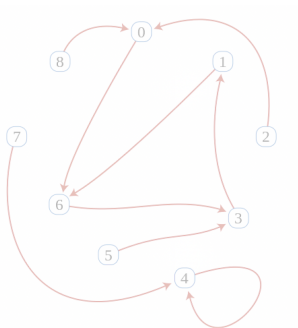




# Element Distinctness, Birthday Paradox, and 1-out Pseudorandom Graphs

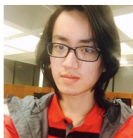


Hongxun Wu

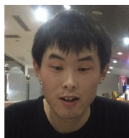
IIS, Tsinghua University

42	3	23	1	12	30	42	15
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# Authors of this work



**Lijie Chen**



**Ce Jin**



**R. Ryan Williams**

我

**Hongxun Wu**

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Lijie Chen, Ce Jin, and R. Ryan Williams are from MIT.

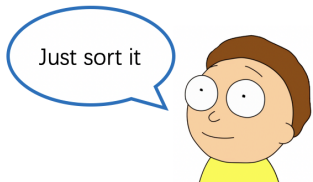
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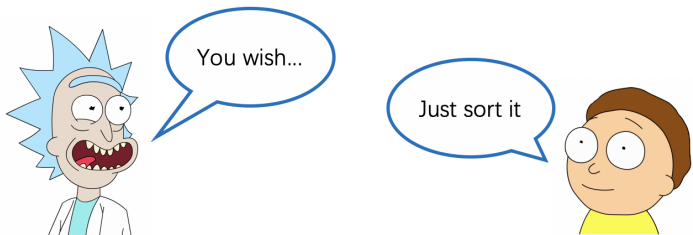
42	3	23	1	12	30	42	15
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- INPUT:  $n$  positive integers  $a_1, a_2, \dots, a_n$  with  $a_i \leq \text{poly}(n)$ .
- Decide whether all  $a$ 's are distinct.

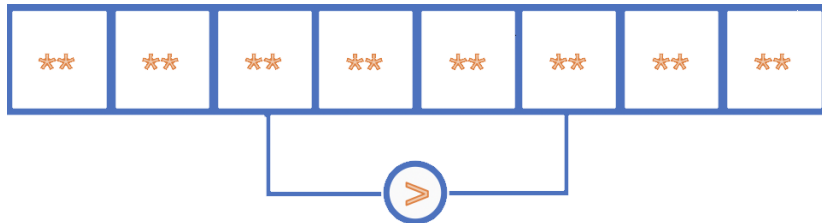
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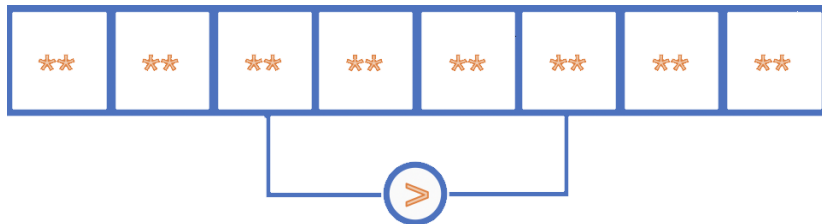


# Comparison model



- No direct access to the INPUT  $a$ .
- Each query  $(i, j)$  returns one of  $a_i < a_j$ ,  $a_i = a_j$ ,  $a_i > a_j$ .

# Comparison model

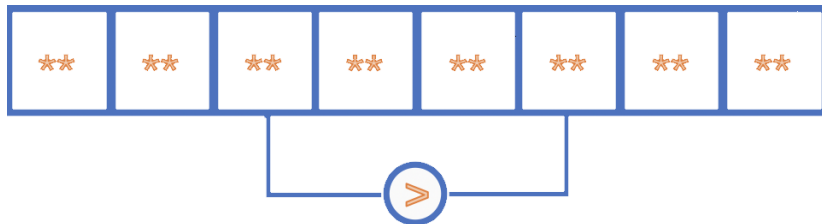


Time-Space tradeoff [BFMADH<sup>+</sup>87, Yao88]

Element distinctness requires  $TS = \Omega(n^{2-o(1)})$  in Comparison model.



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- When  $S = O(\text{polylog } n)$ ,  $T = \Omega(n^{2-o(1)})$ .

# RAM model



- Random access to read-only input.
- Working memory has a (relatively small) size  $S$ .

42	3	23	1	12	30	42	15
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## Time-Space tradeoff [BCM13]

- Assuming the existence of *Random Oracle*, there is an algorithm with  $T^2S = \tilde{O}(n^3)$ .

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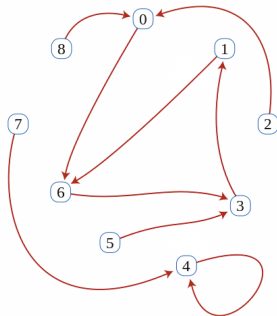
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- When  $S = \tilde{O}(1)$ ,  $T = \tilde{O}(n^{1.5})$ .
- In the rest of this talk, we always assume there is only one collision ( $a_i = a_j$ ).

# 1-out Graph and Birthday Paradox

## Pollard's $\rho$ method [BCM13]

Assuming the existence of *Random Oracle*, when  $S = \tilde{O}(1)$ , there is an algorithm with  $T = \tilde{O}(n^{1.5})$ .

- For random oracle  $R$ , define graph  $x \mapsto R(a_x)$  with  $x \in [n]$ .

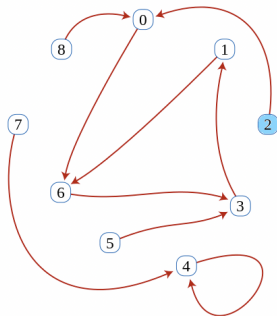


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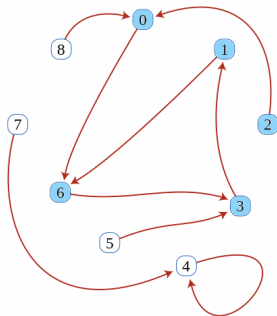


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- Pick a random starting point  $s$ .
- Run Floyd's cycle finding.



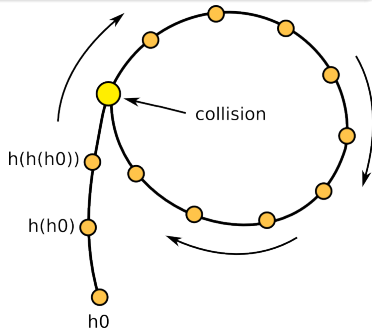


# 1-out Graph and Birthday Paradox

## Birthday Paradox Type Properties [BCM13]

Suppose  $f^*(s)$  is the set of vertices reachable from  $s$ .

- $\mathbb{E}[|f^*(s)|] \leq O(\sqrt{n})$

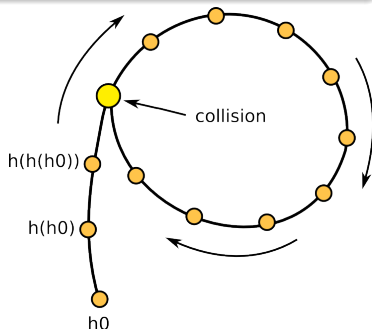


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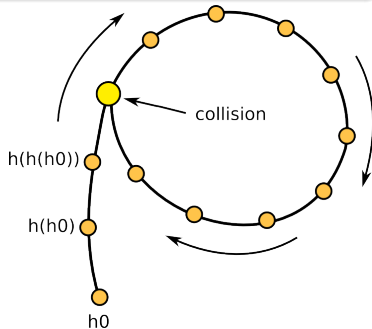


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- So each cycle-finding takes  $O(\sqrt{n})$  time and finds any collision  $u, v$  with probability  $\Omega(1/n)$ .



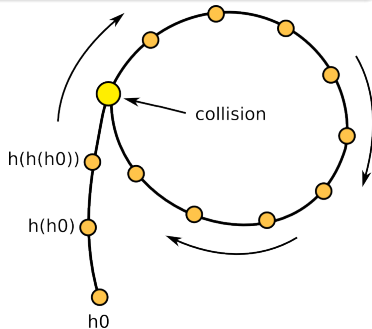
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- So each cycle-finding takes  $O(\sqrt{n})$  time and finds any collision  $u, v$  with probability  $\Omega(1/n)$ .
- Repeat  $O(n)$  times. It takes  $O(n^{1.5})$  time in total.



## Our Main Lemma

There exists a family  $\{r_{\text{seed}}\}$  of hash functions efficiently samplable with seed length  $O(\text{polylog } n)$ , and the graph defined by  $\{r_{\text{seed}}\}$  (instead of *Random Oracle R*) satisfy

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## Our Result

Assuming the existence of *Random Oracle*, when  $S = O(\text{polylog } n)$ , there is a RAM algorithm for Element Distinctness with  $T = \tilde{O}(n^{1.5})$ .

## Low-space Algorithm for Subset Sum [BGNV18]

Assuming the existence of *Random Oracle*, Subset Sum and Knapsack can be solved by a Monte Carlo algorithm in  $O^*(2^{0.86n})$  time, with  $O(\text{poly}(n))$  space.



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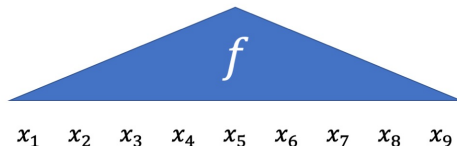
# Construction

# Random Restriction and Håstad's Switching Lemma



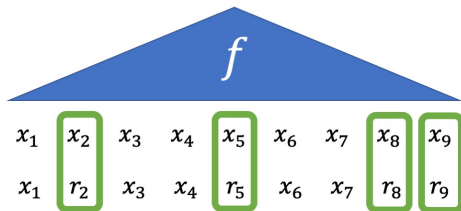
This is Ryan O'Donnell's Youtube lecture which is a masterpiece.

# Iterative Restriction



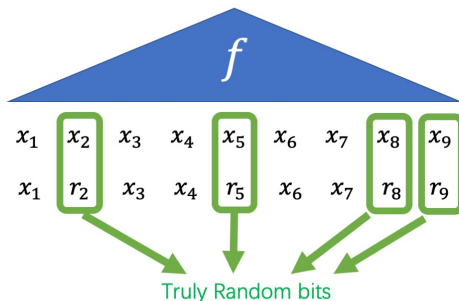
This is the Ajtai-Wigderson Paradigm [AW85] for building PRG.

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# Toy Example: Two levels

Recall the input  $a_1, a_2, \dots, a_n \in [m]$ .

## Two Level Example

Suppose we have the following:

- $O(\text{polylog } n)$ -wise independent functions  $g : [m] \rightarrow \{0, 1\}$  and  $r : [m] \rightarrow [n]$ .
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$$h(a_x) = \begin{cases} R(a_x) & g(a_x) = 0 \\ r(a_x) & g(a_x) = 1 \end{cases}$$

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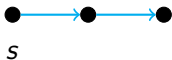
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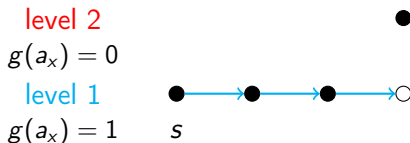


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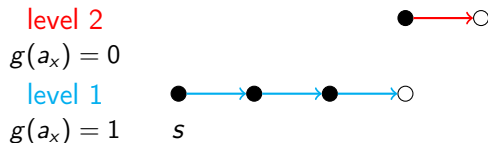


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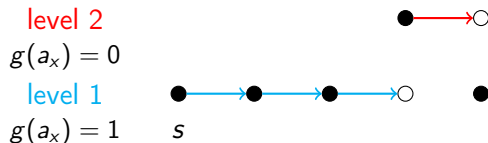


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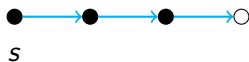
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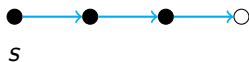
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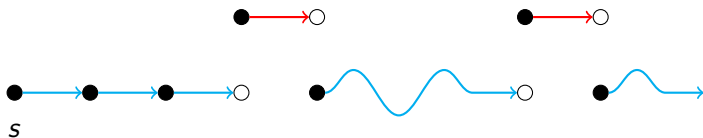
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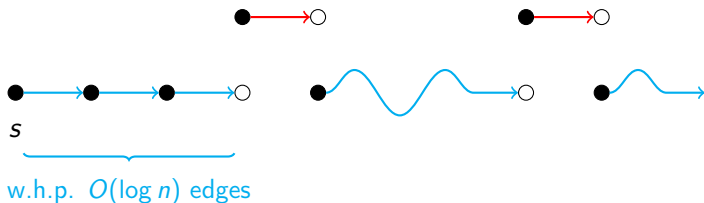
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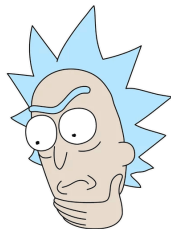
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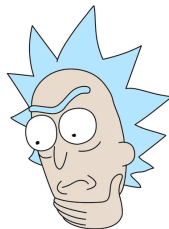


# Sanity Check

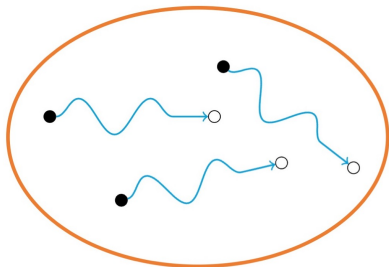


- Why this might be a good idea?

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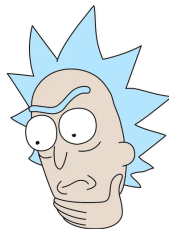


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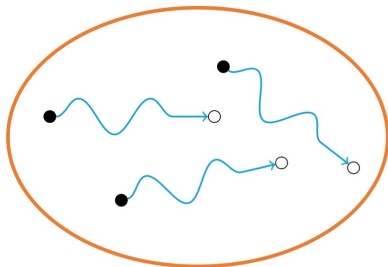


- Each subpath has length  $O(\log n)$ .

# Sanity Check



- Why this might be a good idea?



- Each subpath has length  $O(\log n)$ .
- Every **level 2** edge is an independent sample of a subpath.

# Intuition: Memory Eraser

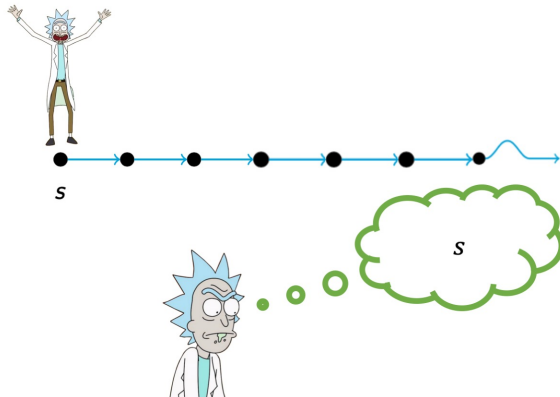
Recall our goal.

## Our Main Lemma

- $\mathbb{E}[|f^*(s)|] \leq O(\sqrt{n})$
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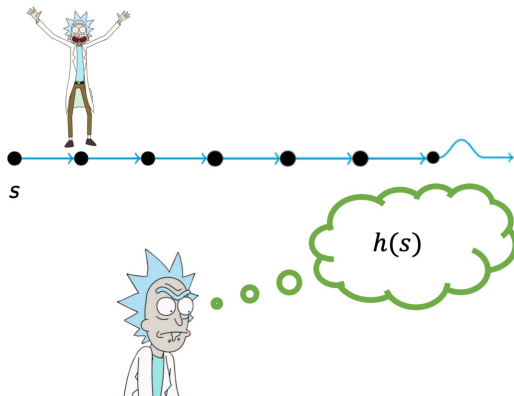


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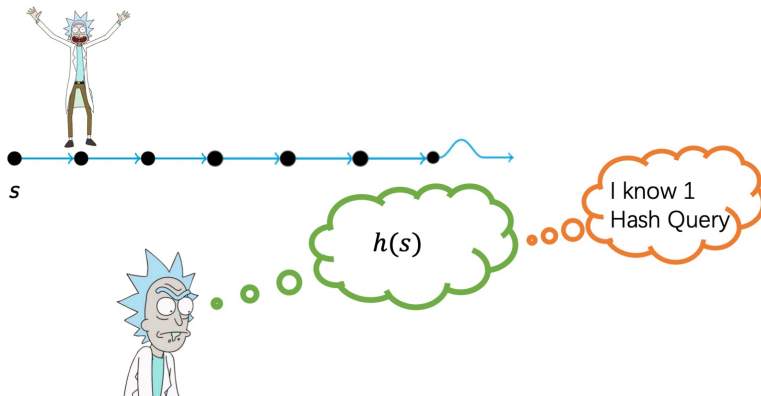
- “Memory” of a random walk: The current vertex it is at.

# Intuition: Memory Eraser



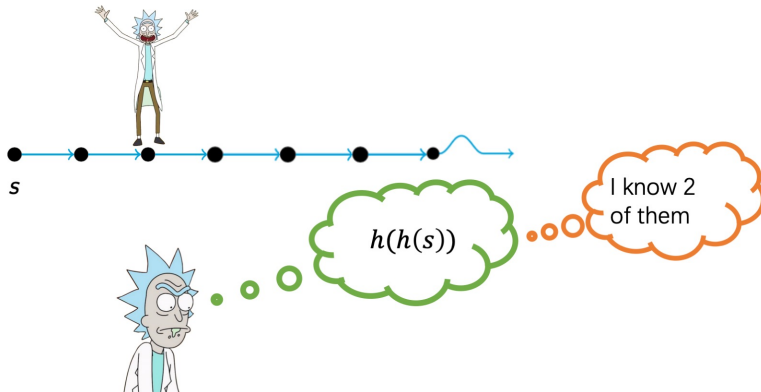
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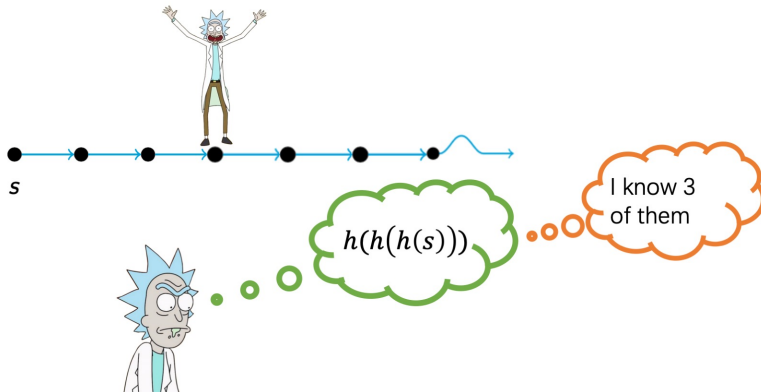
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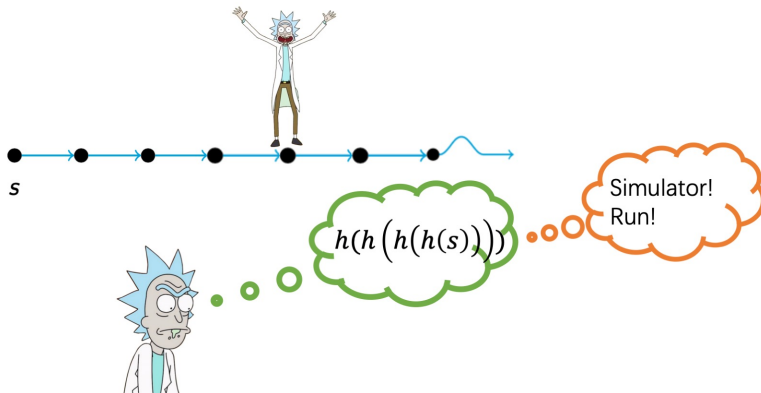
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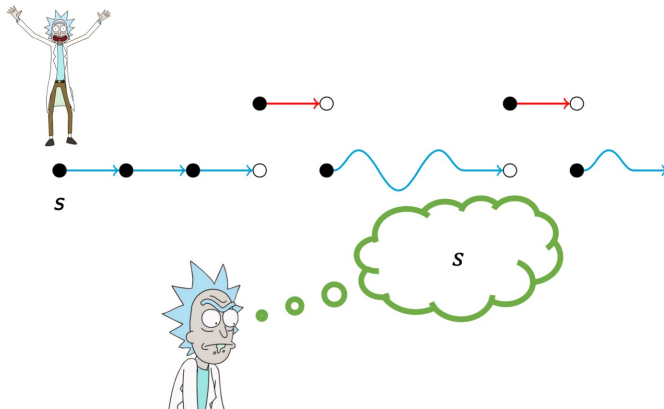
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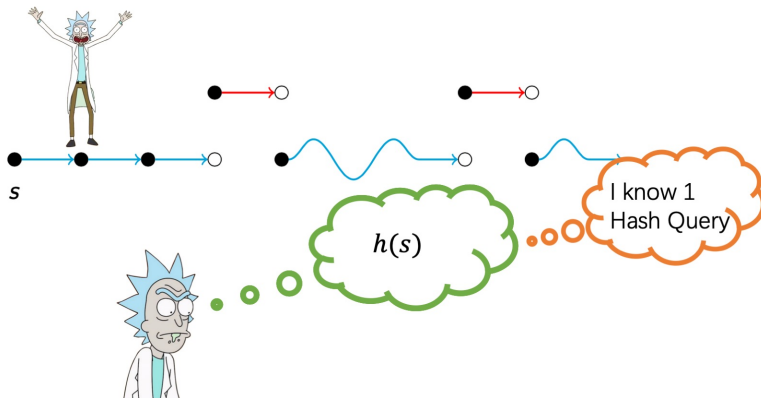
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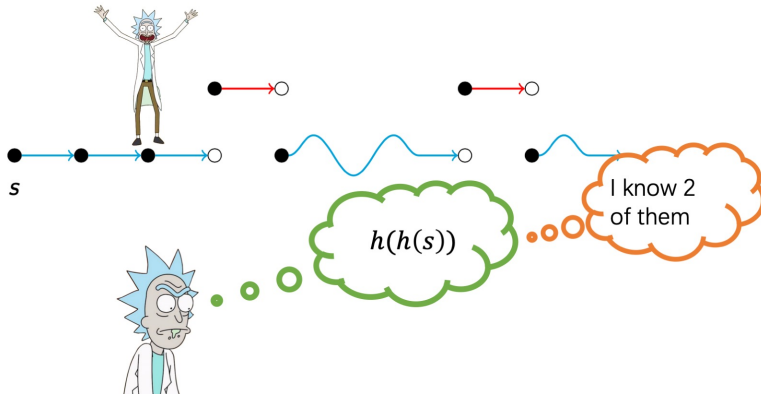
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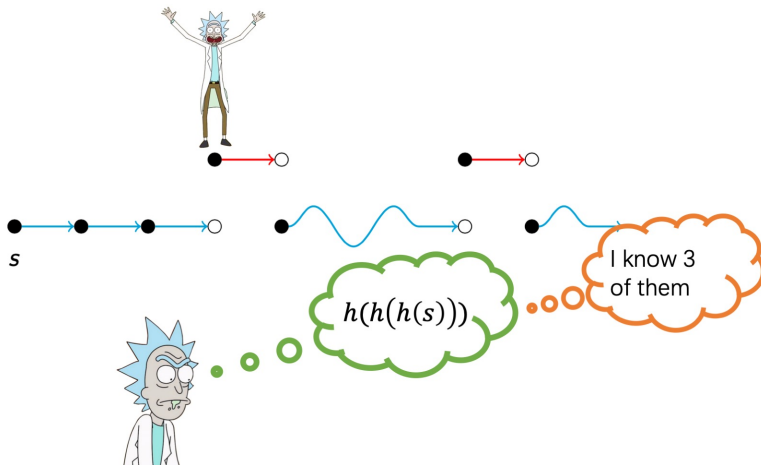


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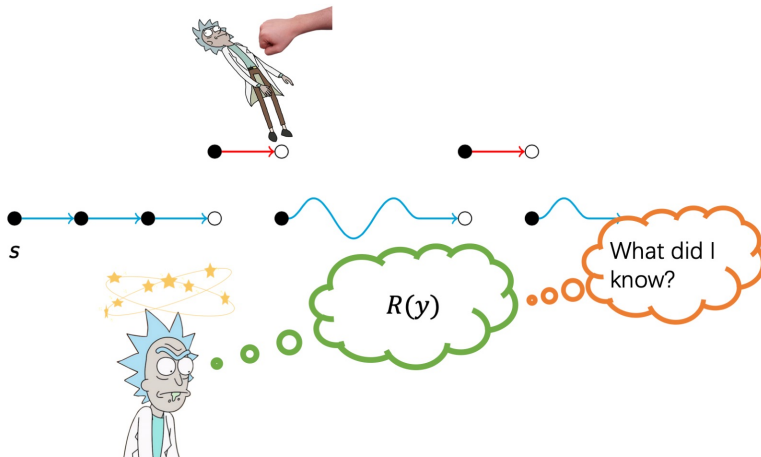
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# Our Construction via Iterative Restriction

## Our Construction

Now we sample  $O(\log n)$  many hash functions  $\{r_i, g_i\}_{i \in [\ell]}$ .

Each  $r_i : [m] \rightarrow [n]$  and  $g_i : [m] \rightarrow [2]$  are  $O(\log n)$ -wise independent.

# Our Construction via Iterative Restriction

## Our Construction

Now we sample  $O(\log n)$  many hash functions  $\{r_i, g_i\}_{i \in [\ell]}$ .

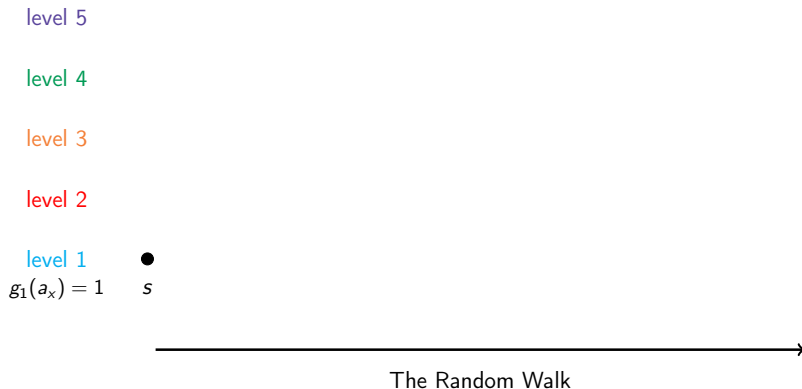
Each  $r_i : [m] \rightarrow [n]$  and  $g_i : [m] \rightarrow [2]$  are  $O(\log n)$ -wise independent.

Then we set  $h_{\ell+1}(a_x) = \perp$  and

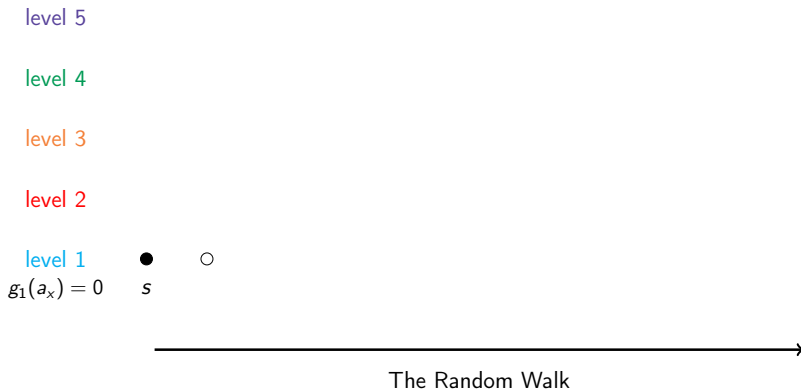
$$h_i(a_x) = \begin{cases} h_{i+1}(a_x) & g_i(a_x) = 0 \\ r_i(a_x) & g_i(a_x) = 1 \end{cases}$$

Finally, we set  $h = h_1$ .

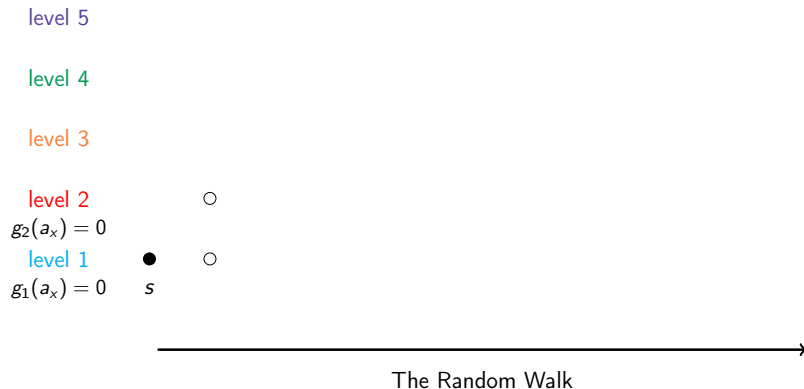
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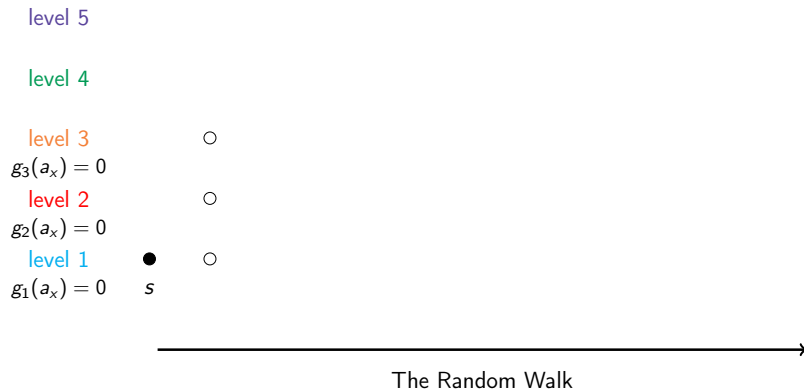


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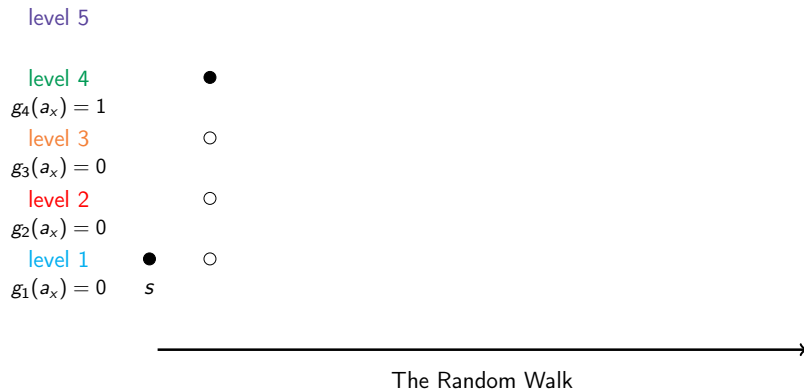




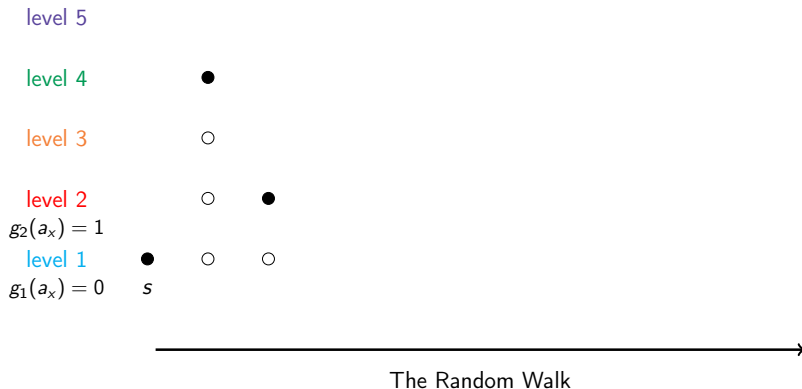
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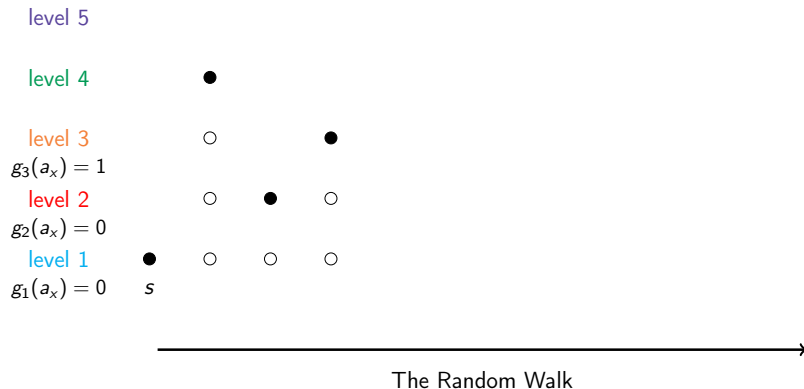
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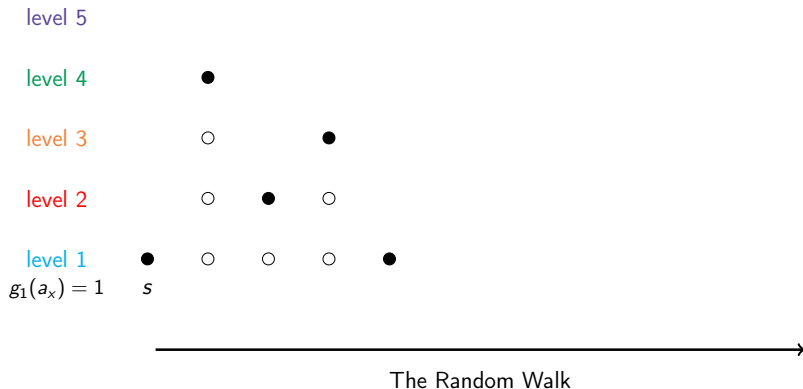
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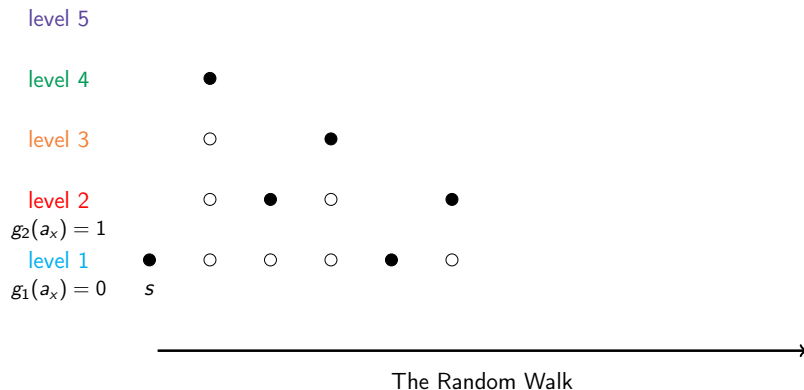
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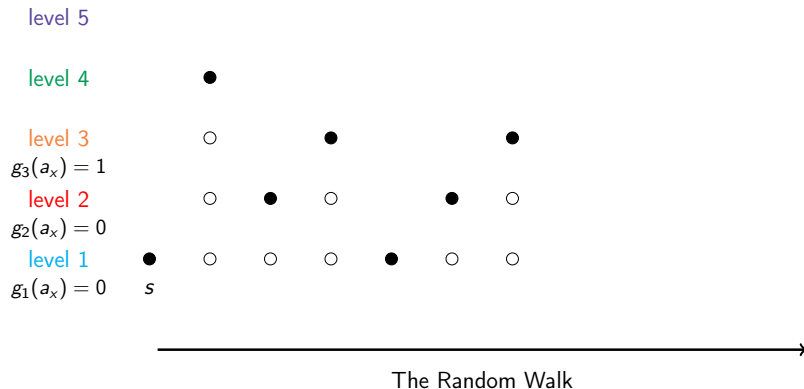
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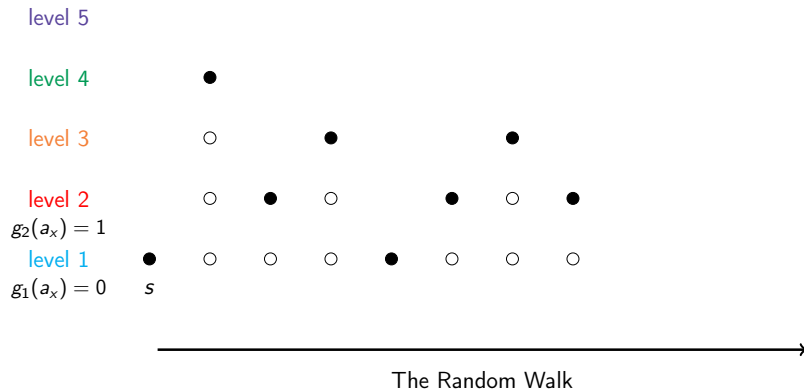
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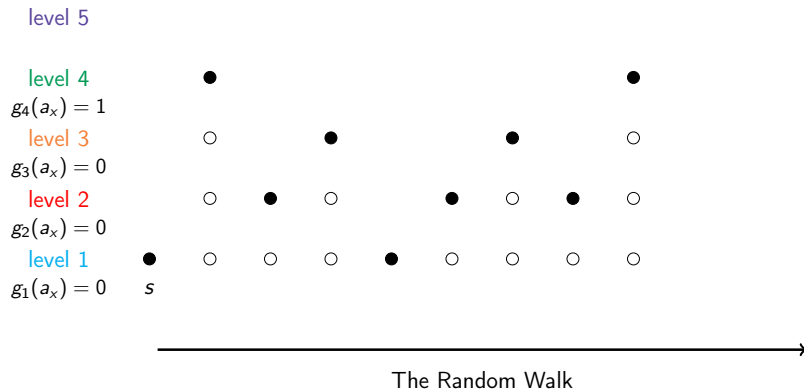


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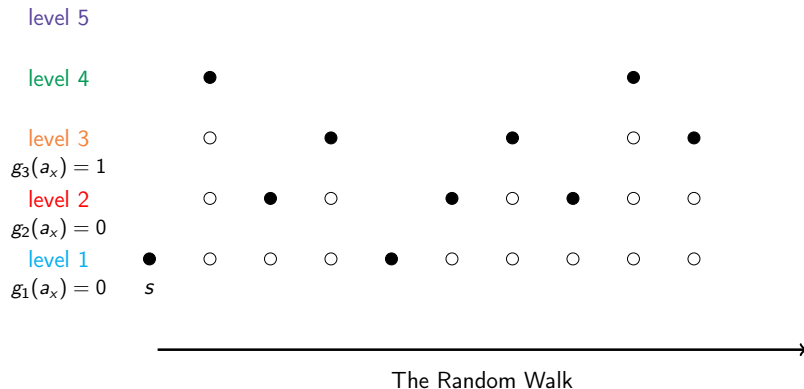




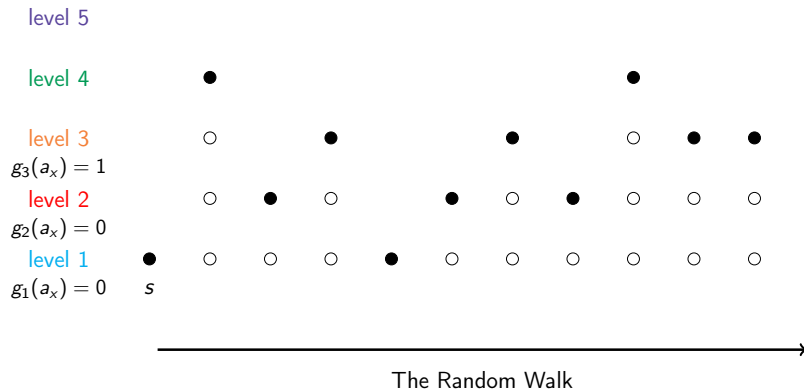
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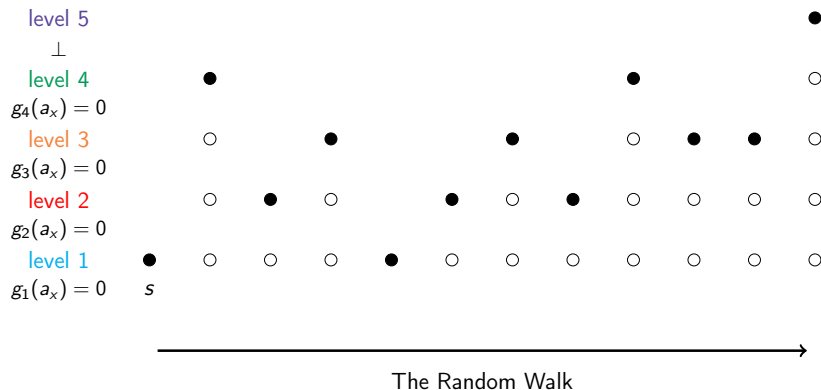
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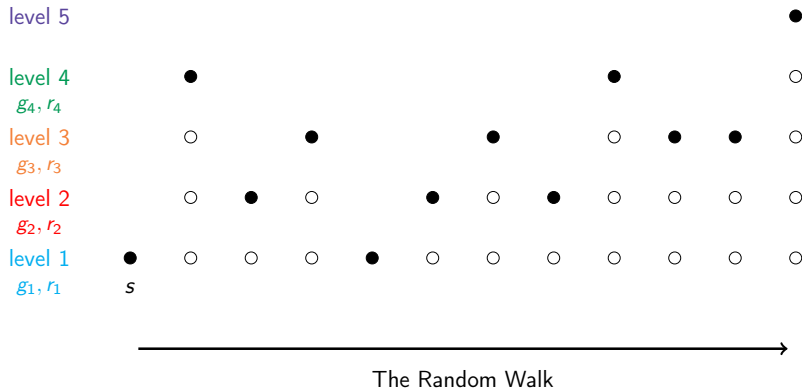


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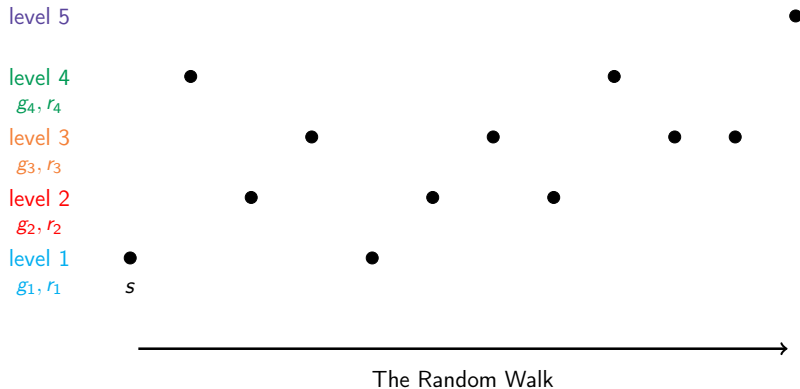


## Key Ideas in Our Analysis

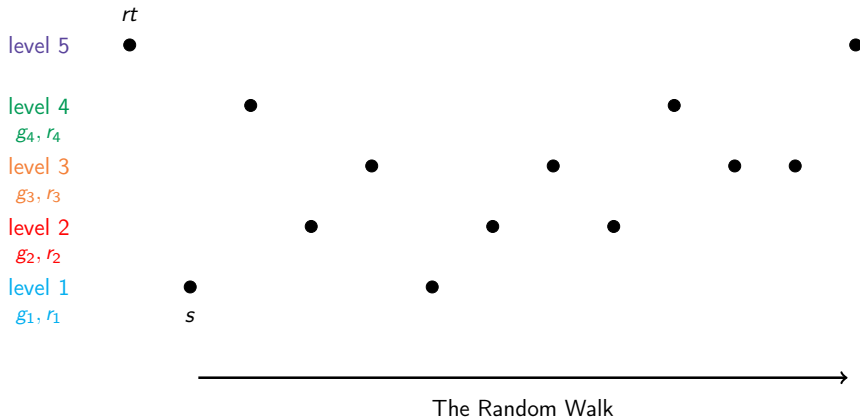
# Dependency Tree



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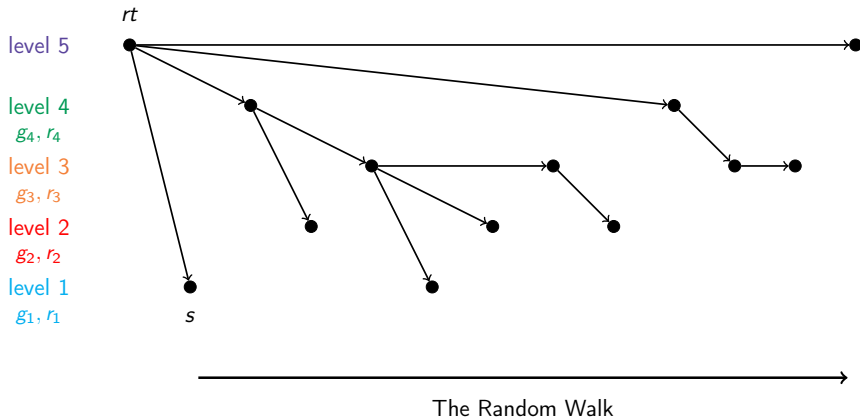


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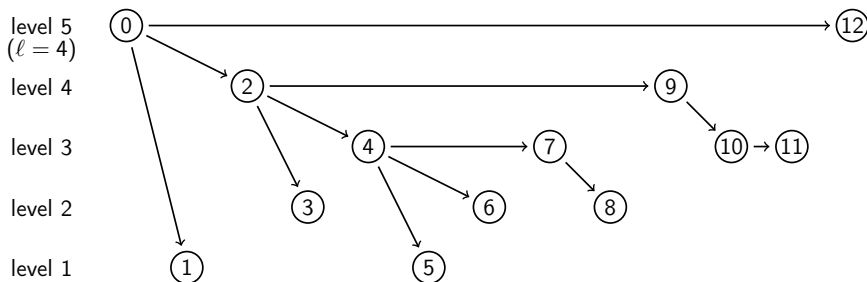




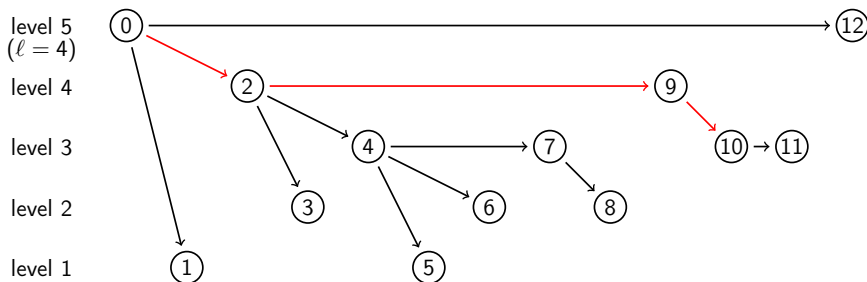
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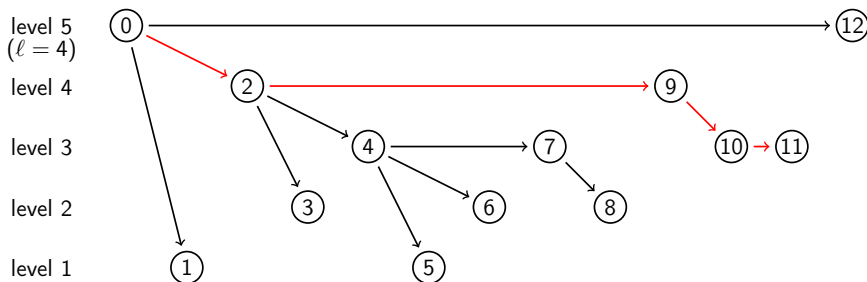


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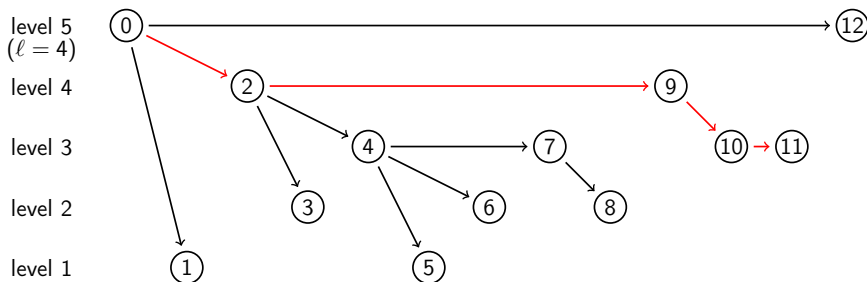
- We index a node by the shape of its path, e.g.  $\vec{k}_{10} = (0, 0, 1, 2)$ .

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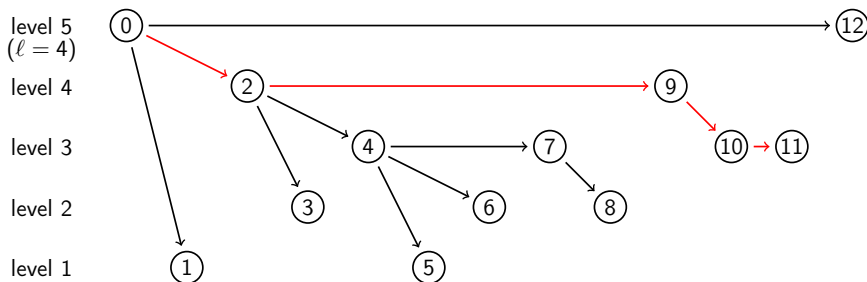
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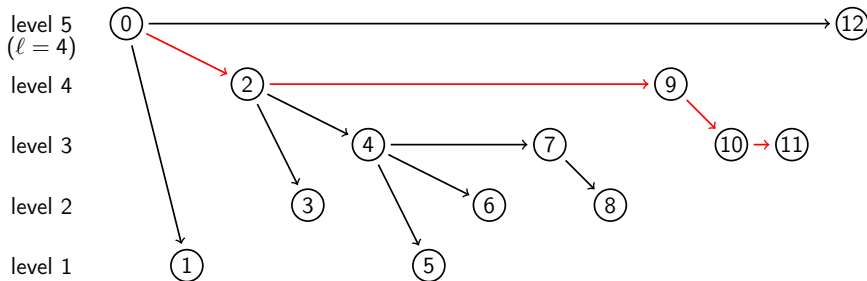
- We index a node by the shape of its path, e.g.  $\vec{k}_{11} = (0, 0, 2, 2)$ .
- Consider  $\vec{k}_x$ . Fix  $x$ ,  $\vec{k}$  is a random variable. Fix  $\vec{k}$ ,  $x$  is a random variable.

# Dependency Tree



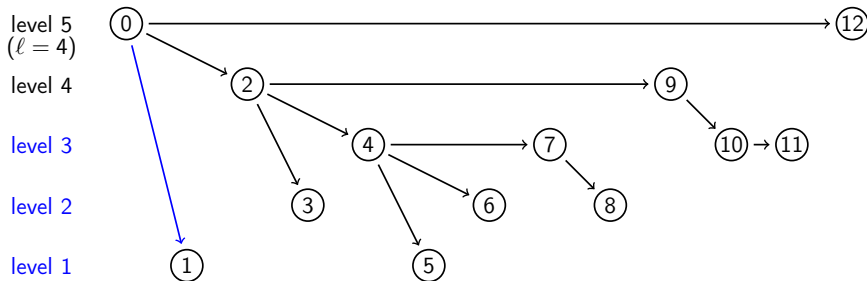
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- We fix index  $\vec{k}$  and let  $x$  be the random variable (which may not exist).

# Memory Eraser on Dependency Tree



- Fix  $\vec{k} = (0, 0, 2, 2)$ .

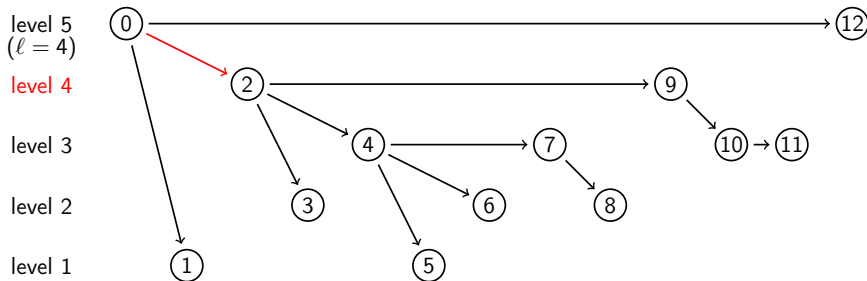
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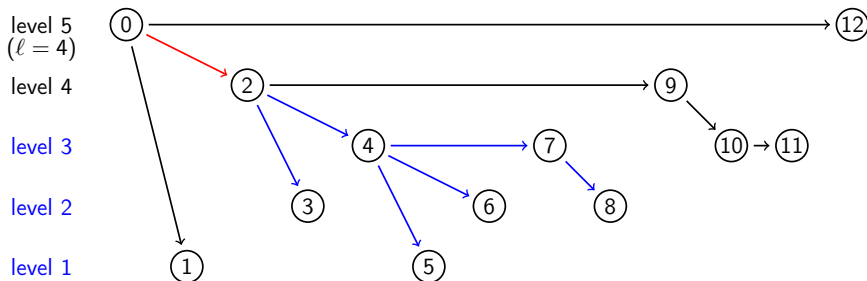


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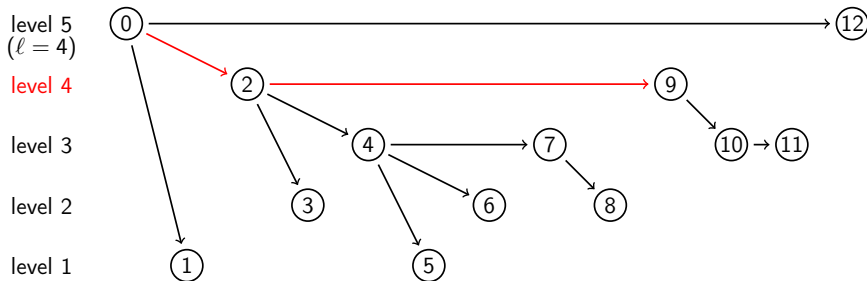
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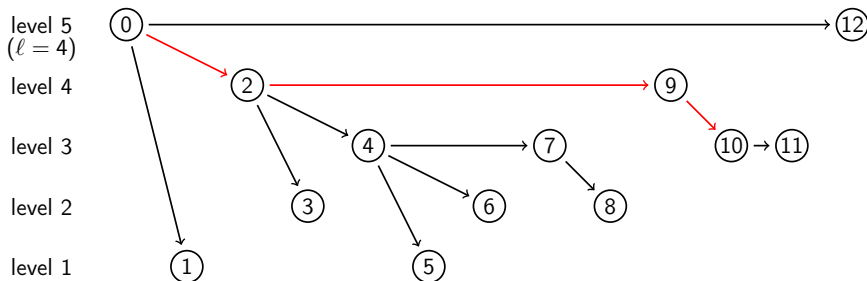
- Fix  $\vec{k} = (0, 0, 2, 2)$ .
- Blue part is a random variable. But it will finally end up with a node with level  $\geq 4$ .

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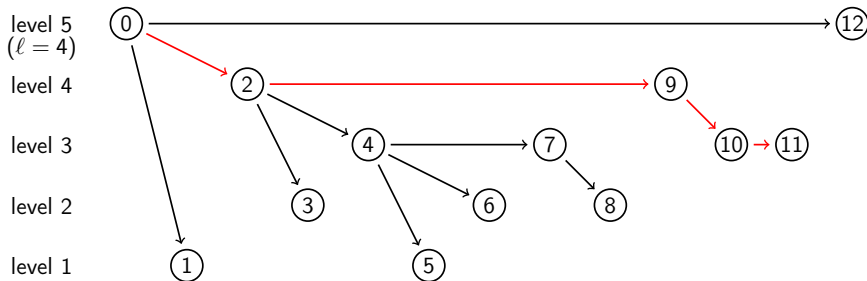
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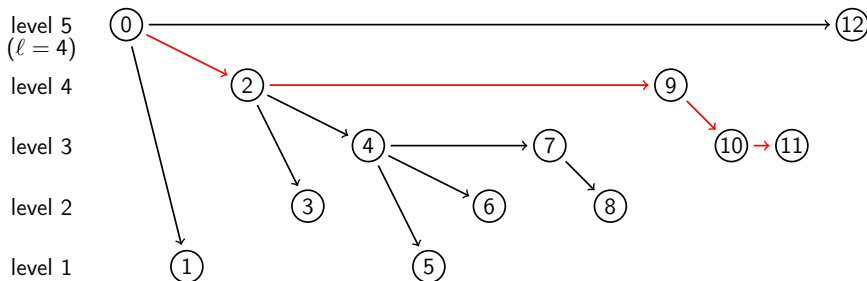
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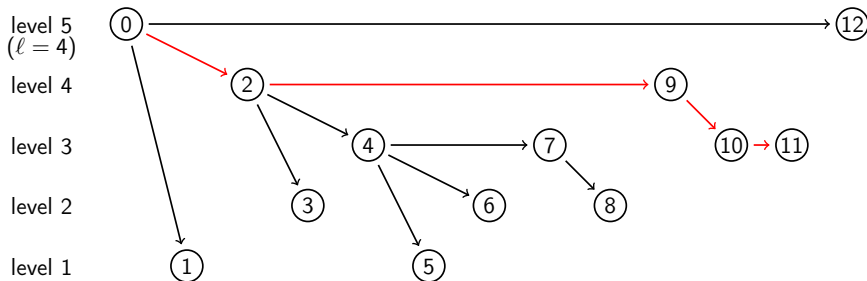
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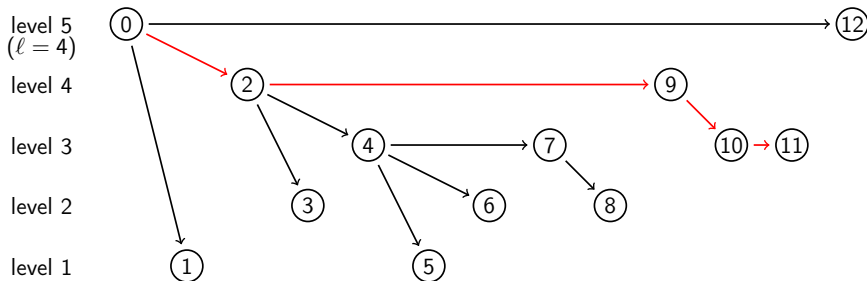
- Fix  $\vec{k} = (0, 0, 2, 2)$ .
- Blue part is a random variable. But it will finally end up with a node with level  $\geq 4$ .
- One issue: What if  $a_{w_2} = a_{w_9}$ ?

# (Locally Simulatable) Extended Walk



- Instead of original walk  $w$ , we look at extended walk  $w^*$ .

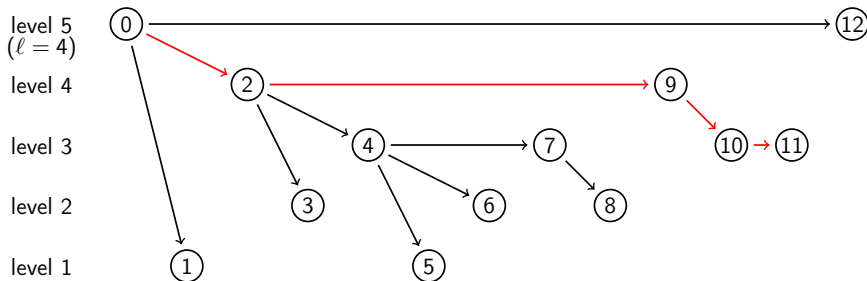
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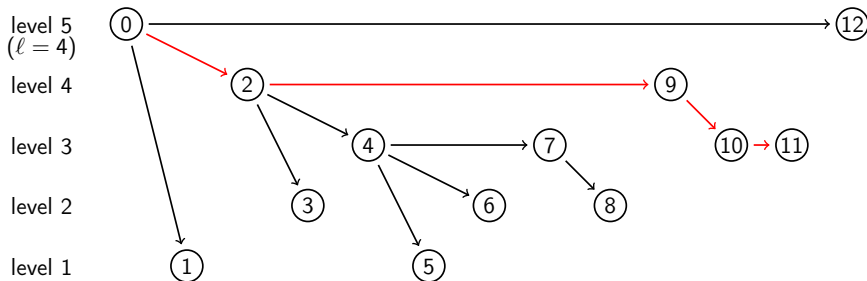


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- $w$  and  $w^*$  agree if  $w^*$  has no collision  $a_{w_i^*} = a_{w_j^*}$ .

# Good = All - Bad

Recall our goal.

## Our Main Lemma

- $\mathbb{E}[|f^*(s)|] \leq O(\sqrt{n})$
- $\Pr[u \in f^*(s)] \geq \Omega(1/\sqrt{n}), \forall u \in [n]$
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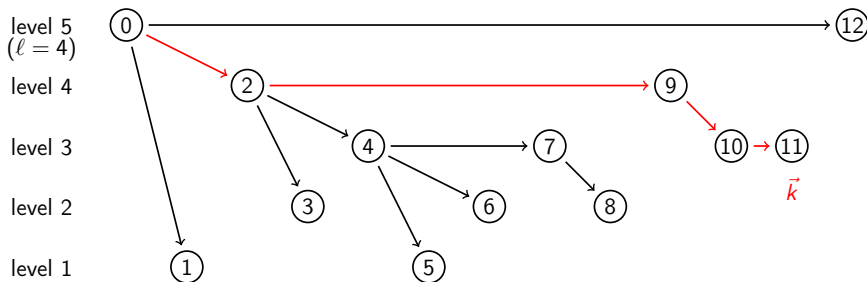
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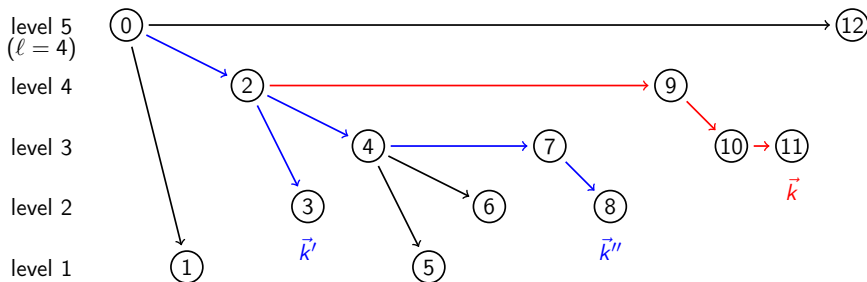
$$\begin{aligned} & E[\#\{t | w_t^* = u, \exists t' \neq t'', a_{w_{t'}^*} = a_{w_{t''}^*}\}] \\ & \leq E[\#\{t, t' \neq t'' | w_t^* = u, a_{w_{t'}^*} = a_{w_{t''}^*}\}] \end{aligned}$$

# Good = All - Bad



$$E[\#\{t | w_t^* = u\}] = \sum_{\vec{k}} \frac{2^{-(k_1 + k_2 + \dots + k_\ell)}}{n}$$

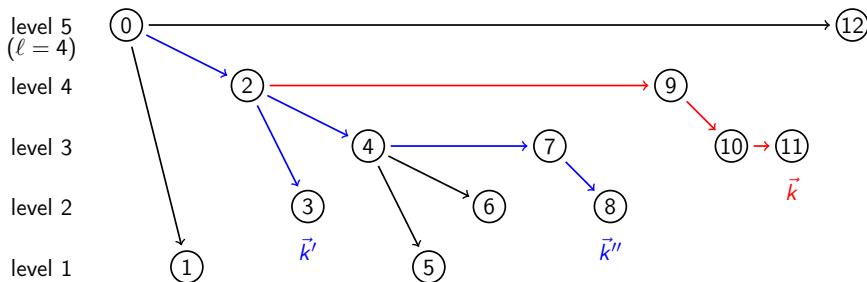
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$$E[\#\{t, t' \neq t'' | w_t^* = u, a_{w_{t'}^*} = a_{w_{t''}^*}\}] = \sum_{\vec{k}, \vec{k}', \vec{k}''} \frac{2^{-\|\vec{k}\|_1 - \|\vec{k}'\|_1 - \|\vec{k}''\|_1}}{n^2}$$

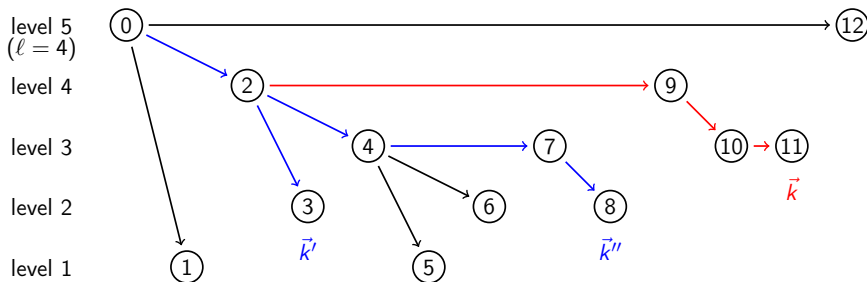


# Good = All - Bad



$$\text{Good} = \sum_{\vec{k}} \frac{2^{-(k_1+k_2+\dots+k_\ell)}}{n} - \sum_{\vec{k}, \vec{k}', \vec{k}''} \frac{2^{-\|\vec{k}\|_1 - \|\vec{k}'\|_1 - \|\vec{k}''\|_1}}{n^2}$$

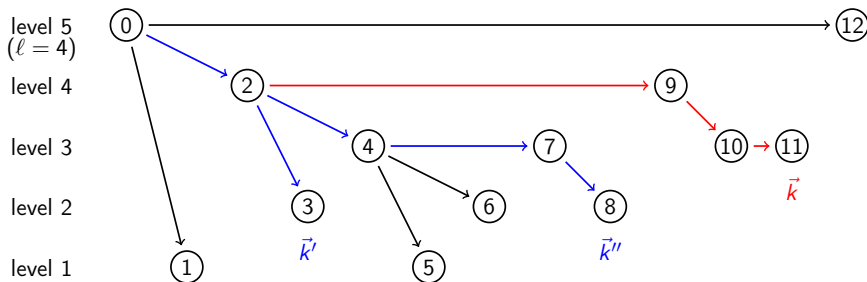
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$$\sum_{\vec{k}} \frac{2^{-(k_1+k_2+\dots+k_\ell)}}{n} = \frac{1}{n} \prod_{i=1}^{\ell} \sum_{k_i=0}^{\infty} 2^{-k_i} = \frac{2^\ell}{n}$$

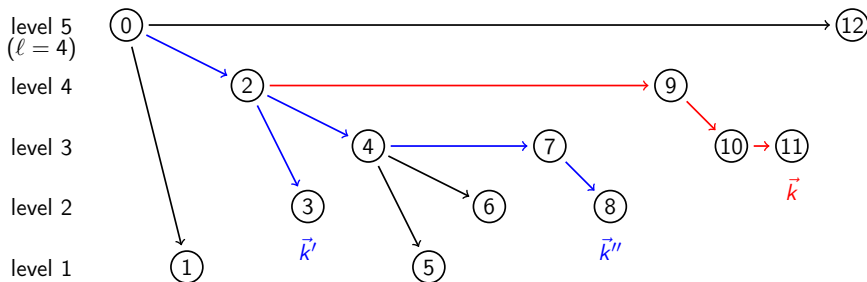
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$$\sum_{\vec{k}, \vec{k}', \vec{k}''} \frac{2^{-\|\vec{k}\|_1 - \|\vec{k}'\|_1 - \|\vec{k}''\|_1}}{n^2} = \frac{8^\ell}{n^2}$$

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$$\text{Good} = \sum_{\vec{k}} \frac{2^{-(k_1+k_2+\dots+k_\ell)}}{n} - \sum_{\vec{k}, \vec{k}', \vec{k}''} \frac{2^{-\|\vec{k}\|_1 - \|\vec{k}'\|_1 - \|\vec{k}''\|_1}}{n^2} = \frac{2^\ell}{n} - \frac{8^\ell}{n^2}$$

$$\text{Let } \ell \leftarrow \frac{1}{2} \log n - 100. \quad \frac{2^\ell}{n} - \frac{8^\ell}{n^2} = \frac{2^{-100}}{\sqrt{n}} - \frac{2^{-300}}{\sqrt{n}} = \Omega\left(\frac{1}{\sqrt{n}}\right).$$

## Our Main Lemma

- $\mathbb{E}[|f^*(s)|] \leq O(\sqrt{n})$
- $\Pr[u \in f^*(s)] \geq \Omega(1/\sqrt{n}), \forall u \in [n]$
- Even for this simple case, there is so much more technical challenges that is hidden in this talk.

# Open Problems

- **Time-space Tradeoffs**

In this work, we only solved the case when  $S = \tilde{O}(1)$ . Can we extend it to the full tradeoff?

- **Shorter Seed Length**

In this work, our seed length is  $O(\log^3 n \log \log n)$ . Can this be improved?

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