mathcal{D}^{Y_{f(X)}}(f(X)) = 1]| \leq \frac{(S + \log 1/\gamma) \cdot T}{P} + \gamma$$

and

$$\mathbb{P}[\mathcal{D}^X(f(X)) = 1] \leq 2^{(S+2 \log 1/\gamma)T/P} \cdot \mathbb{P}[\mathcal{D}^{Y_{f(X)}}(f(X)) = 1] + 2\gamma.$$

Claim: $E[S_Z] \leq S$ and $\Pr\left[S_{f(X)} > S + \log \frac{1}{\gamma}\right] \leq \gamma$

Key Fact: $\Pr[f(X) = z] \leq 2^{-S_z}$

$$\Pr\left[S_{f(X)} > S + \log \frac{1}{\gamma}\right] = \sum_{\substack{z \in \{0, 1\}^S \text{ s.t.} \\ S_z > S + \log \frac{1}{\gamma}}} \Pr[f(X) = z] \leq 2^S \times 2^{-(S + \log \frac{1}{\gamma})} \leq \gamma$$

Claim 4. $\mathbb{E}_z[S_z] \leq S$ and $\mathbb{P}[S_{f(X)} > S + \log 1/\gamma] \leq \gamma$.

Proof. Observe that $H_\infty(X_z) = H_\infty(X|Z = z) = H(X|Z = z)$ since, conditioned on $Z = z$, X is distributed uniformly over all values x with $f(x) = z$. Therefore,

$$\begin{aligned} \mathbb{E}_z[S_z] &= N \log M - \mathbb{E}_z[H_\infty(X|Z = z)] = N \log M - \mathbb{E}_z[H(X|Z = z)] \\ &= N \log M - H(X|Z) \leq S. \end{aligned}$$

Again due to the uniformity of X , $\mathbb{P}[f(X) = z] = 2^{-S_z}$. Hence,

$$\mathbb{P}[S_{f(X)} > S + \log 1/\gamma] = \sum_{z \in \{0,1\}^S : S_z > S + \log 1/\gamma} \mathbb{P}[f(X) = z] \leq 2^S \cdot 2^{-(S + \log 1/\gamma)} \leq \gamma.$$

□

Lemma 1. *Let X be distributed uniformly over $[M]^N$ and $Z := f(X)$, where $f : [M]^N \rightarrow \{0, 1\}^S$ is an arbitrary function. For any $\gamma > 0$ and $P \in \mathbb{N}$, there exists a family $\{Y_z\}_{z \in \{0, 1\}^S}$ of convex combinations Y_z of P -bit-fixing (N, M) -sources such that for any distinguisher D taking an S -bit input and querying at most $T < P$ coordinates of its oracle,*

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and

$$\mathbb{P}[\mathcal{D}^X(f(X)) = 1] \leq 2^{(S+2 \log 1/\gamma)T/P} \cdot \mathbb{P}[\mathcal{D}^{Y_{f(X)}}(f(X)) = 1] + 2\gamma.$$

$$\begin{aligned} \mathbb{P}[\mathcal{D}^X(f(X)) = 1] &\leq \mathbb{P}[\mathcal{D}^X(f(X)) = 1, S_{f(X)} \leq S + \log 1/\gamma] + \mathbb{P}[S_{f(X)} > S + \log 1/\gamma] \\ &\leq \left(2^{(S+2 \log 1/\gamma)T/P} \cdot \mathbb{P}[\mathcal{D}^{Y_{f(X)}}(f(X)) = 1, S_{f(X)} \leq S + \log 1/\gamma] + \gamma \right) + \gamma \\ &\leq 2^{(S+2 \log 1/\gamma)T/P} \cdot \mathbb{P}[\mathcal{D}^{Y_{f(X)}}(f(X)) = 1] + 2\gamma, \end{aligned}$$

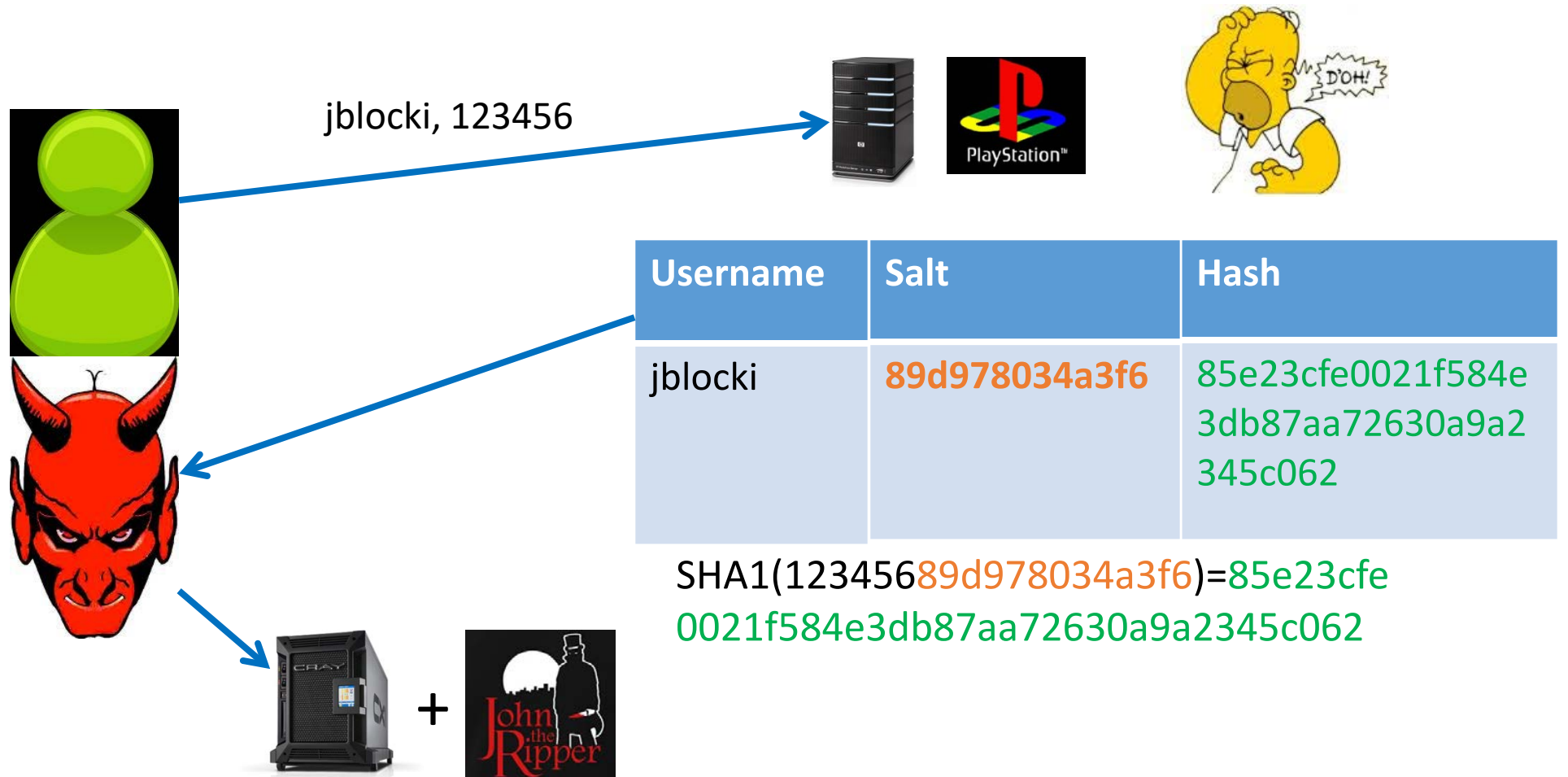
Memory Hard Functions, Random Oracles, Graph Pebbling and Extractor Arguments



Jeremiah Blocki



Motivation: Password Storage



Offline Attacks: A Common Problem

- Password breaches at major companies have affected ~~millions~~ **billions** of user accounts.

LastPass ****

SONY

ebay

ASHLEY
MADISON®
Life is short. Have an affair.®

Linked in

Dropbox

AdultFriendFinder®

rockyou

Zappos
the web's most popular shoe store!

YAHOO!

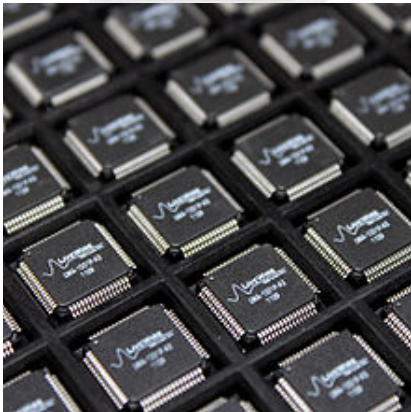
Adobe

GAWKER

livingsocial

Goal: Moderately Expensive Hash Function

Fast on PC and
Expensive on ASIC?



password hashing competition

(2013-2015)

<https://password-hashing.net/>

password hashing competition

(2013-2015)



We recommend that
you use Argon2...

<https://password-hashing.net/>

password hashing competition

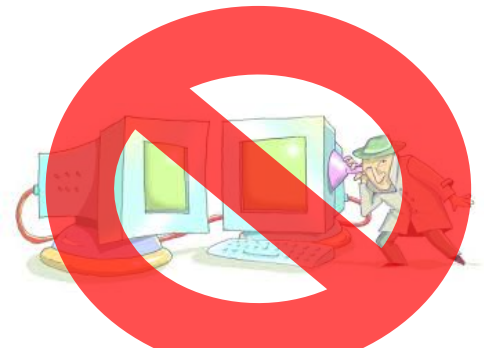
(2013-2015)

<https://password-hashing.net/>



We recommend that
you use Argon2...

There are two main versions of
Argon2, **Argon2i** and Argon2d.
Argon2i is the safest against side-
channel attacks

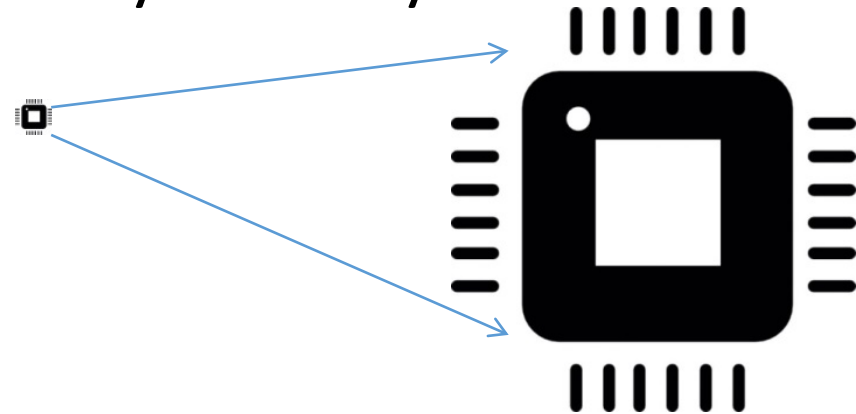


Memory Hard Function (MHF)

- **Intuition:** computation costs dominated by memory costs



vs.



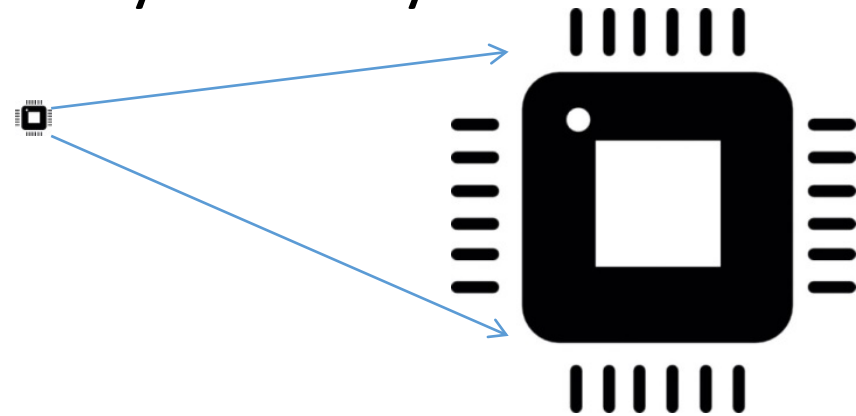
- **Goal:** force attacker to lock up large amounts of memory for duration of computation
 - Expensive even on customized hardware

Memory Hard Function (MHF)

- **Intuition:** computation costs dominated by memory costs



vs.



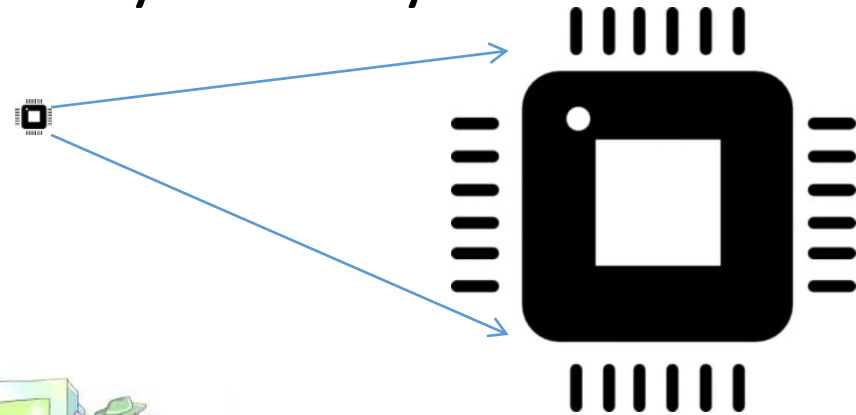
sCrypt

Memory Hard Function (MHF)

- **Intuition:** computation costs dominated by memory costs



vs.



sCrypt

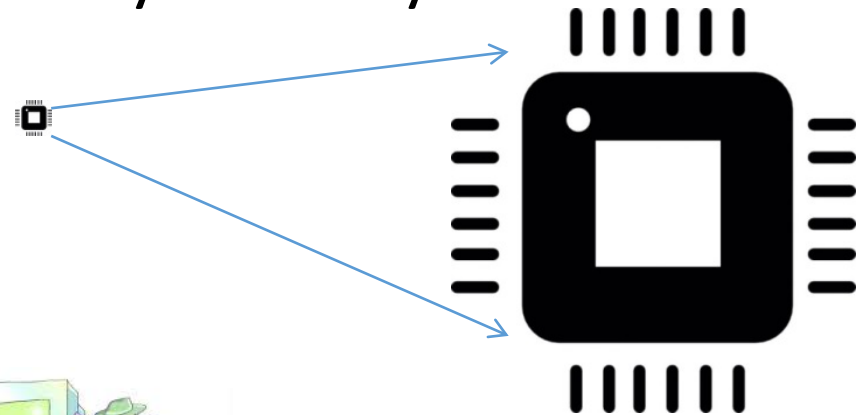


Memory Hard Function (MHF)

- **Intuition:** computation costs dominated by memory costs



vs.



sCrypt



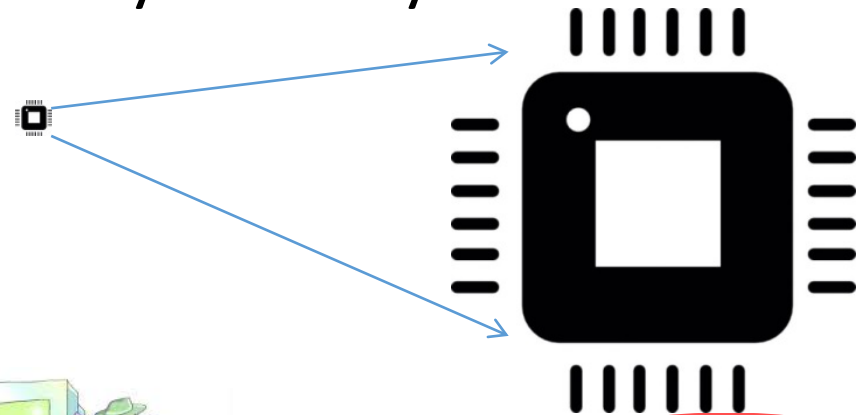
- Data Independent Memory Hard Function (iMHF)
 - Memory access pattern should not depend on input

Memory Hard Function (MHF)

- **Intuition:** computation costs dominated by memory costs



vs.



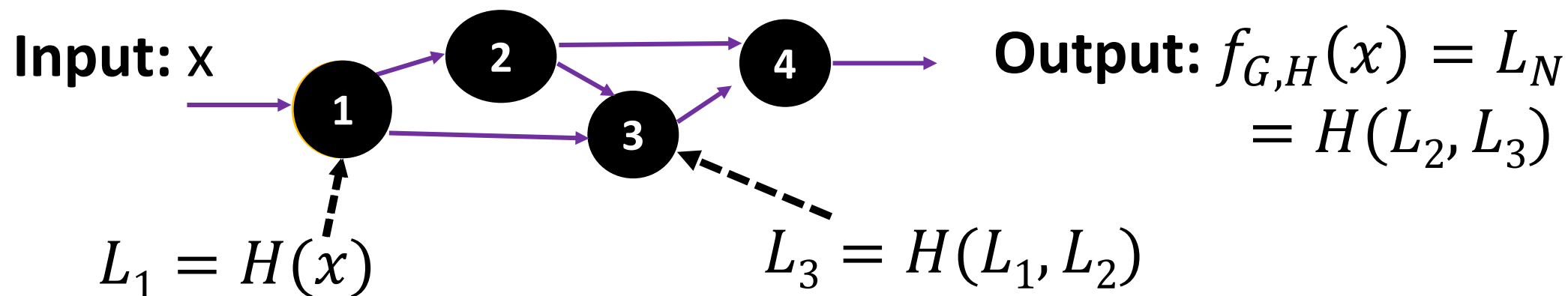
sCrypt



- Data Independent Memory Hard Function (iMHF)
 - Memory access pattern should not depend on input

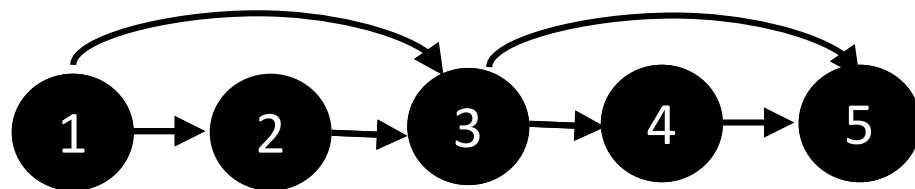


Data-Independent Memory Hard Function $f_{G,H}$

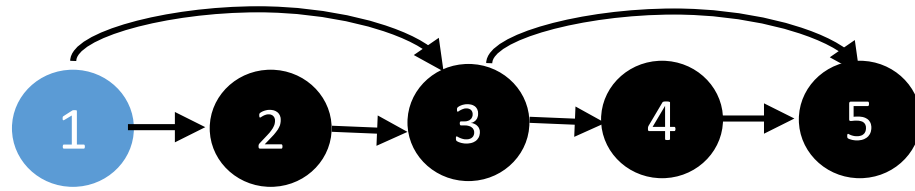


- $H: \{0,1\}^{2k} \rightarrow \{0,1\}^k$ (Random Oracle)
- DAG G (encodes data-dependencies)
 - Maximum indegree: $\delta = O(1)$
 - $N = 2^n$ nodes

Evaluating an iMHF (pebbling)



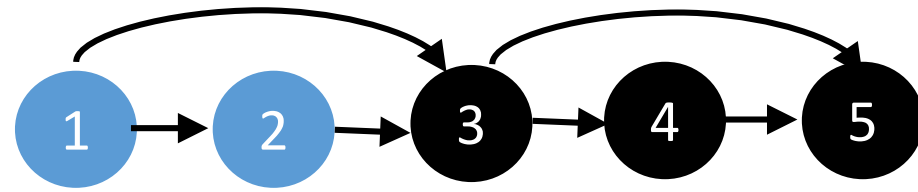
Evaluating an iMHF (**pebbling**)



$$P_1 = \{1\}$$

(data value L_1 stored in memory)

Evaluating an iMHF (pebbling)

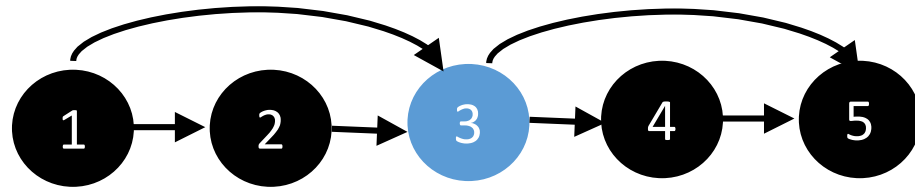


$$P_1 = \{1\}$$

$$P_2 = \{1, 2\}$$

(data values L_1 and L_2 stored in memory)

Evaluating an iMHF (pebbling)

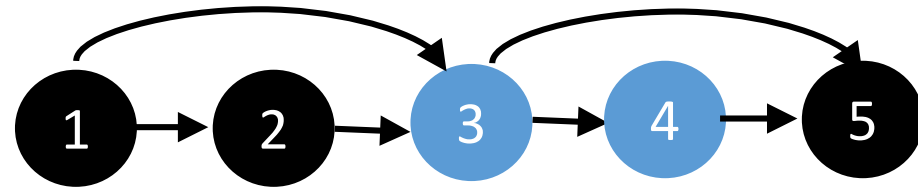


$$P_1 = \{1\}$$

$$P_2 = \{1, 2\}$$

$$P_3 = \{3\}$$

Evaluating an iMHF (pebbling)



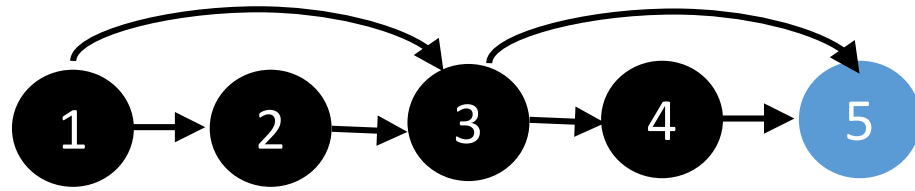
$$P_1 = \{1\}$$

$$P_2 = \{1, 2\}$$

$$P_3 = \{3\}$$

$$P_4 = \{3, 4\}$$

Evaluating an iMHF (pebbling)



$$P_1 = \{1\}$$

$$P_2 = \{1, 2\}$$

$$P_3 = \{3\}$$

$$P_4 = \{3, 4\}$$

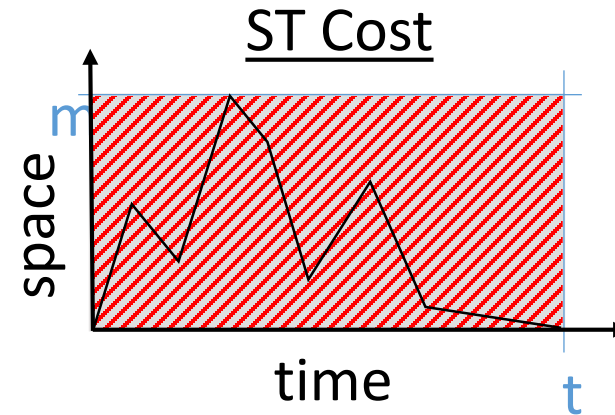
$$P_5 = \{5\}$$

Measuring Pebbling Cost: Attempt 1

- Space $\times$ Time (ST)-Complexity

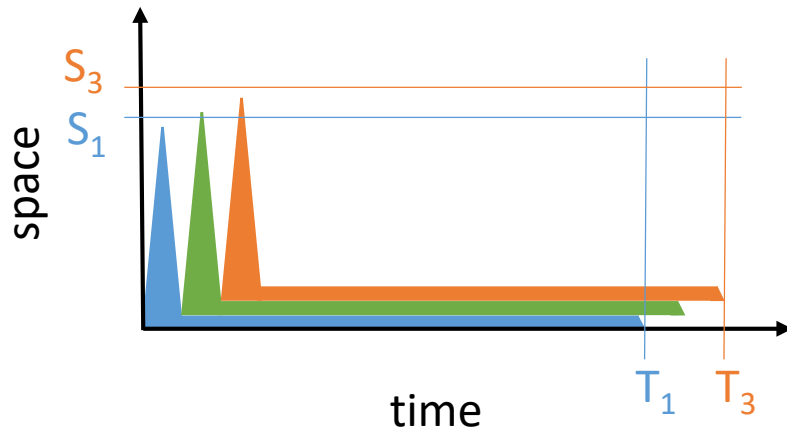
$$ST(G) = \min_{\vec{P}} \left(t_{\vec{P}} \times \max_{i \leq t_{\vec{P}}} |P_i| \right)$$

- Rich Theory
 - Space-time tradeoffs
 - But not appropriate for password hashing



Amortization and Parallelism

- Problem: for parallel computation ST-complexity can scale badly in the number of evaluations of a function.



$$ST_1 = S_1 \times T_1 \approx S_3 \times T_3 = ST_3$$

cost of computing f once

cost of computing f three times

[AS15] $\exists$ function f_n (consisting of n RO calls) such that: $ST(f^{\times \sqrt{n}}) = O(ST(f))$

Measuring Pebbling Costs [AS15]

- Cumulative Complexity (CC)

Memory Used at Step i

Approximates
Amortized Area x Time
Complexity of iMHF

$$CC(G) = \min_{\vec{P}} \sum_{i=1}^{t_{\vec{P}}} |P_i|$$

- Guessing two passwords doubles the attackers cost

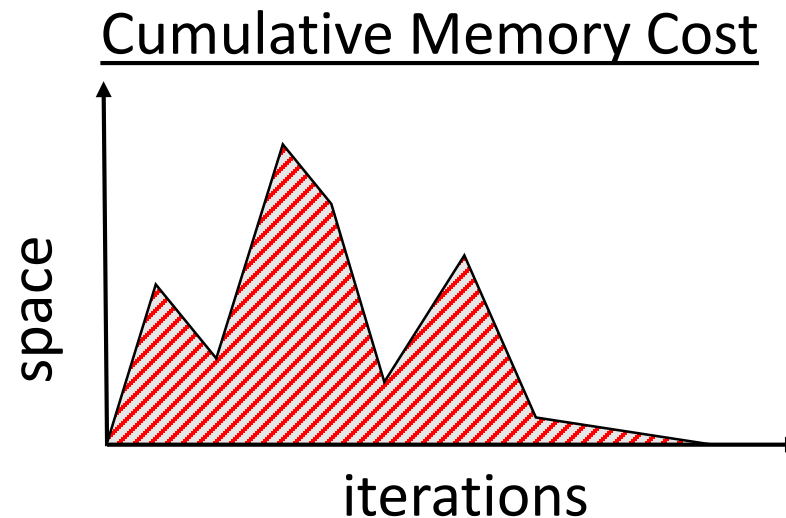
$$CC(G, G) = 2 \times CC(G)$$

Measuring Pebbling Costs [AS15]

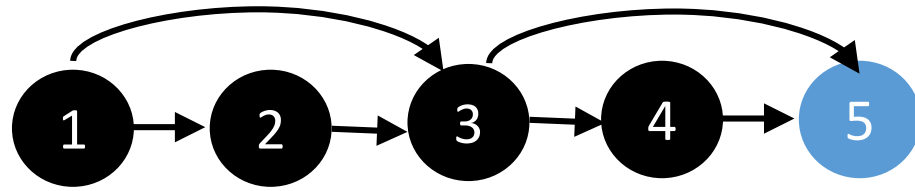
$$CC(G) = \min_{\vec{P}} \sum_{i=1}^{t_{\vec{P}}} |P_i|$$

Approximates
Amortized Area x Time
Complexity of iMHF

Memory Used at Step i



Pebbling Example (CC)



$$P_1 = \{1\}$$

$$P_2 = \{1, 2\}$$

$$P_3 = \{3\}$$

$$P_4 = \{3, 4\}$$

$$P_5 = \{5\}$$

$$\begin{aligned} \text{CC}(G) &\leq \sum_{i=1}^5 |P_i| \\ &= 1 + 2 + 1 + 2 + 1 \\ &= 7 \end{aligned}$$

Desiderata

Find a DAG G on n nodes such that

1. Constant Indegree ($\delta = 2$)
 - Running Time: $n(\delta - 1) = n$
2. $CC(G) \geq \frac{n^2}{\tau}$ for some small value τ .

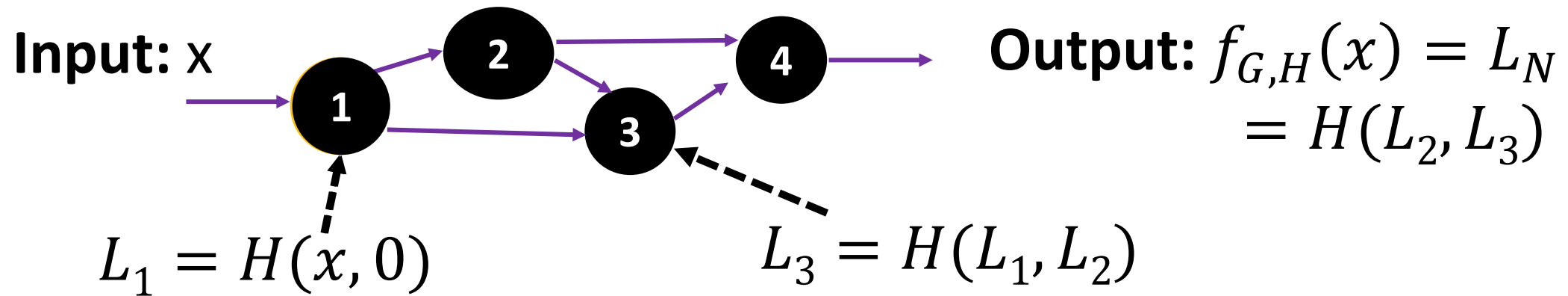


Maximize costs for fixed running time n
(Users are impatient)

DAGs with Maximal $CC(G)$

- **Challenge 1:** Design a constant indegree DAG G maximizing $CC(G)$
 - Depth-Robust Graphs are necessary [AB16] and sufficient [ABP17]
 - Argon2i (PHC winner) is not depth-robust
 - $CC(G) = o(n^{1.767}) \ll n^2$ [AB16,AB17,ABP17,BZ17]
 - Any DAG with constant indegree has $CC(G) = O(n^2 \log \log n / \log n)$ at most
 - Theoretical [ABP17] then practical [ABH17] construction of depth-robust graphs
 - $CC(G) = \Omega(n^2 / \log n)$ [AB16,AB17,ABP17,BZ17]
- **Open Problem 1:** Construct G with $CC(G) = \Omega(n^2 \log \log n / \log n)$
 - Conjecture: [BHKLXZ19] achieves this goal.
- **Open Problem 2:** Tighten constants in upper/lower bounds

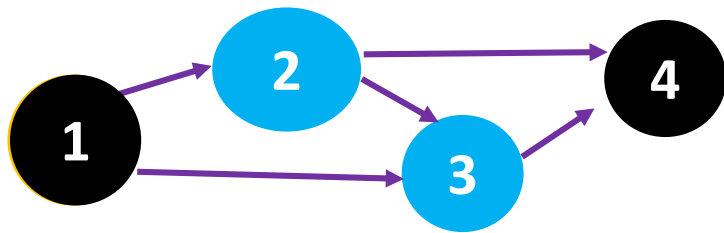
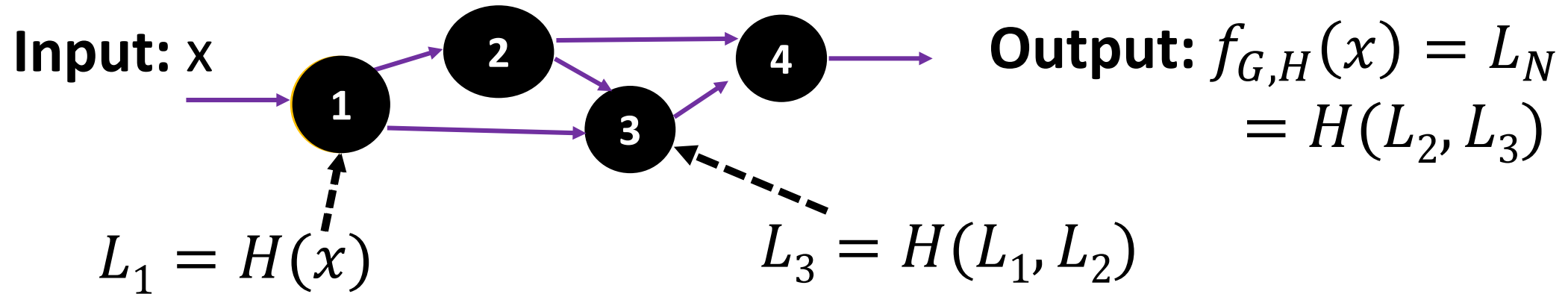
Question: $CC(G) \rightarrow$ cumulative memory cost?



Bad Case: $H(x,y)=x+y \bmod 2^w \rightarrow f_{G,H}(x) = k_G \times x$ e.g., $k_G = 3$ (above)
Independent of input! $k_G = 2^{n-2}$ (complete)

Computing $f_{G,H}(x)$ is fast + requires minimal memory.
(even if pebbling cost $CC(G)$ is large!)

Question: $CC(G) \rightarrow$ cumulative memory cost?



Theorem [AS15]: (in parallel random oracle model)

$$A(x) = f_{G,H}(x) \rightarrow \text{cmc}(A) = \Omega(w \times CC(G))$$

Random Oracle Model (PROM)

- Model hash function H as a random function
 - Algorithms can only interact with H as an oracle
 - **Query:** x
 - **Response:** $H(x)$
 - If we submit the same query you see the same response
 - If x has not been queried, then the value of $H(x)$ is uniform
-
- **Real World:** H instantiated as cryptographic hash function (e.g., SHA3) of fixed length (no Merkle-Damgård)

x	$H(x)$
00 ... 00	r_0
00 ... 01	r_1
...	
...	
11 ... 11	r_{2^n-1}

Random Oracle Model: Prediction Game

Prediction Game: $(x_1, y_1), \dots, (x_k, y_k) \leftarrow A^{H(\cdot)}$ wins the prediction game if

1. $y_1 = H(x_1), \dots, y_k = H(x_k)$ and
2. the inputs $x_1, \dots, x_k$ are all fresh i.e., A never queried $H(x_i)$

Fact 1: Any algorithm $A^{H(\cdot)}$ wins the prediction game with probability at most 2^{-kw} over the choice of $H(\cdot)$.

Intuition: A never queries $H(x_1) \rightarrow$ can view $H(x_1)$ as a (yet to be sampled) random string

Random Oracle Model: Prediction Game

Prediction Game: $(x_1, y_1), \dots, (x_k, y_k) \leftarrow A^{H(\cdot)}$ wins the prediction game if

1. $y_1 = H(x_1), \dots, y_k = H(x_k)$ and
2. the inputs $x_1, \dots, x_k$ are all fresh i.e., A never queried $H(x_i)$

Fact 1: Any algorithm $A^{H(\cdot)}$ wins the prediction game with probability at most 2^{-kw} over the choice of $H(\cdot)$.

Fact 2 (Incompressibility of ROs): Any algorithm $A^{H(\cdot)}(h)$ given a s -bit hint h (which may depend on $H(\cdot)$) wins the prediction game with probability at most 2^{-kw+s}

Proof Intuition: Otherwise we can win without hint with probability $> 2^{-kw}$

Reduction: Guess correct hint h with probability 2^{-s} and run $A^{H(\cdot)}(h)$

Parallel Random Oracle Model (PROM)

- PROM Algorithm $\mathcal{A}(x)$
 - **Initial Input/State:** $\sigma_0 = x$
 - $\left(\sigma_1, \overrightarrow{q_1} = (x_1^1, \dots, x_{r_1}^1)\right) \leftarrow \mathcal{A}(\sigma_0)$
 - New State + Batch of Random Oracle Queries
 - $\overrightarrow{a_1} = (H(x_1^1), \dots, H(x_{r_1}^1))$
 - Answers to Random Oracle Queries
 - $\left(\sigma_2, \overrightarrow{q_2} = (x_1^2, \dots, x_{r_2}^2)\right) \leftarrow \mathcal{A}(\sigma_1, \overrightarrow{a_1})$
 -
 - $\left(\sigma_i, \overrightarrow{q_i} = (x_1^i, \dots, x_{r_i}^i)\right) \leftarrow \mathcal{A}(\sigma_{i-1}, \overrightarrow{a_{i-1}})$
 -
 - $y \leftarrow \mathcal{A}(\sigma_t, \overrightarrow{a_t})$

x	H(x)
00 ... 00	r_0
00 ... 01	r_1
...	
...	
11 ... 11	r_{2^n-1}

One round of computation.

1. $\mathcal{A}$ receives prior answers $\overrightarrow{a_{i-1}}$
2. $\mathcal{A}$ performs arbitrary computation
3. $\mathcal{A}$ outputs $(\sigma_i, \overrightarrow{q_i})$ new state + new queries

Parallel Random Oracle Model (PROM)

- PROM Algorithm $\mathcal{A}(x)$
 - Fixing $\mathcal{A}$, x and H** we get an execution trace

$$\text{Trace}_{\mathcal{A},H}(x) = \{\sigma_i, \vec{q_i}, \vec{a_i}\}_{i=1}^t$$

- Cumulative Memory Cost of Execution Trace

$$\text{cmc}(\text{Trace}_{\mathcal{A},H}(x)) = \sum_{i=1}^t (|\sigma_i| + |\vec{a_i}|)$$

- Cumulative Memory Cost of a Function

$$\text{cmc}(f_{G,H}) = \min_{\mathcal{A},x} \mathbb{E}_H \left[\text{cmc}(\text{Trace}_{\mathcal{A},H}(x)) \right]$$

Min over inputs x and PROM algorithms $\mathcal{A}$ evaluating $f_{G,H}$

Expectation over selection of random oracle

x	$H(x)$
00 ... 00	r_0
00 ... 01	r_1
...	
...	
11 ... 11	r_{2^n-1}

Collision Problem

Collision Problem: Suppose that we are asked to find $x \neq x'$
s.t. $H(x) = H(x')$

What is the probability we can succeed given q queries to the random oracle?

Answer: $\leq q^2 2^{-w}$

Explanation: Let $x_1, \dots, x_q$ be the queries we make

$$\Pr[H(x_{i+1}) \in \{H(x_1), \dots, H(x_i)\}] \leq i \times 2^{-w} \quad (\text{Prob Collision at time } i+1)$$

$$\therefore \Pr[\text{Collision}] \leq \sum_{i \leq q} i \times 2^{-w} \quad (\text{Union Bound over Each Round})$$

x	H(x)
00 ... 00	r_0
00 ... 01	r_1
...	
...	
11 ... 11	r_{2^n-1}

Label Distinctness

Label Distinctness: Suppose we are given a directed acyclic graph G on n nodes $V=\{1,\dots,n\}$ with indegree 2 and such that each node $v > 2$ has two parents $v-1$ and $r(v)<v-1$. Let

Let $x = L_0$ be the initial input (w -bits) and define labels $L_1 = H(x_0, 0^w)$, $L_2 = H(L_1, 0^w)$,

$$L_3 = H(L_2, L_1)$$

$$\dots$$

$$L_v = H(L_{v-1}, L_{r(v)})$$

$$\dots$$

$$L_n = H(L_{n-1}, L_{r(n)})$$

x	$H(x)$
00 ...00	r_0
00 ...01	r_1
...	
...	
11 ...11	r_{2^n-1}

Question: What is the probability that two labels collide?

Label Distinctness

$$L_v = H(\overset{\dots}{L_{v-1}}, L_{r(v)})$$

Question: What is the probability that two labels collide?

Let $\mathbf{U}_i$ be the event that labels $L_1, \dots, L_i$ are all distinct

$$\Pr[\overline{\mathbf{U}}_i | \mathbf{U}_{i-1}] = \Pr[H(\overset{\uparrow}{L_{i-1}}, L_{r(i)}) \in \{L_1, \dots, L_{i-1}\} | \mathbf{U}_{i-1}] \leq (i-1)2^{-w}$$

L_{i-1} unique $\rightarrow$ fresh query!

Union Bound!

Label Distinctness

$$L_v = H(\overset{\dots}{L_{v-1}}, L_{r(v)})$$

Question: What is the probability that two labels collide?

Let $\mathbf{U}_i$ be the event that labels $L_1, \dots, L_i$ are all distinct

$$\Pr[\overline{\mathbf{U}}_i | \mathbf{U}_{i-1}] \leq (i-1)2^{-w}$$

$$\Pr[\overline{\mathbf{U}}_n] \leq \sum_{i \leq n} (i-1) 2^{-w} \leq n^2 2^{-w}$$

Label Collision

$$L_v = H(\overset{\dots}{L_{v-1}}, L_{r(v)})$$



Prelab(v) = $L_{v-1}, L_{r(v)}$

Question: Suppose we can make at most q queries to the random oracle. What is the probability we find some z s.t. $L_v = H(z)$ but $z \neq \mathbf{Prelab}(v)$ for some node v ?

x	H(x)
00 ... 00	r_0
00 ... 01	r_1
...	
...	
11 ... 11	r_{2^n-1}

Label Collision

Question: Suppose we can make at most q queries to the random oracle. What is the probability we find some z s.t. $L_v = H(z)$ but $z \neq \mathbf{Prelab}(v)$ for some node v ?

Answer: at most $nq2^{-w}$

Let z_i be i th query to random oracle such that $z_i \neq \mathbf{Prelab}(v)$ for any node $v \leq n$ then we have

$$\Pr[H(z_i) \in \{L_1, \dots, L_n\}] \leq n2^{-w}$$

$$\Pr[\exists i \leq q. H(z_i) \in \{L_1, \dots, L_n\}] \leq nq2^{-w}$$

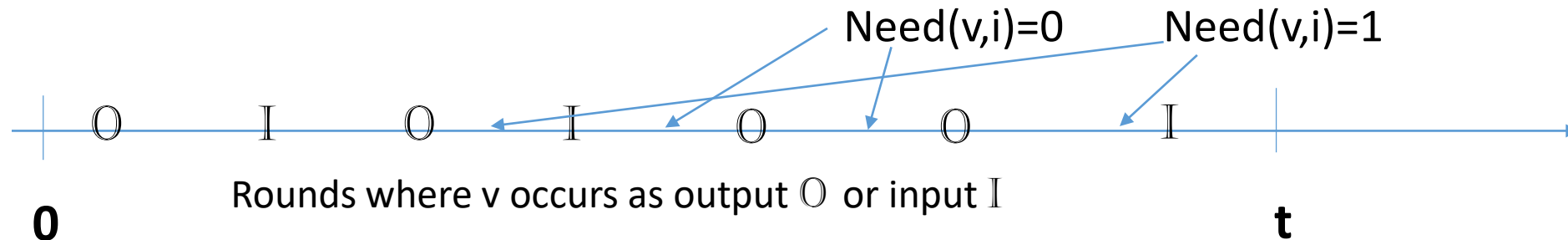
x	$H(x)$
$00 \dots 00$	r_0
$00 \dots 01$	r_1
$\dots$	
$\dots$	
$11 \dots 11$	r_{2^n-1}

Ex Post Facto Pebbling

- **Fixing $\mathcal{A}$, $\mathbf{x}$ and $\mathbf{H}$** we get an execution trace

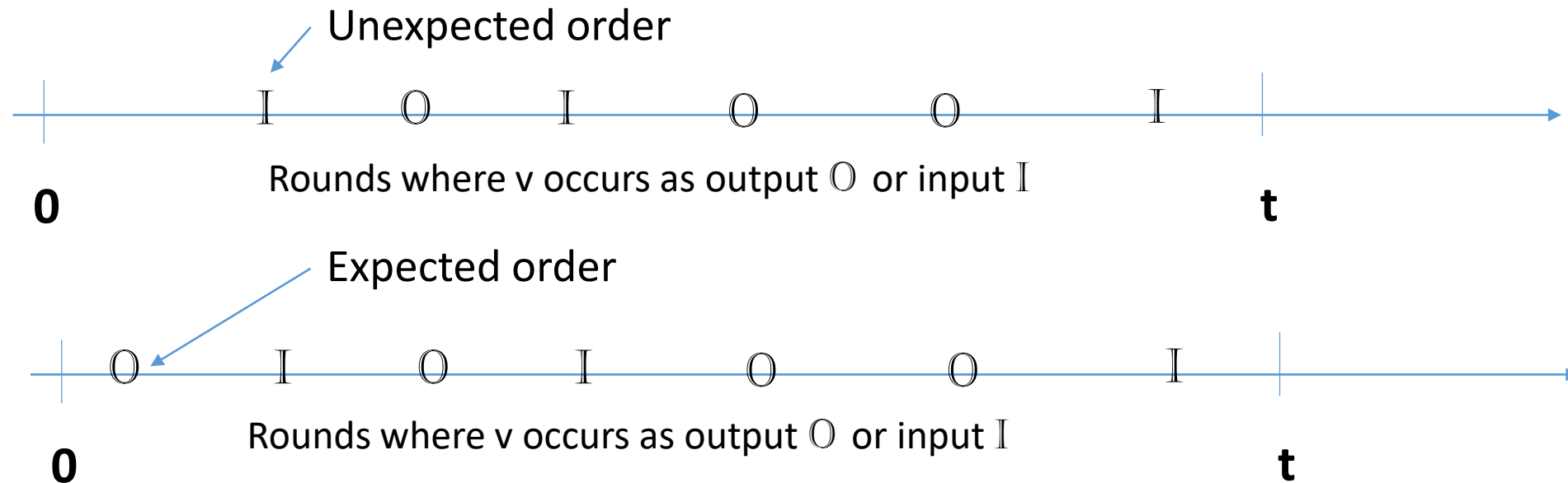
$$\text{Trace}_{\mathcal{A}, \mathbf{H}}(\mathbf{x}) = \{\sigma_i, \vec{q_i}, \vec{a_i}\}_{i=1}^t$$

- Track L_v for each node v
 - Note rounds where L_v appear as the input to random oracle query?
 - Note rounds does L_v appear as an the output to a random oracle query?
 - Define $\text{Need}(v,i)=1$ if and only if the next time (after round i) label L_v appears it is as an input; otherwise $\text{Need}(v,i)=0$
- $P_i = \{v : \text{Need}(v, i) = 1\}$



Ex Post Facto Pebbling

- $P_i = \{v : \text{Need}(v, i) = 1\} \rightarrow$ does this give us a legal pebbling?
- $\text{Order}(v)$ be the bad event L_v is used as an RO input before it has appeared as an output



Ex Post Facto Pebbling

- $P_i = \{v : \text{Need}(v, i) = 1\} \rightarrow$ does this give us a legal pebbling?

Claim 1: Suppose that $\mathcal{A}$ computes $f_{G,H}$ and makes at most q random oracle queries then $P = P_1, \dots, P_t$ is a legal pebbling (except with probability $O(qn2^{-w})$).

Proof Sketch:

Observation 1: If the bad event $\text{Order}(v)$ never occurs for any node v then the pebbling is legal (follows from definition of $\text{Need}(v, i)$)

Ex Post Facto Pebbling

- $P_i = \{v : \text{Need}(v, i) = 1\} \rightarrow$ does this give us a legal pebbling?

Claim 1: Suppose that $\mathcal{A}$ computes $f_{G,H}$ and makes at most q random oracle queries then $P = P_1, \dots, P_t$ is a legal pebbling (except with probability $O(qn2^{-w})$).

Proof Sketch:

Observation 2: If L_v has not yet appeared as output then the probability a particular query includes L_v as input early is at most 2^{-w}

$\rightarrow \Pr[\text{Order}(v)] \leq q2^{-w}$ (Union Bound over all q queries)

(L_v can be viewed as random w -bit string before it first appears)

Ex Post Facto Pebbling

- $P_i = \{v : \text{Need}(v, i) = 1\} \rightarrow$ does this give us a legal pebbling?

Claim 1: Suppose that $\mathcal{A}$ computes $f_{G,H}$ and makes at most q random oracle queries then $P = P_1, \dots, P_t$ is a legal pebbling (except with probability $O(qn2^{-w})$).

Proof Sketch: Let $\text{Order}(v)$ be the bad event L_v is used as an RO input before it has appeared as an output. Union Bounding

$$\Pr[\exists v \text{ Order}(v)] \leq n\Pr[\text{Order}(v)] \leq nq2^{-w}$$

(L_v can be viewed as random w -bit string before it first appears)

Ex Post Facto Pebbling

- **Fixing $\mathcal{A}$, $\mathbf{x}$ and $\mathbf{H}$** we get an execution trace

$$\text{Trace}_{\mathcal{A}, \mathbf{H}}(\mathbf{x}) = \{\sigma_i, \vec{q}_i, \vec{a}_i\}_{i=1}^t$$

Claim 1: Suppose that $\mathcal{A}$ computes $f_{G, \mathbf{H}}$ and makes at most q random oracle queries then $P = P_1, \dots, P_t$ is a legal pebbling (except with probability $O(qn2^{-w})$).

Observation: If P is legal then $\text{CC}(P) \geq \text{CC}(G)$

(definition of $\text{CC}(G)$ as best pebbling of G)

Extractor Argument

- **Fixing $\mathcal{A}$, $\mathbf{x}$ and $\mathbf{H}$** we get an execution trace

$$\text{Trace}_{\mathcal{A}, \mathbf{H}}(\mathbf{x}) = \{\sigma_i, \overrightarrow{q_i}, \overrightarrow{a_i}\}_{i=1}^t$$

Observation: $\text{CC}(\mathbf{P}) \geq \text{CC}(G)$ (definition of $\text{CC}(G)$)

Claim 2: For each round i we have $|\sigma_i| + |\overrightarrow{a_{i-1}}| \geq w|P_i|/2$

Proof Idea: Extractor argument. Suppose for contradiction that $|\sigma_i| + |\overrightarrow{a_{i-1}}| < w|P_i|/2$.

We will build an extractor that outputs $|P_i|$ labels given a hint of size $w|P_i|/2 + o(w|P_i|)$. This yields a contradiction of incompressibility!

Extractor Hint

Claim 2: For each round i we have $|\sigma_i| + |a_{i-1}| \geq w|P_i|/2$

Hint: h

- Initial State: $\sigma_i, \overrightarrow{a_{i-1}}$ (used to simulate $\mathcal{A}$ at most $w|P_i|/2$ bits)
- Encoding of P_i ($|P_i| \log n$ bits)
- For each $v \in P_i$ index i_v of next random oracle query where label L_v appears as input ($|P_i| \log q$ bits)
- For each $v \in P_i$ index o_v of next random oracle query where label L_v appears as output ($|P_i| \log q$ bits)
- **Total Hint Length:** $w|P_i|/2 + o(w|P_t|)$.

Extractor argument. Suppose for contradiction that $|\sigma_i| < w|P_t|/2$.

We will build an extractor that outputs $|P_t|$ labels given a hint of size $|\sigma_i| + o(w|P_t|)$. This yields a contradiction of incompressibility!

Extractor: Simulating Attacker

Random Oracle
 $H: \{0,1\}^* \rightarrow \{0,1\}^w$

Extractor E
 Hint: $h = (\sigma_i, \overrightarrow{a_{i-1}} P_i, \dots)$

P_i	Label	Input Query	Output Query
v_1	???	$(i+2, 4)$	$(i+10, 5)$
v_2	???	$(i+1, 2)$	$(i+2, 1)$
...	...		

$\sigma_{i+1}, \overrightarrow{q_i},$
 $\overrightarrow{a_i} = (H(\overrightarrow{q_i}[1]), H(\overrightarrow{q_i}[2]), \dots,)$
Simulate
 $\mathcal{A}(\sigma_i, \overrightarrow{a_{i-1}})$

Extractor: Simulating Attacker

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Extractor E
 Hint: $h = (\sigma_i, \overrightarrow{a_{i-1}} P_i, \dots)$

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...	...		

$\sigma_{i+2}, \overrightarrow{q_{i+1}},$

Simulate
 $\mathcal{A}(\sigma_{i+1}, \overrightarrow{a_i})$

Extract!
 $\overrightarrow{q_{i+1}}[2]$ contains L_{v_2}

Extractor: Simulating Attacker

Random Oracle
 $H: \{0,1\}^* \rightarrow \{0,1\}^w$

Extractor E
 Hint: $h = (\sigma_i, \overrightarrow{a_{i-1}} P_i, \dots)$

P_i	Label	Input Query	Output Query
v_1	???	$(i+2, 4)$	$(i+10, 5)$
v_2	L_{v_2}	$(i+1, 2)$	$(i+2, 1)$
...	...		

$\sigma_{i+2}, \overrightarrow{q_{i+1}},$
 $\overrightarrow{a_{i+1}} = (H(\overrightarrow{q_{i+1}}[1]), H(\overrightarrow{q_{i+1}}[2]), \dots,)$
Simulate
 $\mathcal{A}(\sigma_{i+1}, \overrightarrow{a_i})$

Extract!
 $\overrightarrow{q_{i+1}}[2]$ contains L_{v_2}

Extractor: Simulating Attacker

Random Oracle
 $H: \{0,1\}^* \rightarrow \{0,1\}^w$

Extractor E
 Hint: $h = (\sigma_i, \overrightarrow{a_{i-1}} P_i, \dots)$

P_i	Label	Input Query	Output Query
v_1	???	(i+2,4)	(i+10,5)
v_2	L_{v_2}	(i+1,2)	(i+2,1)
...	...		

$\sigma_{i+3}, \overrightarrow{q_{i+2}}$

Simulate
 $\mathcal{A}(\sigma_{i+2}, \overrightarrow{a_{i+1}})$

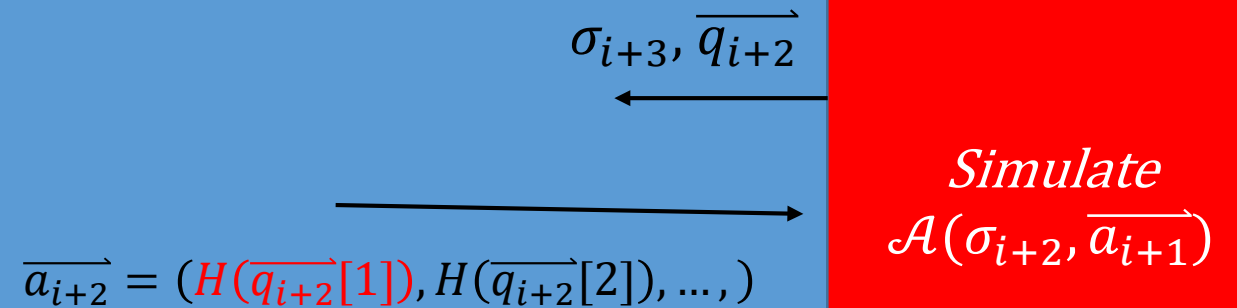
Extract! $H(\overrightarrow{q_{i+2}}[4]) = L_{v_1}$

Extractor: Simulating Attacker

Random Oracle
 $H: \{0,1\}^* \rightarrow \{0,1\}^w$

Extractor E
 Hint: $h = (\sigma_i, \overrightarrow{a_{i-1}} P_i, \dots)$

P_i	Label	Input Query	Output Query
v_1	L_{v_1}	$(i+2, 4)$	$(i+10, 5)$
v_2	L_{v_2}	$(i+1, 2)$	$(i+2, 1)$
...	...		



Danger! $H(\overrightarrow{q_{i+2}}[1]) = L_{v_2}$
 Do not submit this query!

Extractor: Simulating Attacker

Random Oracle
 $H: \{0,1\}^* \rightarrow \{0,1\}^w$

Extractor E
 Hint: $h = (\sigma_i, \overrightarrow{a_{i-1}} P_i, \dots)$

P_i	Label	Input Query	Output of Query
v_1	L_{v_1}	$(i+2, 4)$	$(i+10, 5)$
v_2	L_{v_2}	$(i+1, 2)$	$\overrightarrow{q_{i+2}}[1]$
...	...		

$\overrightarrow{a_{i+2}} = (L_{v_2}, H(\overrightarrow{q_{i+2}}[2]), \dots)$

$\sigma_{i+3}, \overrightarrow{q_{i+2}}$

Simulate
 $\mathcal{A}(\sigma_{i+2}, \overrightarrow{a_{i+1}})$

Danger! $H(\overrightarrow{q_{i+2}}[1]) = L_{v_2}$
 Do not submit this query!

Extractor: Simulating Attacker

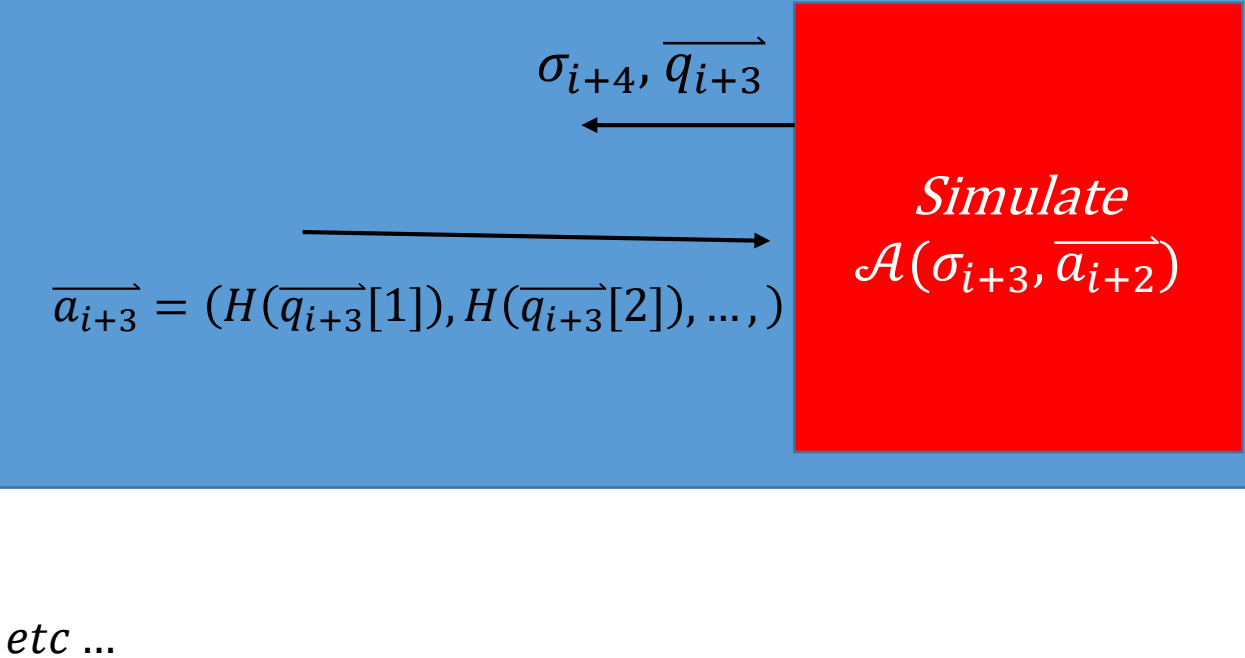
Random Oracle

$H: \{0,1\}^* \rightarrow \{0,1\}^w$

Extractor E

Hint: $h = (\sigma_i, \overrightarrow{a_{i-1}} P_i, \dots)$

P_i	Label	Input Query	Output of Query
v_1	L_{v_1}	$(i+2,4)$	$(i+10,5)$
v_2	L_{v_2}	$(i+1,2)$	$\overrightarrow{q_{i+2}}[1]$
...	...		

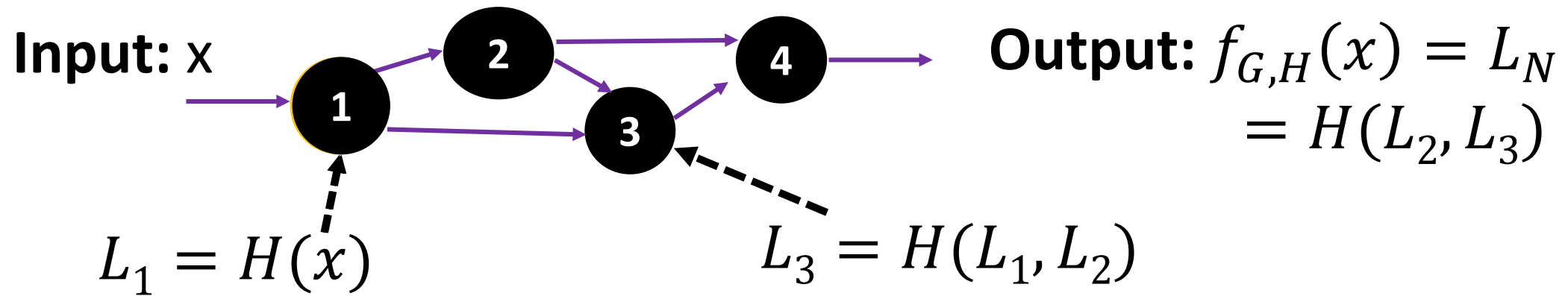


Extractor: Simulating Attacker

Claim 2: For each round i we have $|\sigma_i| \geq w|P_i|/2$

Hint:

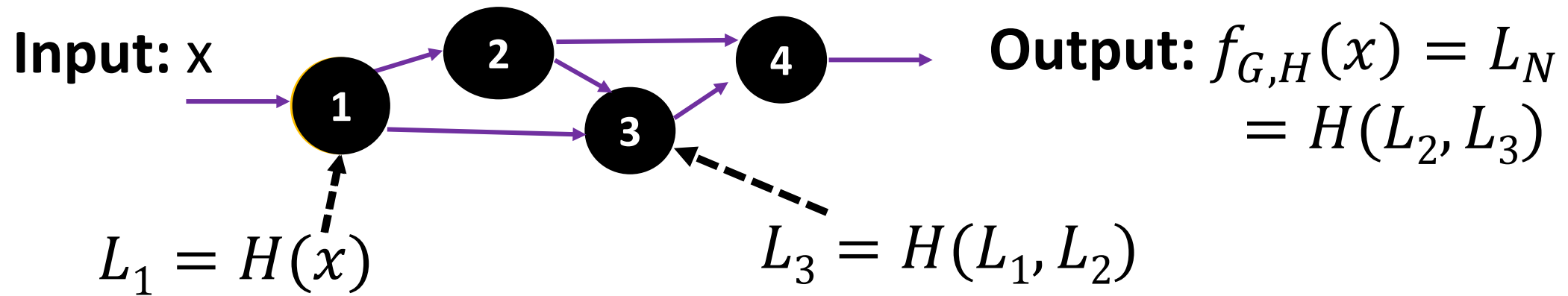
- simulate $\mathcal{A}$ from initial state: σ_i
 - Forward random oracle queries to $H(\cdot)$ (* One Exception Below *)
- For each $v \in P_i$ wait for first query where L_v appears as input and record L_v (by definition of P_i this occurs before L_v appears as output)
- For each $v \in P_i$ wait for first query o_v which produces output L_v
 - Do not forward this query to $H(\cdot)$
 - Simply record the response L_v
 - Technical Note: Extractor can simply run naïve evaluation algorithm for $f_{G,H}(x)$ after simulating $\mathcal{A}$ to ensure that for each $v \in P_i$ there is some round where L_v is output



Extractor:

- Outputs L_v for each $v \in P_i$
- Generate remaining labels L_v for each $v \notin P_i$
 - Can be done querying random oracle at x_v s.t. $H(x_v) = L_v$
- Yields k “fresh” input output pairs (x_v, L_v) for each $v \in P_i$ as long as all labels L_v are distinct

$$\Pr[\exists(u, v). L_v = L_u] \leq n^2 2^{-w}$$



Extractor: Yields $k = |P_i|$ “fresh” input output pairs (x_v, L_v) for each $v \in P_i$ as long as all labels L_v are distinct and pebbling is legal

$$\Pr[\exists(u, v). L_v = L_u] \leq n^2 2^{-w}$$

$$\rightarrow \Pr[\text{Success}] \geq 1 - n^2 2^{-w} - qn 2^{-w}$$

Contradiction! Extractor can succeed with probability at most $2^{-kw/2+o(kw)}$

Reflection: Extractor Argument

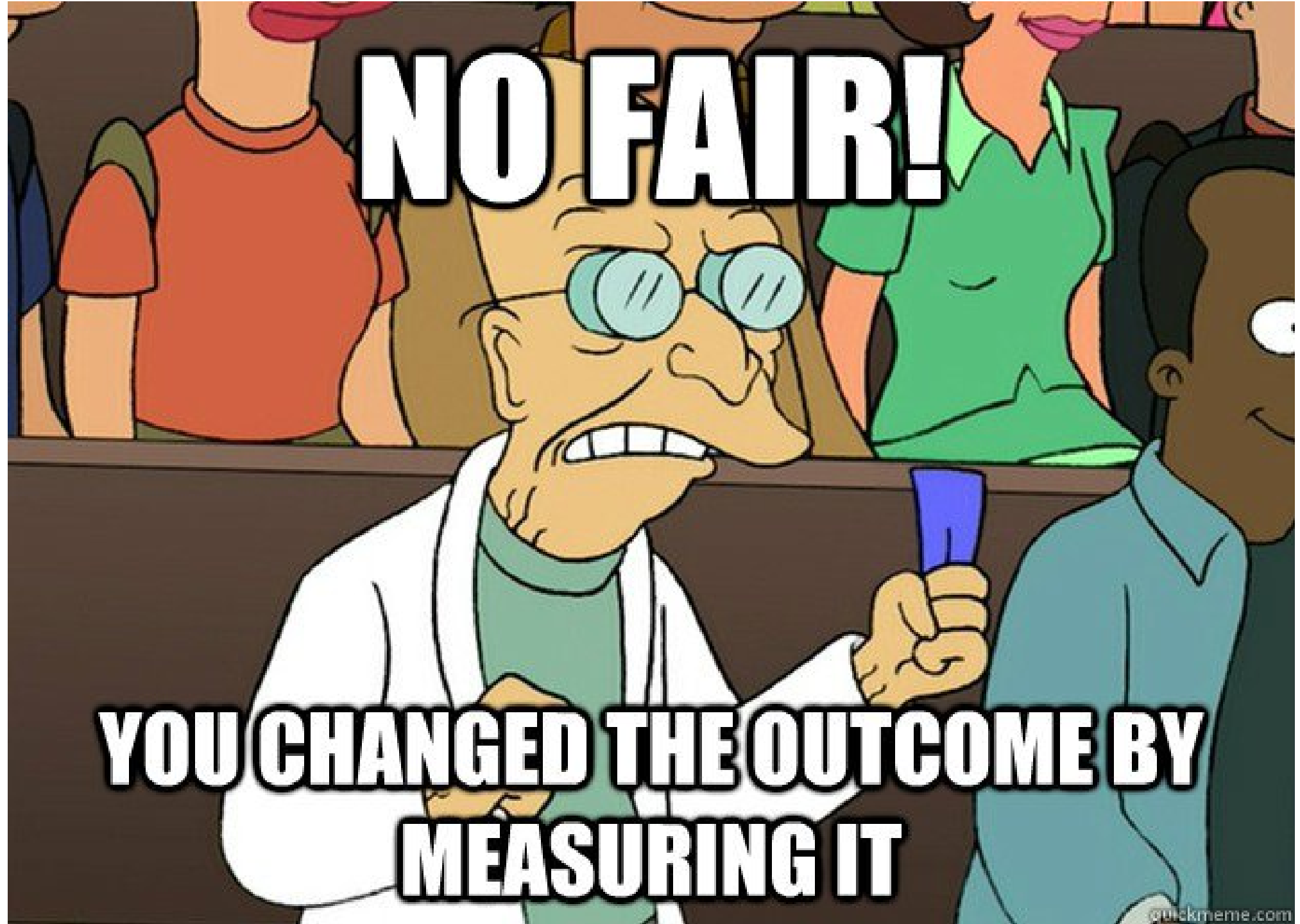
- What properties of the random oracle did we use?
- Simulatability/Delayed Sampling:
 - Can view $H(x)$ as uniformly random string that is yet to be sampled
 - (until x is actually queried)
 - used to analyze the probability that a label L_v appears out of order (also collisions)
- Extractability of Queries:
 - When attacker submits random oracle query the extractor gets to see the query (and the response)

Quantum Random Oracle Model

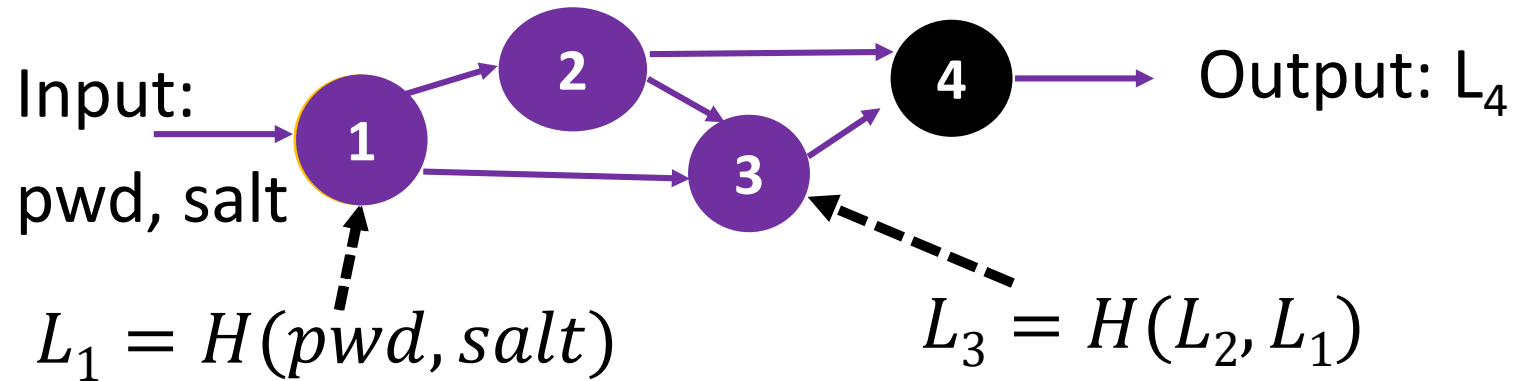
- *Similar to classical random oracle model except that input is an entangled quantum state*

$$\sum_x \alpha_x |x, y\rangle \xrightarrow{H} \sum_x \alpha_x |x, y \oplus H(x)\rangle$$

- Realistic model for any realization of the random oracle e.g., can implement SHA3 as a quantum circuit
- **Challenge:** extractor needs to view random oracle queries



Evaluating an iMHF (pebbling)



Pebbling Rules : $\vec{P} = P_1, \dots, P_t \subset V$ s.t.

- $P_{i+1} \subset P_i \cup \{x \in V \mid \text{parents}(x) \subset P_{i+1}\}$ (need dependent values)
- $n \in P_t$ (must finish and output L_n)

Measuring Pebbling Costs [AS15]

- Cumulative Complexity (CC)

Memory Used at Step i

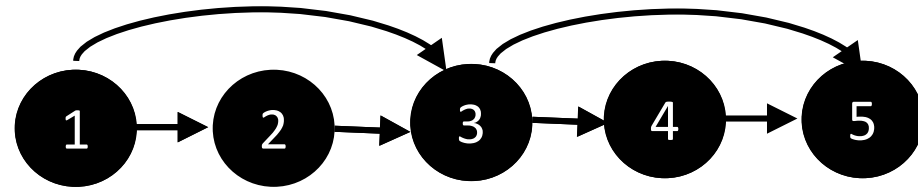
Approximates
Amortized Area x Time
Complexity of iMHF

$$CC(G) = \min_{\vec{P}} \sum_{i=1}^{t_{\vec{P}}} |P_i|$$

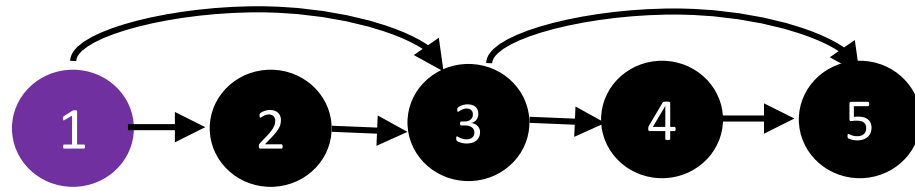
- Guessing two passwords doubles the attackers cost

$$CC(G, G) = 2 \times CC(G)$$

Naïve: Pebbling Strategy

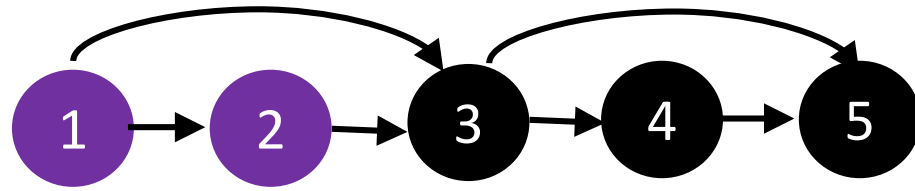


Naïve: Pebbling Strategy



$$P_1 = \{1\}$$

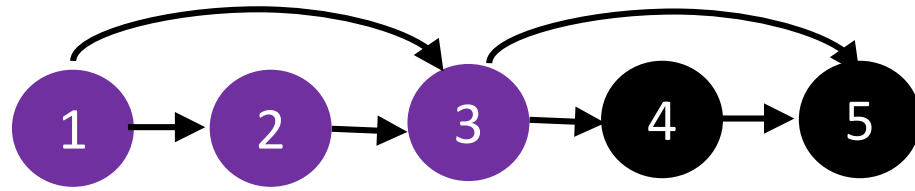
Naïve: Pebbling Strategy



$$P_1 = \{1\}$$

$$P_2 = \{1, 2\}$$

Naïve: Pebbling Strategy

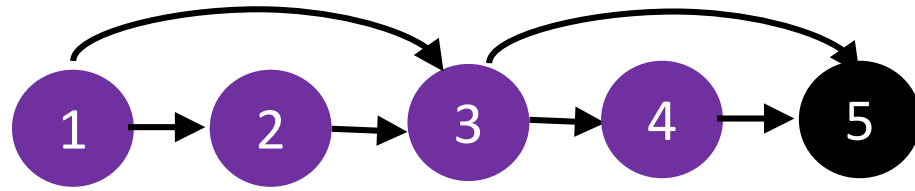


$$P_1 = \{1\}$$

$$P_2 = \{1, 2\}$$

$$P_3 = \{1, 2, 3\}$$

Naïve: Pebbling Strategy



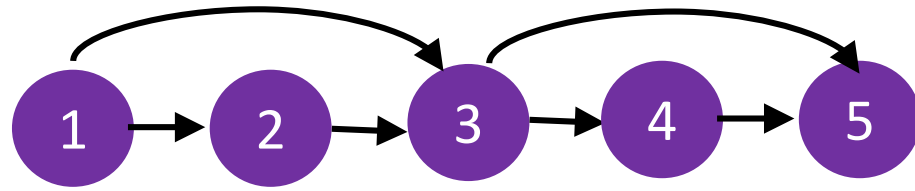
$$P_1 = \{1\}$$

$$P_2 = \{1, 2\}$$

$$P_3 = \{1, 2, 3\}$$

$$P_4 = \{1, 2, 3, 4\}$$

Naïve: Pebbling Strategy



$$P_1 = \{1\}$$

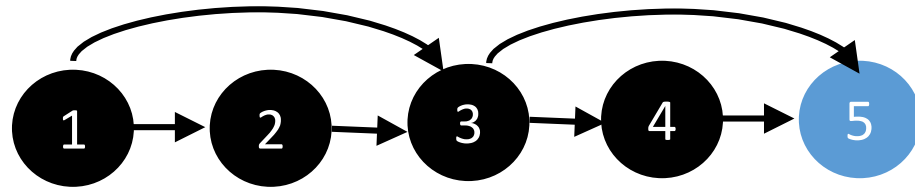
$$P_2 = \{1, 2\}$$

$$P_3 = \{1, 2, 3\}$$

$$P_4 = \{1, 2, 3, 4\}$$

$$P_5 = \{1, 2, 3, 4, 5\}$$

Naïve: Pebbling Strategy (CC)



$$P_1 = \{1\}$$

$$P_2 = \{1, 2\}$$

$$P_3 = \{1, 2, 3\}$$

$$P_4 = \{1, 2, 3, 4\}$$

$$P_5 = \{1, 2, 3, 4, 5\}$$

$$\begin{aligned} \text{CC}(G) &\leq \sum_{i=1}^5 |P_i| \\ &= 1 + 2 + 3 + 4 + 5 \\ &= 15 \end{aligned}$$

Naïve Pebbling Algorithms

- Naïve (Pebble in Topological Order)
 - Never discard pebbles
 - Legal Pebbling Strategy for any DAG!
 - Pebbling Time: n
 - Sequential: Place one new pebble on the graph in each round

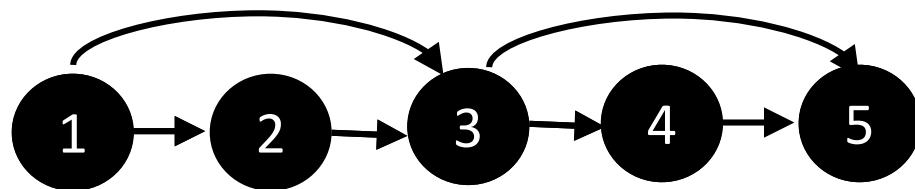


Theorem: *Any DAG G has $CC(G) \leq \sum_{i \leq n} i = \frac{n(n+1)}{2}$*

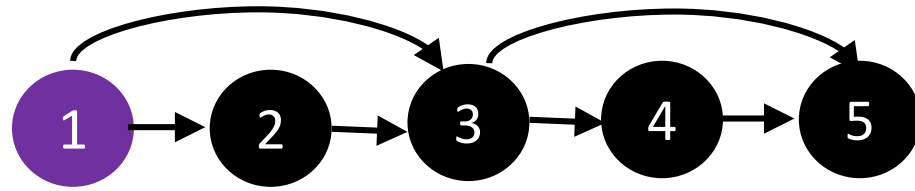
Proof: *Naïve pebbling strategy is legal strategy for any DAG G !*

Question: Can we find a DAG G with $CC(G) = \Omega(n^2)$?

Improved Pebbling

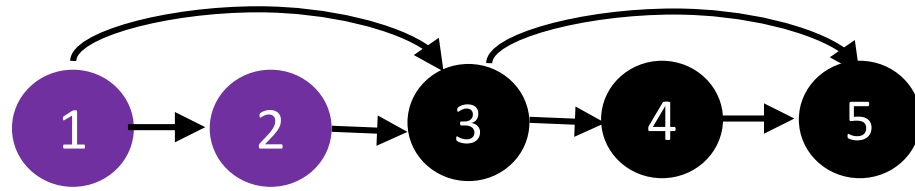


Improved Pebbling



$$P_1 = \{1\}$$

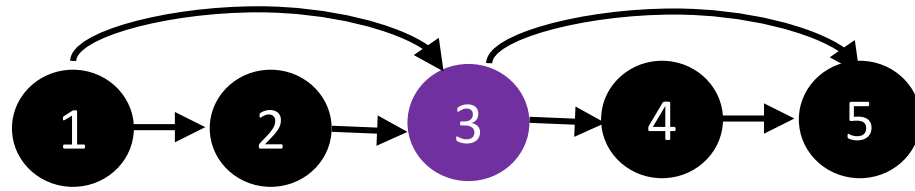
Improved Pebbling



$$P_1 = \{1\}$$

$$P_2 = \{1, 2\}$$

Improved Pebbling

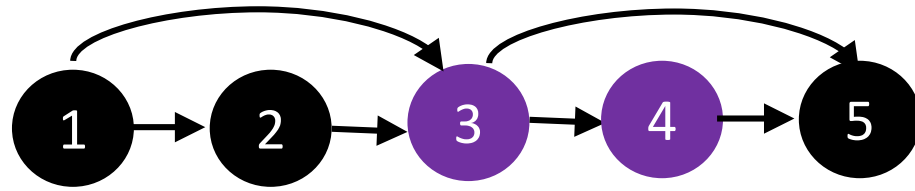


$$P_1 = \{1\}$$

$$P_2 = \{1, 2\}$$

$$P_3 = \{3\}$$

Improved Pebbling



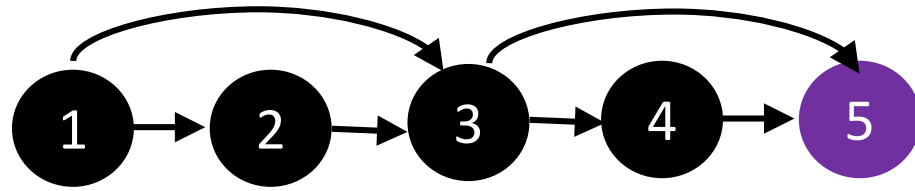
$$P_1 = \{1\}$$

$$P_2 = \{1, 2\}$$

$$P_3 = \{3\}$$

$$P_4 = \{3, 4\}$$

Improved Pebbling



$$P_1 = \{1\}$$

$$P_2 = \{1, 2\}$$

$$P_3 = \{3\}$$

$$P_4 = \{3, 4\}$$

$$P_5 = \{5\}$$

Graphs with High CC

Theorem: *Any DAG G has $CC(G) \leq \sum_{i \leq n} i = \frac{n(n+1)}{2}$*

Proof: *Naïve pebbling strategy is legal strategy for any DAG G !*

Question: Can we find a DAG G with $CC(G) = \Omega(n^2)$?

Claim: The complete DAG has $CC(G) \geq \sum_{i \leq n-1} i = \frac{n(n-1)}{2} = \Omega(n^2)$?

Proof: Consider the round immediately before we first place a pebble on node $i+1$. We must have had pebbles on all of the nodes $\{1, \dots, i\}$.

Question: Can we find a DAG G with $CC(G) = \Omega(n^2)$ and low indegree?

Why do we care about indegree?

In practice the random oracle is instantiated with a function $H: \{0, 1\}^{2\lambda} \rightarrow \{0, 1\}^\lambda$
Label of node v is obtained by hashing labels of v 's parents.

Node v has two parents (u and w) $\Rightarrow L_v = H(L_u, L_w) \Rightarrow$ One oracle to H used to compute label

Node v has three parents (u, w, x) $\Rightarrow L_v = H(H(L_u, L_w), L_x) \Rightarrow$ Two oracle queries to H to compute label

Node v has four parents (u, w, x, y) $\Rightarrow L_v = H(H(H(L_u, L_w), L_x), L_y) \Rightarrow$ Three oracle queries to H to compute label

Node v has k parents $\Rightarrow k-1$ oracle queries to H to compute label

Running time to evaluate $f_{G,H}$ is proportional to $n \times \text{indeg}(G)$

Desiderata

Find a DAG G on n nodes such that

1. Constant Indegree ($\delta = 2$)
 - Running Time: $n(\delta - 1) = n$
2. $CC(G) \geq \frac{n^2}{\tau}$ for some small value τ .



Maximize costs for fixed running time n
(Users are impatient)

Outline

- Motivation
- Data Independent Memory Hard Functions (iMHFs)
- **Our Attacks**
 - General Attack on Non Depth Robust DAGs
 - Existing iMHFs are not Depth Robust
 - Ideal iMHFs don't exist
- Subsequent Results (Depth-Robustness is Sufficient)
- Open Questions

Depth-Robustness: A Necessary Property

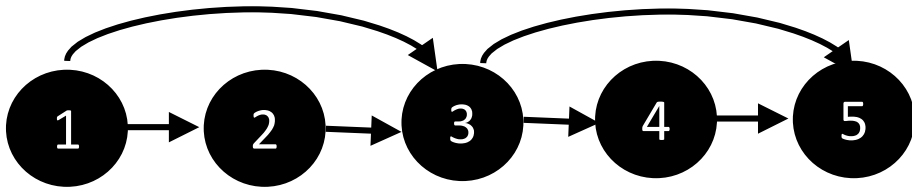


Depth Robustness

Definition: A DAG $G=(V,E)$ is (e,d) -reducible if there exists $S \subseteq V$ s.t. $|S| \leq e$ and $\text{depth}(G-S) \leq d$.

Otherwise, we say that G is (e,d) -depth robust.

Example: (1,2)-reducible

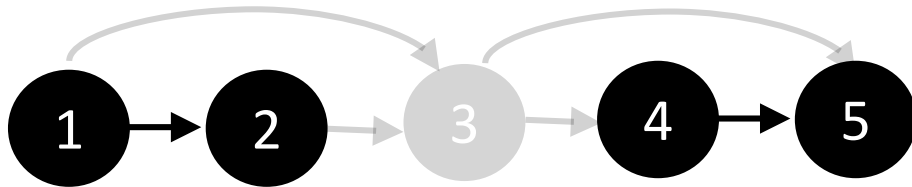


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Otherwise, we say that G is (e,d) -depth robust.

Example: (1,2)-reducible



Attacking (e,d)-reducible DAGs

- Input: $|S| \leq e$ such that $\text{depth}(G-S) = d$, $g > d$
- **Light Phase (g rounds):** Discard most pebbles!
 - Goal: Pebble the next g nodes in g (sequential) steps
 - Low Memory (only keep pebbles on S and on parents of new nodes)
 - Lasts a ``long'' time
- **Balloon Phase (d rounds):** Greedily Recover Missing Pebbles
 - Goal: Recover needed pebbles for upcoming light phase
 - Expensive, but quick (at most d steps in parallel).

Attacking (e,d)-reducible DAGs

Algorithm 1: GenPeb (G, S, g, d)

Arguments: $G = (V, E)$, $S \subseteq V$, $g \in [\text{depth}(G - S), n]$, $d \geq \text{depth}(G - S)$

```
1 for  $i = 1$  to  $n$  do
2   Pebble node  $i$ .
3    $l \leftarrow \lfloor i/g \rfloor * g + d + 1$ 
4   if  $i \bmod g \in [d]$  then                                     // Balloon Phase
5      $d' \leftarrow d - (i \bmod g) + 1$ 
6      $N \leftarrow \text{need}(l, l + g, d')$ 
7     Pebble every  $v \in N$  which has all parents pebbled.
8     Remove pebble from any  $v \notin K$  where  $K \leftarrow S \cup \text{keep}(i, i + g) \cup \{n\}$ .
9   else                                                         // Light Phase
10     $K \leftarrow S \cup \text{parents}(i, i + g) \cup \{n\}$ 
11    Remove pebbles from all  $v \notin K$ .
12  end
13 end
```

Main Theorem

Theorem (Depth-Robustness is a necessary condition): If G is (e,d) -reducible then there is an (efficient) attack A such that

$$E_R(A) \leq en + \delta gn + \frac{n}{g}nd + nR + \frac{n}{g}nR.$$

Main Theorem

Theorem (Depth-Robustness is a necessary condition): If G is (e,d) -reducible then there is an (efficient) attack A such that

$$E_R(A) \leq en + \delta gn + \frac{n}{g}nd + nR + \frac{n}{g}nR.$$

Upper bounds pebbles
on nodes $x \in S$, where

$$|S| = e$$
$$\text{depth}(G-S) \leq d$$

#pebbling rounds

Main Theorem

Theorem (Depth-Robustness is a necessary condition): If G is (e,d) -reducible then there is an (efficient) attack A such that

$$E_R(A) \leq en + \delta gn + \frac{n}{g}nd + nR + \frac{n}{g}nR.$$

Maintain pebbles on parents of next g nodes to be pebbled.

#pebbling rounds

Main Theorem

Theorem (Depth-Robustness is a necessary condition): If G is not (e,d) -node robust then is an (efficient) attack A such that

$$E_R(A) \leq en + \delta gn + \frac{n}{g}nd + nR + \frac{n}{g}nR.$$

#balloon phases

Length of a balloon phase

Max #pebbles on G
In each round of balloon phase

Main Theorem

Theorem (Depth-Robustness is a necessary condition): If G is not (e,d) -node robust then there is an (efficient) attack A such that

$$E_R(A) \leq en + \delta gn + \frac{n}{g}nd + nR + \frac{n}{g}nR.$$

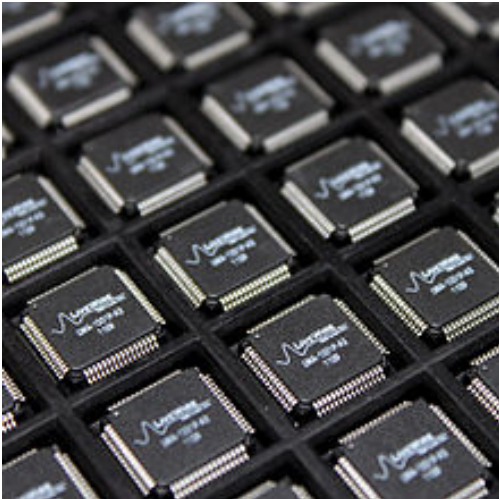
$$\text{Set } g = \sqrt{nd}$$

$$E_R(A) = O(en + \sqrt{n^3d}).$$

In particular, $E_R(A) = o(n^2)$ for $e,d=o(n)$.

Question

Are existing iMHF candidates based on depth-robust DAGs?



iMHF Candidates

- Catena [FLW15]
 - Special Recognition at Password Hashing Competition
 - Two Variants: Dragonfly and Double-Butterfly
 - Security proofs in sequential space-time model
- Balloon Hashing [CBS16]
 - Newer proposal (three variants in original proposal)
- Argon2 [BDK15]
 - Winner of the Password Hashing Competition
 - Argon2i (data-independent mode) is recommended for Password Hashing
- This Talk: Focus on Argon2i-A (version from Password Hashing Competition)
 - Attack ideas do extend to Argon2i-B (latest version)



Attack Outline

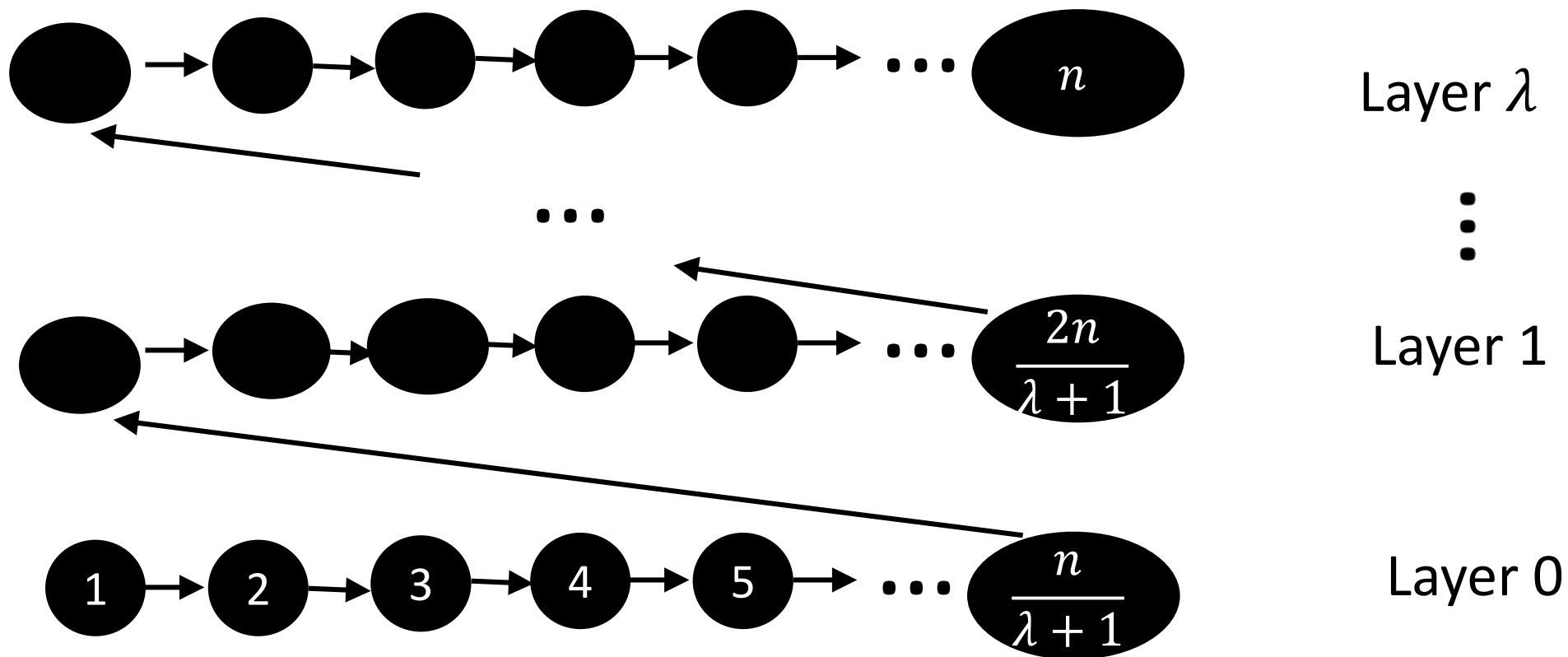
- Show that any “layered DAG” is reducible
 - Note: Catena DAGs are layered DAGs
- Show that an Argon2i DAG is *almost* a “layered DAG.”
 - Turn Argon2i into layered DAG by deleting a few nodes
 - Hence, an Argon2i DAG is also reducible.

Catena

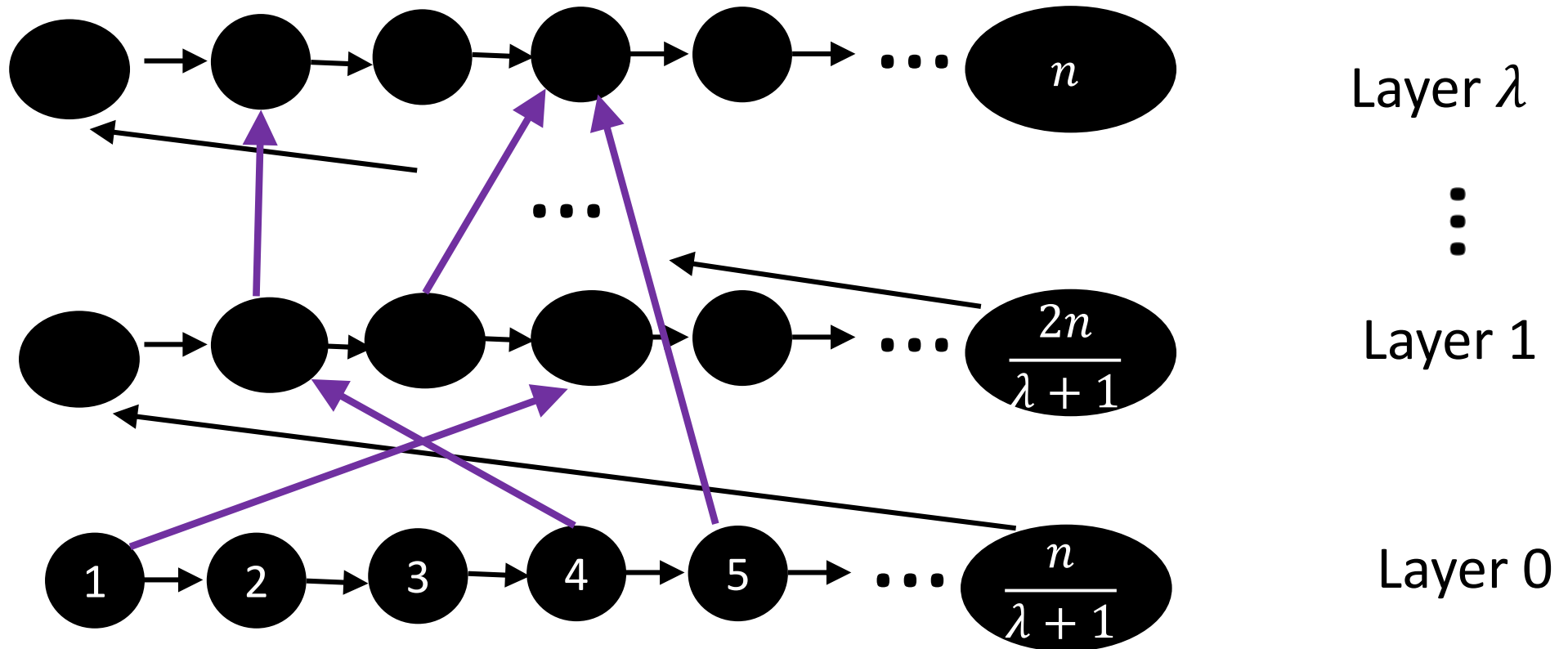


- Catena Bit Reversal DAG (BRG_{λ}^n)
 - λ -layers of nodes ($\lambda \leq 5$)
 - Edges between layers correspond to the bit-reversal operation
 - **Theorem[LT82]:** $\text{sST}(\text{BRG}_1^n) = \Omega(n^2)$
- Catena Butterfly (DBG_{λ}^n)
 - $\lambda = O(\log n)$ -layers of nodes
 - Edges between layers correspond to FFT
 - DBG_{λ}^n is a “super-concentrator.”
 - **Theorem[LT82]** $\Rightarrow \text{sST}(\text{BRG}_1^n) = \Omega\left(\frac{n^2}{\log(n)}\right)$

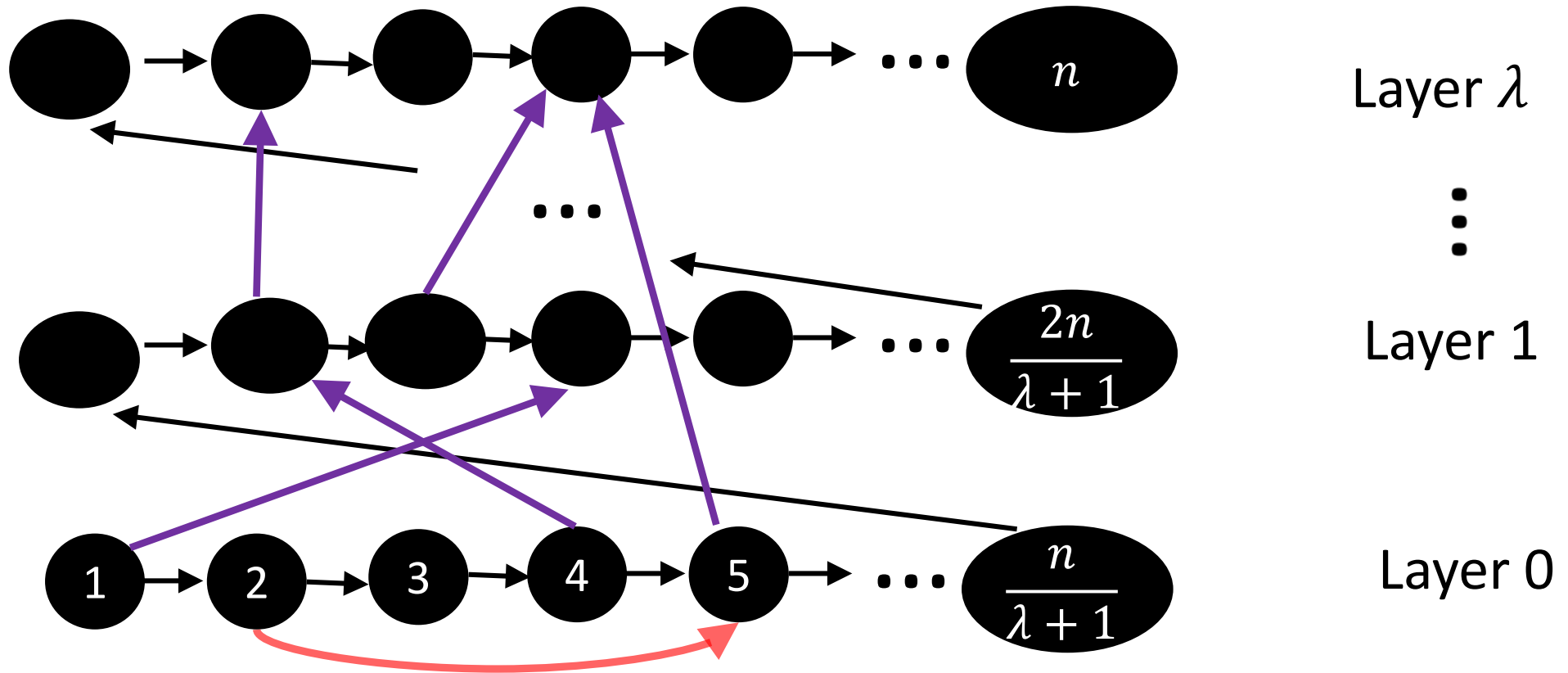
λ -Layered DAG (Catena)



λ -Layered DAG (Catena)



λ -Layered DAG (Catena)

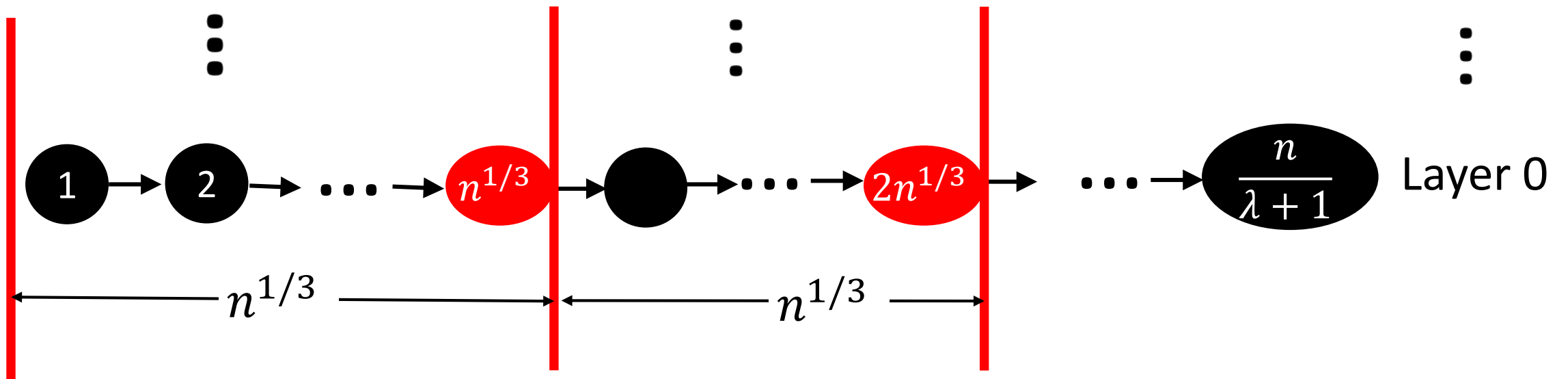


Disallowed! All edges must go to a higher layer (except for $(i, i+1)$)

Layered Graphs are Reducible

Theorem (Layered Graphs Not Depth Robust): Let G be a λ -Layered DAG then G is $\left(n^{2/3}, n^{1/3}(\lambda + 1)\right)$ -reducible.

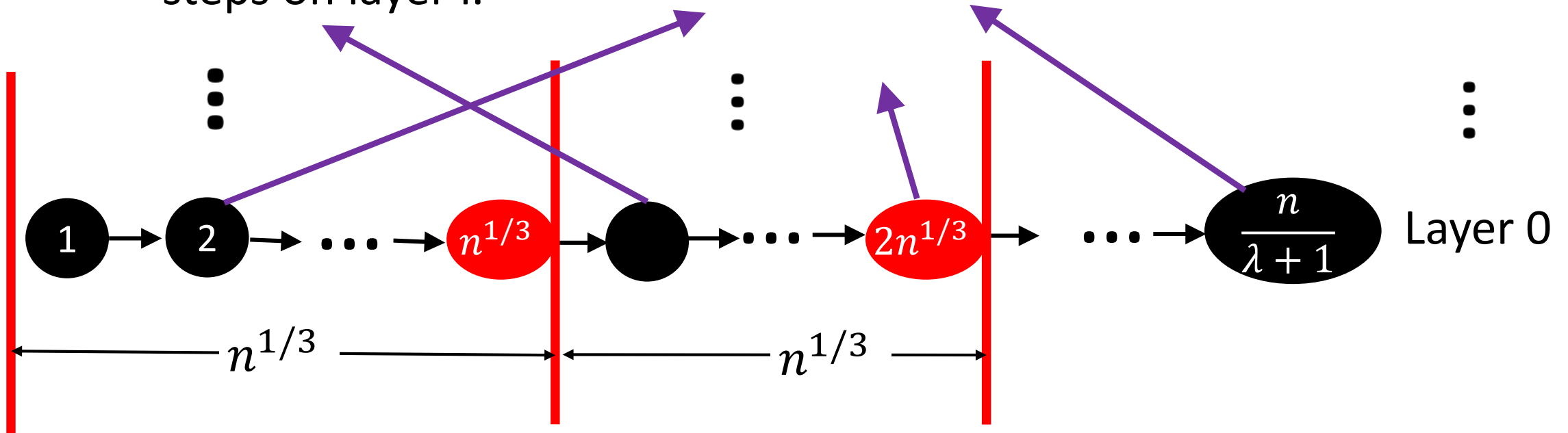
Proof: Let $\mathbf{S} = \{i \times n^{1/3} \mid i \leq n^{2/3}\}$ any path p can spend at most $n^{1/3}$ steps on layer i .



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Corollary: $E_R(G) \leq O(\lambda n^{5/3})$.

Attack Quality: $\text{Quality}_R(A) = \Omega\left(\frac{n^{1/3}}{\lambda}\right)$.

Previous Attacks on Catena

- [AS15] $CC(BRG_1^n) \leq O(n^{1.5})$
 - Gap between cumulative cost $O(n^{1.5})$ and sequential space-time cost $\Omega(n^2)$
- [BK15] $ST(BRG_\lambda^n) \leq O(n^{1.8})$ for $\lambda > 1$.
- Our result $CC(BRG_\lambda^n) \leq O(n^{1.67})$ *

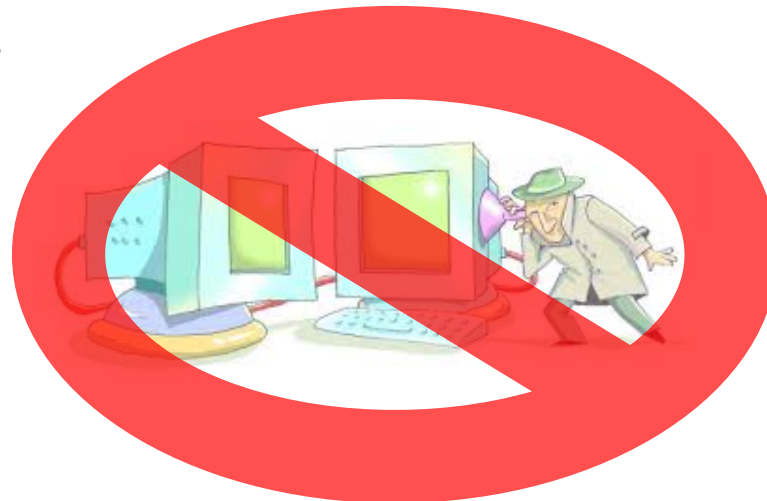
* Applies to all Catena variants.

Argon2i [BDK]

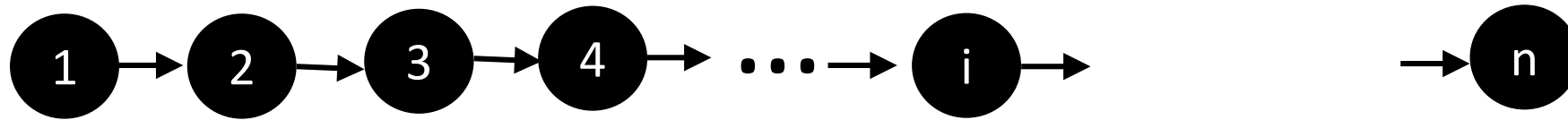
- Argon2: Winner of the password hashing competition[2015]



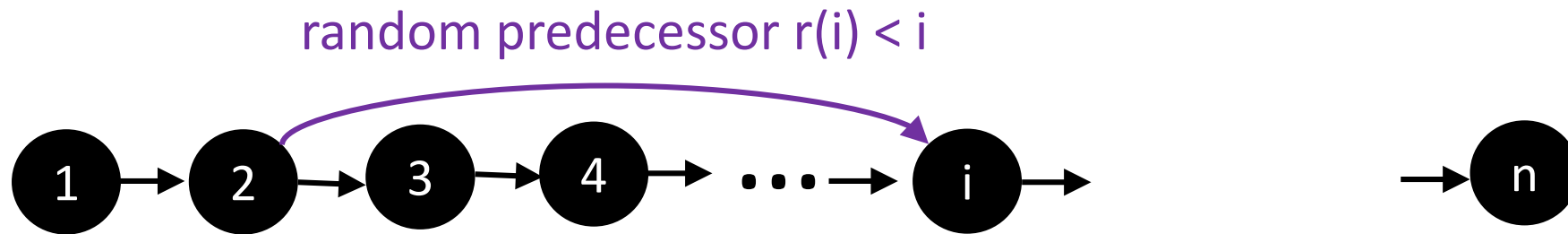
- Authors recommend Argon2i variant (data-independent) for password hashing.



Argon2i

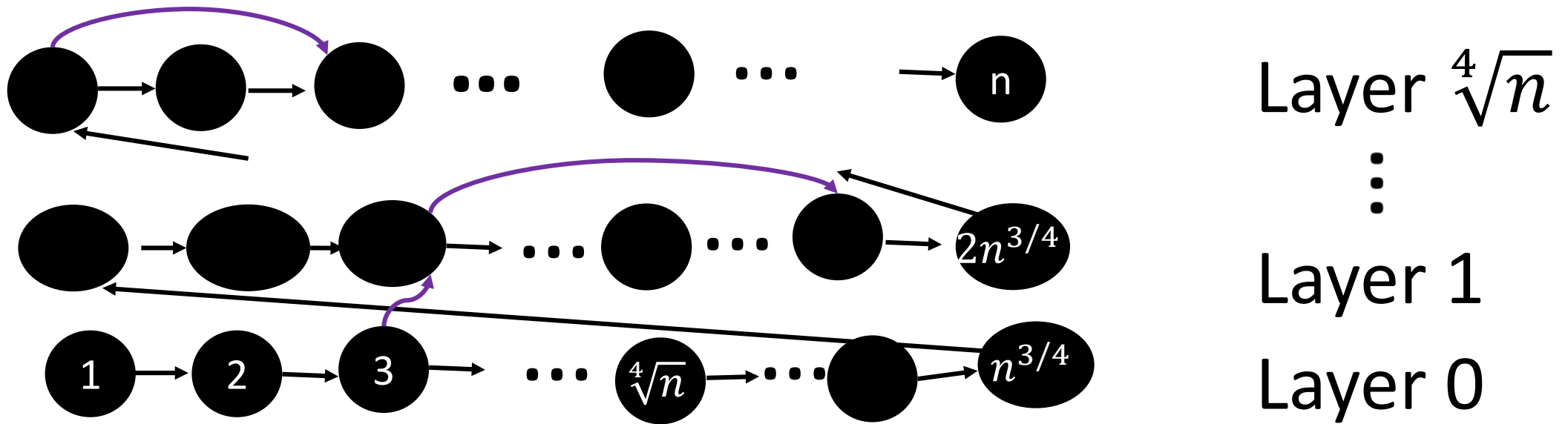


Argon2i



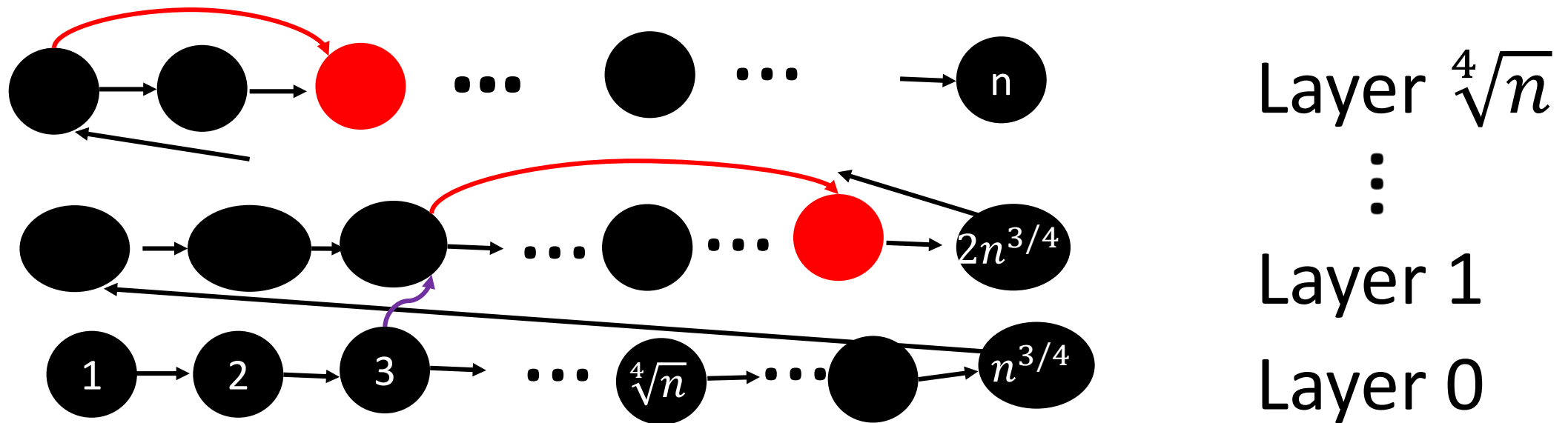
Indegree: $\delta = 2$

Argon2i is a layered DAG (almost)



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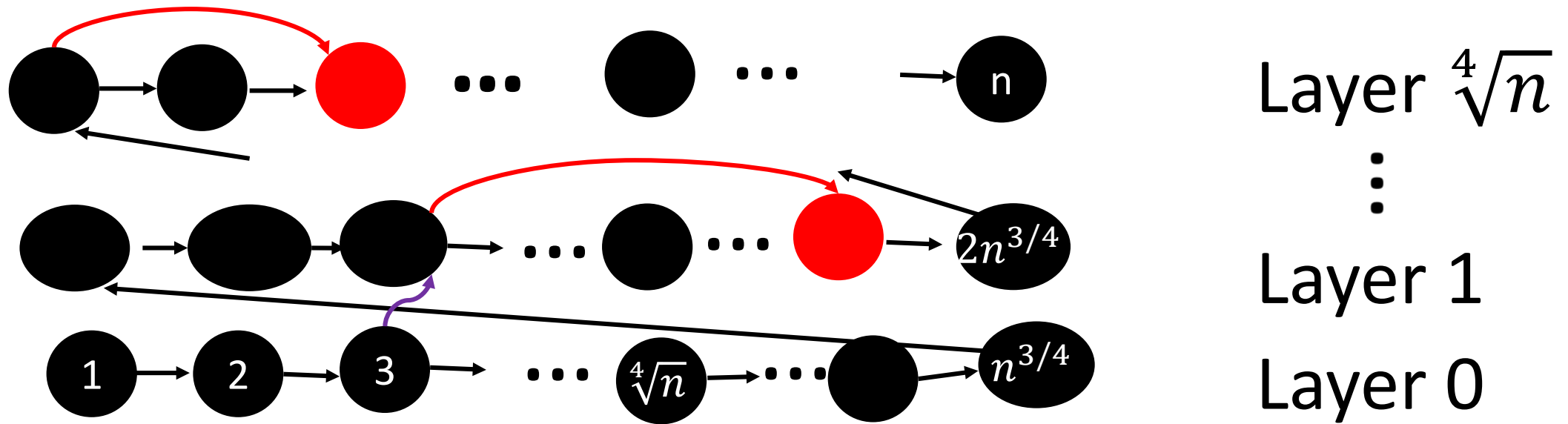
Definition: $S_2 = \{v_i \mid v_{r(i)} \text{ and } v_i \text{ in same layer}\}$



Claim: $E[S_2] = O(n^{3/4} \log n)$

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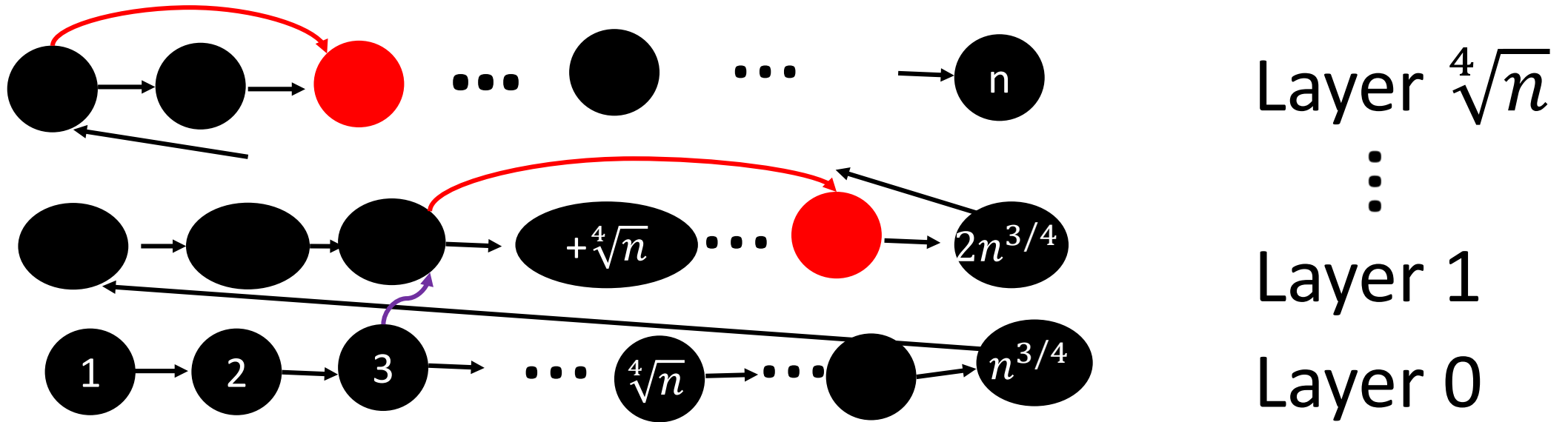


$$\Pr[v \in S_2 \mid v \text{ in Layer } i] \leq \frac{1}{i}$$

$$E[\text{Layer } i \cap S_2] \leq \frac{n^{3/4}}{i}$$

Argon2i is a layered DAG (almost)

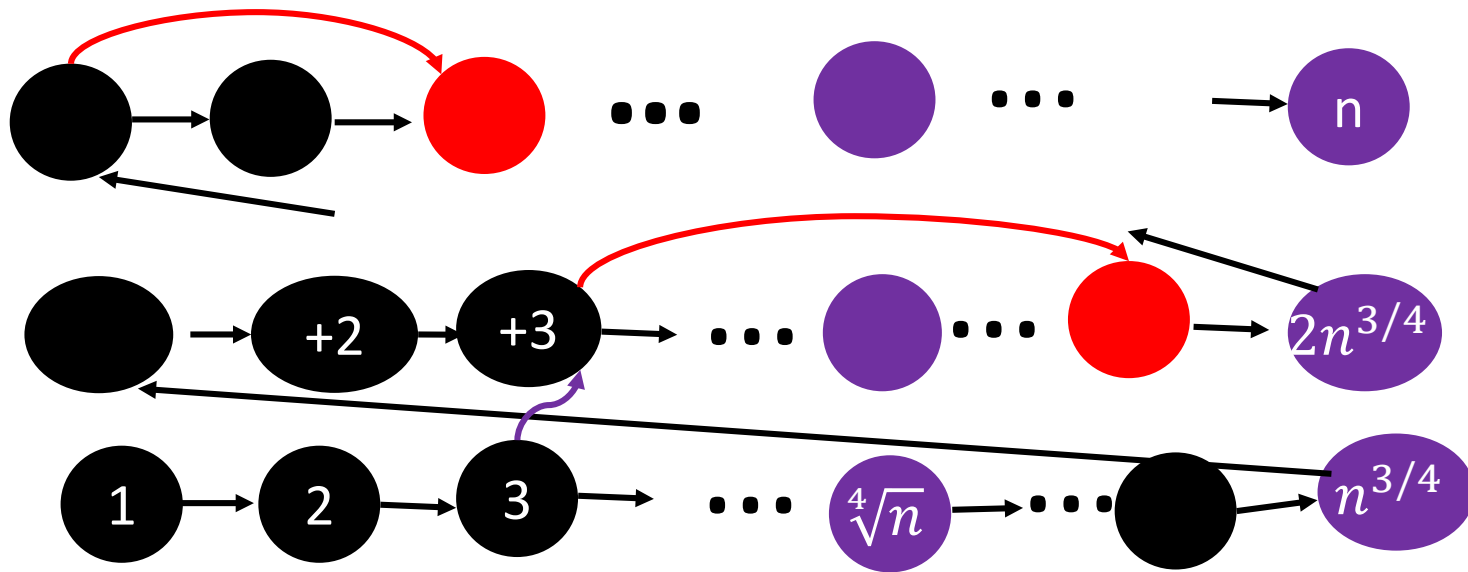
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Argon2i is a layered DAG (almost)

Let $S = S_1 + S_2$

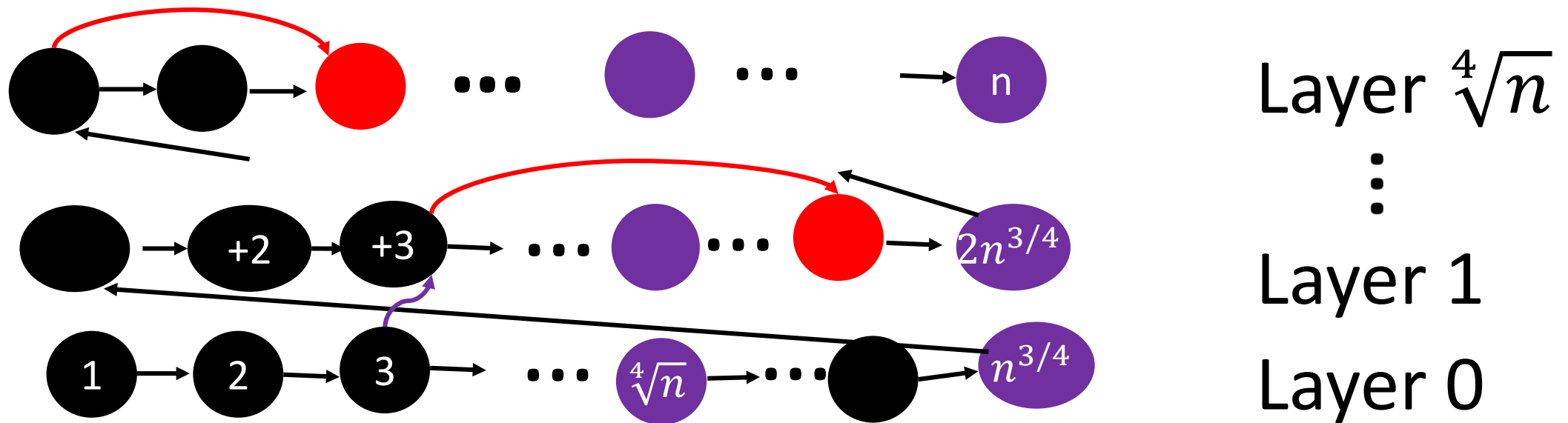


Layer $\sqrt[4]{n}$
 $\vdots$
 Layer 1
 Layer 0

Fact: $E[S] = O(n^{3/4} \log n)$ and $\text{depth}(G-S) \leq \sqrt{n}$.

Argon2i is a layered DAG (almost)

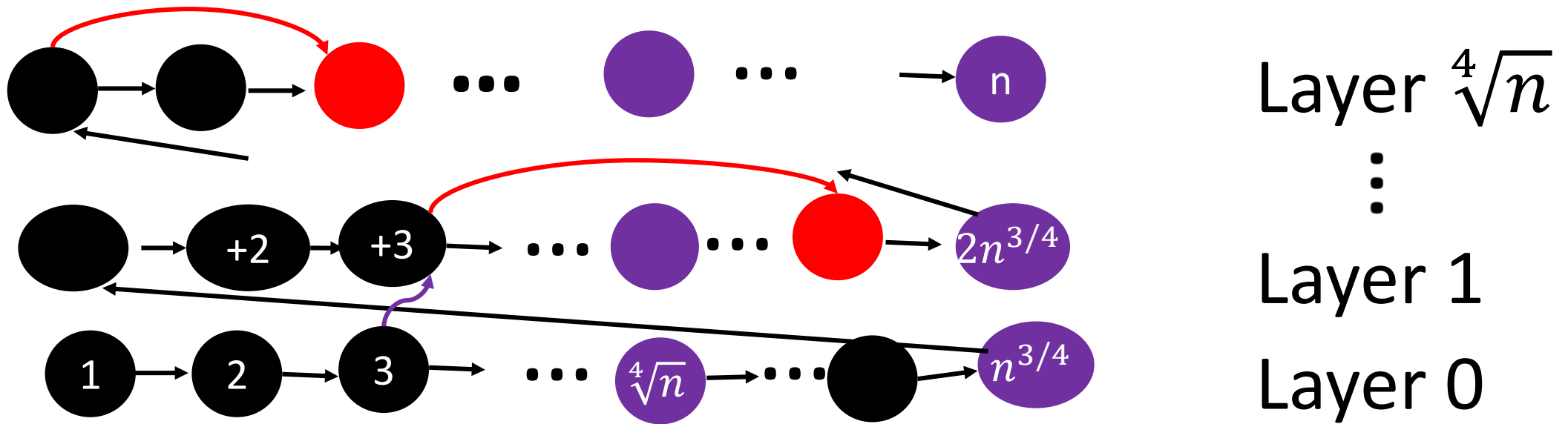
Let $S = S_1 + S_2$



Theorem: G is $(2n^{3/4} \log n, \sqrt{n})$ -reducible with high probability.

Argon2i is a layered DAG (almost)

Let $S = S_1 + S_2$



Corollary: $ER(G) \leq O(n^{7/4} \log n)$.

$Quality_R(A) \leq \Omega\left(\frac{n^{1/4}}{\log n}\right)$.

Ideal iMHFs Don't Exist



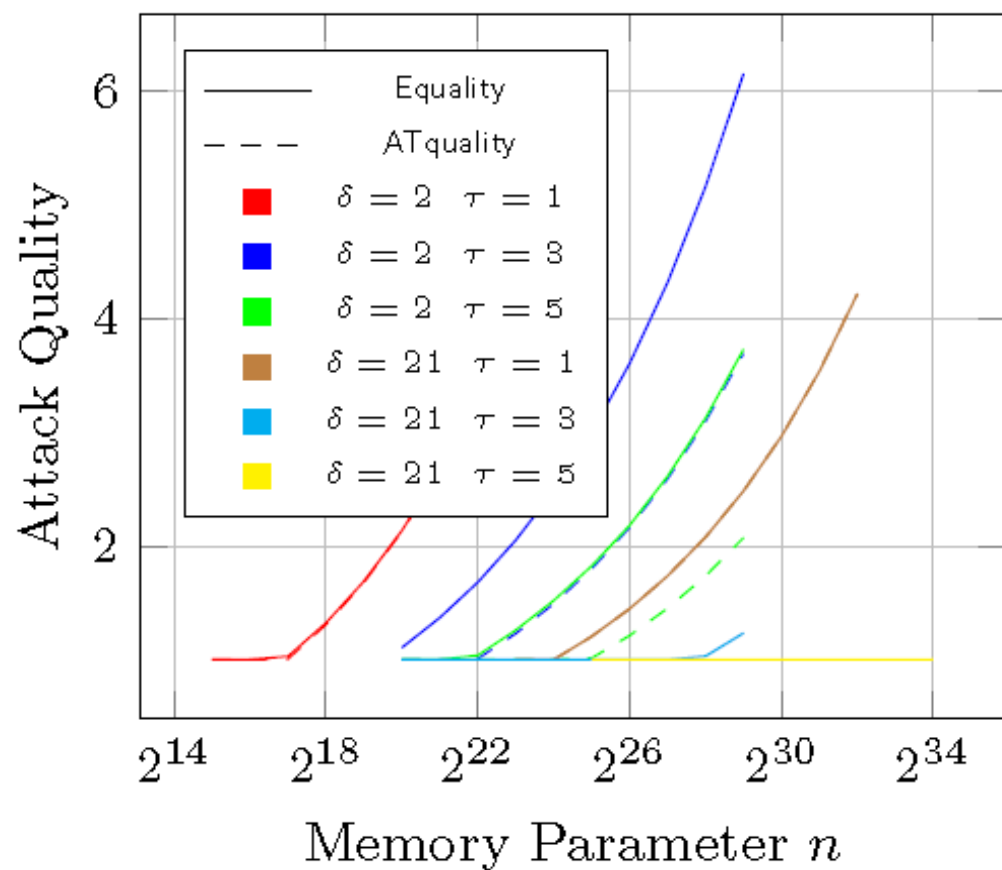
- **Thm:** If G has n nodes and constant in-degree $\delta=O(1)$ then G is :

$$\left(O\left(\frac{n \log \log n}{\log(n)}\right), \frac{n}{\log^2 n} \right)\text{-reducible.}$$

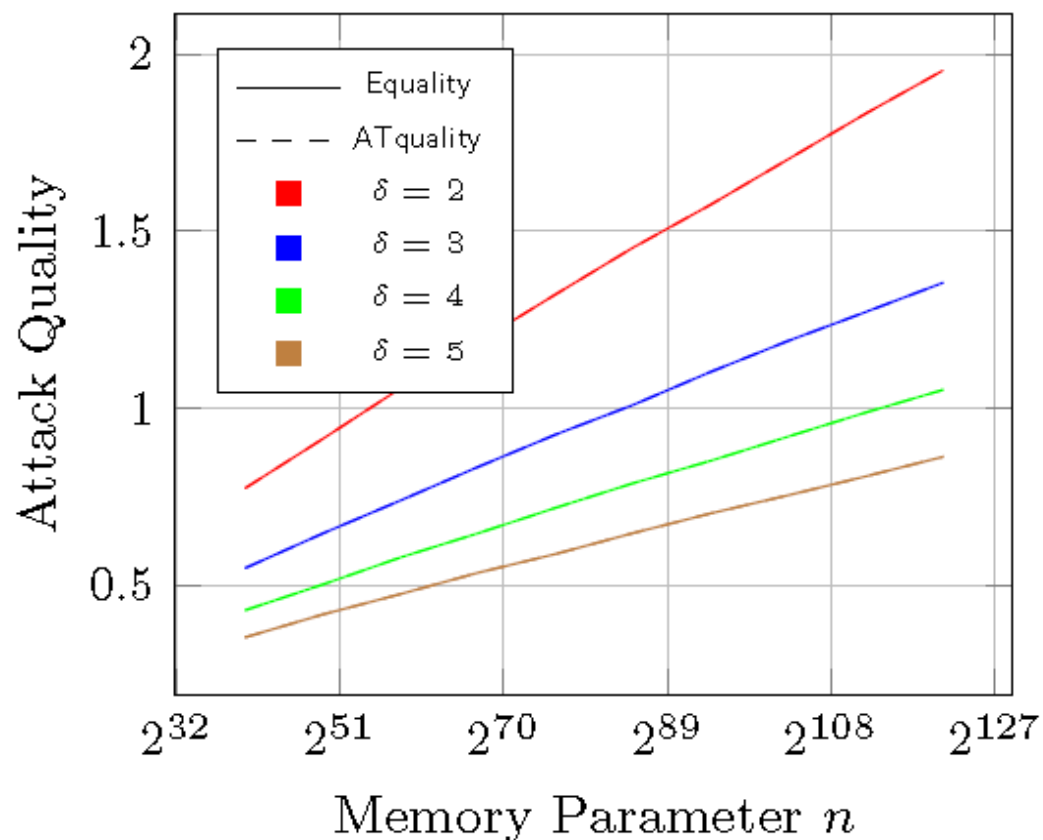
- **Thm:** If G has n nodes and constant in-degree then:

$$\forall \varepsilon > 0 \quad E_R(G) = o\left(\frac{n^2}{\log(n)^{1-\varepsilon}} + nR\right)$$

Practical Consequences ($R = 3,000$)



(a) Argon2i and SB



(b) Ideal iMHF

THEORY vs PRACTICE



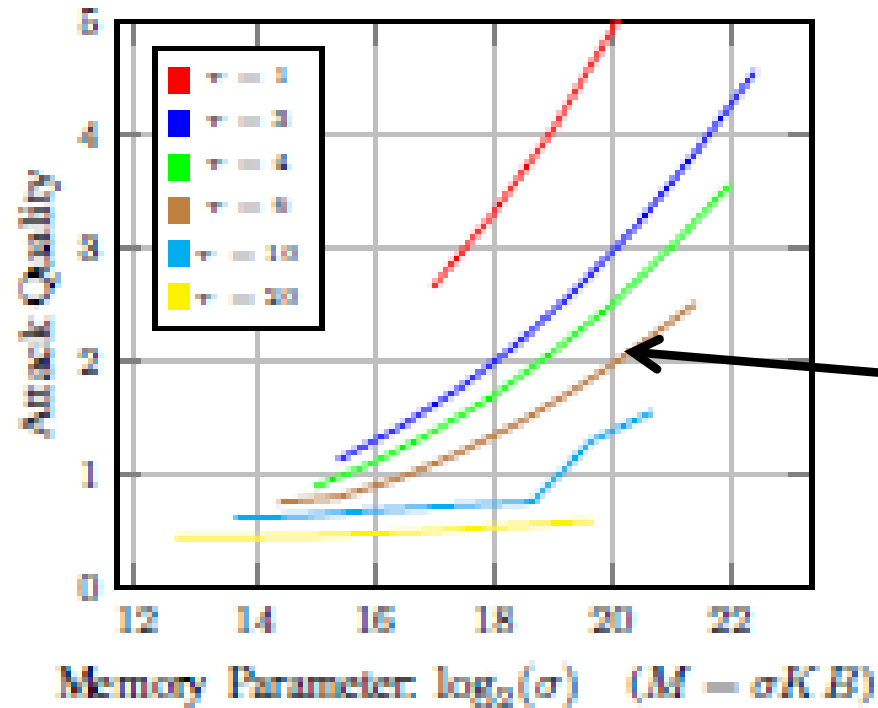
Drama: Are the attacks 'Practical'

- Argon2i team: No, at least for realistic attacks.
- Recent: Argon2i-B submitted to IRTF (Internet Research Task Force) for standardization.
- New Result [AB16b]:
 - New heuristics to reduce overhead by constant factor
 - Simulate the attack on real instances



New Simulation Results :

[AB16b]



Parameter setting could easily be chosen when following Argon2i-B guidelines

Pessimistic Argon 2i-B parameter

Figure 1: Argon2i-B Attack Quality

Attack on Argon 2i-B is practical even for pessimistic parameter ranges (brown line).

Outline

- Motivation
- Data Independent Memory Hard Functions (iMHFs)
- Attacks
- **Constructing iMHFs (New!)**
 - **Depth-Robustness is *sufficient***
- Conclusions and Open Questions

Depth-Robustness is Sufficient! [ABP16]

Key Theorem: Let $G=(V,E)$ be (e,d) -depth robust then $CC(G) \geq ed$.

Implications: There exists a constant indegree graph G with

$$CC(G) \geq \Omega\left(\frac{n^2}{\log n}\right).$$

Previous Best [AS15]: $\Omega\left(\frac{n^2}{\log^{10} n}\right)$

[AB16]: For all constant indegree graphs $CC(G) = O\left(\frac{n^2 \log \log n}{\log n}\right)$.

Depth-Robustness is Sufficient! [ABP16]

Proof: Let $P_1, \dots, P_t$ denote an (optimal) pebbling of G . For $0 < i < d$ define

$$S_i = P_i \cup P_{d+i} \cup P_{2d+i} \cup \dots$$

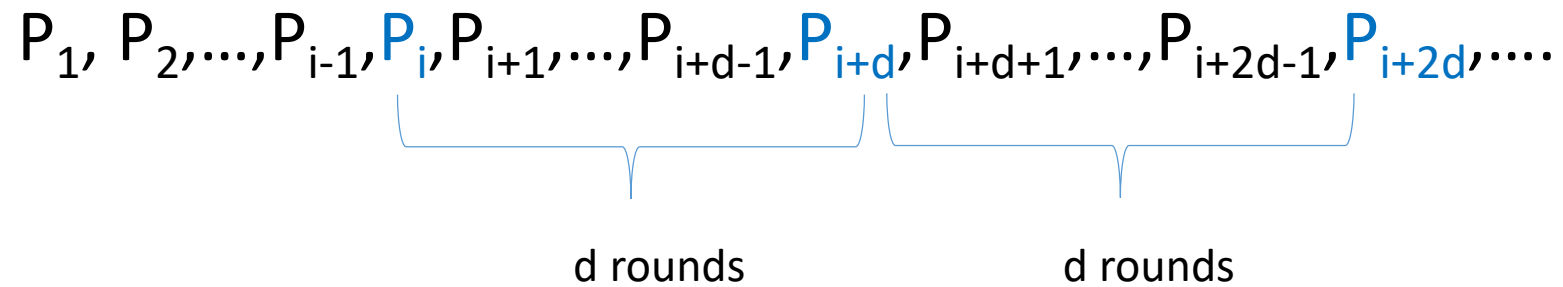
one of the sets S_i has size at most $CC(G)/d$. Now we claim that

$$d \geq \text{depth}(G - S_i)$$

because any path in $G - S_i$ must have been completely pebbled at some point. Thus, it must have been pebbled entirely during some interval of length d . Thus, G is $(CC(G)/d, d)$ -reducible. It follows that $CC(G) \geq ed$.

Proof by Picture

$$S_i = P_i \cup P_{d+i} \cup P_{2d+i} \cup \dots$$



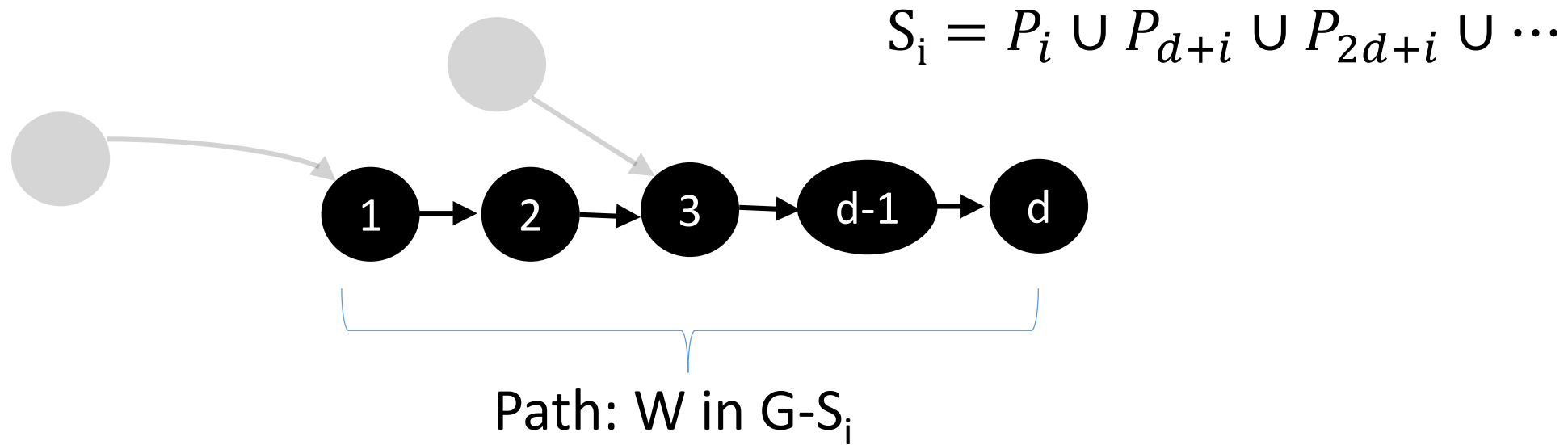
Claim: $|S_i| \geq e$

Implication

Claim: $|S_i| \geq e$

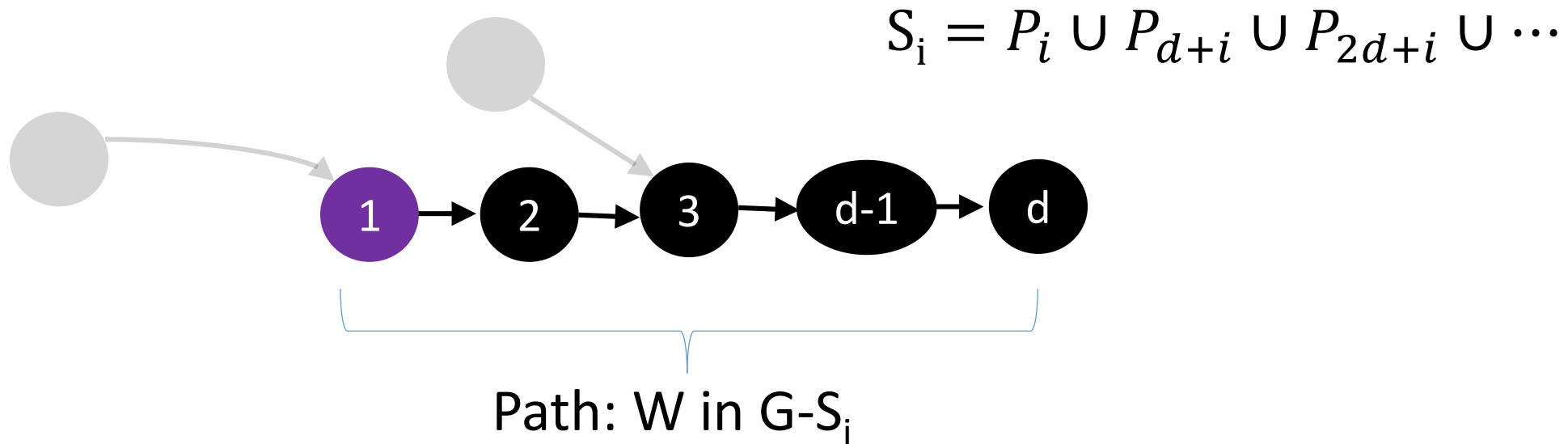
$$CC(G) \geq \sum_t |P_t| \geq \sum_{i=1}^d |S_i| \geq \sum_{i=1}^d e \geq ed$$

Contradiction by Picture



Step i: W contains no pebbles since $P_i \subset S_i$

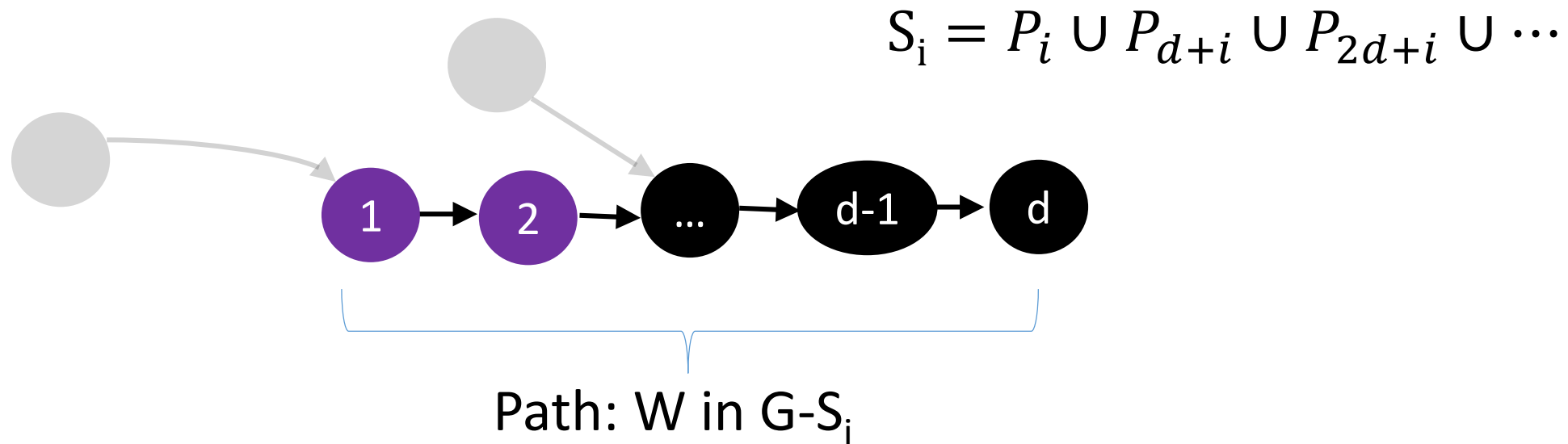
Contradiction by Picture



Step i : W contains no pebbles since $P_i \subset S_i$

Step $i+1$: $W-\{1\}$ contains no pebbles

Contradiction by Picture

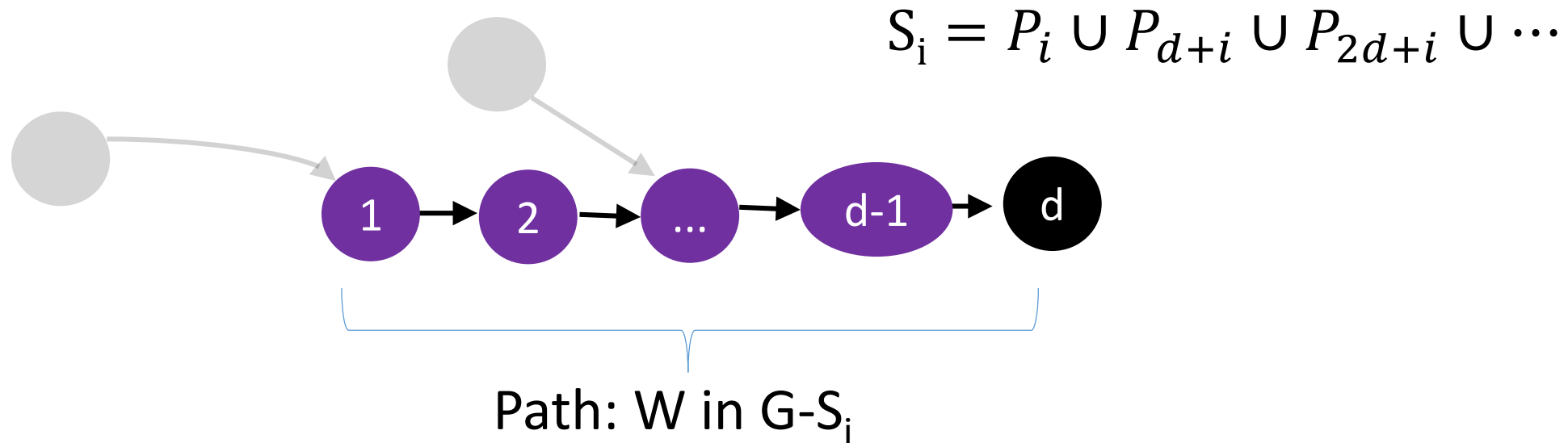


Step i : W contains no pebbles since $P_i \subset S_i$

Step $i+1$: $W-\{1\}$ contains no pebbles

Step $i+2$: $W-\{1,2\}$ contains no pebbles

Contradiction by Picture



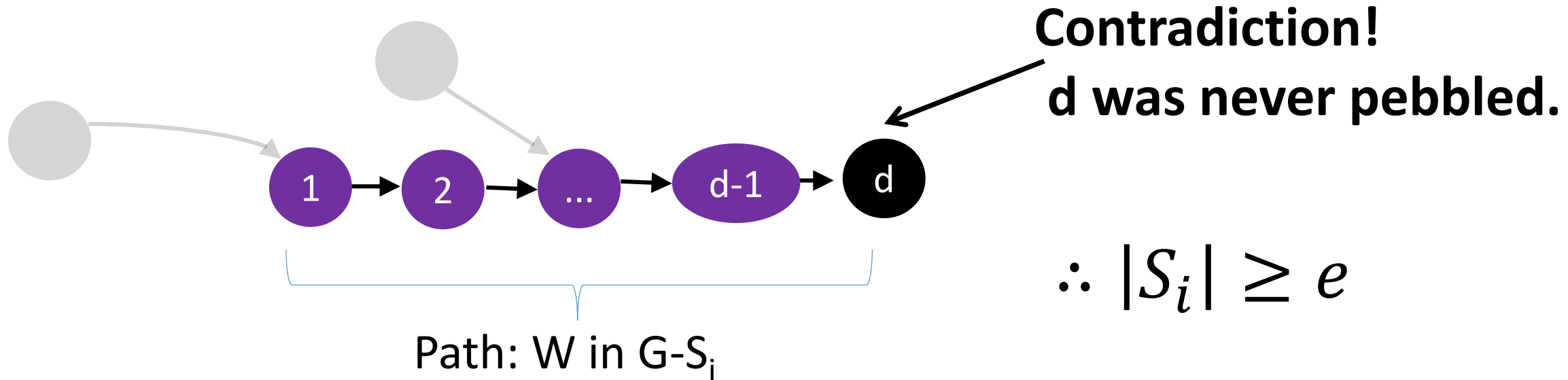
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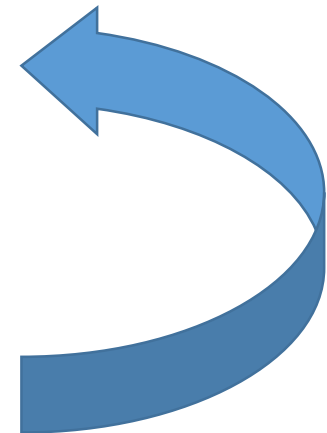
Step $i+d-1$: $W-\{1,\dots,d-1\}$ contains no pebbles

Contradiction by Picture



Step $i+d$: W contains no pebbles since $P_{i+d} \subset S_i$

Step $i+d-1$: $W-\{1, \dots, d-1\}$ contains no pebbles



Positive Result: Consequences

Theorem [ABP16]: Let $G=(V,E)$ be (e,d) -depth robust then $E_R(G) \geq ed$.

Theorem[EGS75]: There is an $(\Omega(n), \Omega(n))$ -depth robust DAG G with indegree $\delta = O(\log n)$.

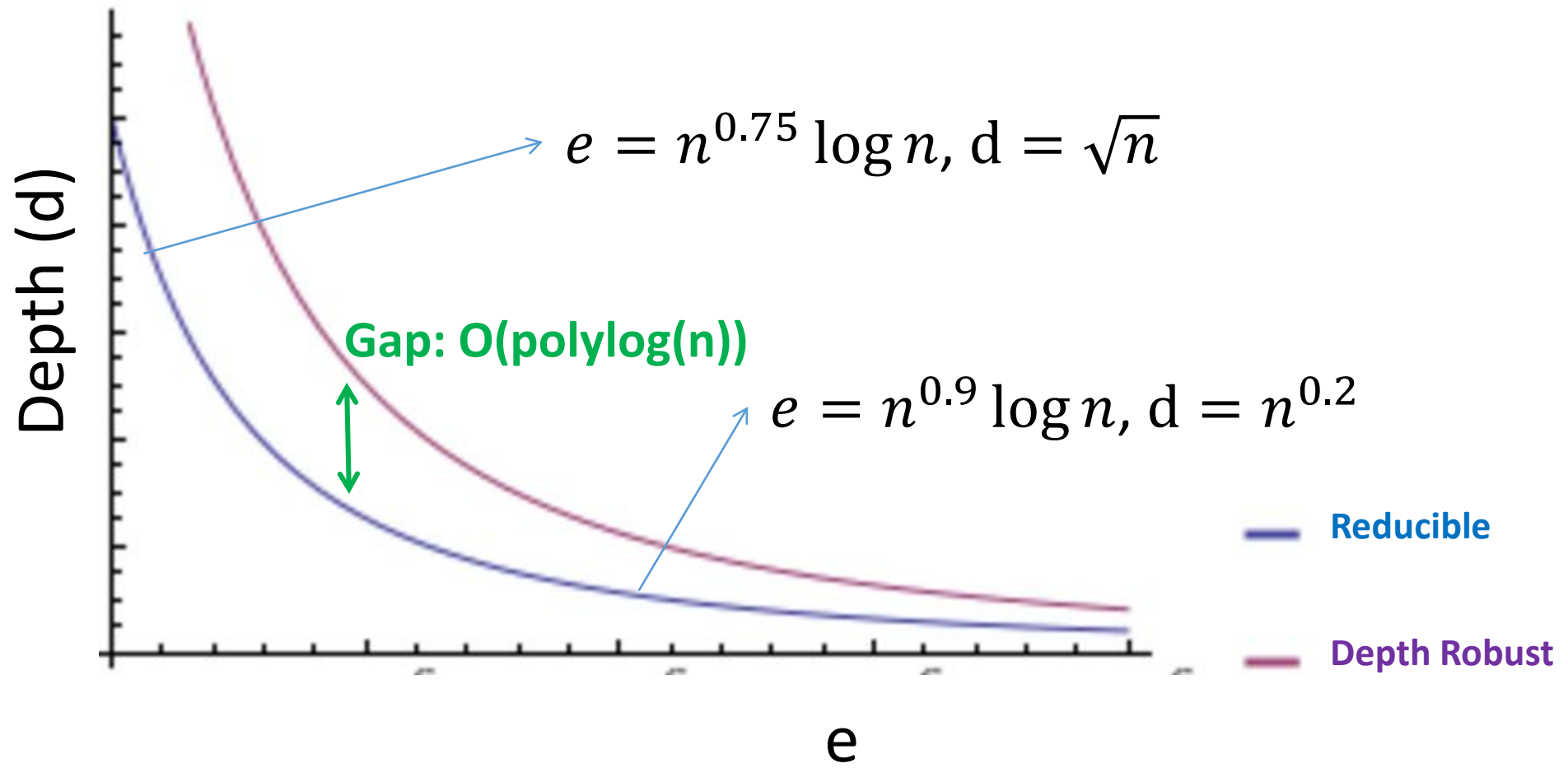
Theorem [ABP16] There is a DAG G with maximum indegree $\delta = 2$ and $E_R(G) = \Omega\left(\frac{n^2}{\log n}\right)$. Furthermore, there is a sequential pebbling algorithm N with cost $E_R(N) = O\left(\frac{n^2}{\log n}\right)$.

More New Results

MHF	Upper Bound	Lower Bound
Argon2i-A	$\tilde{O}(n^{1.71})$ [ABP16] $\tilde{O}(n^{1.75})$ [This work]	$\tilde{\Omega}(n^{1.66})$ [ABP16]
Catena	$\tilde{O}(n^{1.618})$ [ABP16] $\tilde{O}(n^{1.67})$ [This work]	$\tilde{\Omega}(n^{1.5})$ [ABP16]
SCRIPT (data dependent)	$O(n^2)$ [Naïve, P12]	$\Omega(n^2)$ [ACPRT16]

Idea: Apply our attack recursively during balloon phases

(e,d)-reducible curve for Argon2i-A



Recursive Attack

$$CC(G) \leq en + \frac{n}{e} nd$$

$$CC(G) \leq en + \frac{n}{e} CC(G')$$

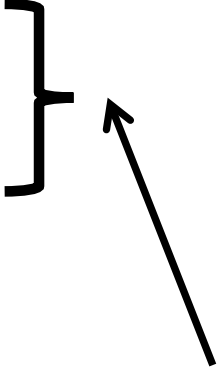
$$CC(G) \leq e_1 n + \frac{n}{e_1} \left(e_2 d_1 + \frac{n}{e_2} d_2 n \right)$$

...

Conclusions

- Depth-robustness is a necessary and sufficient for secure iMHFs
 - [AB16] [ABP16]
- Big Challenge: Improved Constructions of Depth-Robust Graphs
 - We already have constructions in theory [EGS77, PR80, ...]
 - But constants matter!

More Open Questions

- Computational Complexity of Pebbling
 - NP-Hard to determine $CC(G)$ [BZ16]
 - Hardness of Approximation?
 - What is $CC(\text{Argon2i-B})$?
 - Upper Bound: $O(n^{1.8})$ [AB16b]
 - Recursive attack: $O(n^{1.77})$ [BZ16b]+[ABP16]
 - Lower Bound: $\Omega(n^{1.66})$ [BZ16b]
- 
- Large Gap Remains**

Thanks for Listening

