

This class: "secure computation on secret data"

So far we've seen FHE / lattice techniques

FHE:  $E_{pk}(x) \xrightarrow[\text{Dec}]{\text{Eval}} f(x)$

No circuit-dependent comm.

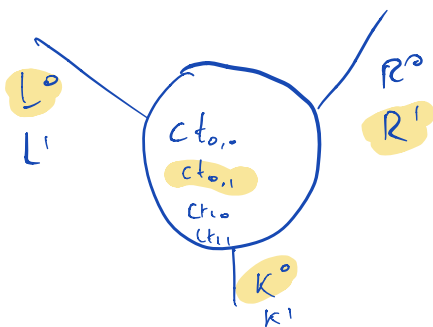
⇒ Narrow band of assumptions (lattice based)

Conceptually: eggs in one basket

Practical: heavy, slow

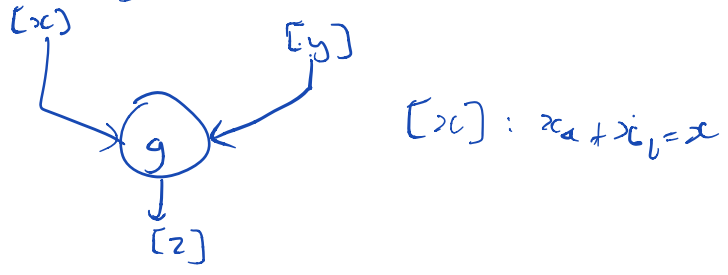
} not true for GSW/CC

### Garbled Circuits



General idea: Progress through circuit gate by gate obtaining wire labels

Secret-sharing based: GMW/BLW



real idea: progress through circuit gate by gate maintaining this invariant

Compare & Contrast

FHE	CC/GMW/BLW
Success comm.	Comm. per gate
Narrow band of assumptions (lattices) <ul style="list-style-type: none"> <li>- Conceptually, eggs in one basket</li> <li>- Practical: powerful crypto runs slower</li> </ul>	Generically instantiable (OT, OWFs) <ul style="list-style-type: none"> <li>- Fast in practice with lower grade crypto (eg. AES, elliptic curves)</li> </ul>

SS: secret-sharing analogue of FHE

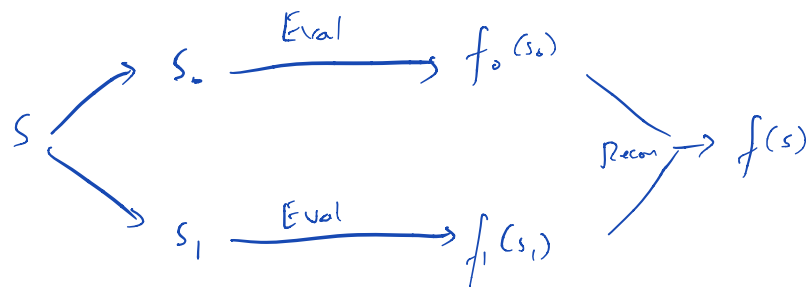
Beal 86

→ distributed

Boyle Gilboa

15hr-13

→ non-interactive evaluation

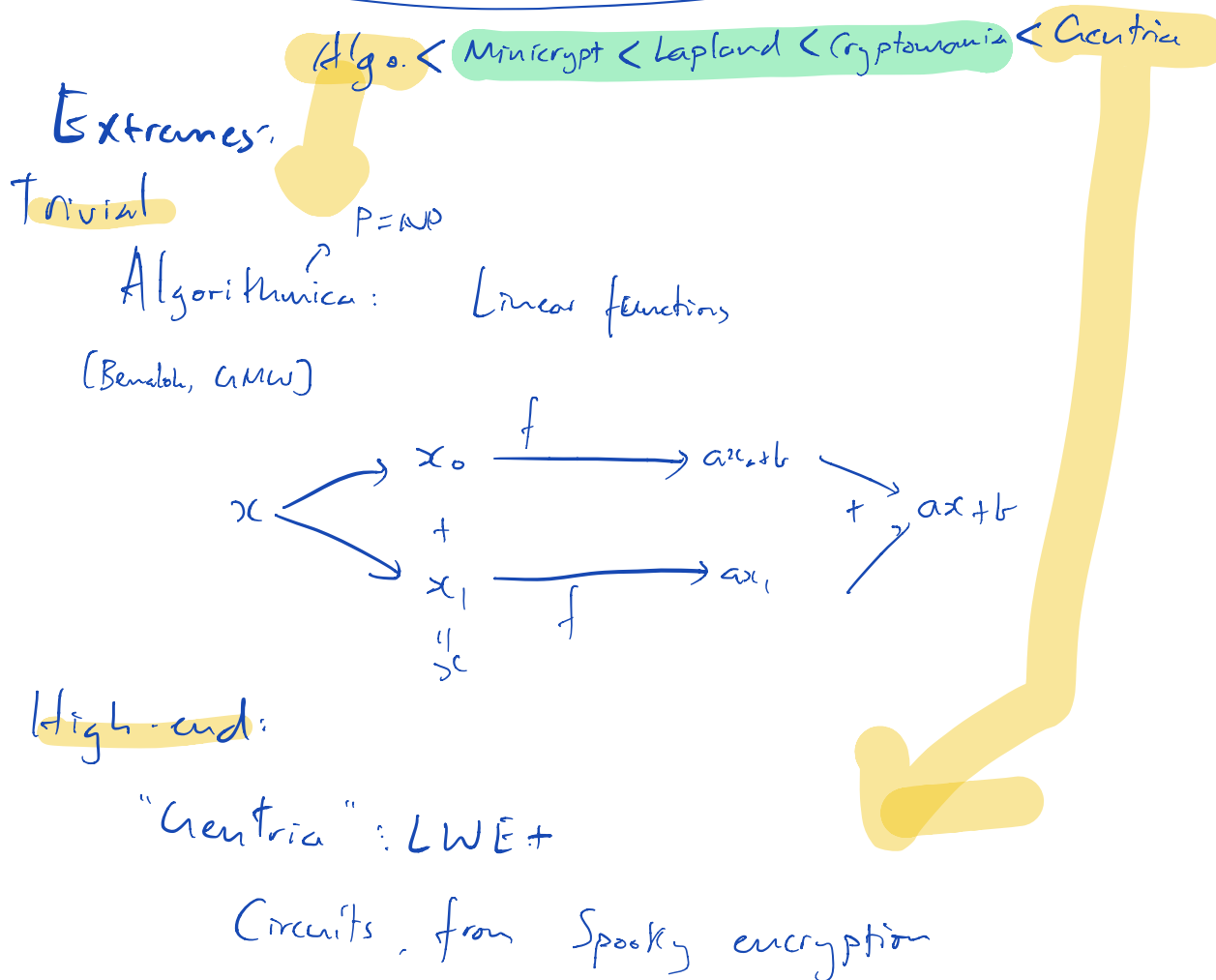


Can we realize this with a broader class of assumptions than FHE?

if. with weaker, faster primitives while also maintaining meaningful efficiency

It's been a few years:

Shai's Worlds of HSS (a la Impagliazzo)



interesting stuff is what  
lies in between

## Cryptomania:

Branching programs from specific structured assumptions

re.: DDH, Paillier, LWE  
Cust generic PKE / OT)

DDH construction is Eysen's talk

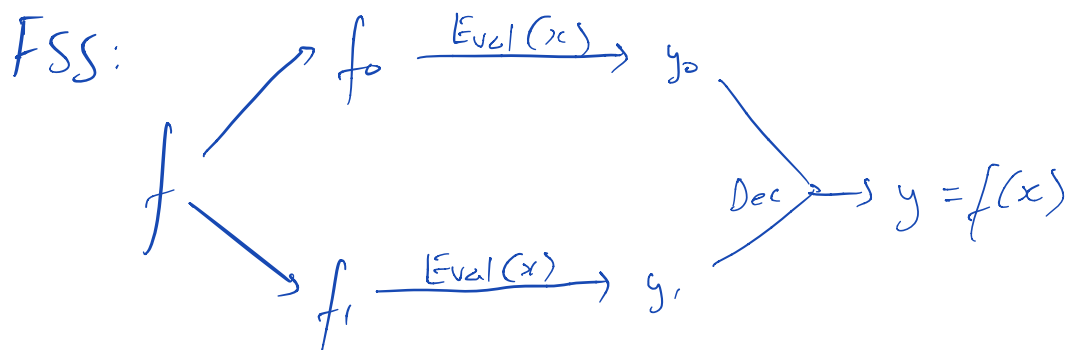
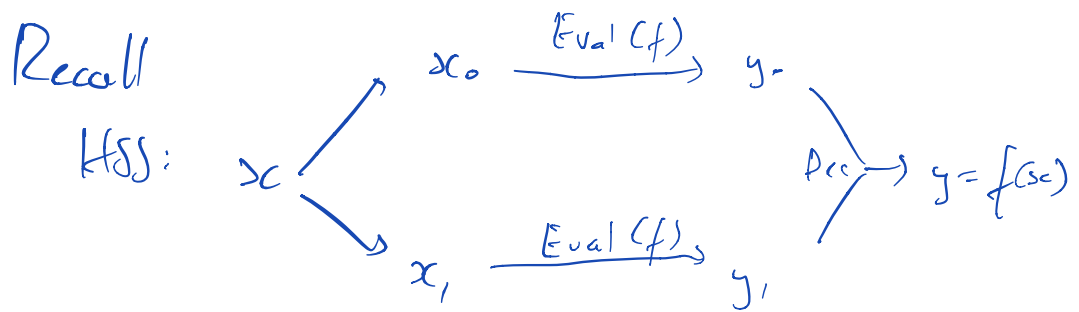
Lapland: Constant degree multivariate polynomials high  
Pseudorandom Correlation Generators, etc. } noise  
Expand: OT, OLE, etc. from LPN parameters  
not known to give PKE. Exciting MPC work

Minicrypt: One-way functions

⇒ Point functions + (intervals, decision trees)

Here the results & exposition framed better as the dual notions of  
Function Secret Sharing

# Function Secret Sharing (FSS)



Parameters:  $p \geq n$  parties, function class  $\mathcal{F}$ , secret parameter  $\lambda$

Gen:  $1^\lambda, f \mapsto k_1, k_2, \dots, k_p$  ( $p$ -parties)

Eval:  $i, k_i, x \mapsto y_i$

Dec:  $y_1, y_2, \dots, y_D \mapsto y$

Correctness:  $\forall f \in \mathcal{F}, x \in \text{Domain}(f)$

$\forall k_1, \dots, k_n \leftarrow \text{Gen}(1^\lambda, f),$

$$\text{Dec}(\text{Eval}(C_1, k_1, x), \dots, \text{Eval}(C_n, k_n, x)) = f(x)$$

Security:  $m$ -party,  $t$ -secure FSS: for  $\mathcal{F}$

$\forall S \subseteq [m]$  s.t.  $|S| = t, \exists \text{PPT Sim}$   
s.t.  $\forall f \in \mathcal{F}$ , the following are indist.:

Real( $1^\lambda$ ):  $k_1, \dots, k_m \leftarrow \text{Gen}(1^\lambda, f)$   
output  $(k_i)_{i \in S}$

Ideal( $1^\lambda$ ): output  $\text{Sim}(1^\lambda, S)$

$\uparrow$   
can include leakage

$$\text{Real}_A \approx_c \text{Ideal}_A$$

Let's rule out

Unwanted constructions:

Gen( $f$ ): interpret  $f$  as bit-string  $\in \{0,1\}^{|f|}$

Sample  $f_0, f_1 \leftarrow \{0,1\}^{|f|}$

$$f_0 \oplus f_1 = f$$

output  $f_0, f_1$

Eval( $(f_i, x)$ ): output  $f_i, x \ni y_i$

Dec( $(y_i)$ ): reconstruct  $f = f_0 \oplus f_1$

output  $f(x)$

"Function privacy"? from Dec

Gen( $f$ ):  $\tilde{c}, (x_{i_0}, x_{i_1})_{i \in [n]} \leftarrow G_b(f)$

output  $f_0 = \tilde{c}, f_1 = (x_{i_0}, x_{i_1})_{i \in [n]}$

Eval( $(i, f_i, x)$ ): if  $i=0$  output  $\tilde{c}$   
else output  $(x_{j \neq i})_{j \in [n]}$



Dec( $y, y_i$ ): output  $E_V(\tilde{C}, \tilde{X})$

Note: works for one evaluation, for many evals need to re-randomize  $\tilde{C}, \tilde{X}$

Unsatisfying: output shares are massive, real work done by Dec

Therefore: - Linear decoding procedure: Dec:  $\sum y_i$

Not found  $\left[ \begin{array}{l} - \text{succinctness: share output size comparable to plain output} \\ - \text{Compressibility} \end{array} \right.$

Properties become clear with an application

Specifically constructing FSS for class of point functions, aka Distributed Point Functions

Point function:

$$f_{a,b}(x) = \begin{cases} b & \text{if } x=a \\ 0 & \text{everywhere else} \end{cases}$$

FSS for point functions, elegant soln. to PIR  
(aka DPF)

Private Information Retrieval

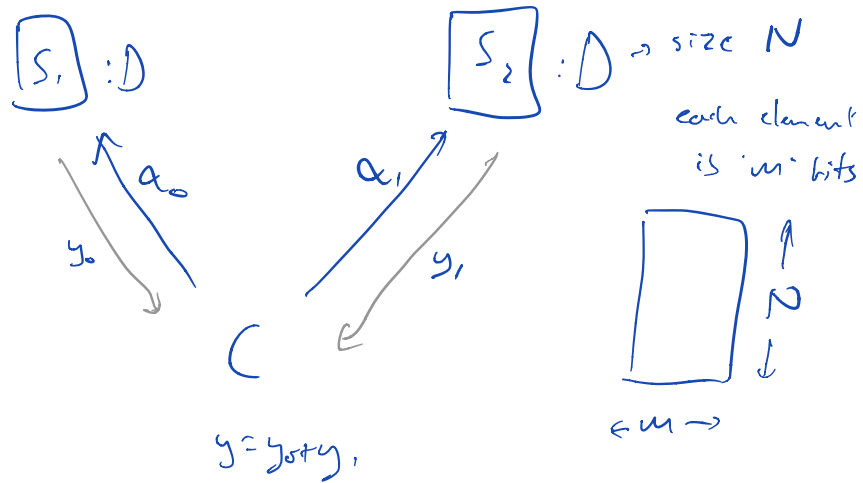
- 'Public' database  $D$
- Client 'C' wishes to read entry at location 'a' without revealing 'a' to database holder

We wish to achieve this without sending  
D to client

Long history, someone else will cover

## 2. Server case

Non-colluding servers



Solution with FSS for point functions

$C$  defines point function  $f_{\alpha,1}$

$$\text{i.e., } f_{\alpha,1}(x) = \begin{cases} 1 & \text{if } x = \alpha \\ 0 & \text{otherwise, } x \in [N] \setminus \alpha \end{cases}$$

Note: domain of  $f$  is size of database  $N$

②  $k_1, k_2 \leftarrow \text{Gen}(f_{\alpha,1})$

③ Send  $k_1$  to  $S_1$ ,  $k_2$  to  $S_2$

$$S_i = y_i = \sum_{j \in \mathbb{N}} x_j \cdot \text{Eval}(i, k_i, j)$$

• send  $y_i$  to  $C$

↓  
just in bits

(same size as actual output)

$C$ : output  $x_c = y_0 + y_1$

Correctness:

$$x_c = y_0 + y_1$$

$$= \left( \sum_j x_j \cdot \text{Eval}(\phi, k_0, j) \right) + \left( \sum_j x_j \cdot \text{Eval}(\alpha, k_1, j) \right)$$

$$= \sum_{j \in \mathbb{N}} x_j \cdot \left( \text{Eval}(\phi, k_0, j) + \text{Eval}(\alpha, k_1, j) \right)$$

↓  
 $f_{\alpha, 1}(j) \equiv$  correctness of  
FSS

$$= \sum_{j \in \mathbb{N}} x_j \cdot f_{\alpha,1}(j)$$

$$\downarrow$$

$$\begin{cases} 1 & \text{if } j = \alpha \\ 0 & \text{otherwise} \end{cases}$$

only nonzero value in the sum is  $j = \alpha$

$$= x_\alpha \cdot 1$$

Security: each  $S_i$  only gets one share of  $f_{\alpha,1} \Rightarrow$  servers know  $\mathcal{F}$  (i.e. that it is a pt. fn.) but they don't know which point  $\Rightarrow$  no info abt  $\alpha$

Technical: view of each server is composable, simply run  $S_{\text{sum}}(1^i)$  of FSS scheme  
View server  $i = S_{\text{sum}}(1^i, i)$

## Efficiency:

Computation for  $C$ : 1 FSS gen  
Communication complexity

•  $C$  transmits  $k_i$  to  $S_i$

•  $S_i$  sends  $y_i$  to  $C$

↓  
same size as  $x_i$

Key size matters!

Ruling out another trivial instantiation:

additively share the entire truth table of  $f$

$$\text{i.e. } K_1 = (k_{11}, k_{12}, \dots, k_{1N})$$

$$K_2 = (k_{21}, k_{22}, \dots, k_{2N})$$

such that  $k_{1i} \oplus k_{2i} = f(i)$

client work and comm. linear in  $N$

⇒ not interesting

interesting from this line of work:

Thm. Assuming OWFs, there is  
a two key FSS scheme for  
the family of point functions with  
key size  $O(\lambda \cdot \log N)$

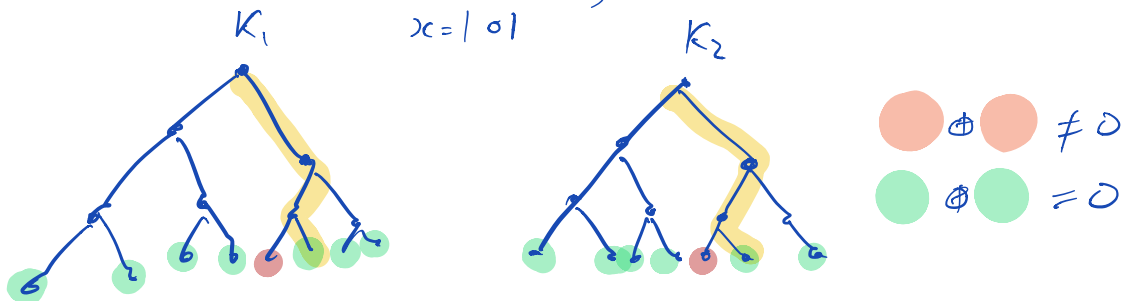
High level idea:

$K_1, K_2$  will define GGM style

binary tree with  $N$  leaves

where each leaf is an 'evaluation point'

assuming a length doubling PRG:



In GCM: trees fully specified by  $K$   
 here: bit much to ask, we also  
 supply some kind of helper "correction  
 word" for each level of the tree.

Building blocks: weak homomorphism + conditional correction

Idea ① 'weak homomorphism' from PRG to additive  
 secret sharing

$$\text{Let } [s] = (s_1, s_2) : s_1 \oplus s_2 = s$$

$$G: \{0,1\}^\lambda \mapsto \{0,1\}^{2\lambda+2}$$

$$\text{Define } G([s]) = (G(s_1), G(s_2)) = [\sigma]$$

abuse of notation



$$G(s_1) \oplus G(s_2)$$

Two cases:

$$1) \text{ if } s=0, s_1=s_2$$

$$G([0]) = (G(s_1), G(s_1)) = [0]$$

$$2) \text{ else } s \neq 0, s_1 \neq s_2$$

$$G([s]) = (G(s_1), G(s_2)) \Rightarrow (\text{pseudo})\text{random} \\ = [\sigma]$$



$\rightarrow G(S_1) \oplus G(S_2)$

Takeaway:  $G([s])$  expands small  $[s] \rightarrow [s]$   
small  $[rand] \rightarrow [rand]$

Idea ②: Conditional correction

Let  $[s] = (s_1, s_2)$ ,  $s_1 \oplus s_2 = s \in \{0, 1\}^k$

$[t] = (t_1, t_2)$ ,  $t_1 \oplus t_2 = t \in \{0, 1\}$

↑  
"control bit"

$c \in \{0, 1\}^k$  : <sup>public</sup> correction word

Locally computable:

$$[s \oplus t \cdot c] = (s_1 \oplus t_1 \cdot c, s_2 \oplus t_2 \cdot c)$$

sanity check:

$$\begin{aligned} s_1 \oplus t_1 \cdot c \oplus s_2 \oplus t_2 \cdot c \\ &= (s_1 \oplus s_2) \oplus (t_1 \oplus t_2) \cdot c \\ &= s \oplus t \cdot c \end{aligned}$$

Syntax:  $[s], [t]$

Expand to child nodes:

apply weak homomorphism and l. correction

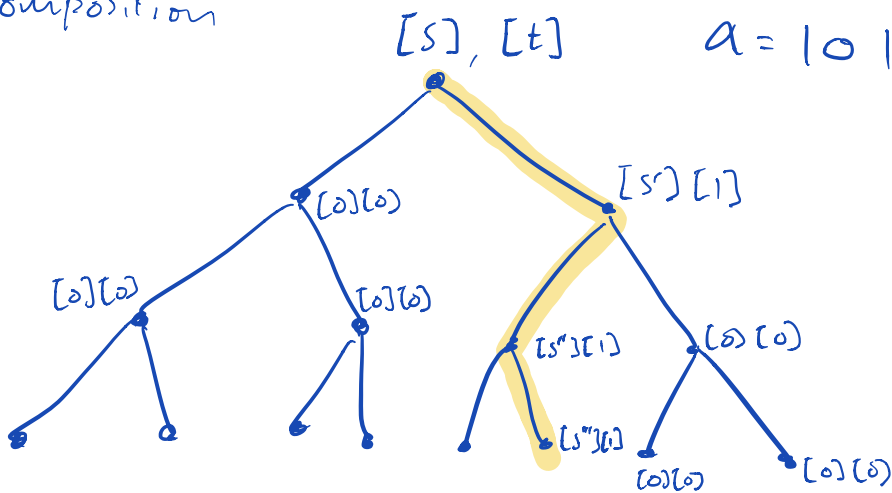
$[s_L], [t_L]$

$[s_R], [t_R]$

$$[s_L, t_L, s_R, t_R] = C([s]) \oplus t \cdot C = [C \oplus t \cdot C]$$

Invariant:  $[s][t] \begin{cases} [0][0] \text{ on special path} \\ [rand][1] \text{ off special path} \end{cases}$

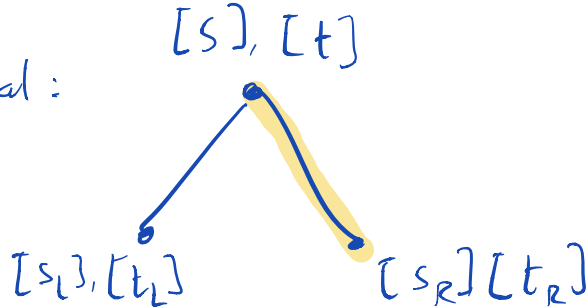
Composition



Two types of parent  $\rightarrow$  children

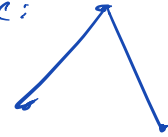
Type I:

Special:  
 $\downarrow$   
 root



expansion

Inactive:



Recall  $[s] = (s_1, s_2)$   $s_1 \oplus s_2 = s$

$$C: \{0,1\}^\lambda \rightarrow \{0,1\}^{2\lambda+2}$$

$$C([s]) = (C(s_1), C(s_2)) = [\sigma]$$

$$\sigma \in \{0,1\}^{2\lambda+2}, \sigma = C(s_1) \oplus C(s_2)$$

Parse  $\sigma_L \parallel \sigma_R = \sigma$

$$\sigma_L, \sigma_R \in \{0,1\}^{\lambda+1}$$

Our goal: set <sup>Correction word</sup>  $C$  such that

Inactive  $[s_L][t_L] = [0][0]$

Active  $[s_R][t_R] = [rand][1]$

Parse  $C = C_L, C_R \in \{0,1\}^{2(\lambda+1)}$

$$[s_L, t_L] = [\sigma_L \oplus t \cdot C_L]$$

$$[0^\lambda, 0] = [\sigma_L \oplus C_L]$$

$$\therefore C_L = \sigma_L$$

What about  $C_R$ ?

$$[s_R, t_R] = [\sigma_R \oplus t \cdot C_R]$$

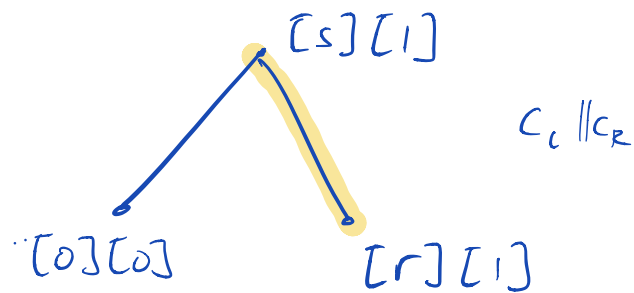
$r \in \{0,1\}^\lambda$

$$[r, 1] = [\sigma_R \oplus C_R]$$

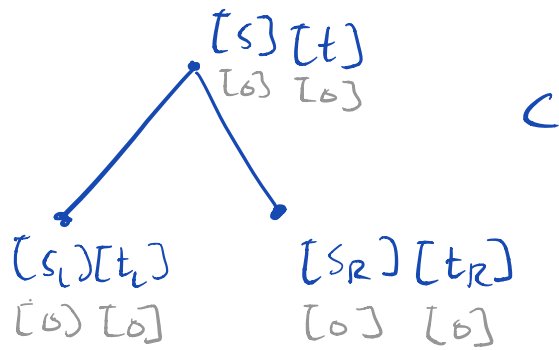
$$\therefore C_R = \sigma_R \oplus (r||1)$$

Note: for a leaf node,  $r = \beta$

Correctness of evaluation



## Type 2 (plain)



Eval.: Same as earlier  
(agnostic to on vs. off spec'd)

$$[s_L, t_L, s_R, t_R] = [\sigma \oplus t \cdot c]$$

Remember expansion is zero-preserving

$$\therefore \sigma = G([s]) = G([0]) = [0]$$

$$\text{Also } [t] = [0]$$

$$\therefore [\sigma \oplus t \cdot c] = [0 \oplus 0] = [0]$$

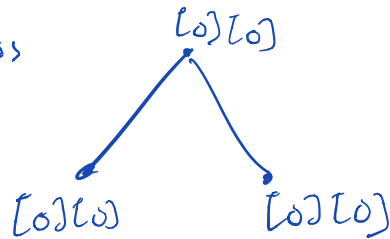
Independent of correction word

∴

$$[s_L, t_L, s_R, t_R] = [\sigma \oplus t \cdot c] = [0, 0, 0, 0]$$

$\Rightarrow$  invariant preserved

Correctness



Putting it together:

Gen:  $f_{\alpha, \beta}$ , say  $|\alpha| = 3$  bits

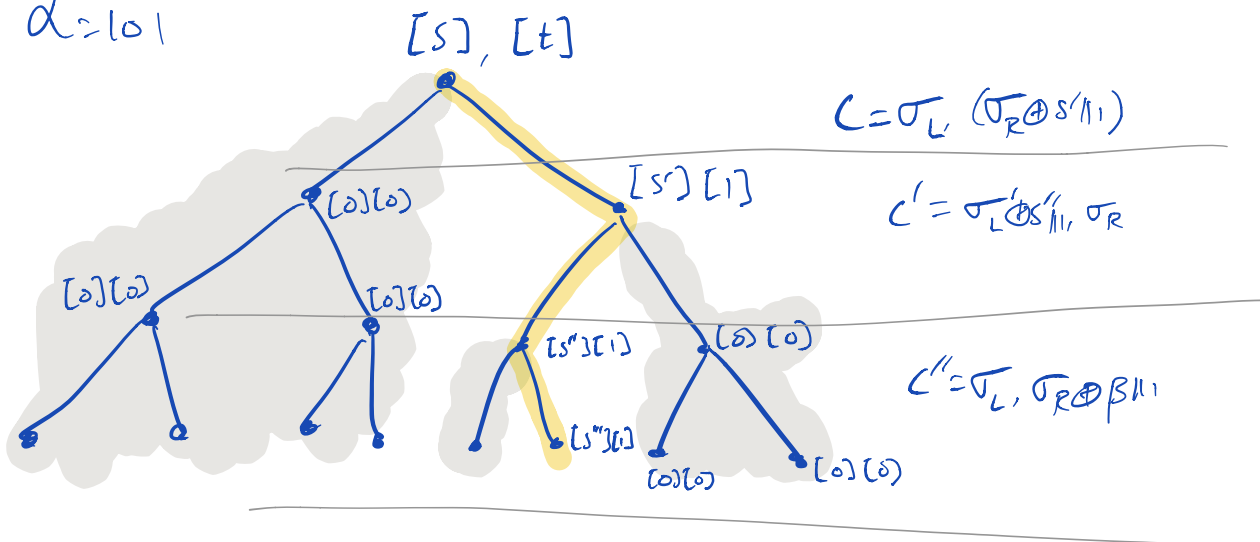
$$[s] = (s_1, s_2) \leftarrow \{0, 1\}^{2\lambda}, [t] \leftarrow \{0, 1\}^2$$

$$[s'] = "$$

$$[s''] = "$$

$$[s'''] = [\beta]$$

$\alpha = 101$

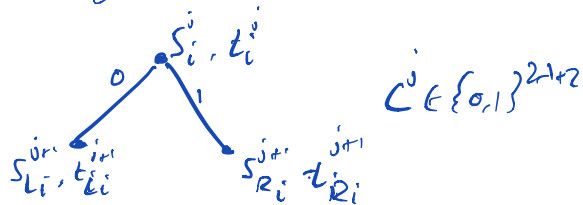


Output keys  $k_i = s_i, C, C', C''$

$k_2 = s_2, C, C', C''$

Eval:  $i, k_i, x = x_1, x_2$

At layer  $j \in |x| = \{0, 1, 2\}$ :



$$s_{L_i}^{j+1}, t_{L_i}^{j+1}, s_{R_i}^{j+1}, t_{R_i}^{j+1} = C(s_i^j) \oplus t_i^j \cdot C$$

if  $x_j = 0$ , set  $s_i^{j+1}, t_i^{j+1} = s_{2i}^{j+1}, t_{L_i}^{j+1}$

else set  $s_i^{j+1} t_i^{j+1} = s_{Ri}^{j+1} t_{Ri}^{j+1}$

# Security:

$$K_i = s_i, t_i, c, c', c''$$

$$H_0 = s_i, t_i, \sigma_L \parallel \sigma_R \oplus s', \sigma_L' \oplus s'' \parallel \sigma_R, \sigma_L \parallel \sigma_R \oplus \beta$$

Hybrid 0:  $\sigma_L \sigma_R = G(ts) = G(s_1) \oplus G(s_2)$

Hybrid 1:  $\sigma_L \sigma_R \leftarrow \{0,1\}^{2\lambda+2}$

$H_0 \approx_c H_1$  by PRC security ( $s_2$  not in view)

$$H_1: \sigma_L' \sigma_R' = G(s_1') \oplus G(s_2')$$

Hybrid 2:  $\sigma_L' \sigma_R' \leftarrow \{0,1\}^{2\lambda+2}$

$\downarrow$   
 $s', s'', \beta$   
independent of  $s$

Hybrid 3:  $\sigma_L'', \sigma_R'' \leftarrow \{0,1\}^{2\lambda+2}$

Hybrid 4 (Simulation):  $s_i, t_i, c, c', c''$  all sampled uniformly



Extension to intervals: simply add FSS for multiple points. Tweaks: comparison

Extending to many parties:

Thm. assuming OWFs,  $\exists$   $p$ -key FSS for Point functions with key length  $O(2^{u/2} \cdot 2^{P/2} \cdot m)$

Assuming  $p$  is const., better than trivial ( $O(2^u \cdot m)$ )

Bonus: Silent OT

PCG: Pseudorandom Correlation Generator

Correlation Generator: GenCor:  $c_1, c_2$   
eg. Beaver triples.



OT Correlation:  $q_i \oplus r_i = \Delta \cdot b_i$

How do we use this?

$H(r_i)$  serve as OTPs to

$H(r_i \oplus \Delta)$  encrypt  $i^{\text{th}}$  message pair

Cor.-robust:  $H(r_{00})$  appears random

$R$  decrypts using  $H(r_i \oplus b_i \cdot \Delta) = H(q_i)$

Task: compress this correlation into  
short seeds  $s_1, s_2$

Thus: Assuming LPN, there is a  
2-key PCC for OT correlations

For some rate  $r$   $m, n, t$

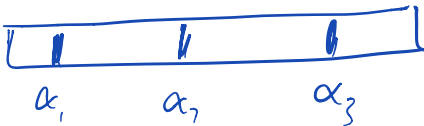
$\vec{\alpha} \alpha_1, \alpha_2 \dots \alpha_t \in [m]$

Define <sup>multi</sup> <sub>n point</sub> function  $f_{\vec{\alpha}, y}^{(z)} = \begin{cases} \Delta & \text{if } z \in \vec{\alpha} \\ 0 & \text{otherwise} \end{cases}$

FSS for multi-point fns (lin. comb. of p.f.)  
produce keys  $K_1, K_2$

So on  $S_1 : K_1, \vec{\alpha}$

$S_2 : K_2, \Delta$

Define  $\vec{b}_i =$  

$b_i = 1$  if  $i \in \vec{\alpha}$   $\Rightarrow$  fully specified by  $S_1$   
0 otherwise

Define  $q_i = \text{Eval}(K_1, i)$

$r_i = \text{Eval}(i, K_2, i)$

$$q_i \oplus r_i = b_i \cdot \Delta$$

Looks like OT correlation, but we're  
not there yet.

This is where LPN comes in

Dual LPN assumption:

$$\begin{array}{c} \uparrow \\ n \\ \downarrow \end{array} \begin{array}{c} \text{parity check matrix} \\ \left[ \begin{array}{c} H \\ \end{array} \right] \\ \leftarrow m \rightarrow \end{array} \cdot \begin{array}{c} \left[ \begin{array}{c} e \\ \end{array} \right] \\ \uparrow \end{array} \approx_c \begin{array}{c} \left[ \begin{array}{c} u \\ \end{array} \right] \\ \uparrow \\ n \\ \downarrow \end{array}$$

binary vector of low HW

sampled according to some distr.

$H$  is public, so matrix mult is a linear operation on the shares

$$E_{\text{expand}}(s_1 = k_1, \vec{a})$$

$$H \begin{bmatrix} a_1 \\ \vdots \\ q_m \end{bmatrix} = \begin{bmatrix} q'_1 \\ \vdots \\ q'_m \end{bmatrix}$$

$$E(s_2 = k_2, \Delta)$$

$$H \begin{bmatrix} r_1 \\ \vdots \\ r_m \end{bmatrix} = \begin{bmatrix} r'_1 \\ \vdots \\ r'_m \end{bmatrix}$$

$$q'_i = \langle H_i, q_i \rangle$$

$$r'_i = \langle H_i, r_i \rangle = \langle H_i, q_i \oplus k_i \Delta \rangle = q'_i \oplus \Delta \langle H_i, k_i \rangle$$

$$= q_i \oplus \Delta \cdot b_i$$

By dual-LPN,  $\vec{b}$  is pseudorandom & specified by  $K_1$   
 $\Delta$  is sampled uniformly specified by  $K_2$

Noise regime not known to be  
enough for PKE