

The Power of NAPs

Compressing OR-proofs via Collision-Resistant Hashing

Séminaire C2
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Nancy

joint work with Mark Simkin

@TCC'24

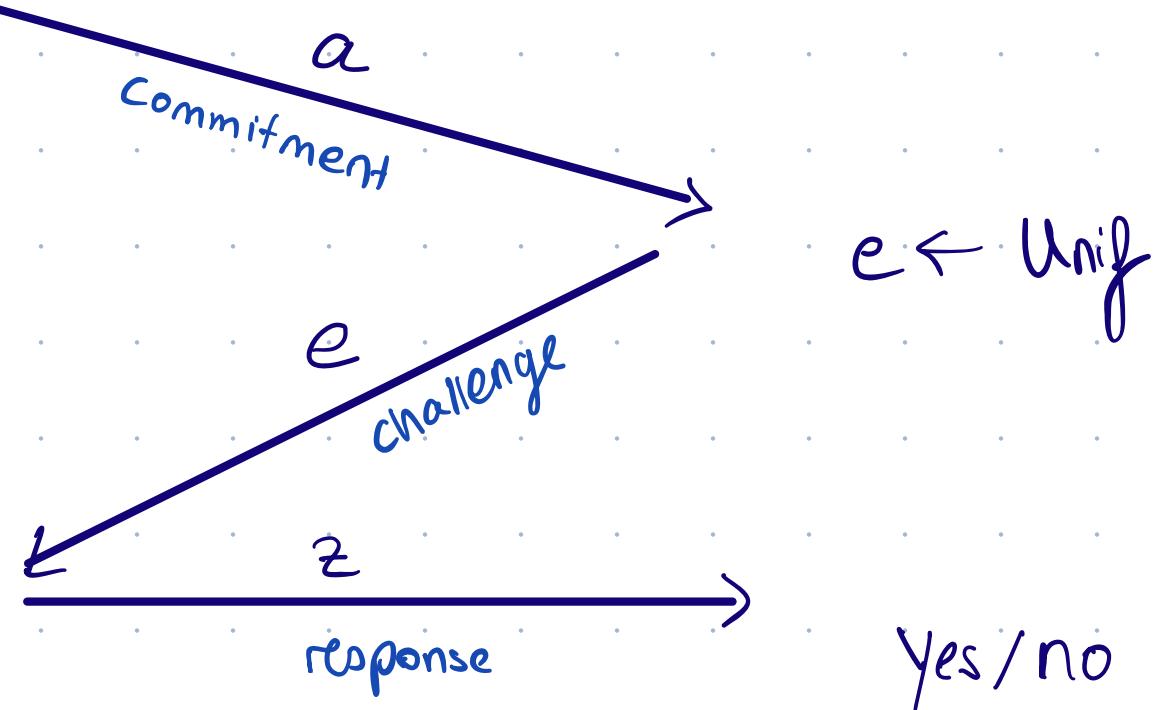
Σ - Protocols

$P(x, \omega)$ witness

$x \in L!$

$V(x)$ statement

Sure?



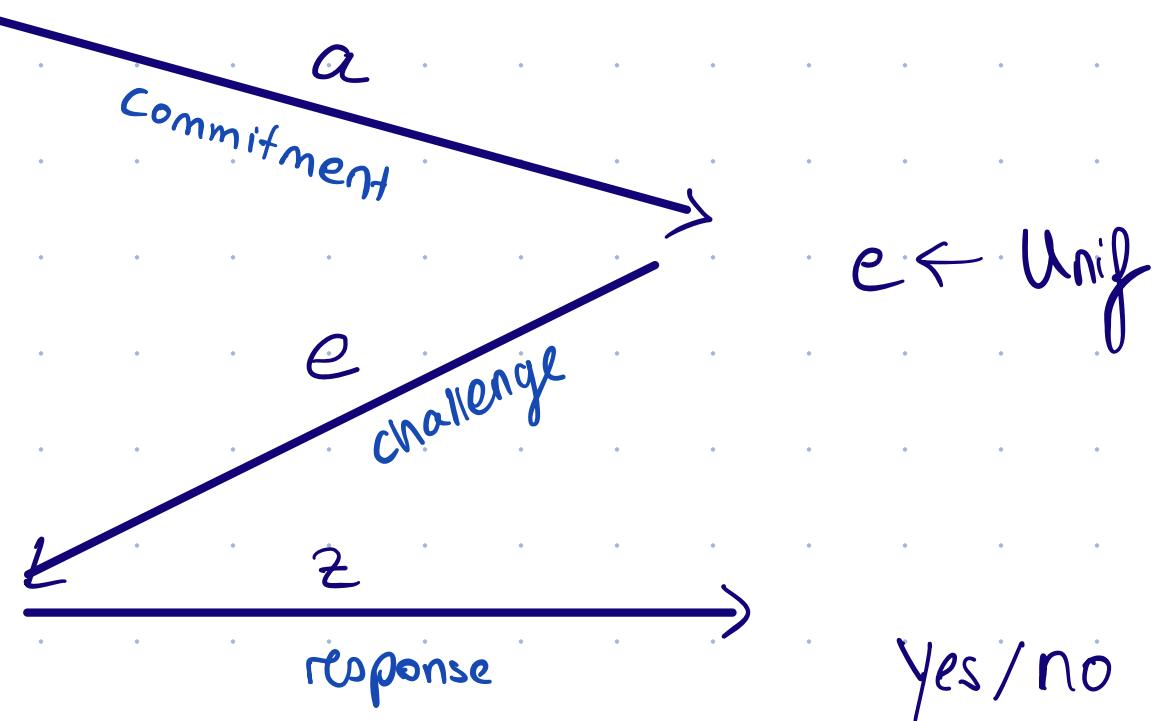
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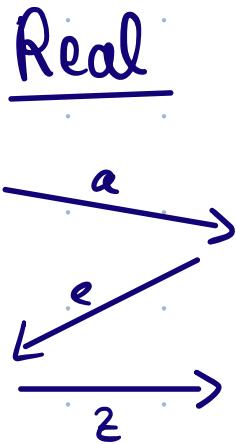


Completeness ~ honest execution succeeds

Soundness ~ P must know witness ω to succeed

Honest-Verifier Zero-Knowledge (HVZK) ~ V doesn't know ω

Honest-Verifier Zero-Knowledge



Simulated

$e \leftarrow \text{Unif}$

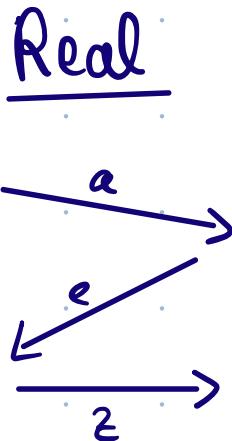
$(a, z) \leftarrow \text{Simulator}(e)$

(a, e, z)

\approx

(a, e, z)

STRONG Honest-Verifier Zero-Knowledge

 (a, e, z)

Simulated

 $e \leftarrow \text{Unif}$ $z \sim \text{Unif}$ $a := \text{Simulator}(e, z)$

(deterministic)

 $\tilde{\sim} (a, e, z)$

[Groel-Green-Hall-Andersen - Kaptchuk '22]

I-Protocol with HVZK $\Rightarrow \Sigma$ -Protocol' with Strong HVZK

Σ -Protocol for Graph Isomorphism Problem

[Goldreich-Micali-Wigderson '86]

$$x = (G_0, G_1)$$

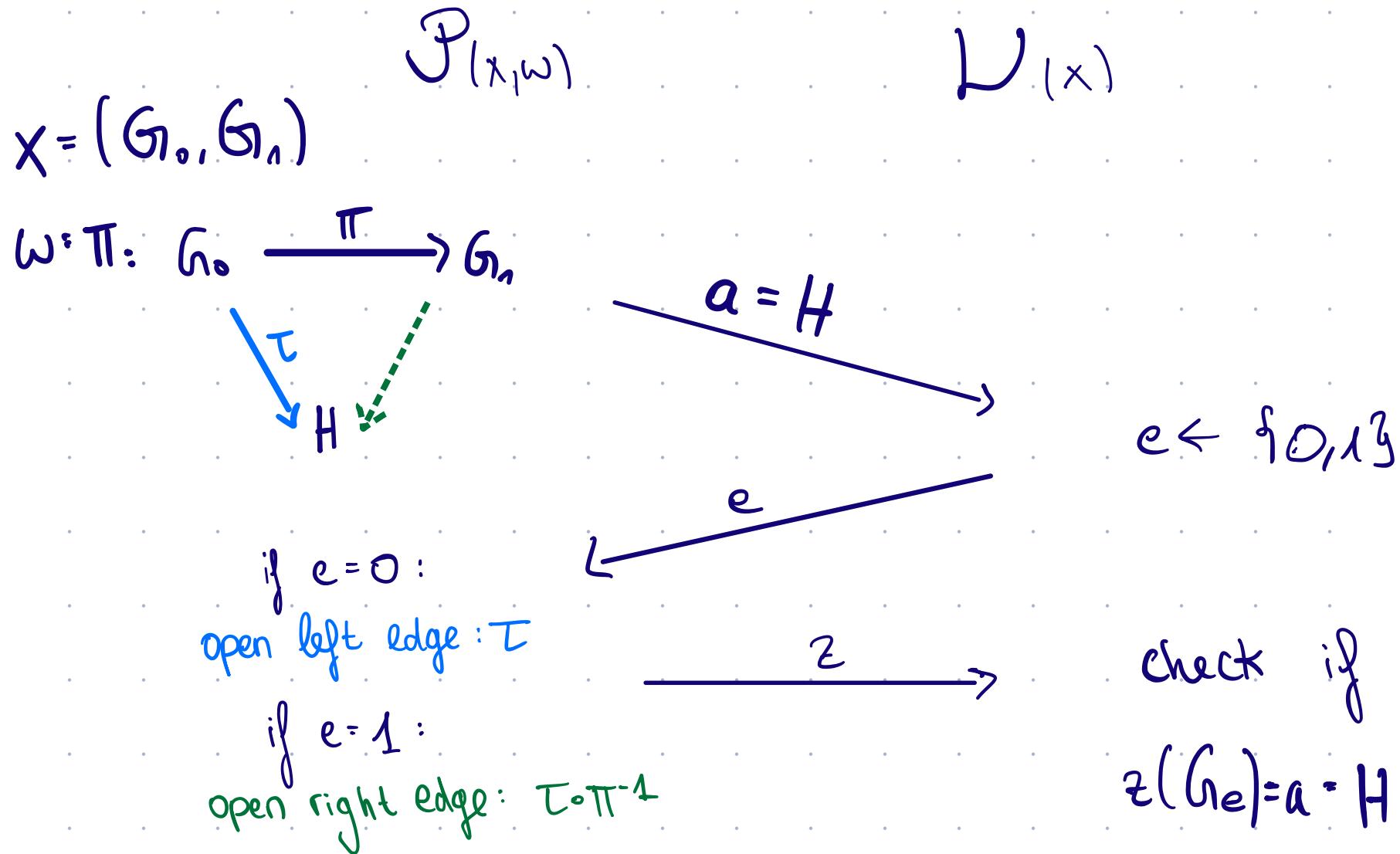
$$\omega: \Pi: G_0 \xrightarrow{\pi} G_1$$

$$\beta_{(x, \omega)}$$

$$\mathcal{U}_x$$

Σ -Protocol for Graph Isomorphism Problem

[Goldreich-Micali-Wigderson '86]



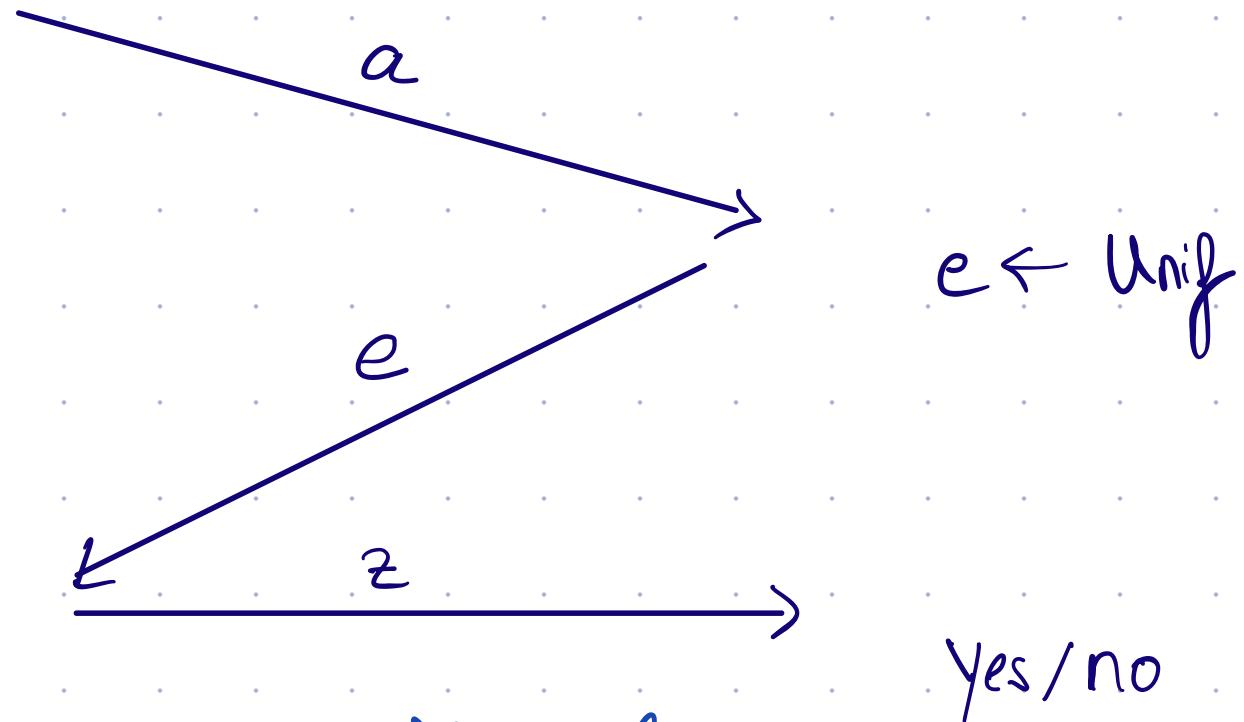
strong
Simulation: for e and z given, set $a := z(G_e)$

Or-Proofs

$$\mathcal{P}(\omega, x_1, x_2, \dots, x_n) \quad \mathcal{V}(x_1, x_2, \dots, x_n)$$

$\exists i \in [n] : x_i \in L$

sure?



Specific enough to be solved efficiently

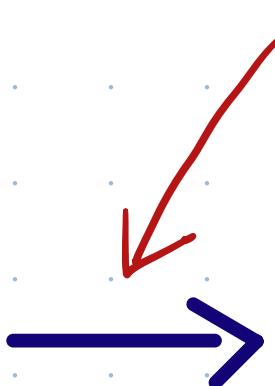
General enough to be useful :

Ring Signatures, electronic voting

Constructing OR-Proofs

required communication overhead?

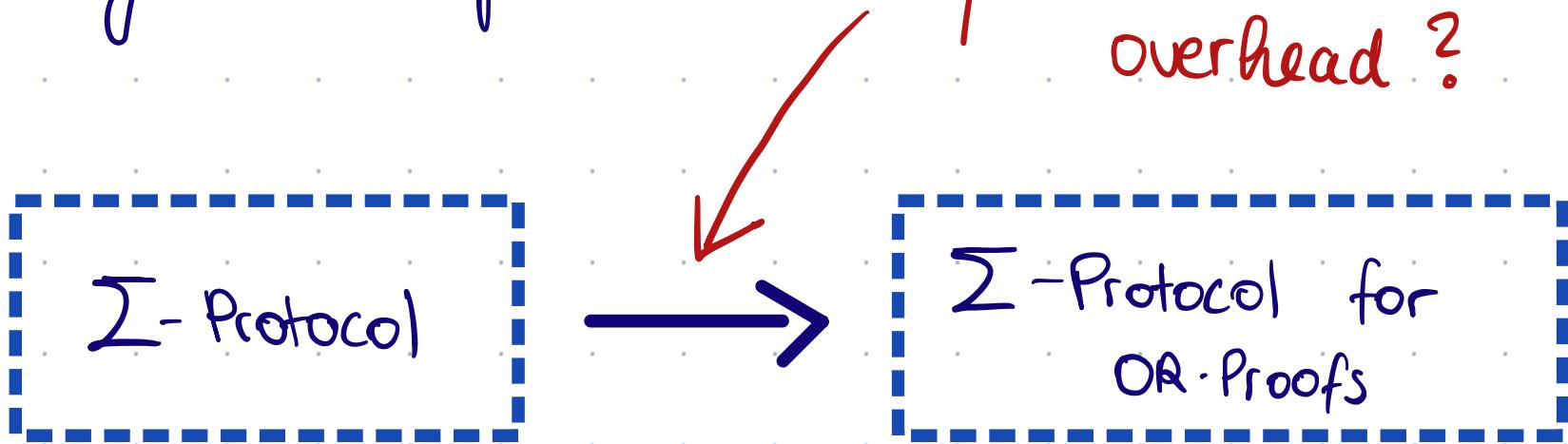
Σ -Protocol



Σ -Protocol for
OR-Proofs

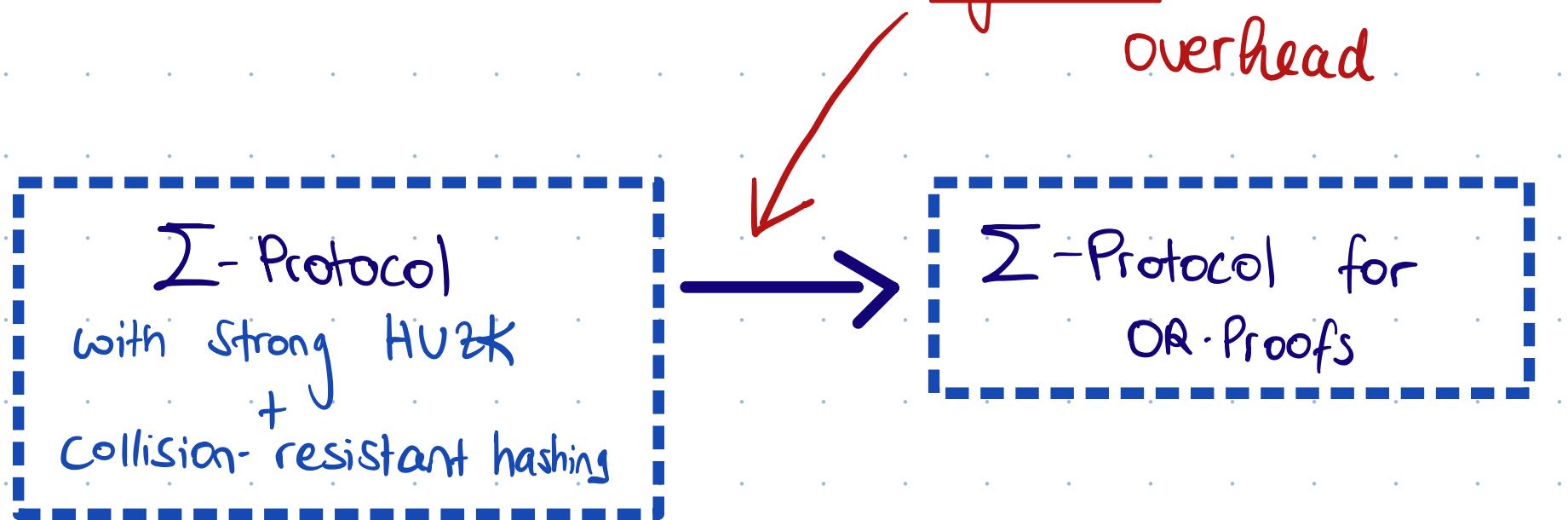
Constructing OR-Proofs

required communication overhead?



- [Cramer, Damgård, Schoenmakers 1994]: any I-Protocol but linear overhead
- From structured hardness assumptions (eg DLog, LWE,...)
good communication complexity, but stronger assumptions
- via MPC-in-the-Head
unstructured assumptions, but large communication complexity

Our Contributions



- + new notion of non-adaptively programmable functions (NAPs)
- + rejection sampling can be explained

Any questions
so far?

Starting Point

$(\omega, x_1) \in L$

\mathcal{P}

[Cramer, Damgård, Schoenmakers, 1994]

(x_1, \dots, x_n)

V

honest: a_1

simulated: $e_2, \dots, e_n \leftarrow \text{Unif}$

$(a_i, z_i) \leftarrow \text{Sim}(e_i)$

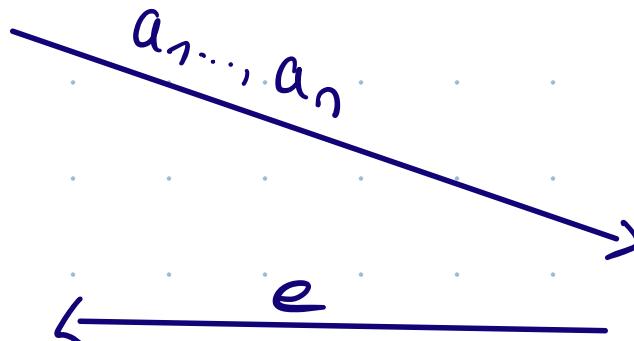
(a_2, e_2, z_2)

\vdots

(a_n, e_n, z_n)

e_1 st $e = e_1 + \dots + e_n$

honest: z_1

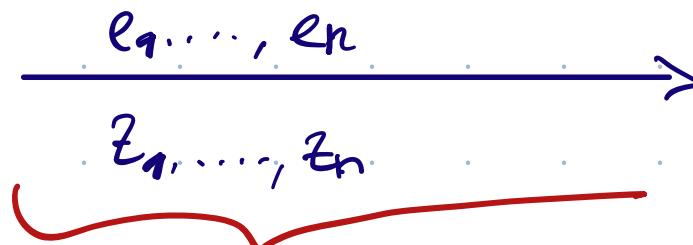


check each

(a_i, e_i, z_i)

$\forall i \in [n]$

and $e = e_1 + \dots + e_n$



linear in n

Our Ideas

P

V

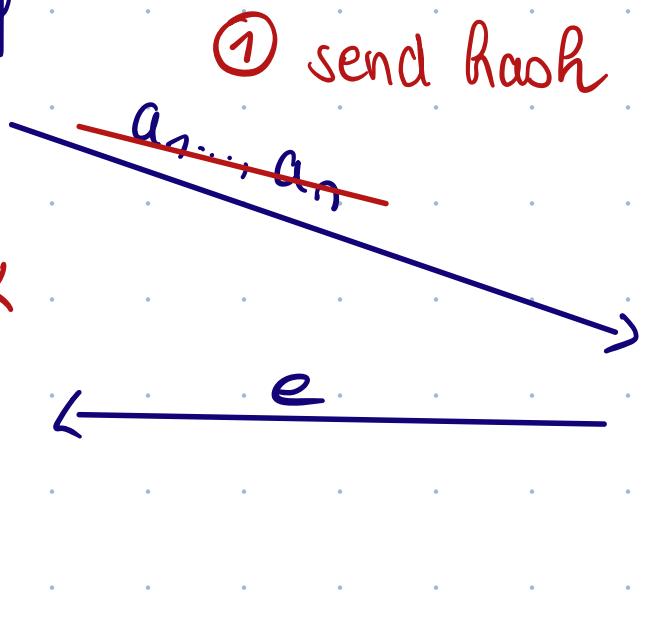
honest: a_1

simulated: $e_2, \dots, e_n \leftarrow$
 $z_2, \dots, z_n \leftarrow \text{Unif}$

$a_i := \text{StrongSim}(e_i, z_i)$

(a_2, e_2, z_2) HVZK

(a_n, e_n, z_n)



e_1 st $e = e_1 + \dots + e_n$

honest: z_1

use seeds to compute

e_1, \dots, e_n

z_1, \dots, z_n

and Strong Simulator

to compute

a_1, \dots, a_n

check each

(a_i, e_i, z_i)

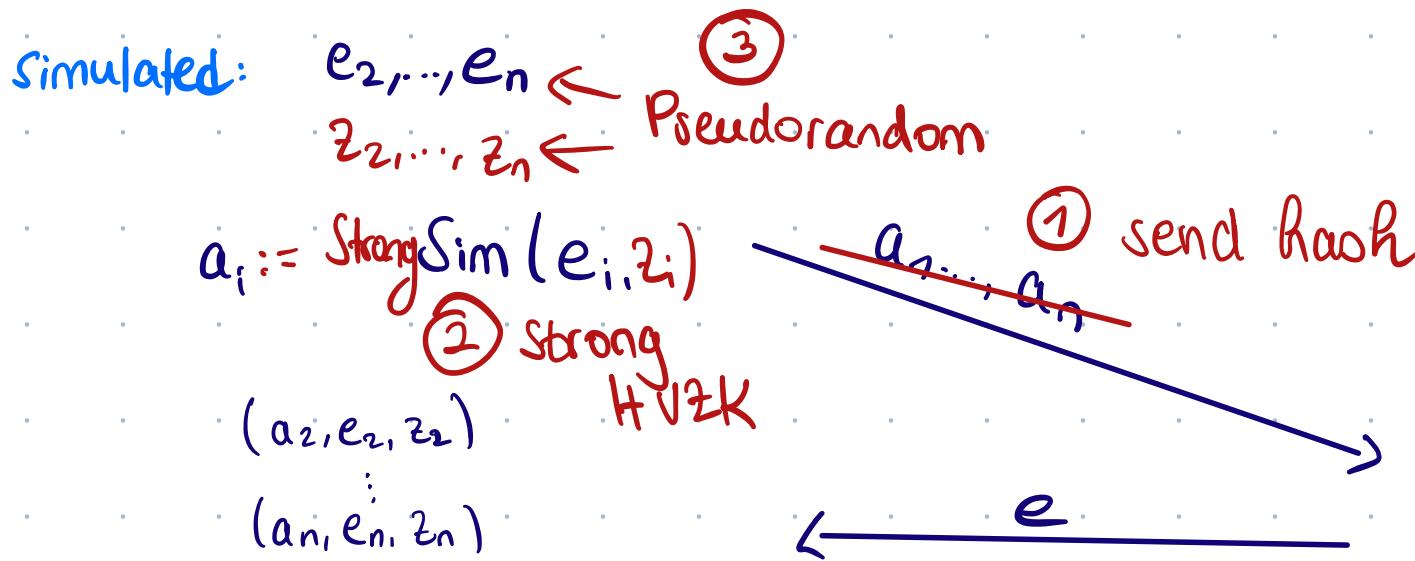
$\forall i \in [n]$

Our Ideas

P

V

honest: a_1



e_1 st $e = e_1 + \dots + e_n$

honest: z_1

④ Needs to program seeds

use seeds to compute
 e_1, \dots, e_n
 z_1, \dots, z_n
and Strong Simulator
to compute
 a_1, \dots, a_n
check each
 (a_i, e_i, z_i)
 $i \in [n]$

What we need is a function

- whose output looks random
- which for the same seed and same input
is deterministic
- which can be privately programmed
- there exists notion of privately programmable PRF's
but they require heavy tools (FHE, iO)

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but they require heavy tools (FHE, iO)



Key observation: we know programming
location during key generation
⇒ MUCH SIMPLER

This is the moment where

we will use the

Power of NAPs !

Non-Adaptively Programmable Functions

$\text{msk} \leftarrow \text{Gen}(* \in [n])$

$e_i \leftarrow \text{Eval}(\text{msk}, i)$

$\text{psk} \leftarrow \text{Prog}(\text{msk}, e^*)$

$e_i \leftarrow \text{PEval}(\text{psk}, i)$

Correctness:

① programming worked

$$\text{PEval}(\text{psk}, i) = e^*$$

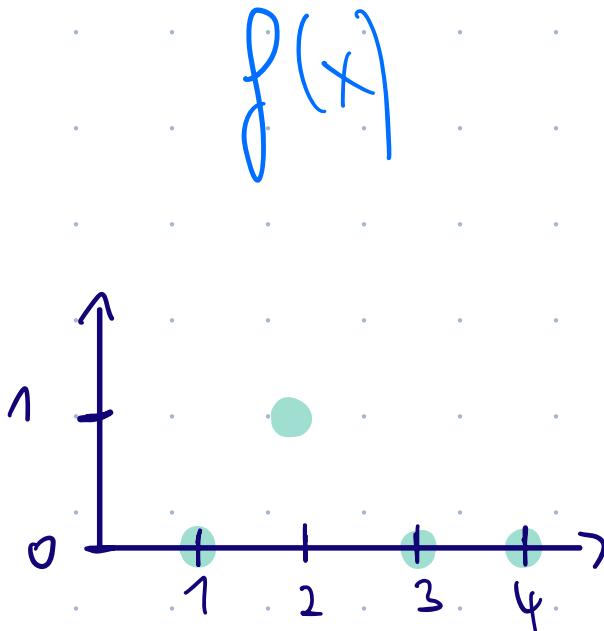
② all other positions unchanged

$$\text{PEval}(\text{psk}, i) = \text{Eval}(\text{msk}, i)$$

$$\forall i \neq *$$

Private Programmability ~ psk does not leak
the position i^*

Point Function



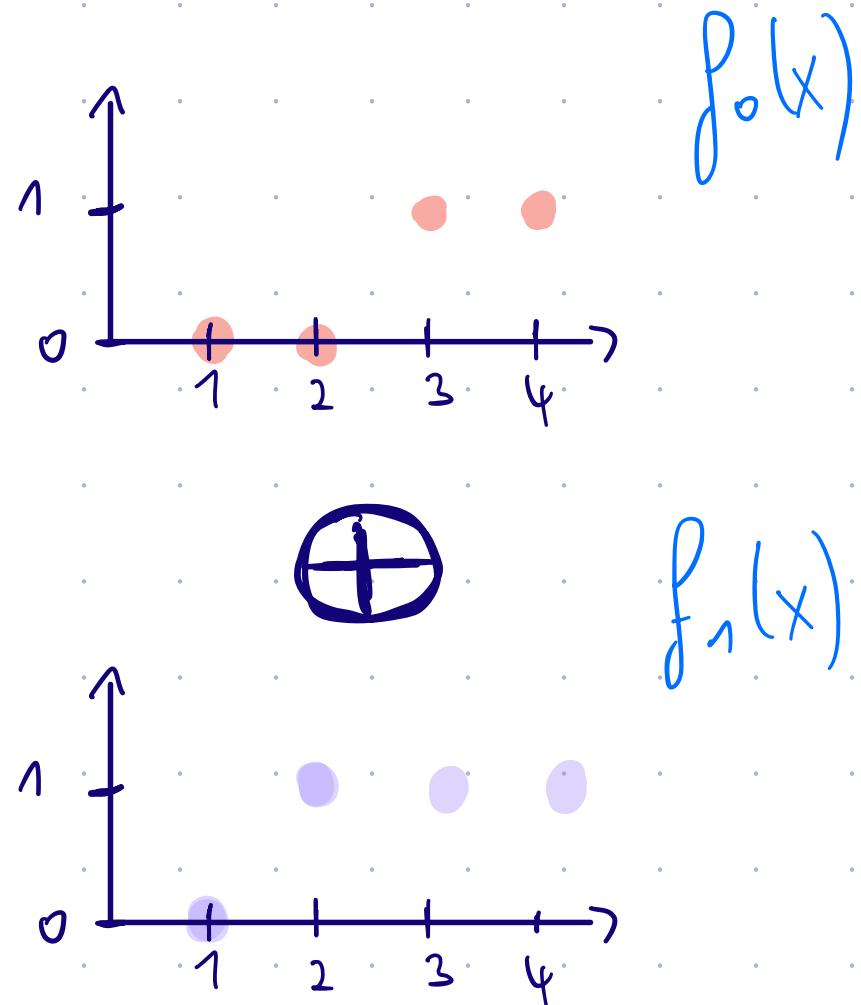
=

$$n=4$$

[Boyle-Gilboa-Ishai'15]

implied by collision-resistant Hashing

Distributed



Constructing NAPs via DPF

$n=4$

$\text{msk} \leftarrow \text{Gen}(* i \in [n])$

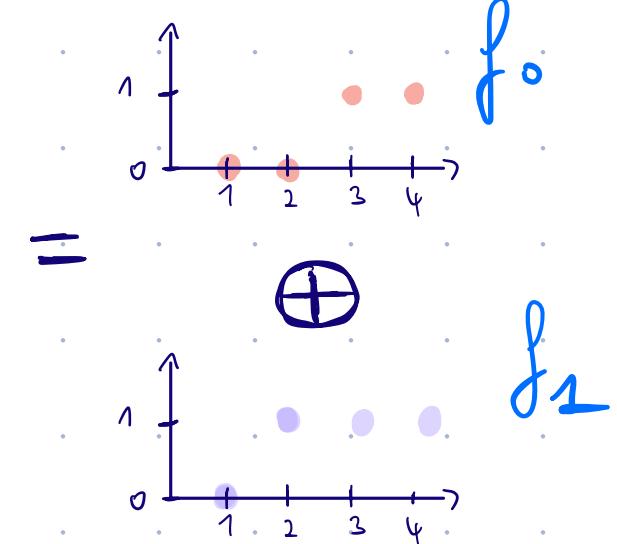
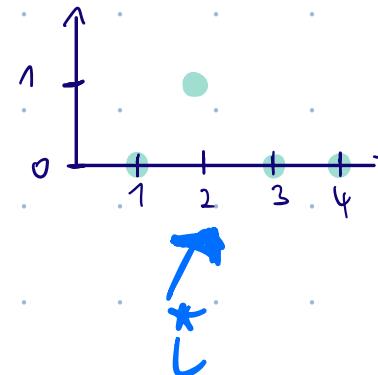
$\text{msk} = (f_0, f_1, \star)$

$e_i \leftarrow \text{Eval}(\text{msk}, i) = f_0(i)$

$\text{psk} \leftarrow \text{Prog}(\text{msk}, e^*)$ either $f_0(t) = e^*$ or $f_1(t) = e^*$!

$e_i \leftarrow \text{PEval}(\text{psk}, i) = f_{0/1}(i)$

for multiple output bits: concatenation



Our Construction

P

V

honest: a_1

simulated: $e_2, \dots, e_n \leftarrow \text{Eval}$
 $z_2, \dots, z_n \leftarrow$

$a_i := \text{StrongSim}(e_i, z_i)$

(a_2, e_2, z_2)

\vdots
 (a_n, e_n, z_n)

$$\xrightarrow{H(a_1, \dots, a_n) = a}$$

$\leftarrow e$

e_1 st $e = e_1 + \dots + e_n$

honest: z_1

$\text{psk}_e \leftarrow \text{Prog}(e_1)$
 $\text{psk}_2 \leftarrow \text{Prog}(z_1)$

$\xrightarrow{\text{pske}, \text{psk}_2}$

$e_1, \dots, e_n \leftarrow \text{PEval}$
 $z_1, \dots, z_n \leftarrow$

$a_i := \text{StrongSim}(e_i, z_i)$

check each

(a_i, e_i, z_i)
 $\forall i \in [n]$

check $e = \sum e_i$

check $H(a_1, \dots, a_n) = a$

From 1-out-of-n to k-out-of-n

1-out-of-n:

simulate
obtain

e_2, \dots, e_n
 e

sum uniquely
determines e_1

k-out-of-n:

simulate
obtain

e_{k+1}, \dots, e_n
 e

uniquely
determine a
polynomial
 $p(x)$ of degree $n-k$



fixes e_1, \dots, e_k

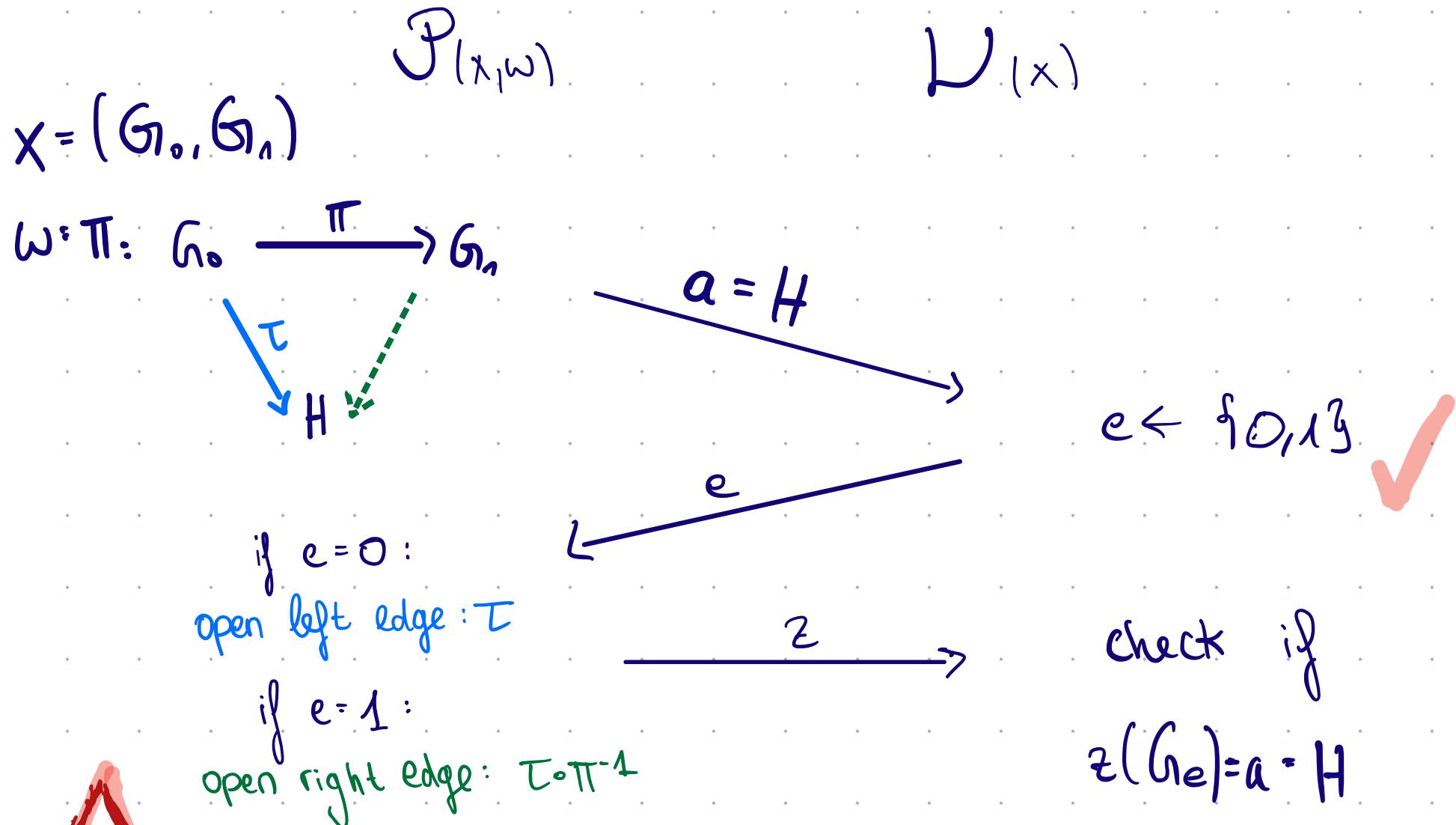
$$p(i) = e_i$$

So... are we done?

Almost...

Σ -Protocol for Graph Isomorphism Problem

[Goldreich-Micali-Wigderson '86]



z random isomorphism between graphs

More general distributions

- use uniform bits as the random coins for sampling other distributions
(e.g. Rejection Sampling)
- Use a NAP to program the random bits
- need a way to go from
 - random bits to a sample (easy)
 - a sample to "fitting" random bits (difficult)



Explainable Samplers

[Lu-Waters '22]

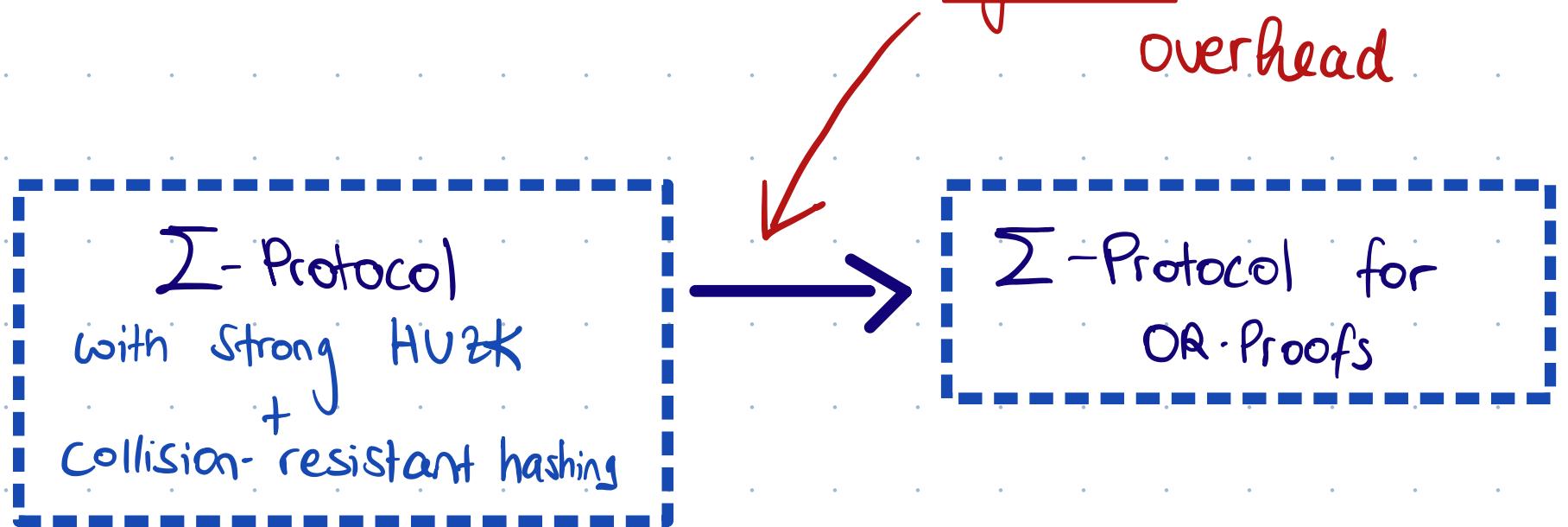
Explainable Samplers

[Lu-Waters '22]

↳ showed that Rejection Sampling in
the context of discrete Gaussians
is explainable

→ we show that Rejection Sampling
is explainable in general

Our Contributions



- + new notion of non-adaptively programmable functions (NAPs)
- + rejection sampling can be explained

Thank you !!