

Approximate Lower Bound Arguments (ALBA)

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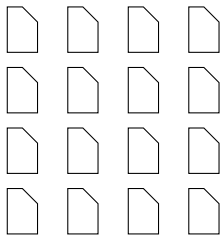
²University of Edinburgh

³Boston University

⁴IOG

Problem Statement

Prover

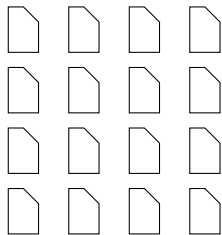


$$R(\boxplus) = 1$$

Problem Statement

goal: “I know $> n_f$ elements $\square$ with $R(\cdot) = 1$ ”

Prover $\longrightarrow$ Verifier

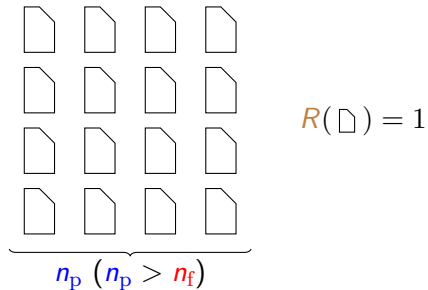


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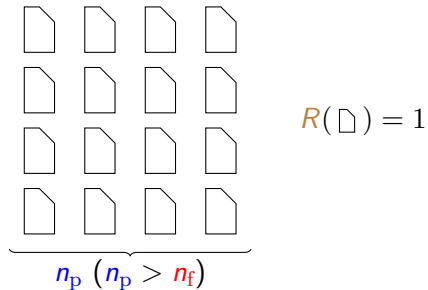
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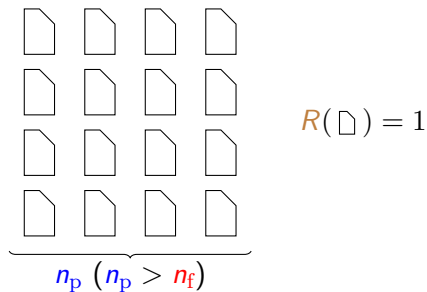
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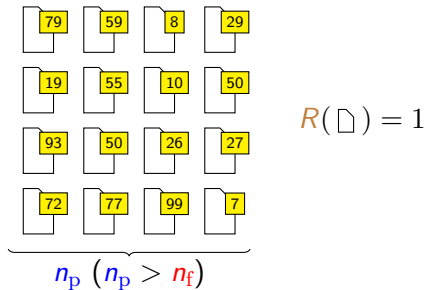


Larger ratio n_p/n_f enables more efficient schemes.

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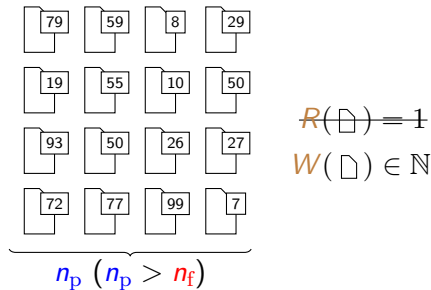


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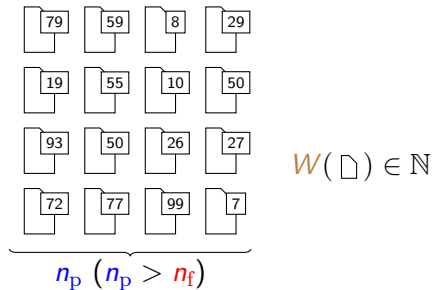
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general goal: “I know $\square$ with $\sum W(\cdot) > n_f$ ”

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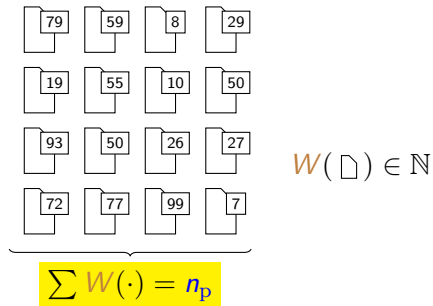


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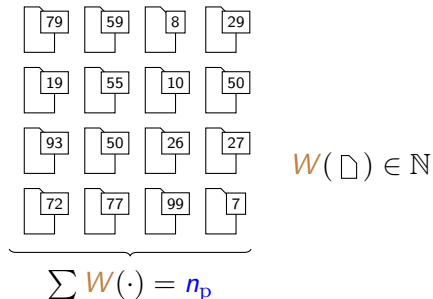


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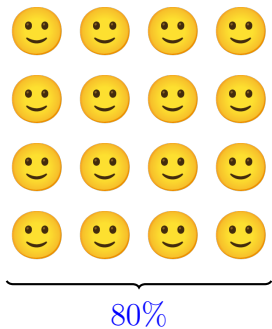
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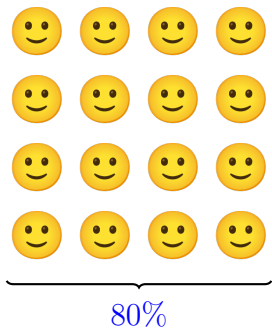
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“Approximate Lower Bound Argument” (ALBA)

Example: Consensus



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$$n_p / n_f = 4$$

History

1985 "Approximate lower bound" term appears first in László Babai's work

1983 Sipser and Gács use an ALBA protocol to prove $BPP \subseteq RP^{NP}$

1986 Goldwasser and Sipser use an ALBA protocol to prove $IP[Q] \subseteq AM[Q + 2]$

Above implementations of ALBA have interaction and large proofs.

Our goal – ALBA for real world applications:

- ▶ minimize proof size
- ▶ non-interactive
- ▶ fast prover & verifier
- ▶ minimize communication in decentralized setting
- ▶ extractability (proof of knowledge)

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Defining ALBA

- ▶ Non-interactive proof system in either
 - ▶ random oracle (RO) model:
prover and verifier have oracle access to random $H : \{0, 1\}^* \rightarrow \{0, 1\}^k$
 - ▶ common reference string (CRS) model:
prover and verifier are given $\text{crs} \leftarrow \text{GenCRS}()$
- ▶ Prover and verifier have oracle access to weight function W
- ▶ Completeness: if prover has elements S_p of total weight $n_p \implies \text{prob. } 1 - \text{negl}$
 - ▶ $\pi \leftarrow \text{Prove}^{H, W}(S_p)$
 - ▶ $\text{Verify}^{H, W}(\pi) = 1$
- ▶ Soundness: if $\mathcal{A}$ makes valid proof $\implies$ extract elements of total weight $> n_f$; negligible knowledge error
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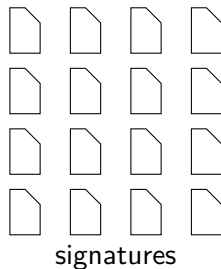
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Applications

- ▶ **Weighted Multisignatures**
 - ▶ Prove that sufficiently many parties signed a message
 - ▶ Proof-of-stake blockchains: prove that parties with sufficient total stake attested to blockchain state
- ▶ Straight-Line Witness Extraction for SNARKs
 - ▶ Straight-line extraction (no rewinding) useful for composability
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Why not use SNARK to implement ALBA?

- ▶ Not possible when the weight function cannot be represented by a single program
- ▶ Too costly when number of elements is large
- ▶ Instead, use ALBA + SNARK
- ▶ Our scheme works in CRS model $\implies$ avoid instantiating random oracle inside a circuit

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“know elements $x_1, \dots, x_k$
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Our Results

Completeness and soundness error $2^{-\lambda}$, $n_p = 2 \cdot n_f$:

proof size (elements)	prover runtime	verifier runtime
$\lambda + \log \lambda + 6$	expected $O(n + \lambda^2)$	$O(\lambda)$

Table: Upper bound

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$\frac{\lambda + \log \lambda + 6}{\log(n_p/n_f)}$	expected $O(n + \lambda^2)$	$O(\lambda)$

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Table: Lower bound

For simplicity...

- ▶ Most constructions unweighted
 - ▶ assume honest prover has n_p elements
- ▶ Simple soundness
 - ▶ no proof of knowledge
 - ▶ assume malicious prover has n_f fixed elements $\implies$ succeeds with negligible probability

Coming next...

- ☒ Definitions
 - Unweighted case
 - ☐ **Prover-inefficient construction**
 - ☐ Telescope construction
 - ☐ Improving prover running time
 - ☐ Decentralized setting
- ☐ Adding weights
- ☐ Applications

Warmup: Prover-inefficient Construction

- ▶ Let proof size be u elements
(u to be chosen later)
- ▶ Consider all u -sequences of elements
- ▶ Honest prover has n_p^u sequences
- ▶ Malicious prover has n_f^u sequences
- ▶ Notice exponential gap $\left(\frac{n_p}{n_f}\right)^u$
- ▶ A valid proof will be a sequence chosen with probability ϵ using RO

Valid proof: $(s_1, \dots, s_u)$ s.t.

- ▶ $H(s_1, \dots, s_u) = 1$;
($\Pr[H(\cdot) = 1] = \epsilon$)

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- ▶ Soundness error bounded using union bound:
“number” · “probability” = $n_f^u \cdot \epsilon$
- ▶ Completeness error bounded by
 $(1 - \epsilon)^{n_p^u} \leq e^{-\epsilon n_p^u}$
- ▶ Setting completeness and soundness errors
 $\leq 2^{-\lambda}$ and calibrating ϵ , we find $u = \frac{\lambda + \log \lambda}{\log(n_p/n_f)}$
suffices (lower bound: $u > \frac{\lambda-3}{\log(n_p/n_f)}$)
- ▶ Exponential prover running time

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- ▶ Exploit the gap $\left(\frac{n_p}{n_f}\right)^u$ in an efficient way
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①

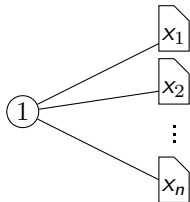
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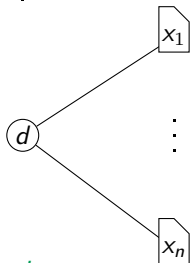
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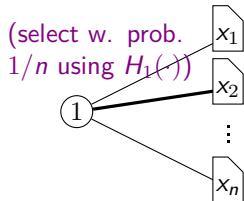


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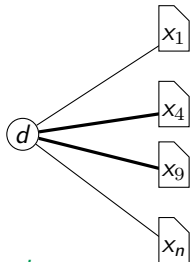


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$\vdots$



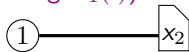
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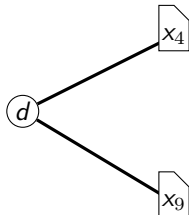
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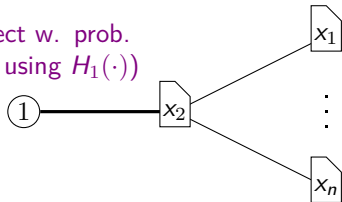
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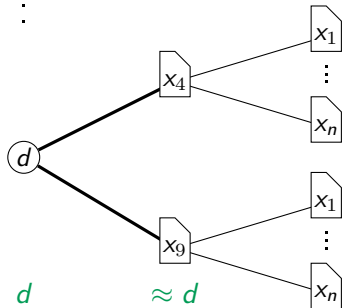
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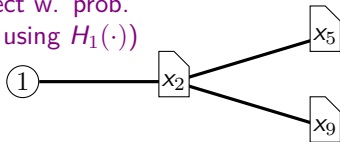
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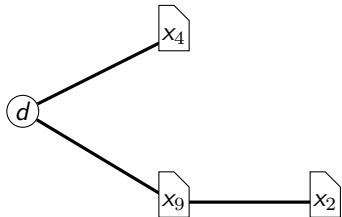
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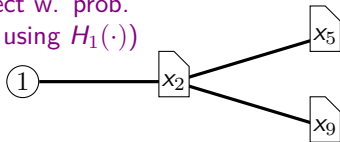


$d \approx d \approx d$

Telescope Construction (cont.)

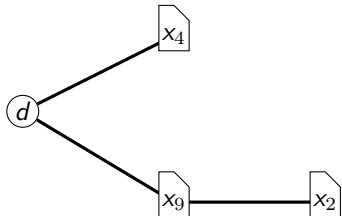
Let $x_1, \dots, x_n$ be honest prover's elements. ($n = n_p$)

(select w. prob.
 $1/n$ using $H_1(\cdot)$)



⋮

⋮
(repeat u times)

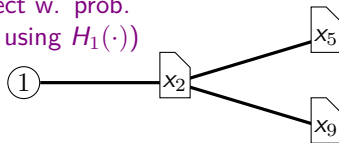


$d \quad \approx d \quad \approx d$

Telescope Construction (cont.)

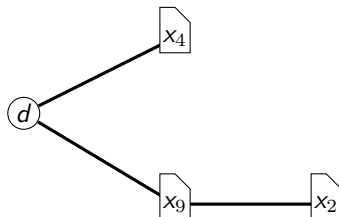
Let $x_1, \dots, x_n$ be honest prover's elements. ($n = n_p$)

(select w. prob.
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⋮

⋮
(repeat u times)



#

d

$\approx d$

$\approx d$

$\approx d$



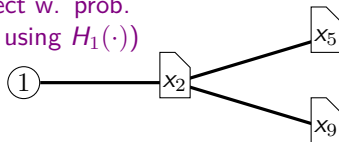
⋮



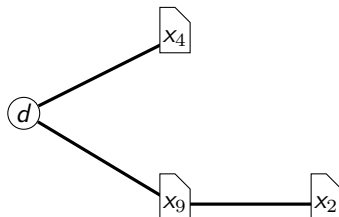
Telescope Construction (cont.)

Let $x_1, \dots, x_n$ be honest prover's elements. ($n = n_p$)

(select w. prob.
 $1/n$ using $H_1(\cdot)$)



⋮



d

$\approx d$

$\approx d$

⋮
(repeat u times)



⋮



Valid proof: $(t, s_1, \dots, s_u)$ s.t.

▶ $1 \leq t \leq d$;

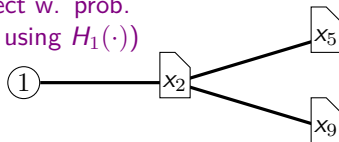
▶ $\forall 1 \leq i \leq u, H_1(t, s_1, \dots, s_i) = 1$;

$(\Pr[H_1(\cdot) = 1] = 1/n)$

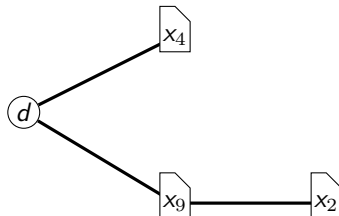
Telescope Construction (cont.)

Let $x_1, \dots, x_n$ be honest prover's elements. ($n = n_p$)

(select w. prob.
 $1/n$ using $H_1(\cdot)$)



⋮



#

d

$\approx d$

$\approx d$

(repeat u times)



(select w. prob.
 q using $H_2(\cdot)$)

Valid proof: $(t, s_1, \dots, s_u)$ s.t.

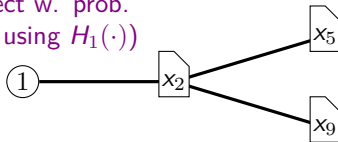
- ▶ $1 \leq t \leq d$;
- ▶ $\forall 1 \leq i \leq u, H_1(t, s_1, \dots, s_i) = 1$;
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$(\Pr[H_1(\cdot) = 1] = 1/n, \Pr[H_2(\cdot) = 1] = q)$

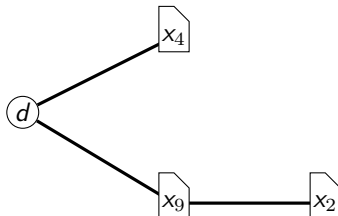
Telescope Construction (cont.)

Let $x_1, \dots, x_n$ be honest prover's elements. ($n = n_p$)

(select w. prob.
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⋮



#

d

$\approx d$

$\approx d$

(repeat u times)



(select w. prob.
 q using $H_2(\cdot)$)

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Telescope Construction (cont.)

Let $x_1, \dots, x_n$ be honest prover's elements. ($n = n_p$)

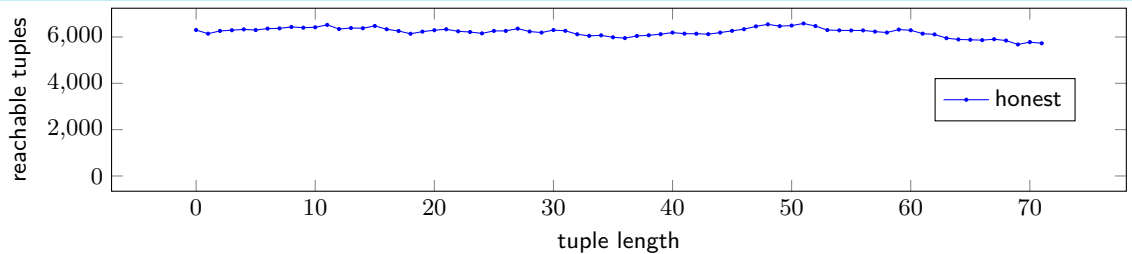
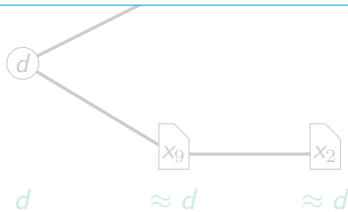


Figure: Telescope simulation: $d = 6300$, $n_p = 1000$, $n_f = 500$



Valid proof: $(t, s_1, \dots, s_u)$ s.t.

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Telescope Construction (cont.)

Let $x_1, \dots, x_n$ be honest prover's elements. ($n = n_p$)

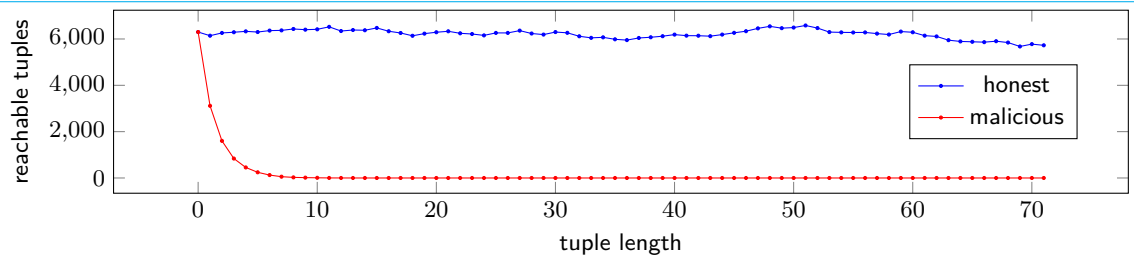
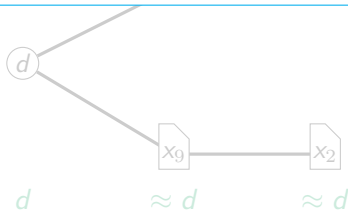


Figure: Telescope simulation: $d = 6300$, $n_p = 1000$, $n_f = 500$



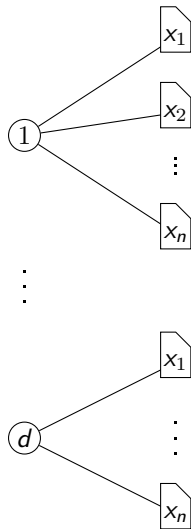
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Efficient Construction: Telescope (cont.)

- ▶ Represent as d trees
- ▶ Prover runs DFS (instead of BFS)
- ▶ Union bound to analyze soundness:
 - ▶ soundness error
$$\text{"number"} \cdot \text{"probability"} = d \cdot n_f^u \cdot \left(\frac{1}{n_p}\right)^u \cdot q$$
- ▶ Recursive formula to analyze completeness:
 - ▶ $f(0) = 1 - q$
 - ▶ $f(k+1) = \left((1 - \frac{1}{n_p}) + \frac{1}{n_p} \cdot f(k)\right)^{n_p}$
 - ▶ completeness error $(f(u))^d$
- ▶ Setting errors $\leq 2^{-\lambda}$, achieve proof size $u = \frac{\lambda + \log \lambda + 2}{\log(n_p/n_f)}$
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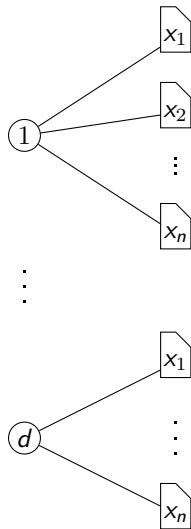
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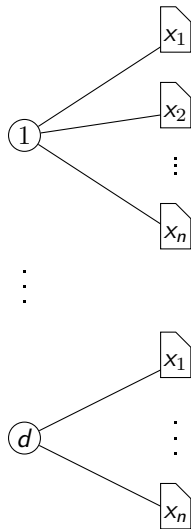
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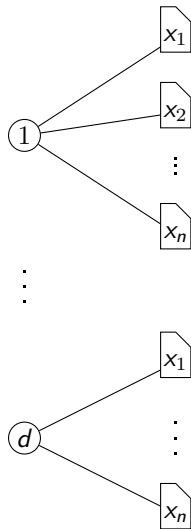
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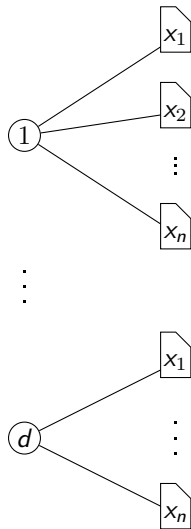
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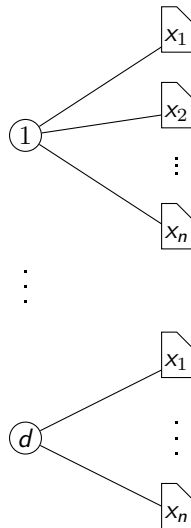
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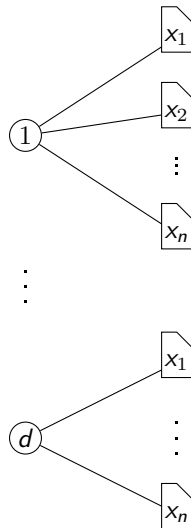
Efficient Construction: Telescope (cont.)

- ▶ To analyze prover running time:
 - ▶ u reachable vertices in a tree in expectation (by linearity of expectation)
 - ▶ a tree succeeds with probability $\Omega(1/\lambda)$
 - ▶ $\implies$ expected running time $O(u \cdot \lambda \cdot n_p) = O(\lambda^2 \cdot n_p)$
 - ▶ also $O(\lambda^3 \cdot n_p)$ w.h.p.



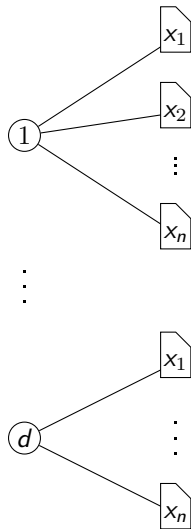
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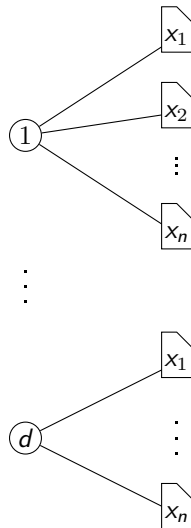
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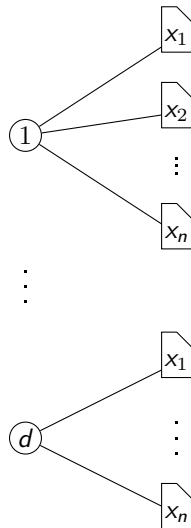
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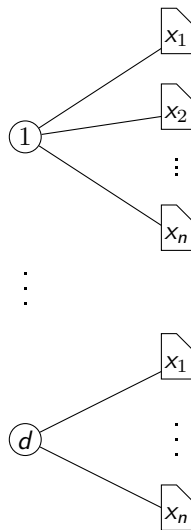


Coming next...

- ☒ Definitions
 - Unweighted case
 - ☒ Prover-inefficient construction
 - ☒ Telescope construction
 - ☐ **Improving prover running time**
 - ☐ Decentralized setting
- ☐ Adding weights
- ☐ Applications

Improving Prover Runtime: Telescope with Prehashing

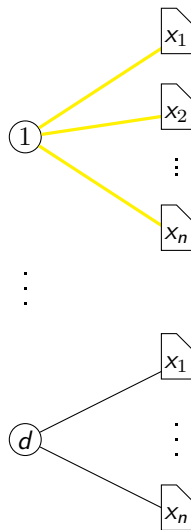
- ▶ Basic Telescope has running time $O(\lambda^2 \cdot n)^1$
- ▶ Optimization inspired by balls-and-bins
- ▶ Hash $x_1, \dots, x_n$ into n bins using $G_0(\cdot) \sim \text{Unif}([n])$
- ▶ $(t, s_1, \dots, s_j)$ has valid extensions in bin $G_1(t, s_1, \dots, s_j) \sim \text{Unif}([n])$



¹ $n = n_p$

Improving Prover Runtime: Telescope with Prehashing

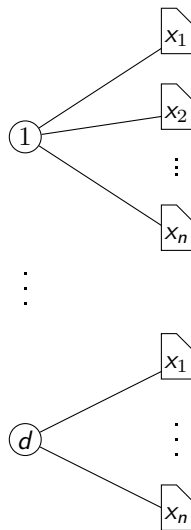
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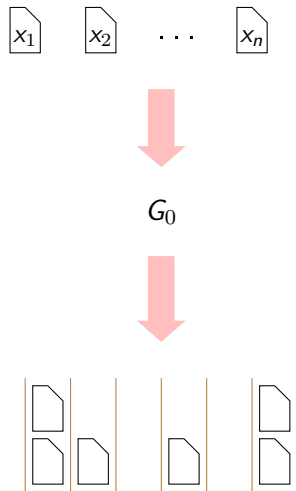
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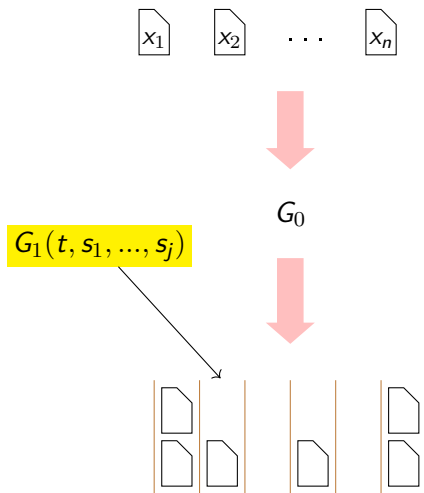
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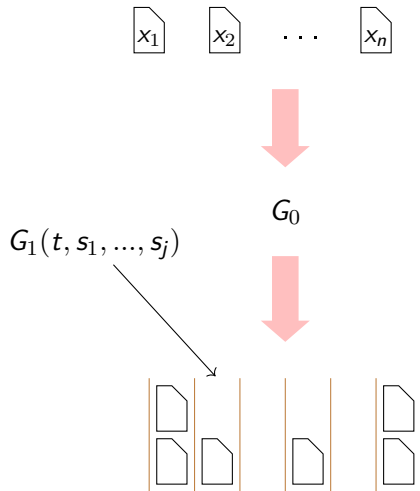
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Valid proof: $(t, s_1, \dots, s_u)$ s.t.

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 - ▶ $\forall 1 \leq i \leq u, G_1(t, s_1, \dots, s_{i-1}) = G_0(s_i)$;
 - ▶ $G_2(t, s_1, \dots, s_u) = 1$;
- $(G_0(\cdot), G_1(\cdot) \sim \text{Unif}([n]), G_2(\cdot) \sim \text{Bernoulli}(q))$

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Improving Prover Runtime: Telescope with Prehashing (cont.)

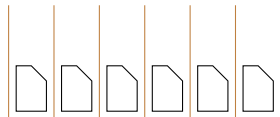
- ▶ Soundness analysis remains the same (union bound)
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- ▶ Need a “good” condition on “balls” distribution
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 - ▶ Markov's inequality approach (when $n_p \leq \Theta(\lambda^2)$):
 - ▶ guarantees “good” condition with moderate prob.
 - ▶ get a scheme with completeness $1/2$; amplify
 - ▶ expected running time $O(n_p + \lambda^2)$
 - ▶ Chernoff inequality approach (when $n_p \geq \Theta(\lambda^3)$):
 - ▶ “good” condition w.h.p. by Chernoff-like analysis
 - ▶ running time $O(n_p + Z)$ where $\mathbb{E}[Z] = \lambda^2$
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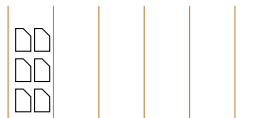
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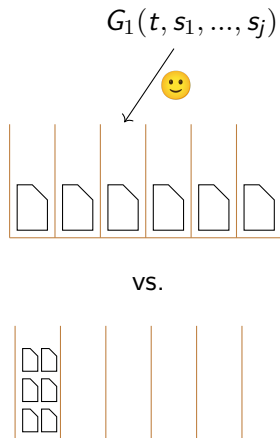


vs.



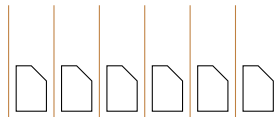
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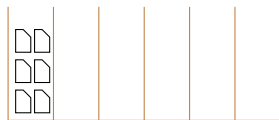


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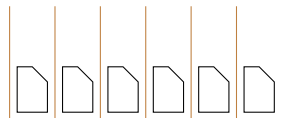
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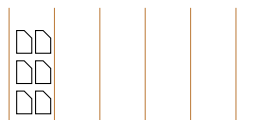
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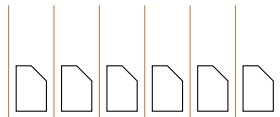
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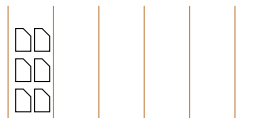
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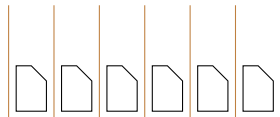


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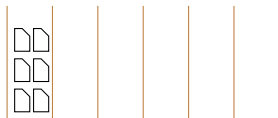


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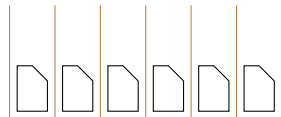


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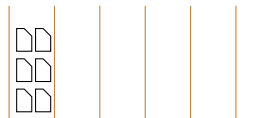


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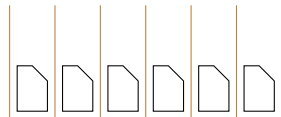


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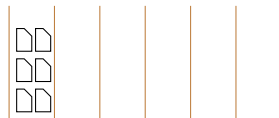


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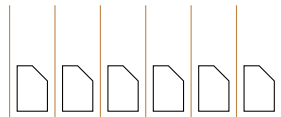


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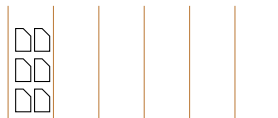


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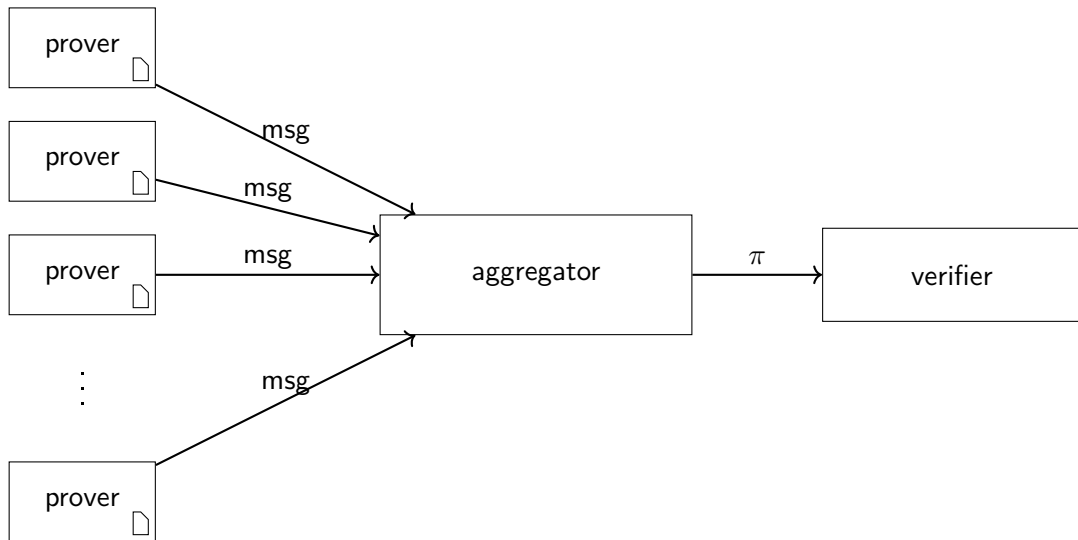
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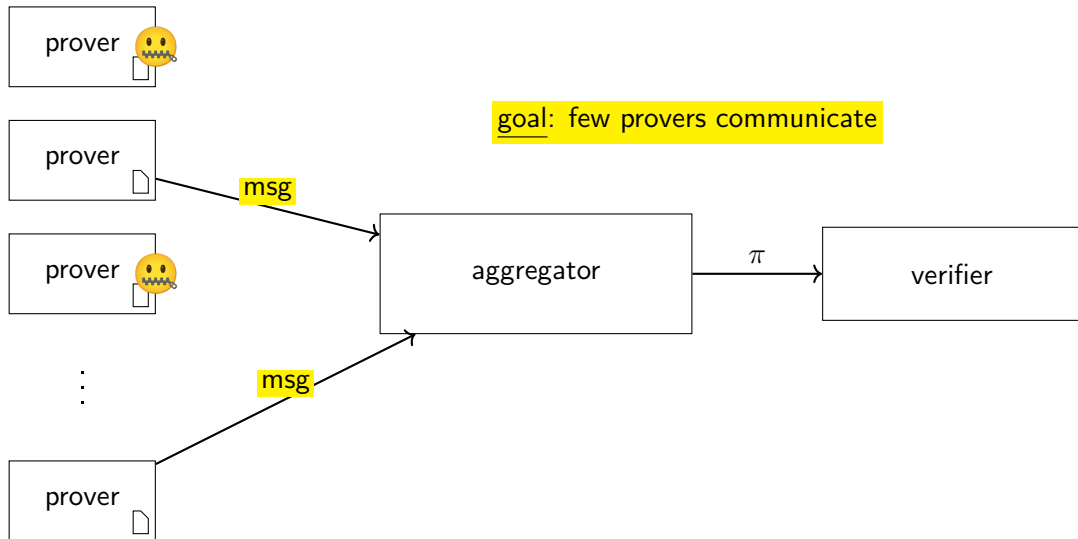
Coming next...

- ☒ Definitions
 - Unweighted case
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 - ☒ Telescope construction
 - ☒ Improving prover running time
 - ☐ **Decentralized setting**
- ☐ Adding weights
- ☐ Applications

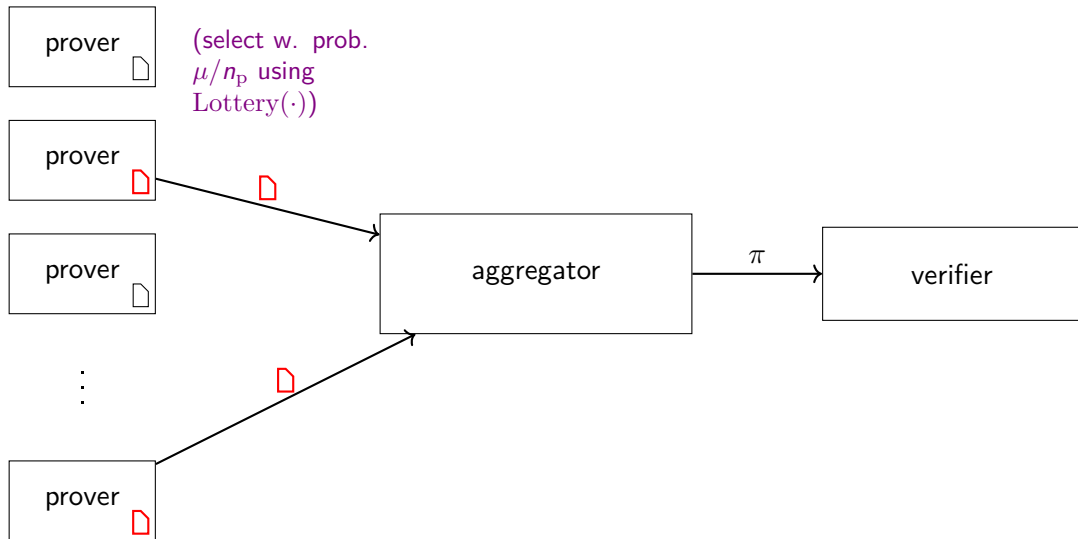
Decentralized ALBA



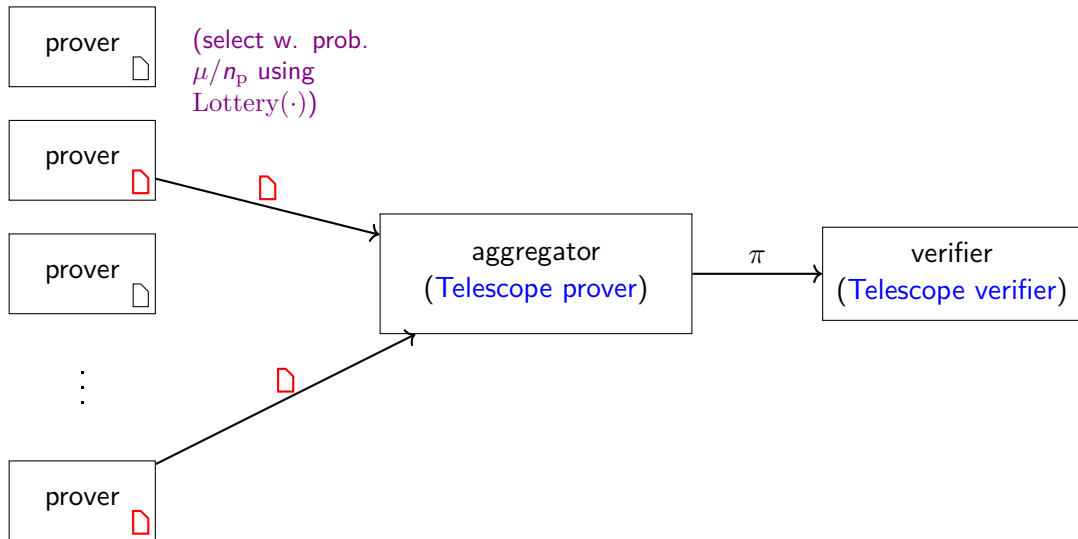
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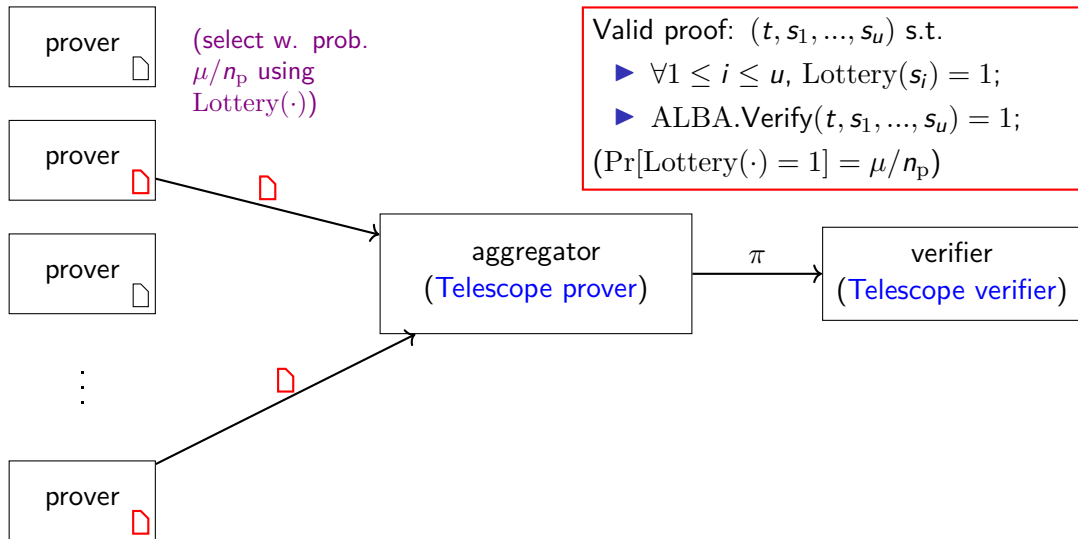
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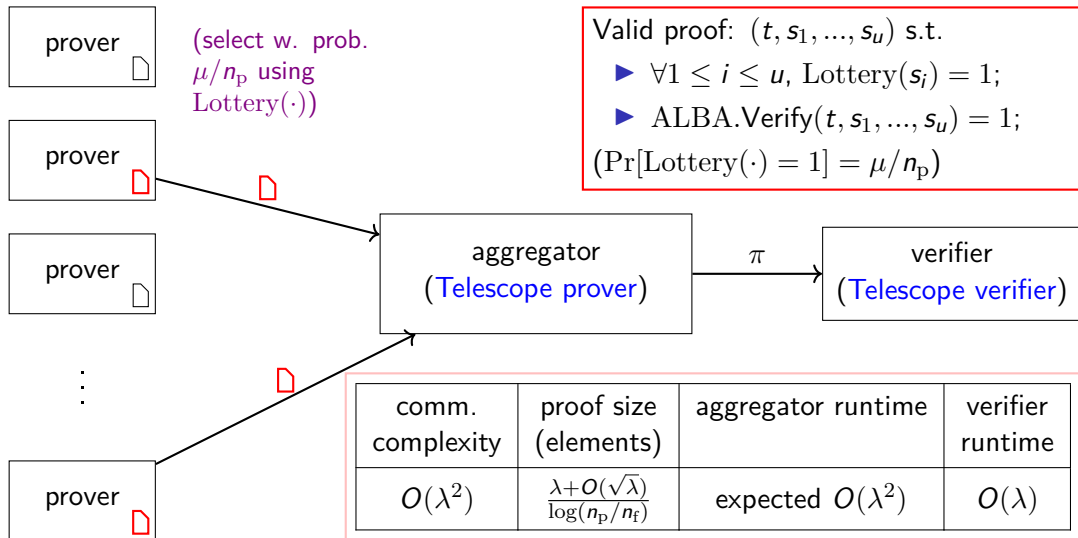
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Adding Weights

- ▶ Back to centralized setting
- ▶ Naive approach
 - ▶ turn weight- w element x into elements $(x, 1), \dots, (x, w)$
 - ▶ inefficient (think of w as $\sim 2^{64}$)
- ▶ Lottery based approach

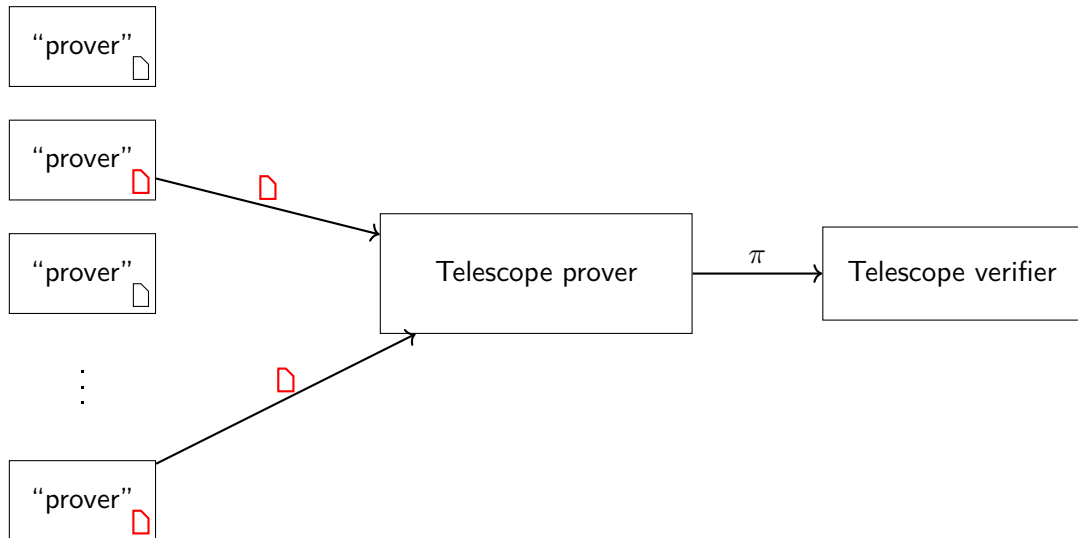
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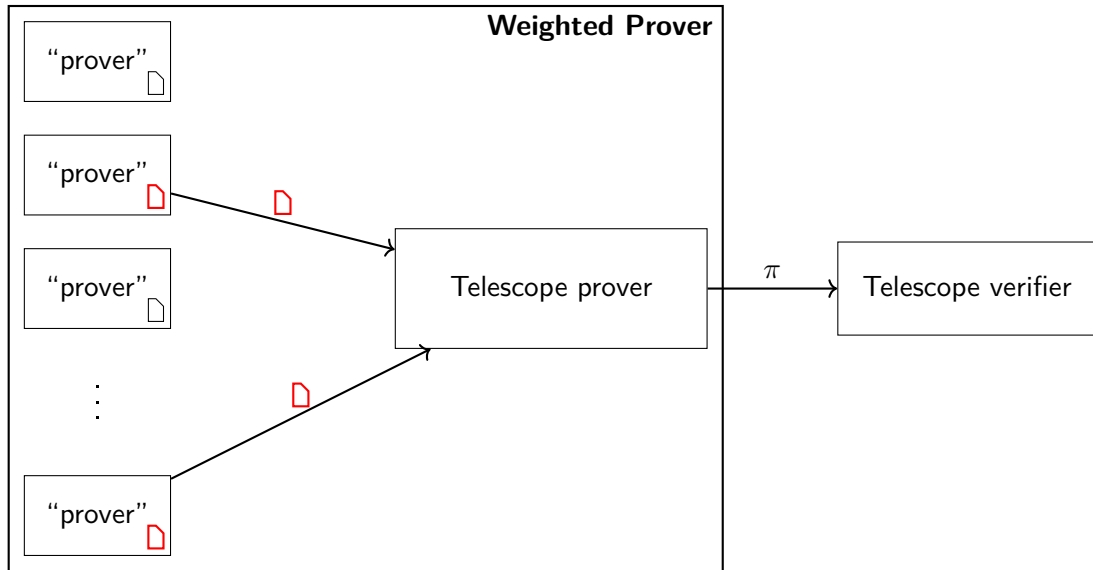
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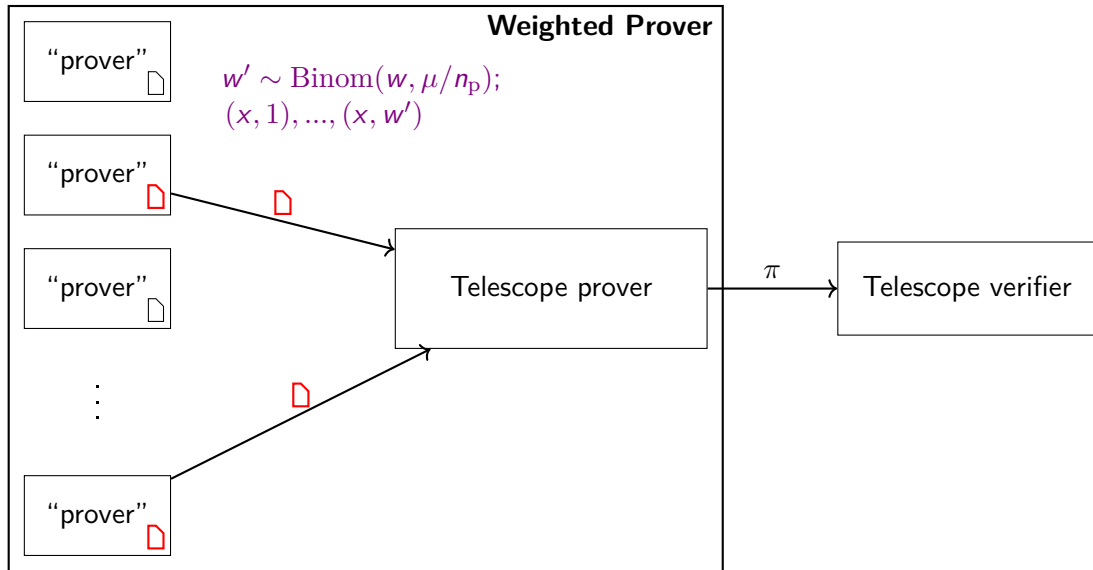
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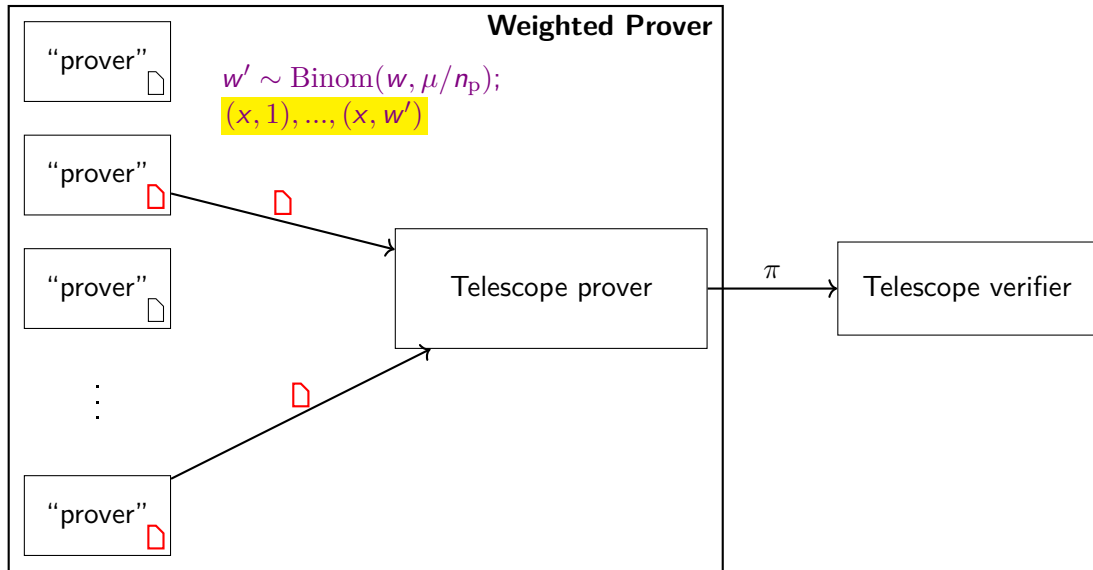
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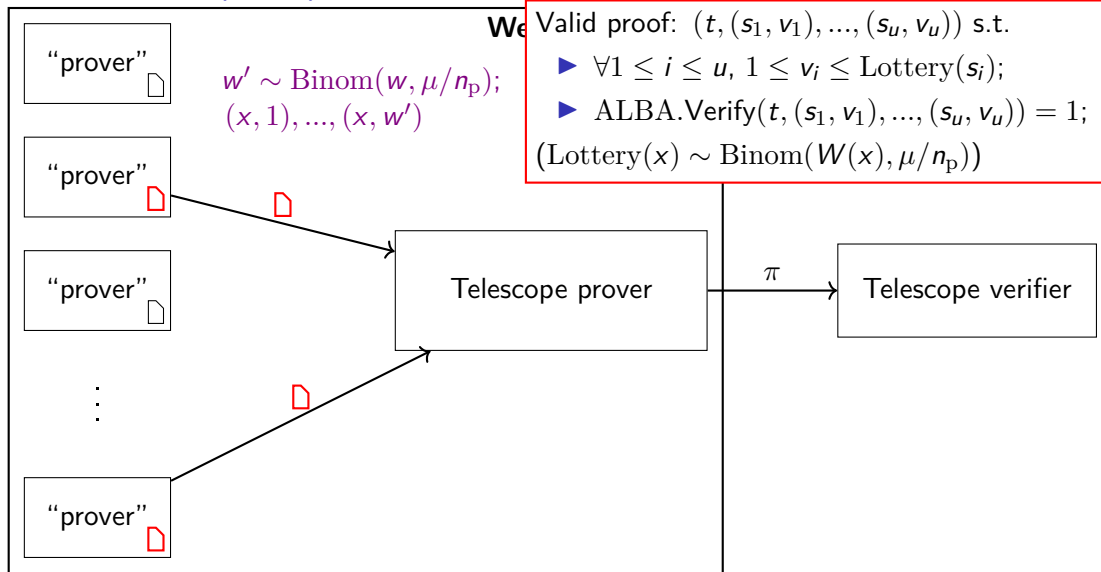
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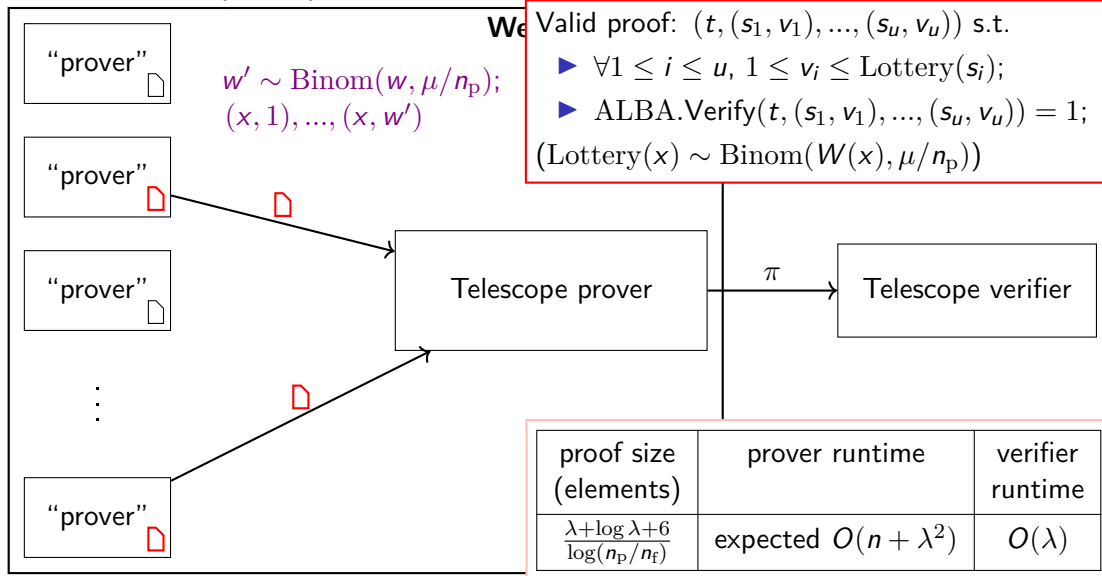
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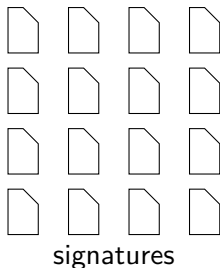


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- ▶ Prove that sufficiently many parties signed a message
- ▶ Proof-of-stake blockchains: prove that parties with sufficient total stake (money) attested to blockchain state
 - ▶ assume 80% honest stake, 20% malicious stake $\implies n_p/n_t = 4$
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 - ▶ signature weight = node's stake
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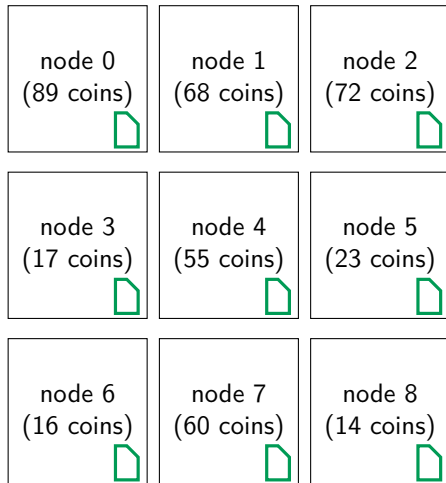
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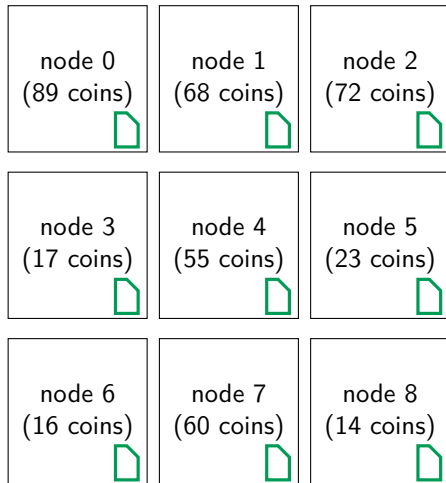
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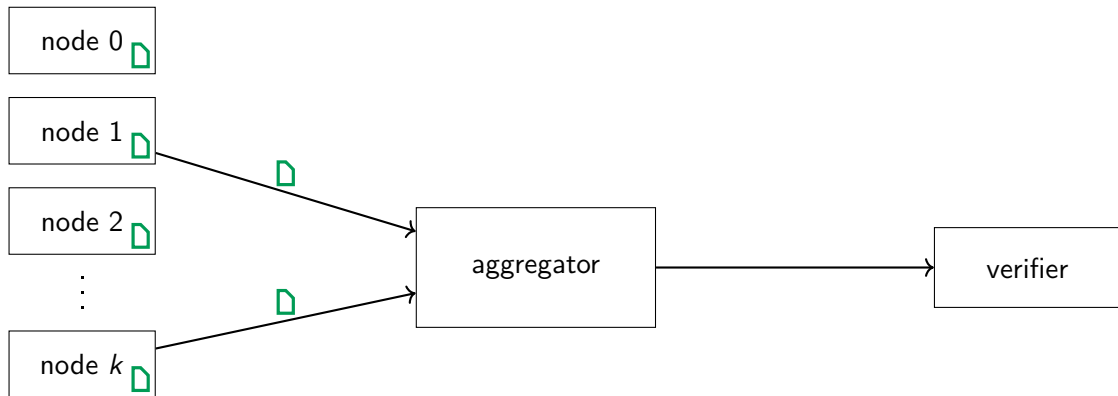
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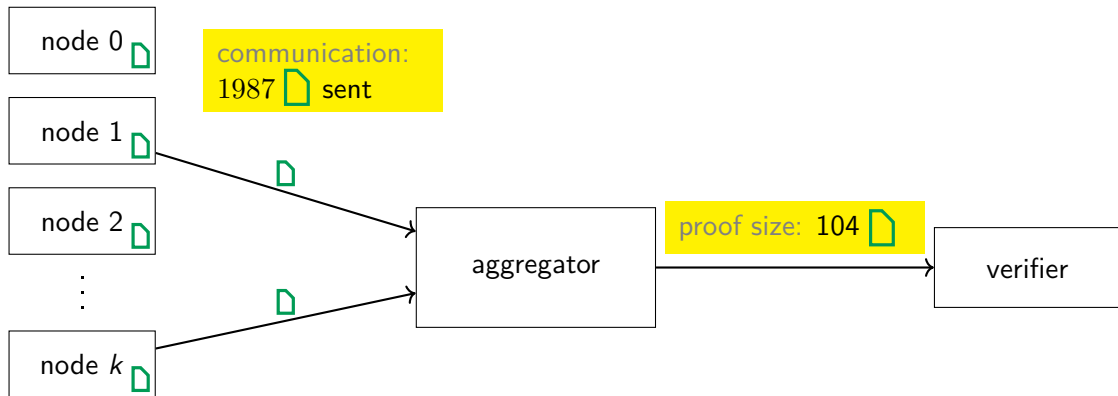
Application 1: Weighted Multisignatures (cont.)

small proof + small communication complexity



Application 1: Weighted Multisignatures (cont.)

small proof + small communication complexity, 128-bit security:



Application 2: Straight-Line Witness Extraction for SNARKs

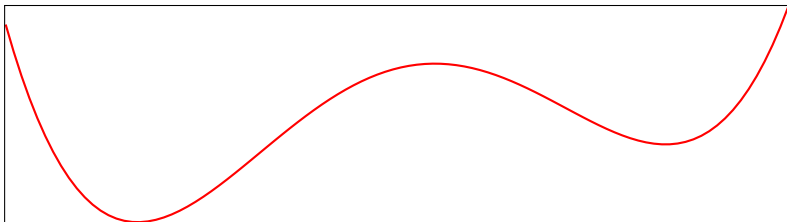
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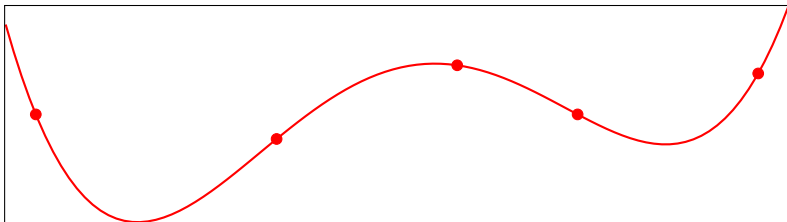
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- ▶ **Observation:** An application of ALBA
- ▶ **Result:** prover queries $2d$ points instead (λ times faster prover); more modular construction



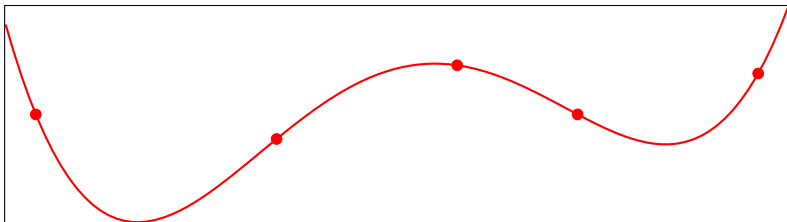
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Additional slides:

- ▶ Lower bounds
- ▶ Table of all results
- ▶ Knowledge extraction (RO, straight-line)
- ▶ ALBA in CRS model

[GKOPTT23] Chaya Ganesh, Yashvanth Kondi, Claudio Orlandi, Mahak Pancholi, Akira Takahashi, and Daniel Tschudi. “Witness-Succinct Universally-Composable SNARKs”. In: *EUROCRYPT 2023, Part II*. Ed. by Carmit Hazay and Martijn Stam. Vol. 14005. LNCS. Springer, Heidelberg, Apr. 2023, pp. 315–346. DOI: 10.1007/978-3-031-30617-4_11.

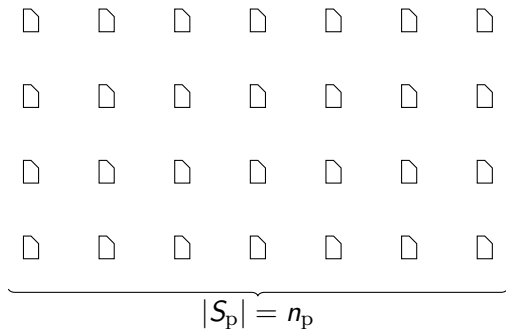
Lower Bounds

Theorem

Any ALBA scheme with completeness & soundness errors $\leq 2^{-\lambda}$ must have $\Omega(\lambda)$ proof size.

Proof outline

- ▶ (random variable) $\pi \leftarrow \text{Prove}^H(S_p)$
- ▶ suppose $|\pi|$ is small
- ▶ take random $S_f \subseteq S_p$ with $|S_f| = n_f$
- ▶ $\Pr_{H, S_f}[\pi \subseteq S_f]$ is big
- ▶ by averaging argument $\exists S'_f$ s.t.
 $\Pr_H[\pi \subseteq S'_f]$ is big
- ▶ $\Pr_H[\pi \subseteq S'_f]$ is small by soundness
- ▶ contradiction



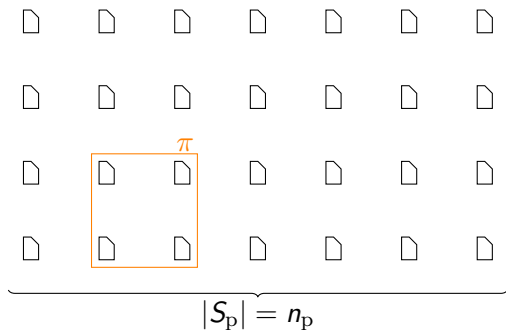
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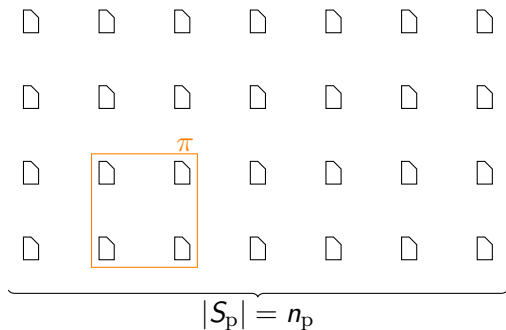
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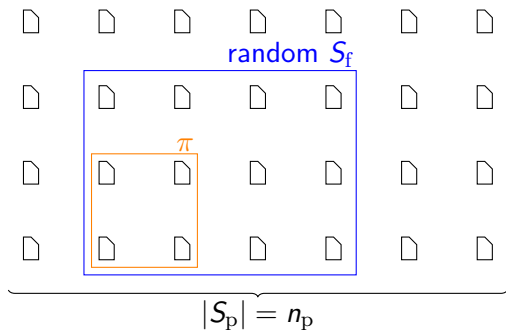
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Any ALBA scheme with completeness & soundness errors $\leq 2^{-\lambda}$ must have $\Omega(\lambda)$ proof size.

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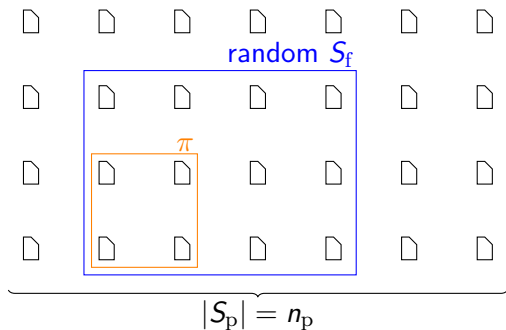
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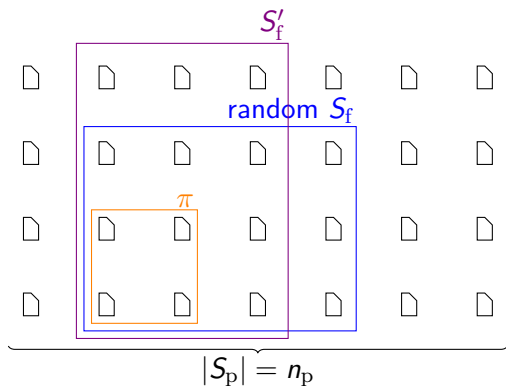
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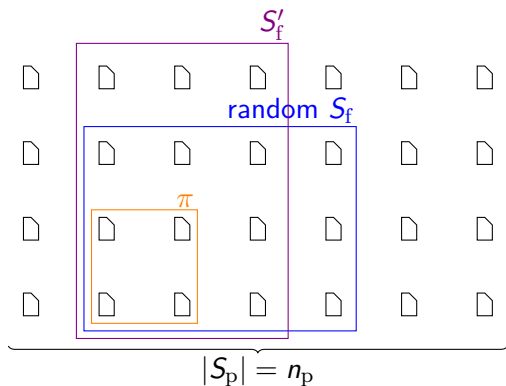
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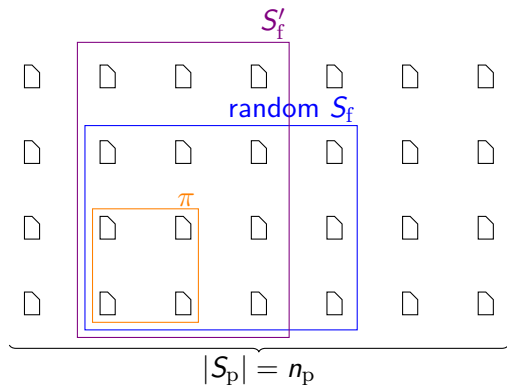
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Lower Bounds (cont.)

scheme	proof size (elements)	comm. rounds	comm. complexity
ALBA	$> \frac{\lambda-3}{\log(n_p/n_f)}$		
decentralized ALBA ¹	$> \frac{\lambda+\Omega(\sqrt{\lambda})}{\log(n_p/n_f)}$	1	$O(\lambda^2)$

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All Results

setting	lower bound	Telescope
ALBA	$> \frac{\lambda-3}{\log(n_p/n_f)}$	$\frac{\lambda+\log \lambda+6}{\log(n_p/n_f)}$
decentralized ALBA; communication $O(\lambda^2)$	$> \frac{\lambda+\Omega(\sqrt{\lambda})}{\log(n_p/n_f)}$	$\frac{\lambda+O(\sqrt{\lambda})}{\log(n_p/n_f)}$

Table: Proof size

scheme	average	worst case
Telescope prover	$O(n + \lambda^2)$	$O(n + \lambda^3)$
decentralized Telescope aggregator; communication $O(\lambda^2)$	$O(\lambda^2)$	$O(\lambda^3)$
Telescope verifier	$O(\lambda)$	$O(\lambda)$

Table: Running time

Knowledge Extraction (RO, straight-line)

- ▶ $\mathcal{A}^{H,W}$ produces valid proof with probability $2^{-\lambda} + \epsilon$
- ▶ **goal:** extract $> n_f$ weight-1 elements with probability ϵ

Theorem

$\text{Extract}^{H,W,\mathcal{A}}$ extracts $> n_f$ elements with probability ϵ

Proof.

$$2^{-\lambda} + \epsilon =$$

$$\Pr[\mathcal{A} \text{ succeeds}] \leq$$

$$\Pr[\mathcal{A} \text{ queries} \leq n_f \text{ elements and succeeds}] +$$

$$\Pr[\mathcal{A} \text{ queries} > n_f \text{ elements}]$$



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Lemma

$$\Pr[\mathcal{A} \text{ queries } \leq n_f \text{ elements and succeeds}] \leq 2^{-\lambda}$$

Issue: adaptive adversary $\implies$ union bound doesn't work

Proof.

- ▶ think about indices as inputs to H_1, H_2
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We achieved:

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when weight function is fixed in advance
- ▶ can get security assuming a bound on the number of RO queries
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Telescope in CRS³ model

- ▶ Replace RO with PRF²
- ▶ CRS = PRF key
- ▶ PRF key need not be secret

²Pseudorandom Function

³Common Reference String

Knowledge Extraction in CRS model

- ▶ Knowledge extraction via rewinding:
 - ▶ suppose $\mathcal{A}^W(\text{crs})$ succeeds with probability $2^{-\lambda} + \epsilon \implies$ extract with probability ϵ
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