

Toward Automated Analysis and Prototyping of Homomorphic Encryption Schemes

Cyrielle FERON

Loïc LAGADEC

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I – Introduction

II – PAnTHERS modeling

III – PAnTHERS analysis

IV – PAnTHERS usage

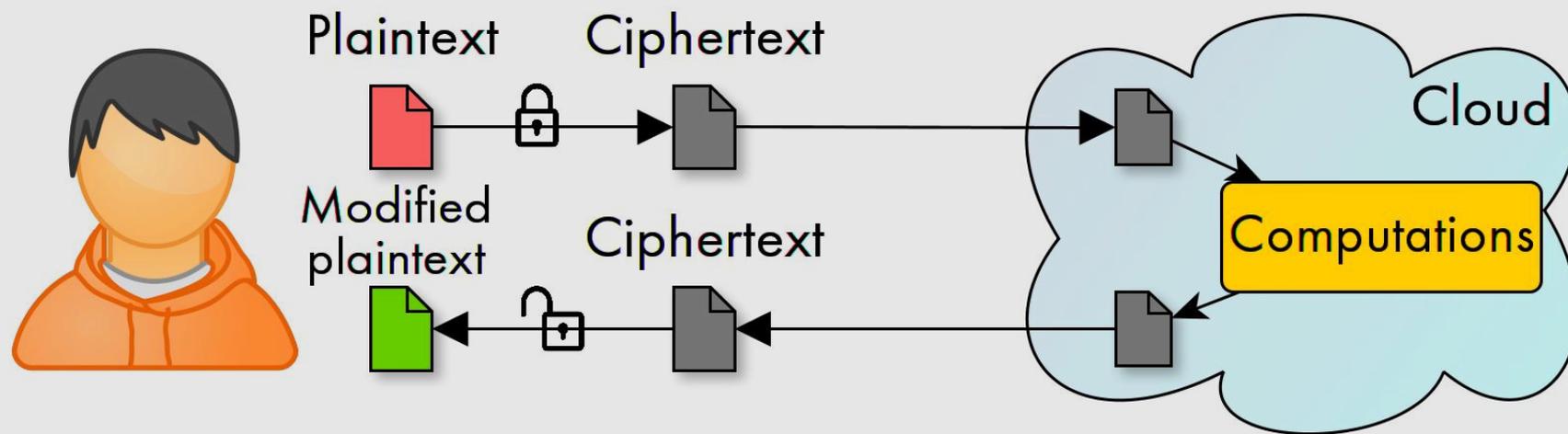
V – Results

VI – Conclusion & future work

I – Introduction

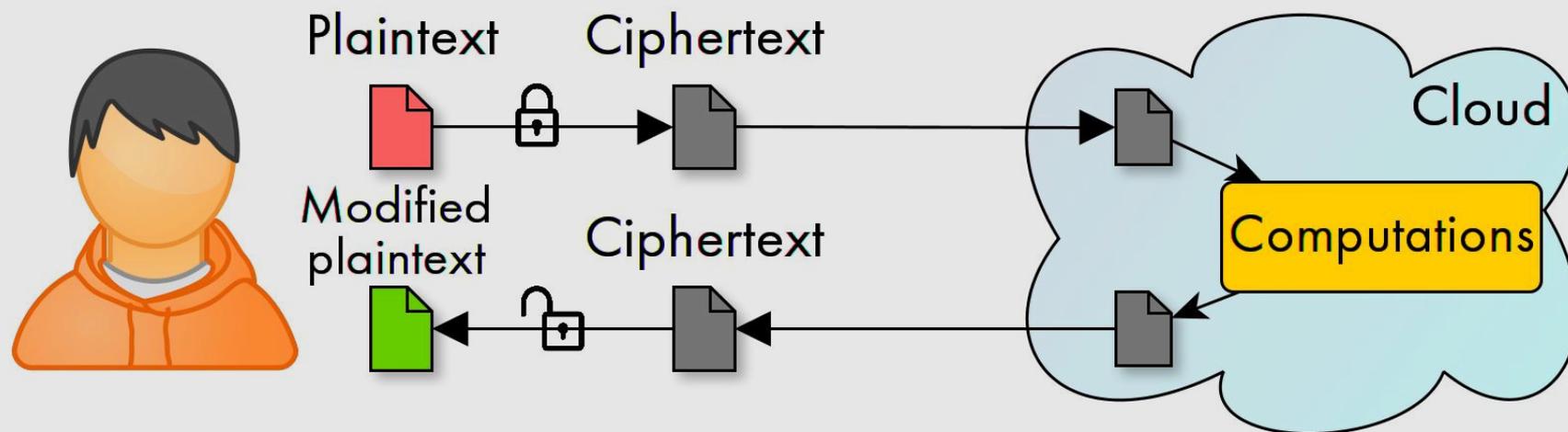
1. Homomorphic Encryption (HE)
2. Goals

Introduction – *Homomorphic Encryption (HE)*



Homomorphic Encryption principle

Introduction – Homomorphic Encryption (HE)

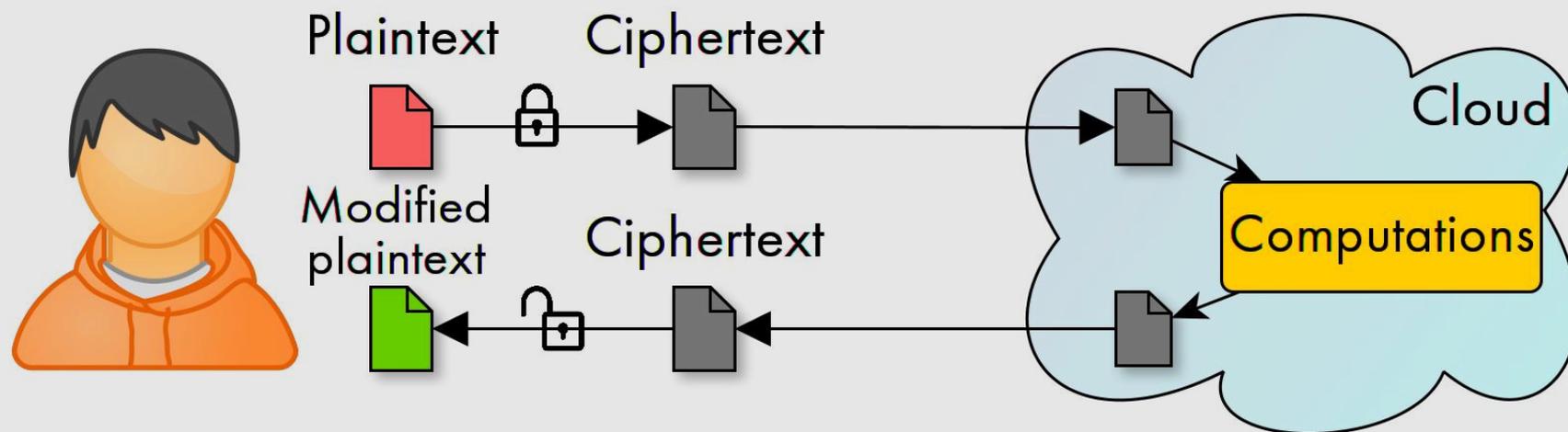


Homomorphic Encryption principle

Advantages :

- No decryption in the Cloud.
- Data are secured during the whole process (transfers and computations).

Introduction – Homomorphic Encryption (HE)



Homomorphic Encryption principle

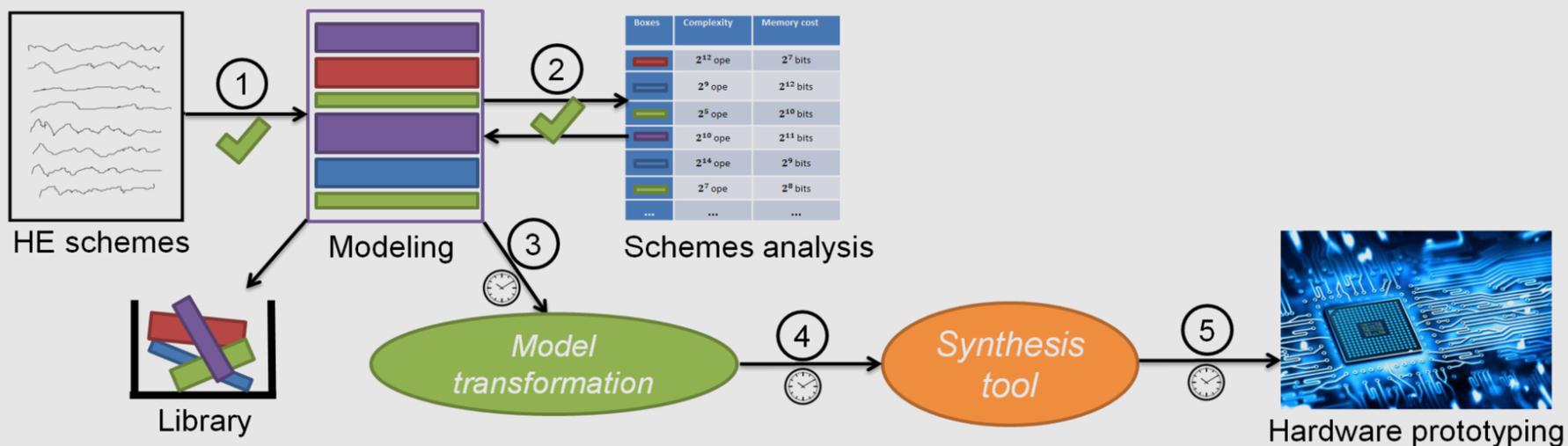
Advantages :

- No decryption in the Cloud.
- Data are secured during the whole process (transfers and computations).

Challenges :

- Active research area
⇒ many HE schemes.
- Important complexity and memory consumption.
- Significant expansion factor.

Develop a **Prototyping and Analysis Tool** for **Homomorphic Encryption Schemes** (**PAnTHERS**) to help improving research on HE schemes.



II – PAnTHERS modeling

1. Atomic and Specific functions
2. HE basic functions
3. Interest

Atomic functions

(= one operation)

Examples:

mult

Inputs : a, b

$c = a \times b$

Output : c

add

Inputs : a, b

$c = a + b$

Output : c

mod

Inputs : a, b

$c = a \% b$

Output : c

rand

Inputs : R, a, b

$c \leftarrow R^{a \times b}$

Output : c

Atomic functions

(= one operation)

Examples:

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$c = a \times b$

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Inputs : R, a, b

$c \leftarrow R^{a \times b}$

Output : c

Specific functions

(= series of Atomic and/or Specific functions)

Example:

distriLWE

*Inputs : q, n, m, k : integers
s : vector of size n*

$A = \text{rand}(R_q, m, n)$

$e = \text{rand}(\chi, m, 1)$

$e = \text{mult}(k, e)$

$b = \text{mult}(A, s)$

$b = \text{add}(e, b)$

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Outputs : b, A

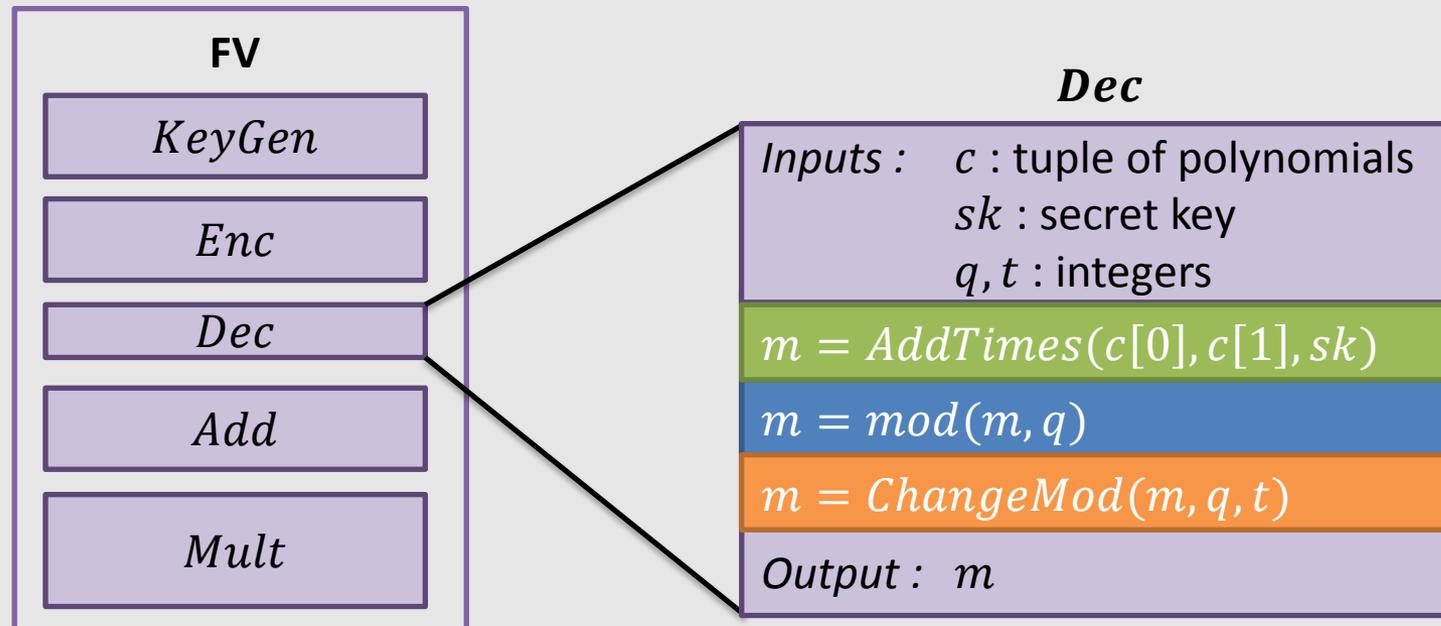
HE basic functions:

- **Series of Atomic and/or Specific functions**
- **5 HE basics: KeyGen, Enc, Dec, Add, Mult**

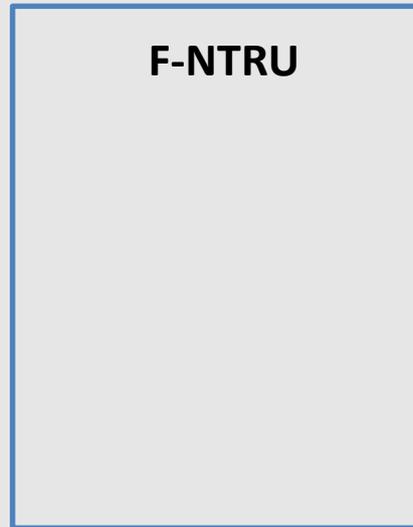
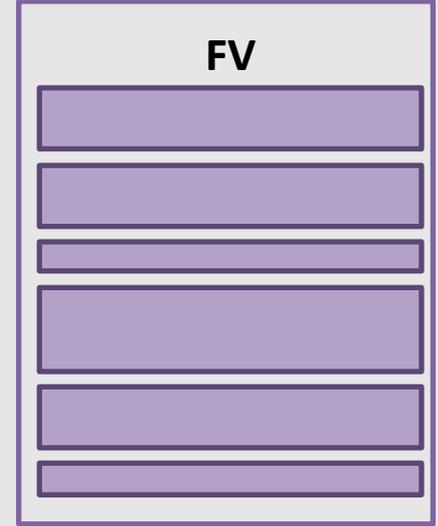
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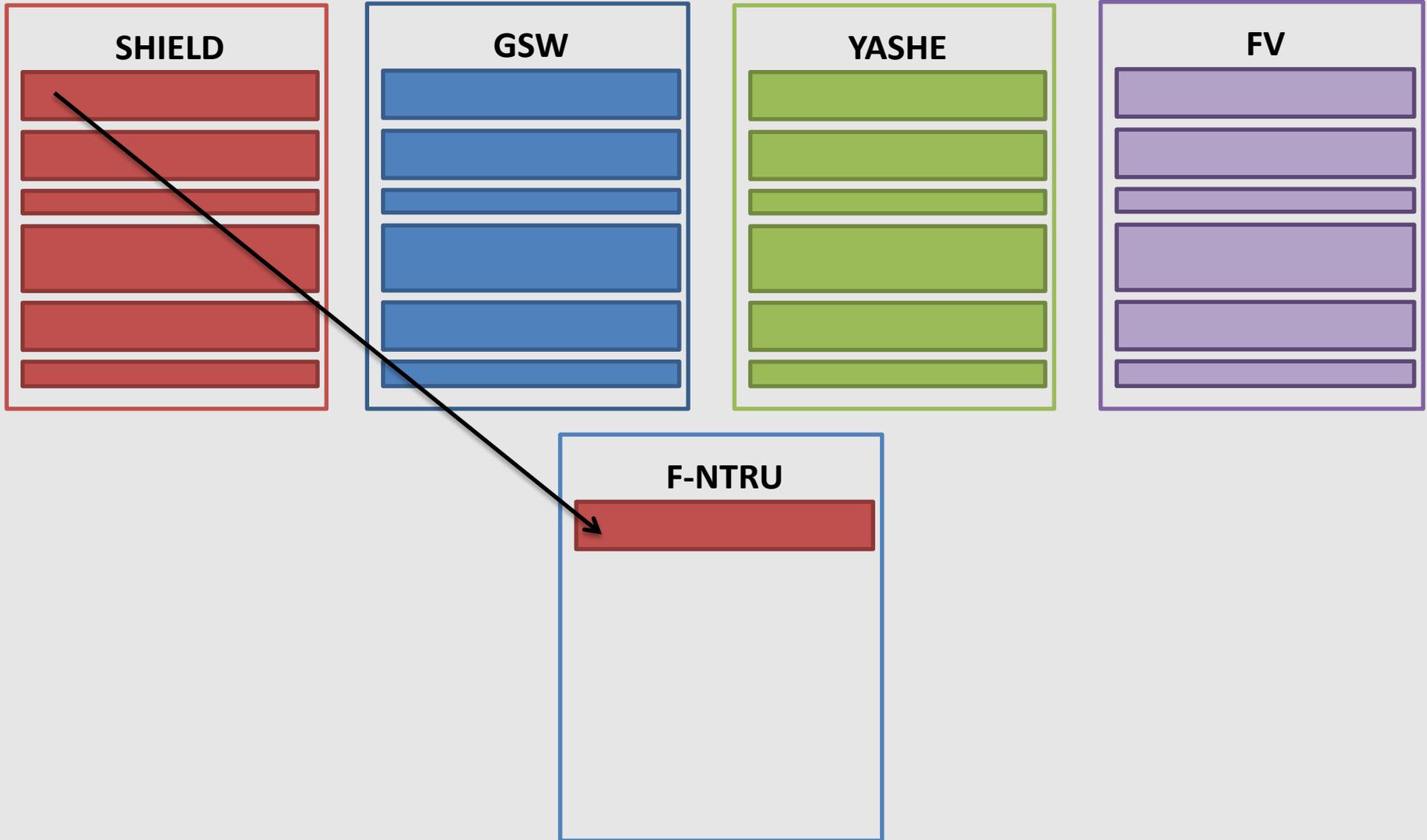
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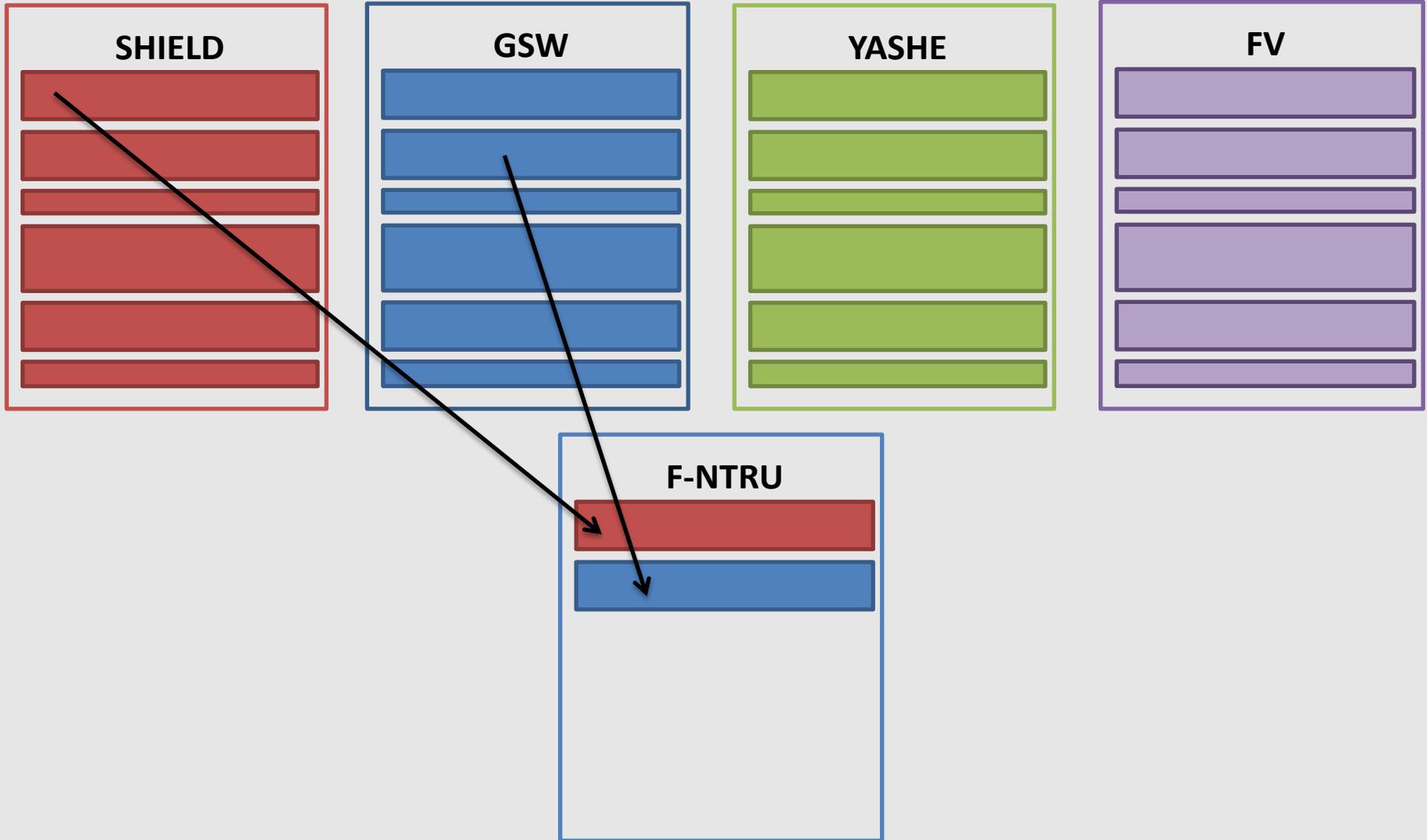
PAnTHERs modeling – *Interest*



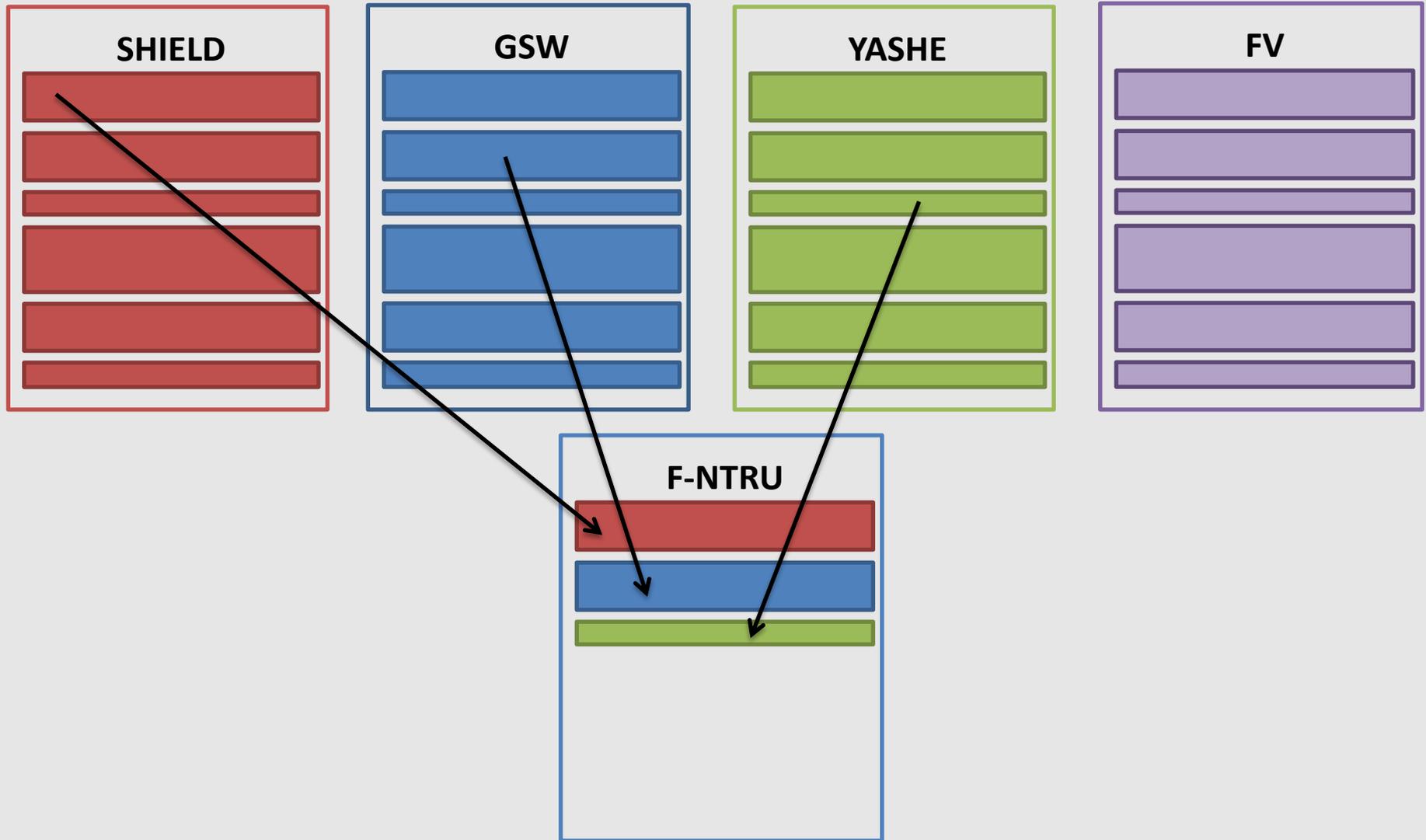
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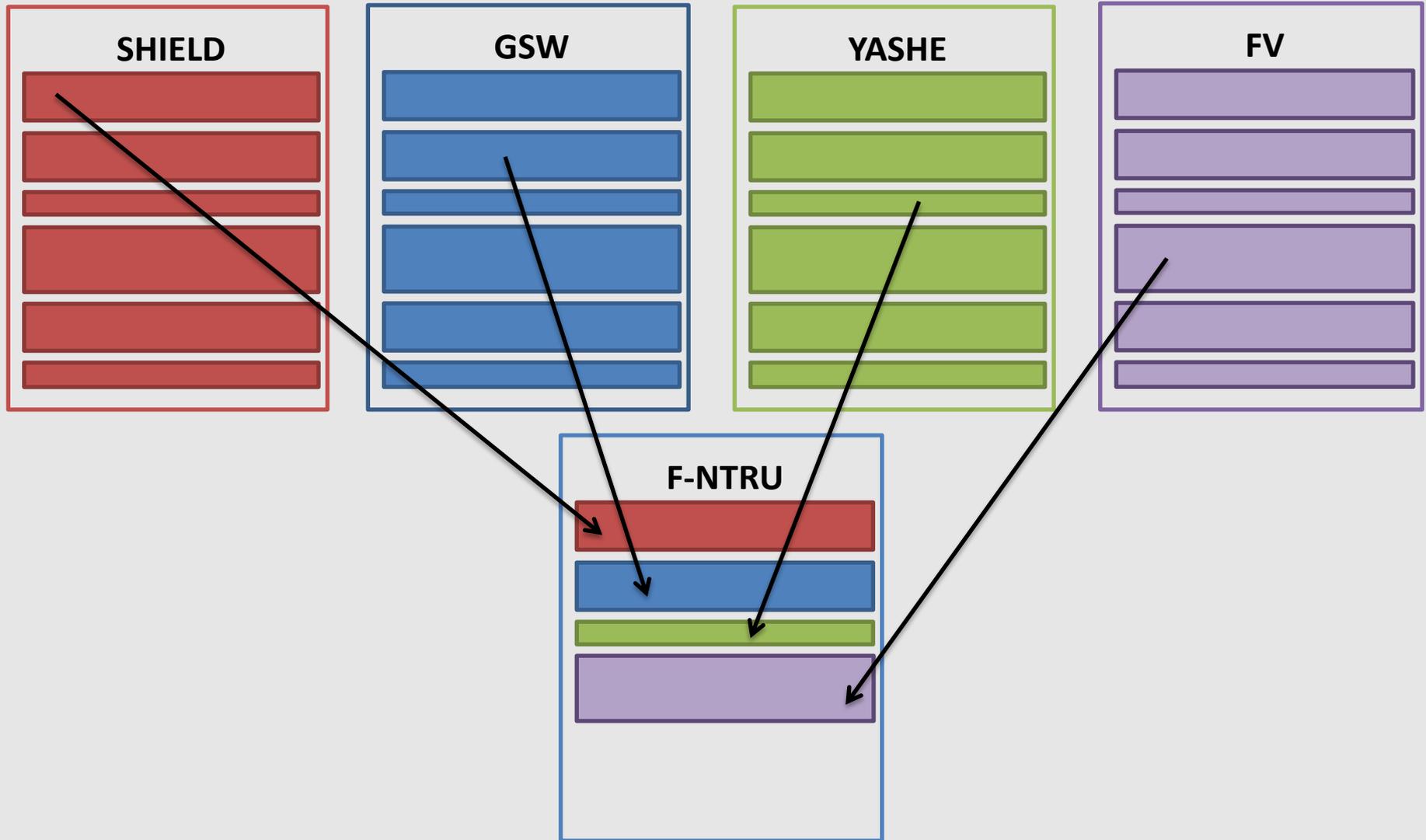
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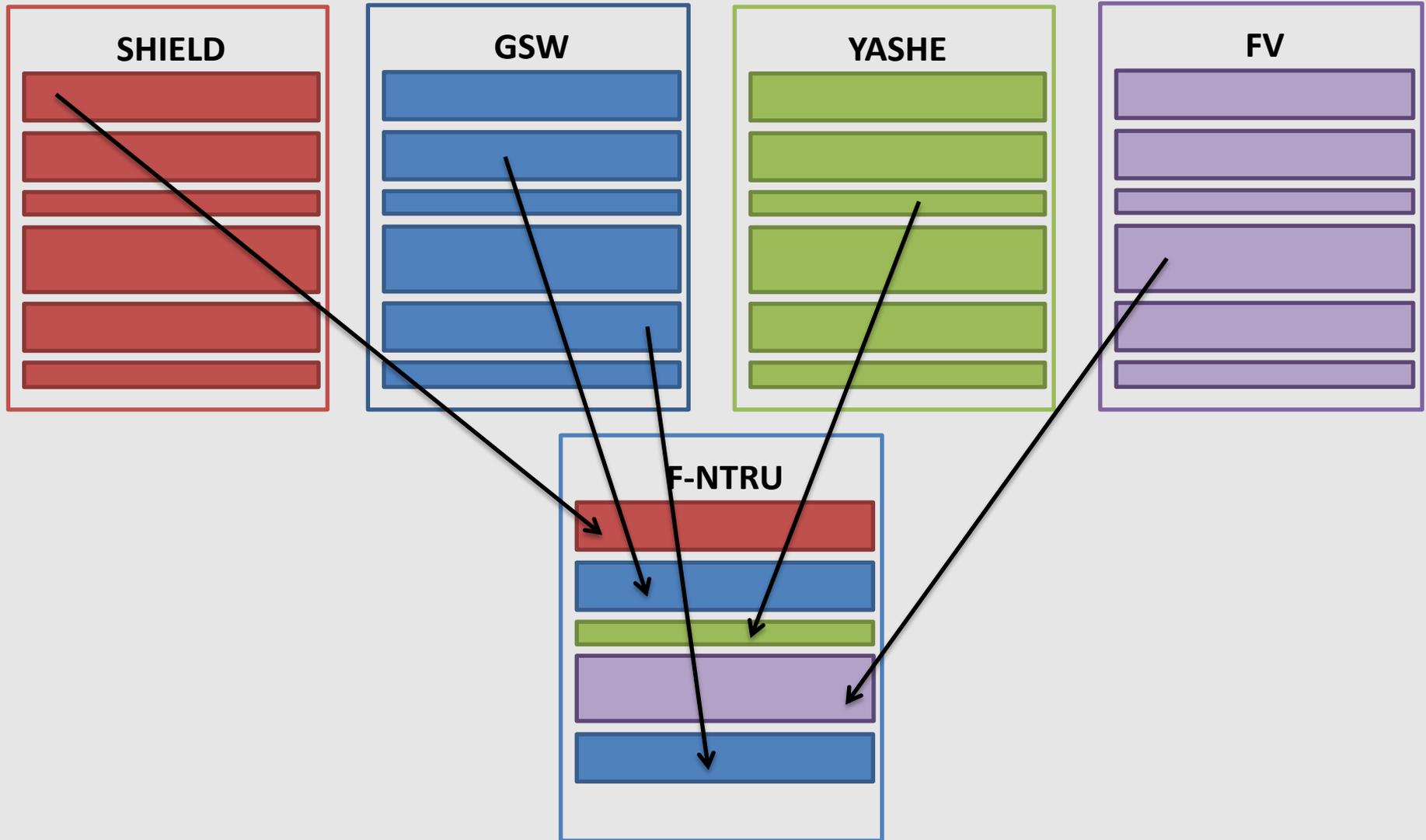
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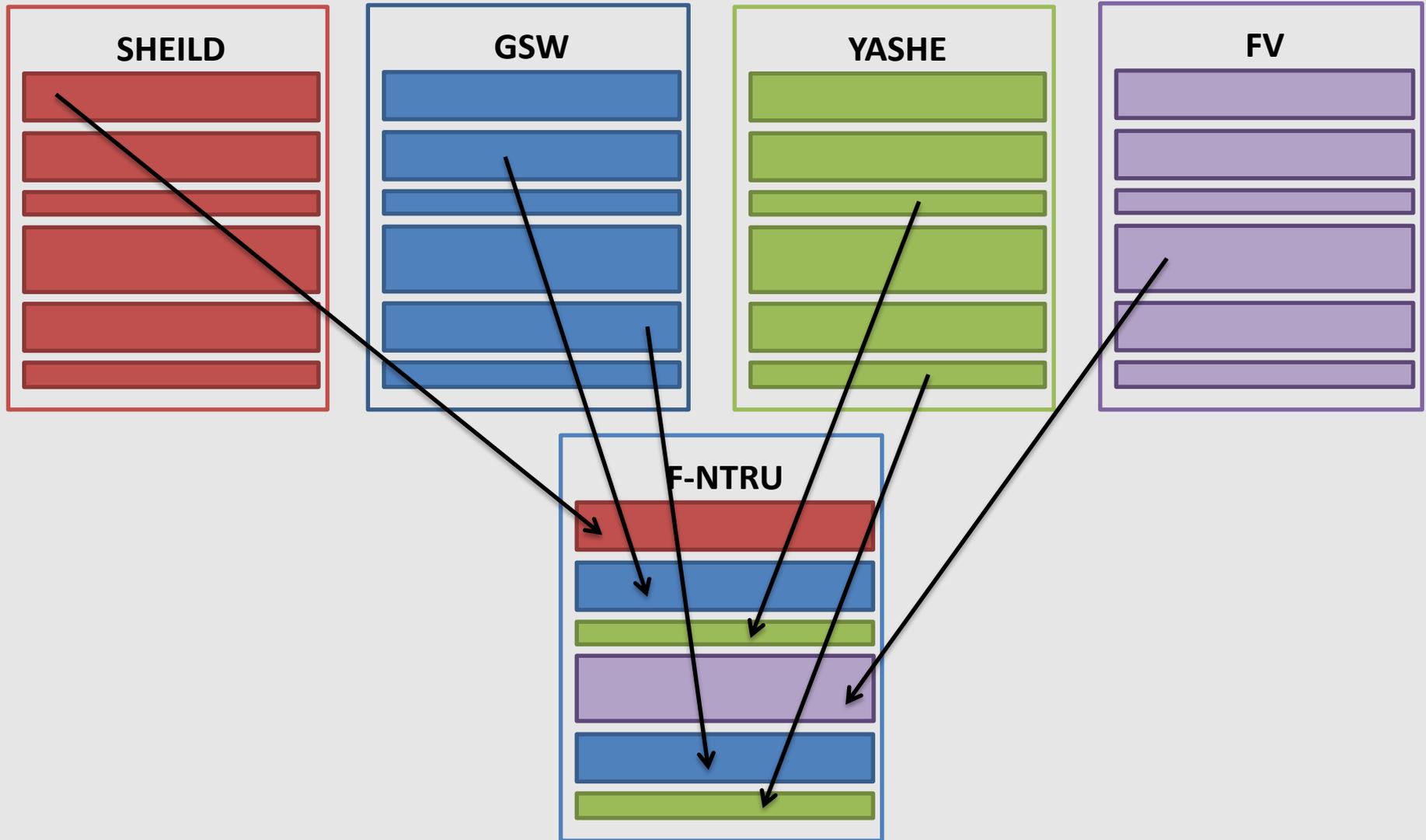
PAnTHERs modeling – *Interest*



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PAnTHERs modeling – *Interest*



III – PAnTHERS analysis

1. Complexity and memory cost
2. Atomics analysis
3. Specific and HE basic analysis
4. HE scheme analysis

Complexity: table containing number of operations performed.

Example:

	MULT	ADD	DIV	MOD	RAND	ROUND
INT	$m \times d$	0	0	0	0	0
POLY	$m \times n$	$m \times n$	0	m	$(n + 1) \cdot m$	0

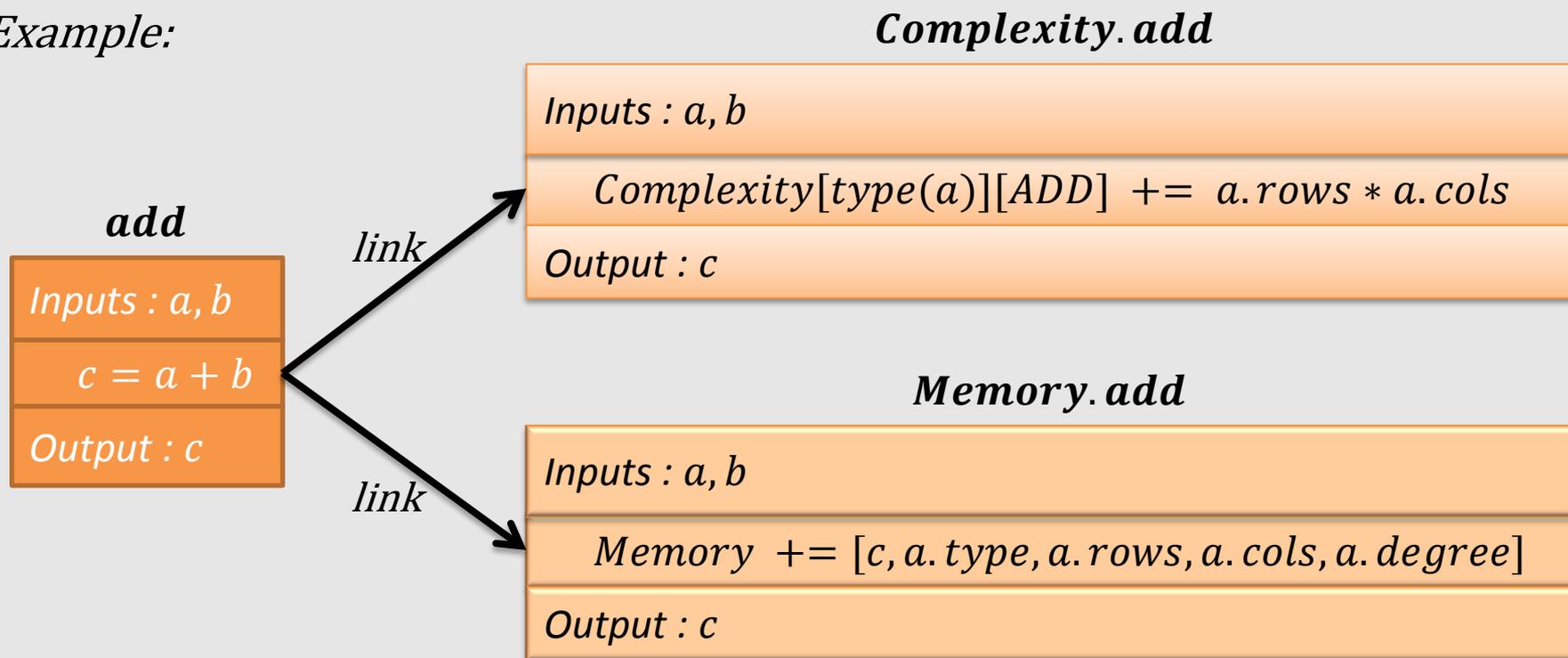
Memory: table containing characteristics of parameters created.

Example:

Name	Rows	Cols	Type	Degree
<i>A</i>	n	m	POLY	2048
<i>c</i>	m	1	POLY	2048
<i>b</i>	m	1	POLY	2048

Atomic functions

Example:



Specific functions

Example:

distriLWE

Inputs : q, n, m, k : integers
 s : vector of size n

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Complexity.distriLWE

Inputs : q, n, m, k : integers
 s : vector of size n

$A = \text{Complexity.rand}(R_q, m, n)$

$e = \text{Complexity.rand}(\chi, m, 1)$

$e = \text{Complexity.mult}(k, e)$

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HE basic functions

Example:

FVDec

Inputs : c : tuple of polynomials
 sk : secret key

$m = \text{AddTimes}(c[0], c[1], sk)$

$m = \text{mod}(m, q)$

$m = \text{ChangeMod}(m, q, t)$

Output : m

HE basic functions

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Memory.FVDec

Inputs : c : tuple of polynomials
 sk : secret key

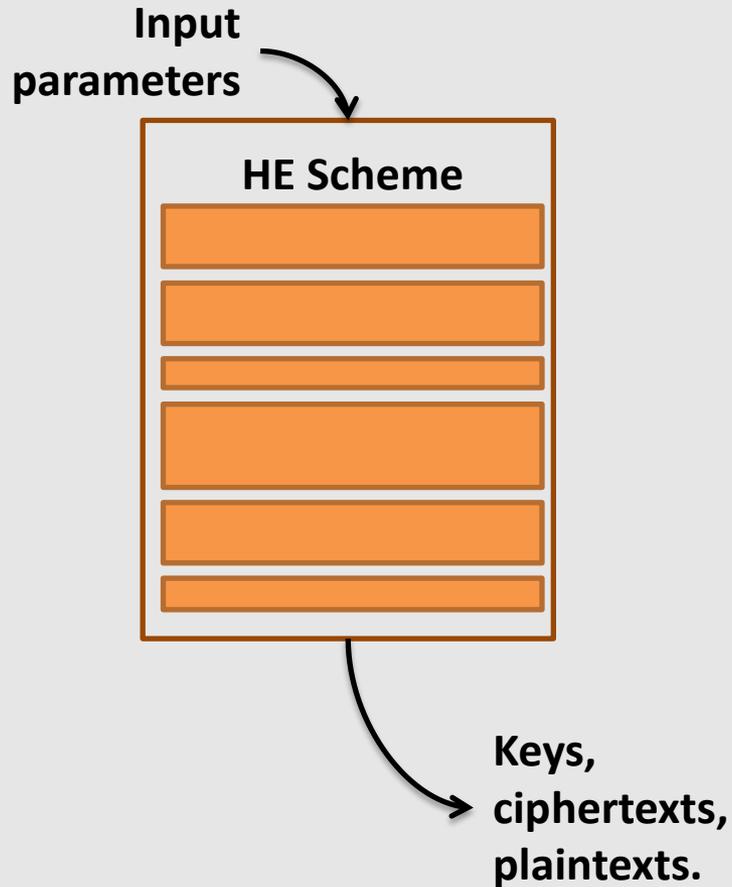
$m = \text{Memory.AddTimes}(c[0], c[1], sk)$

$m = \text{Memory.mod}(m, q)$

$m = \text{Memory.ChangeMod}(m, q, t)$

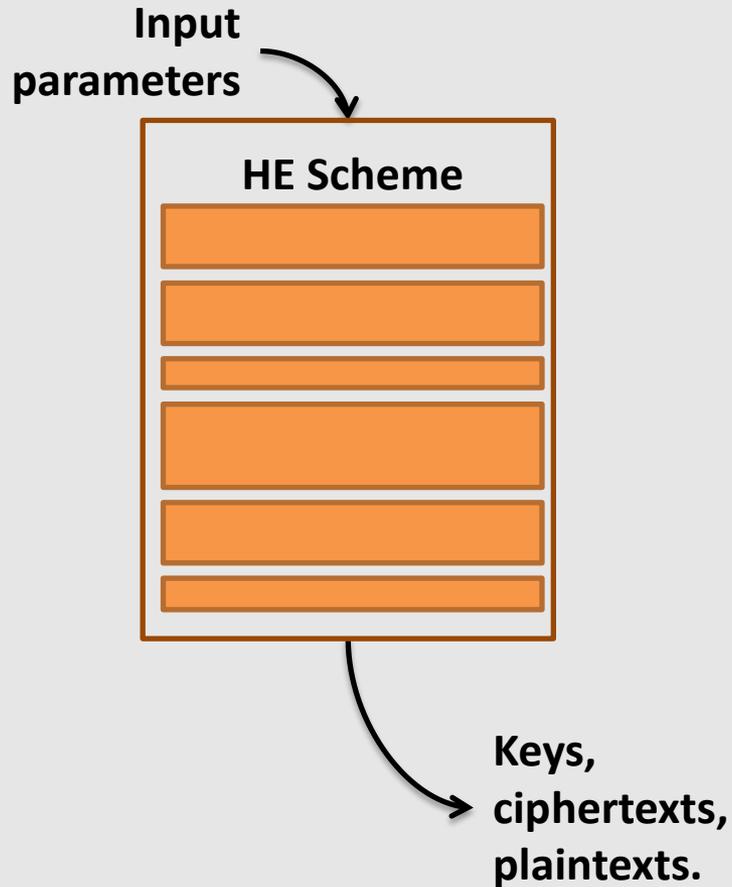
Output : m

Execution of a HE scheme

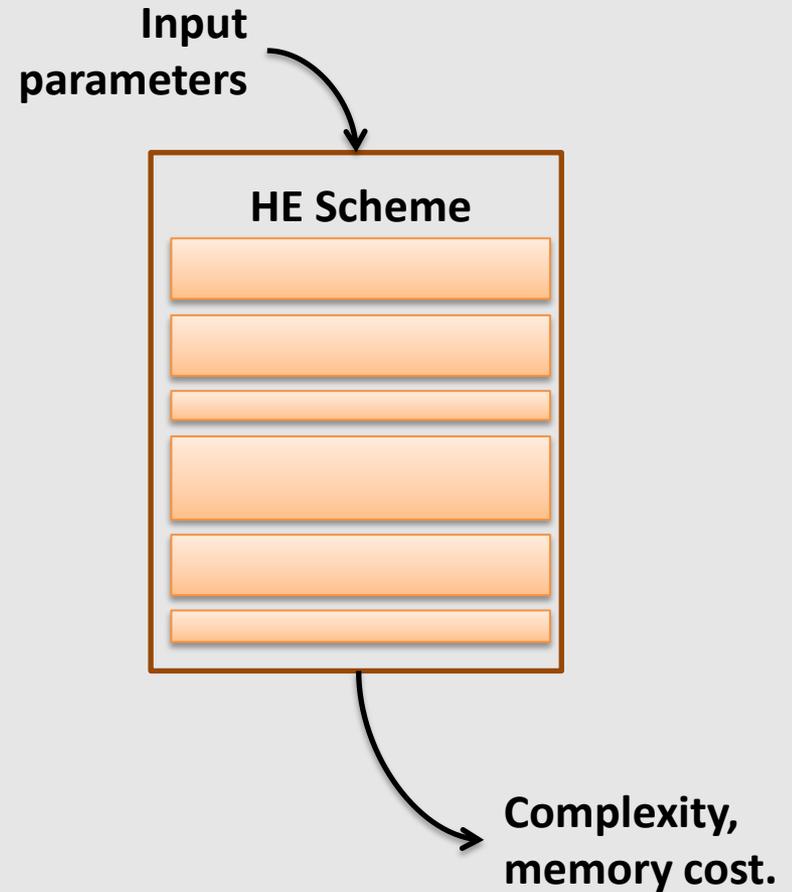


PAnTHERs analysis – HE scheme analysis

Execution of a HE scheme

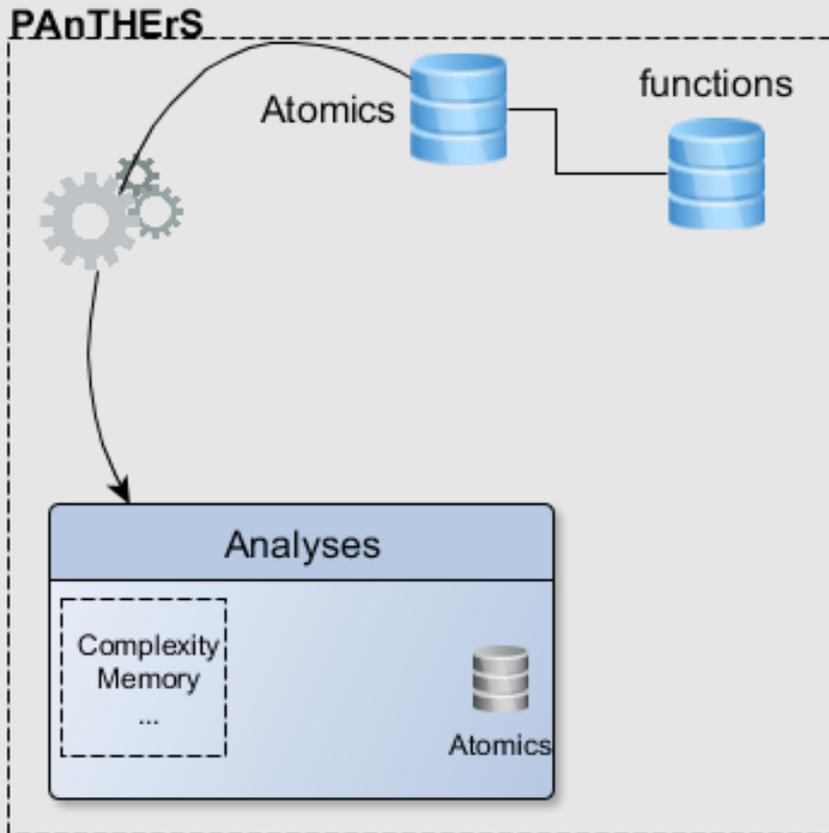


Execution of HE scheme analysis



IV – PAnTHERS usage

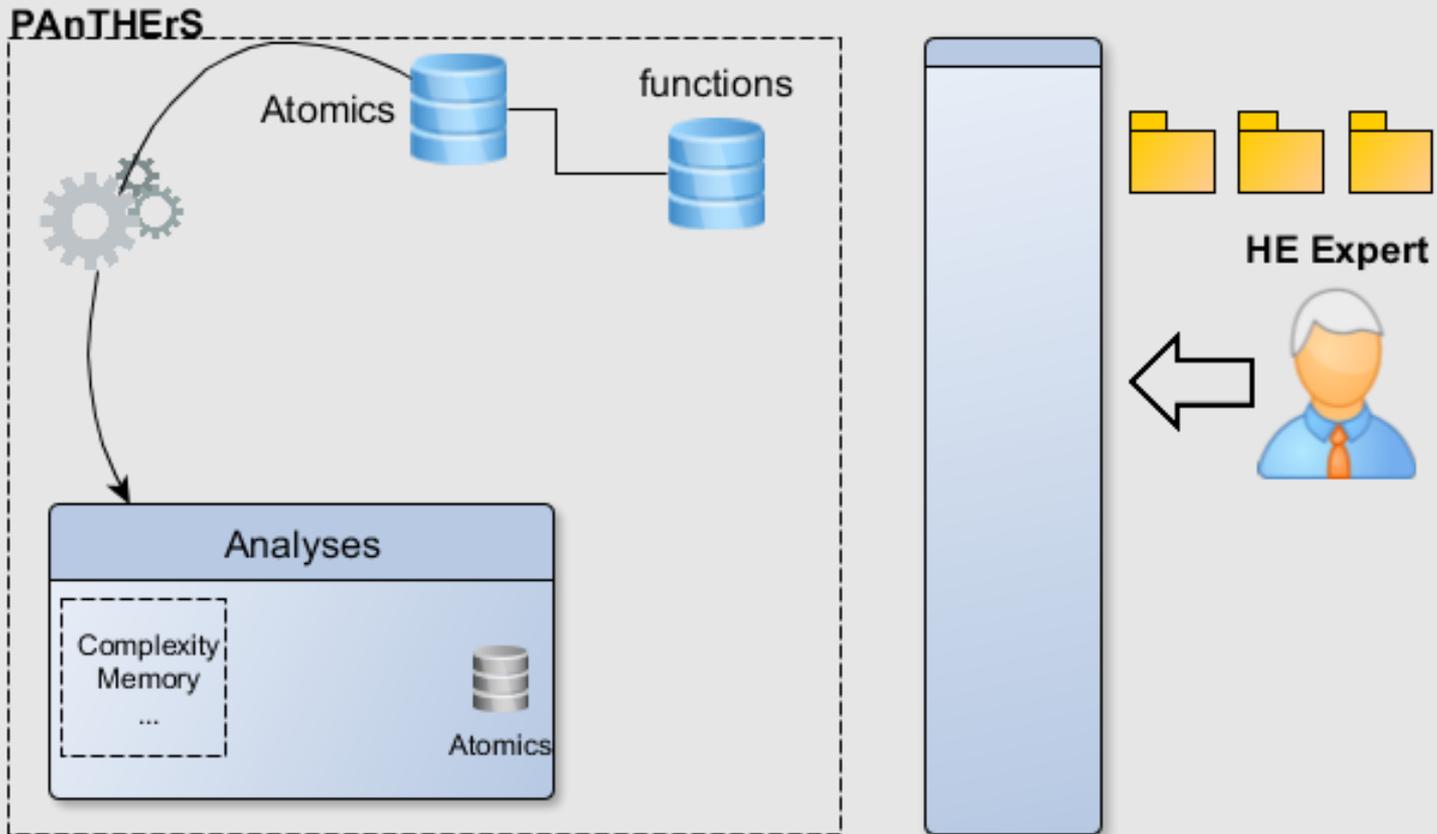
PAnTHERs usage



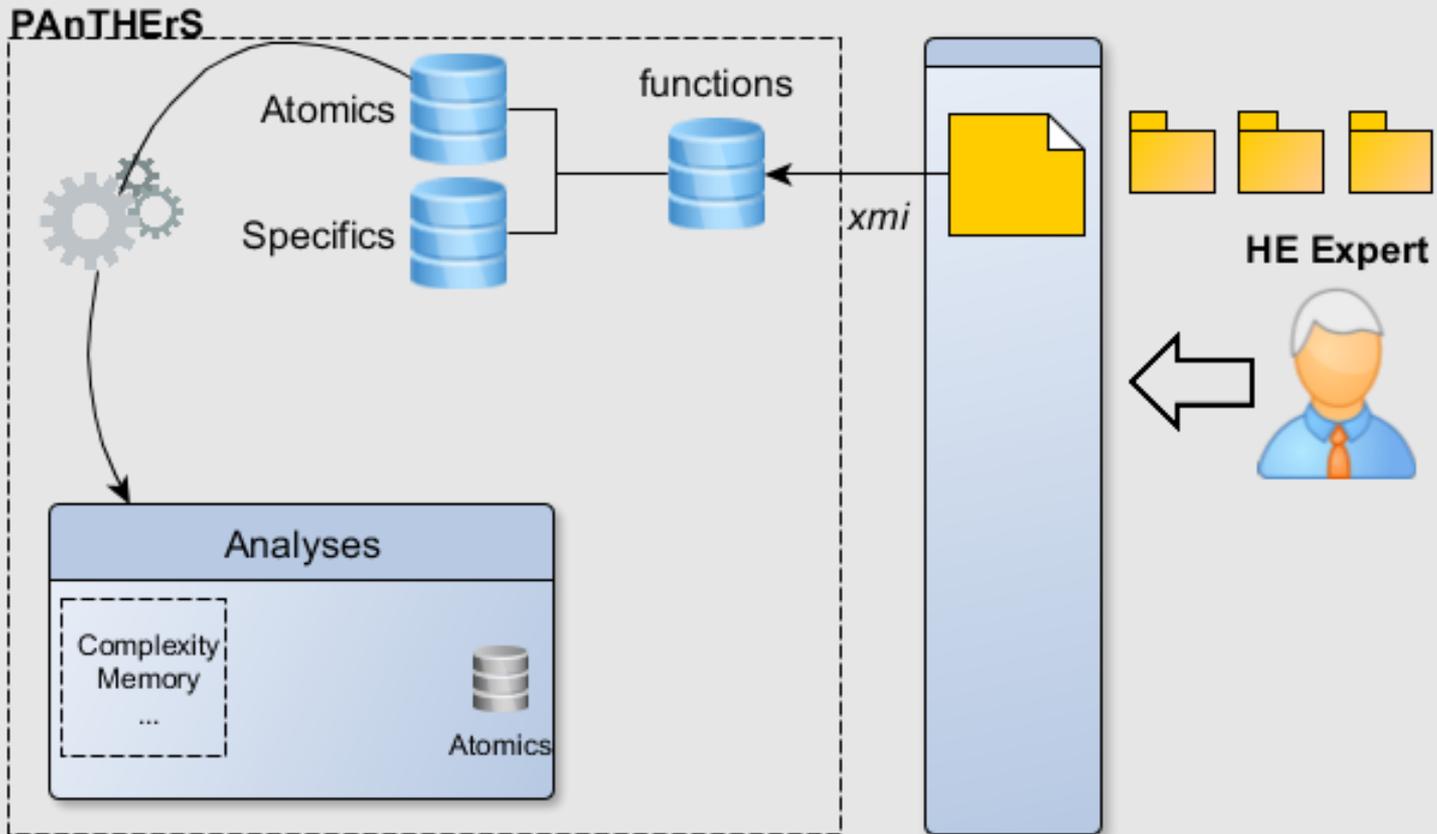
HE Expert



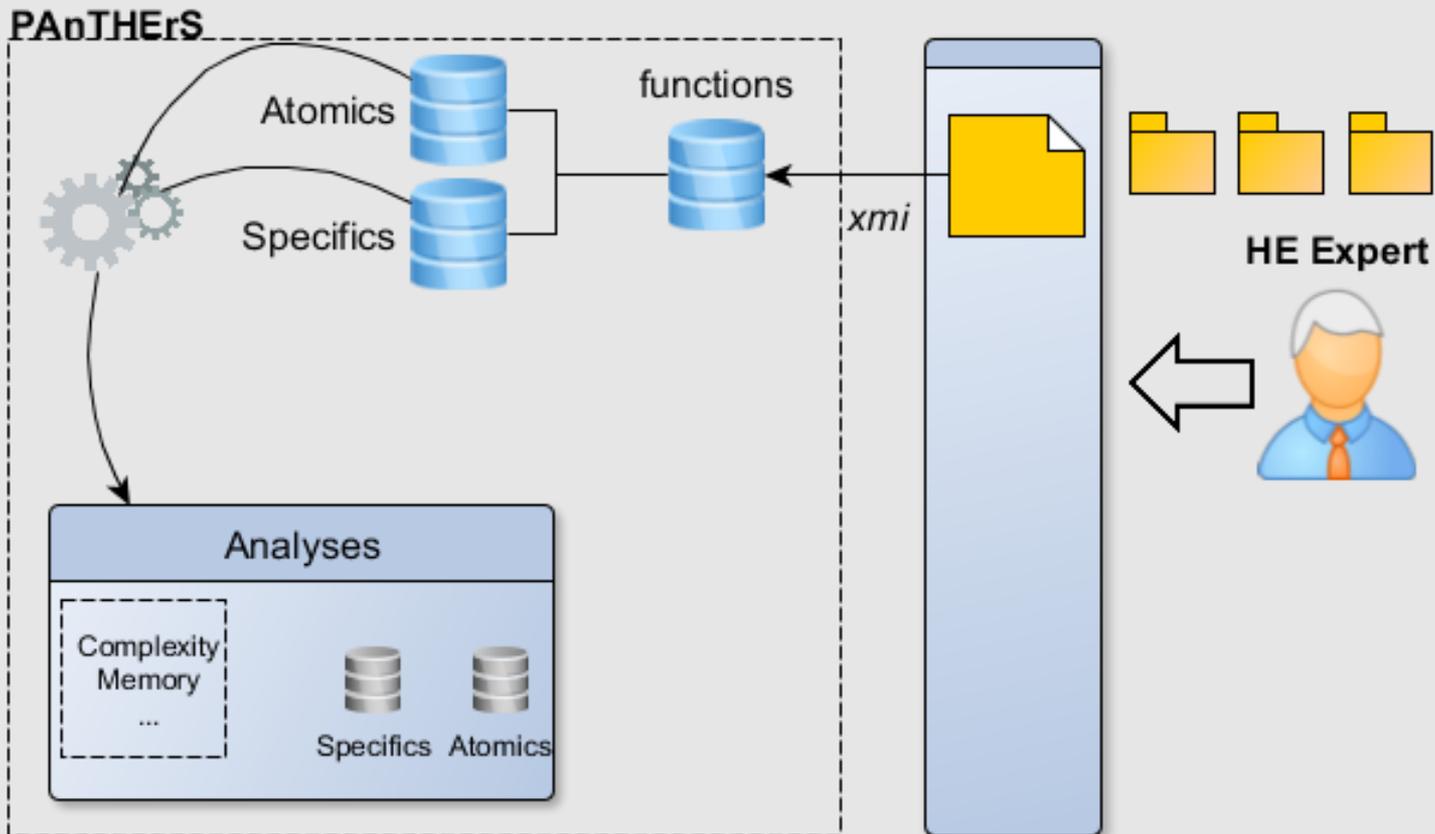
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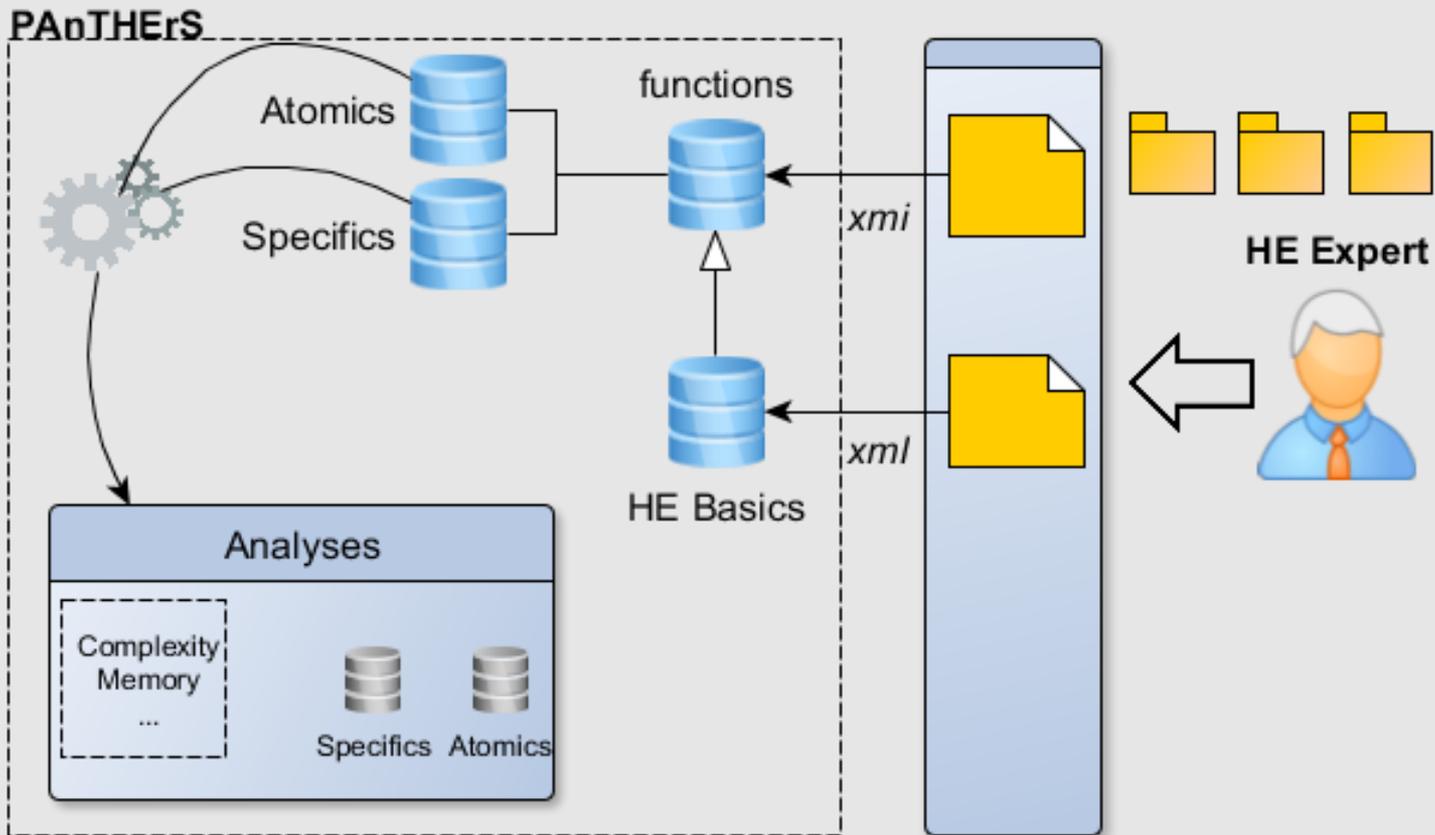
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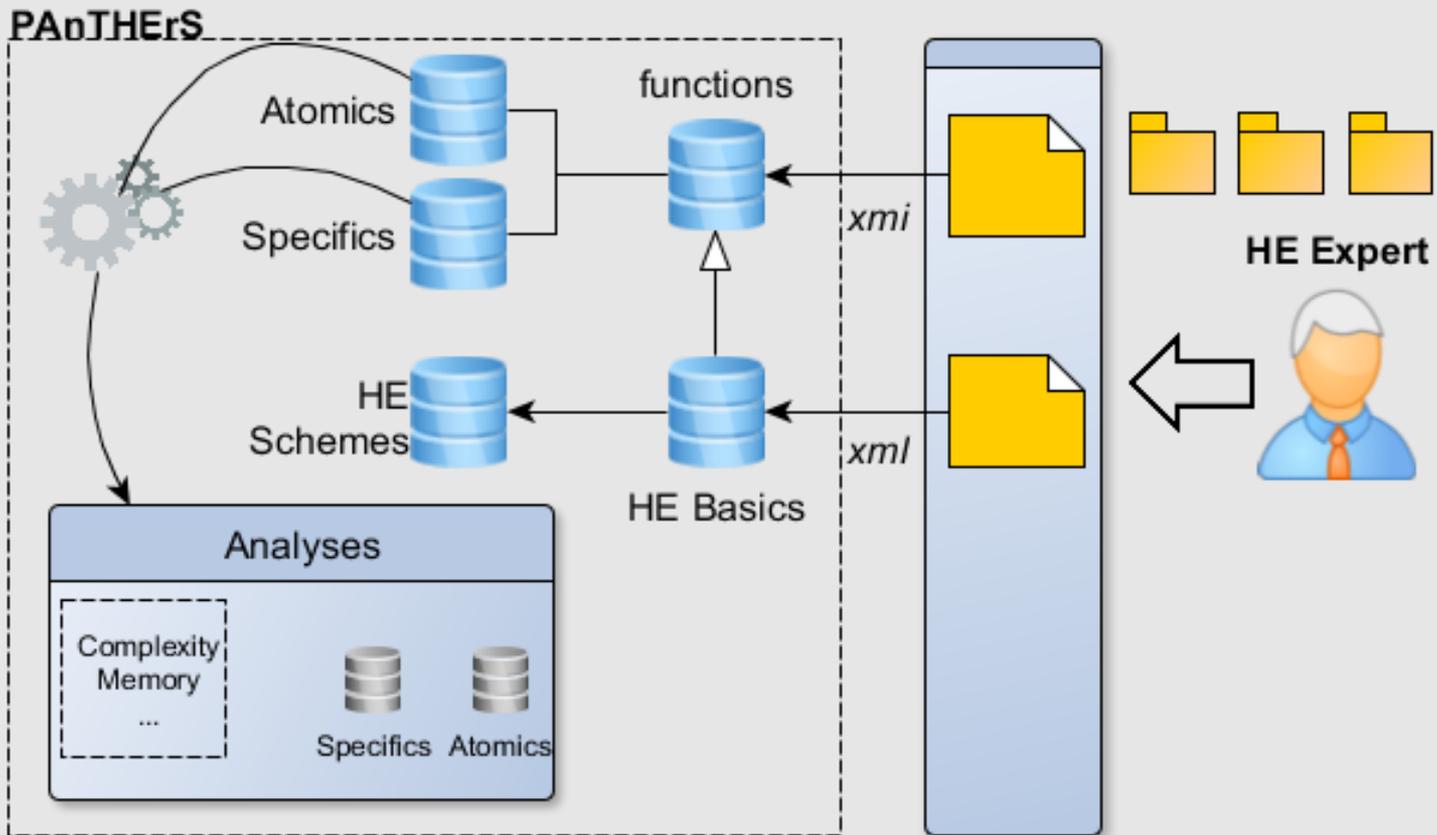
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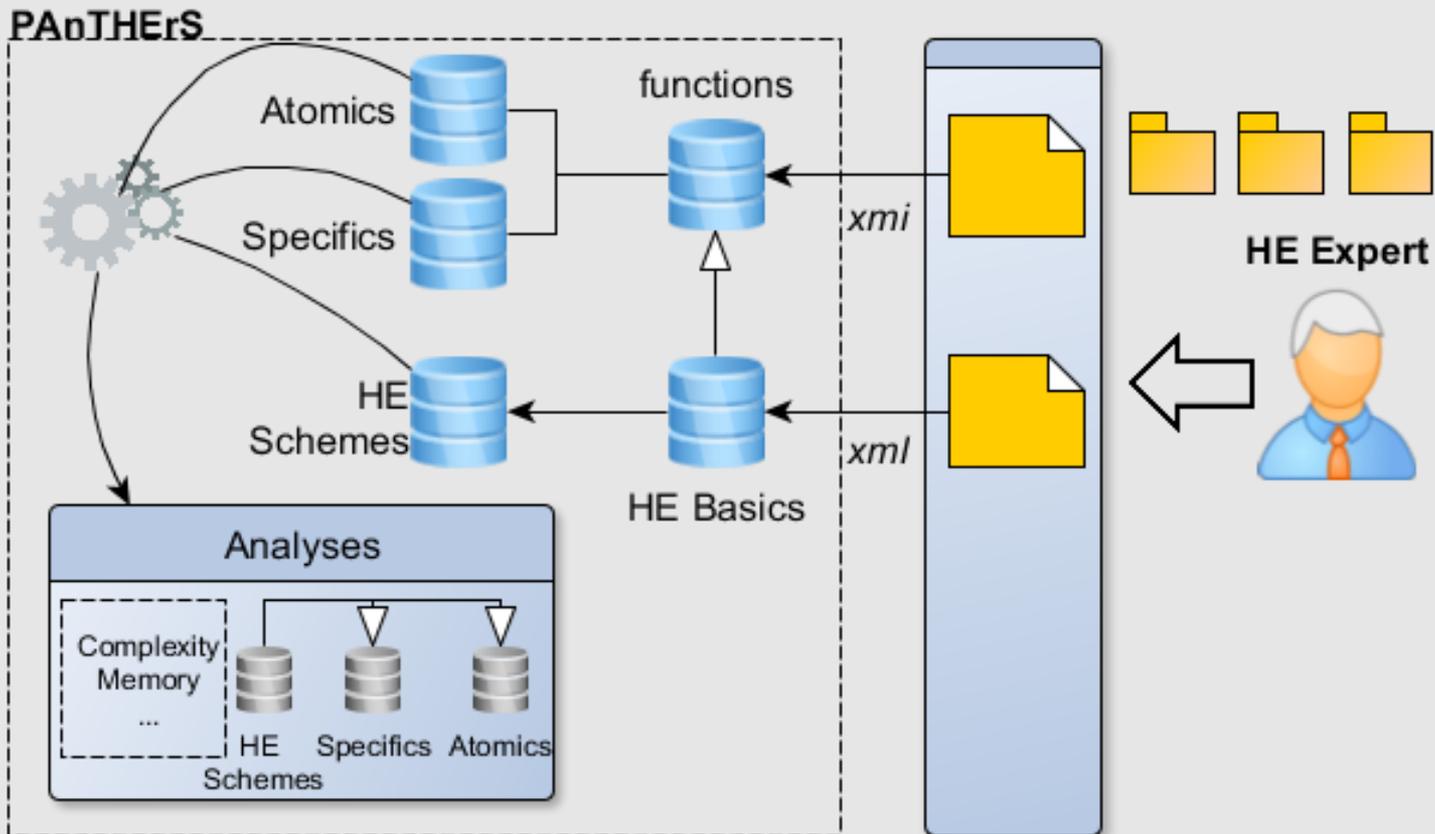
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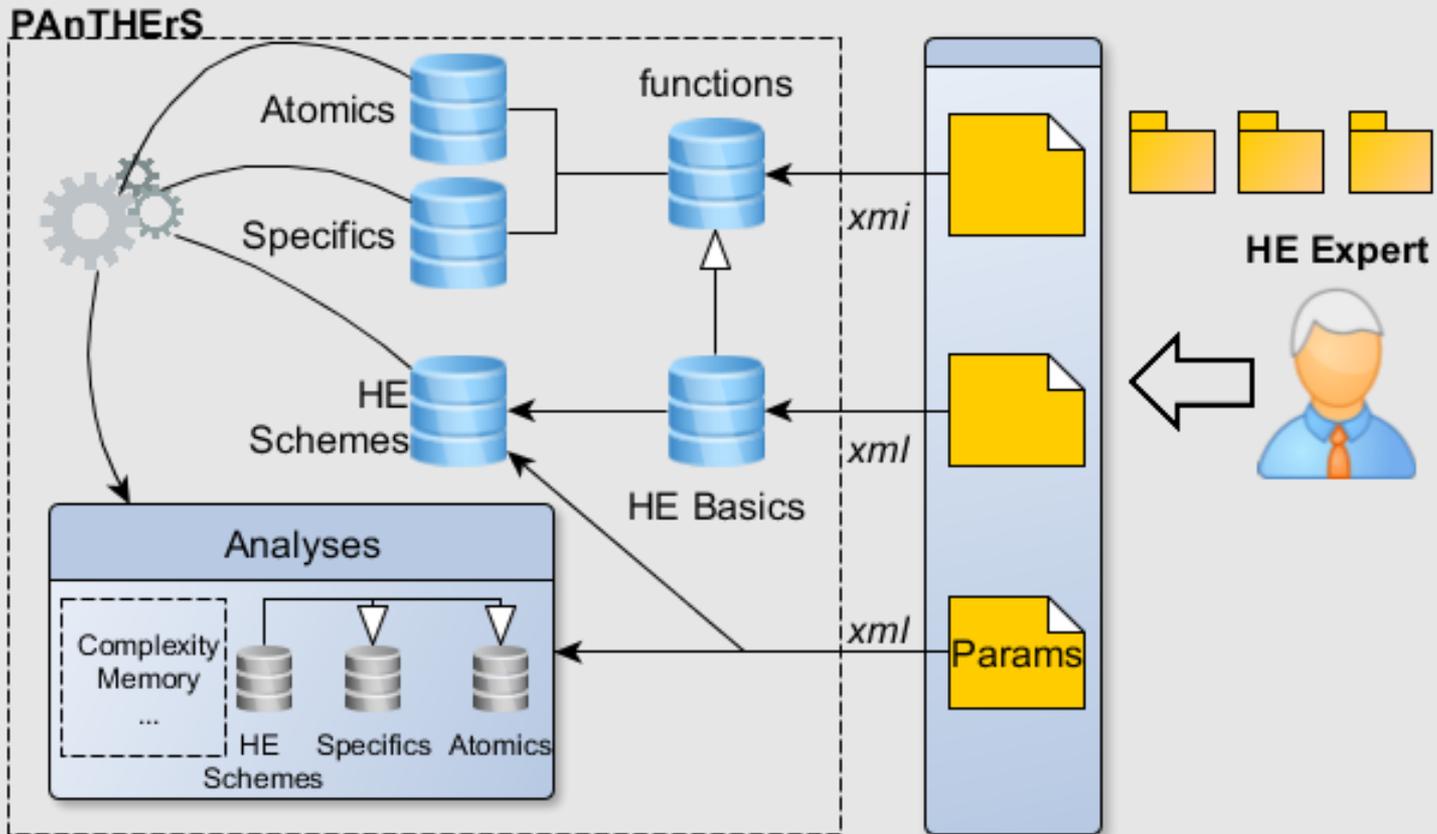
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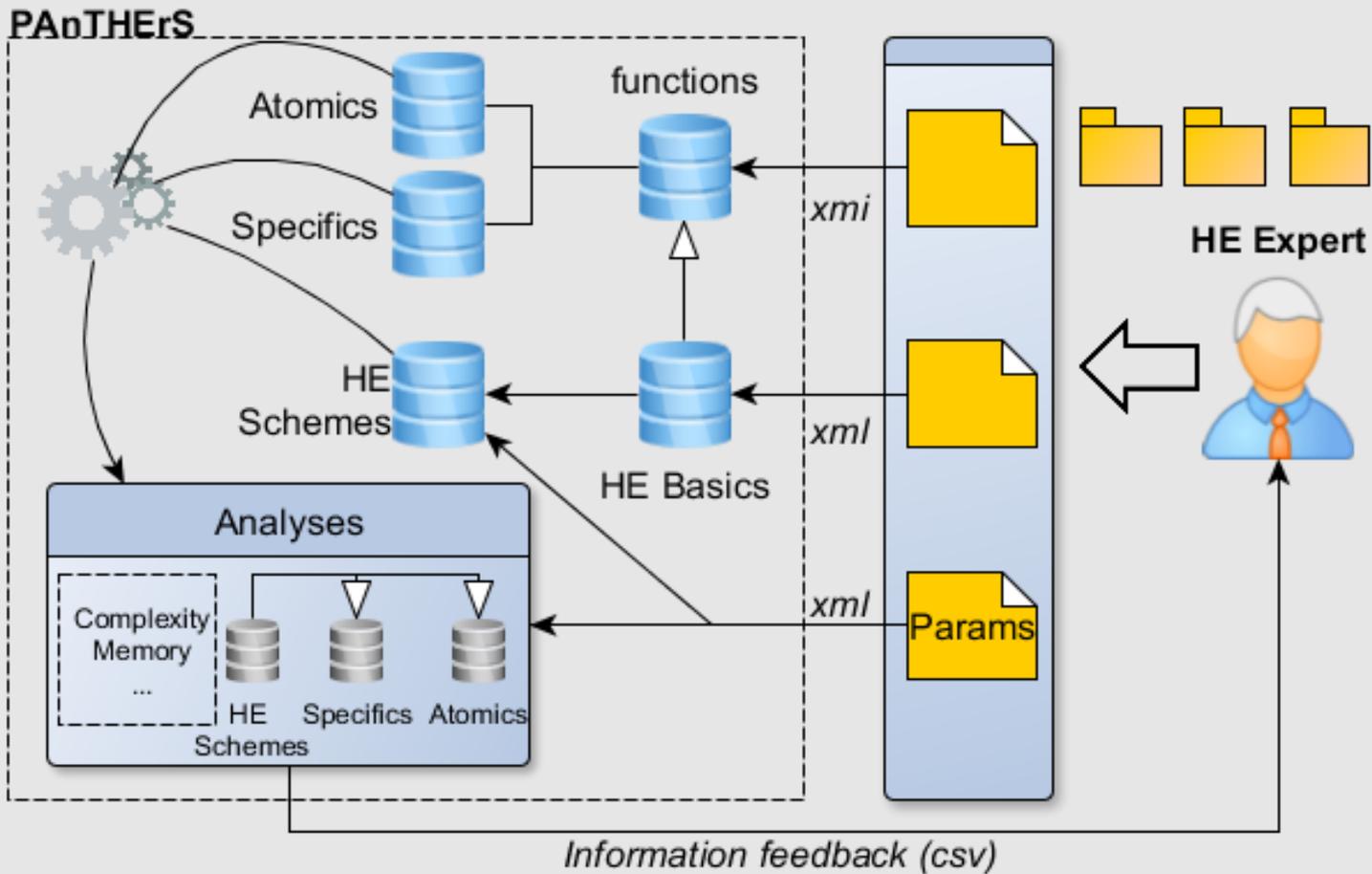
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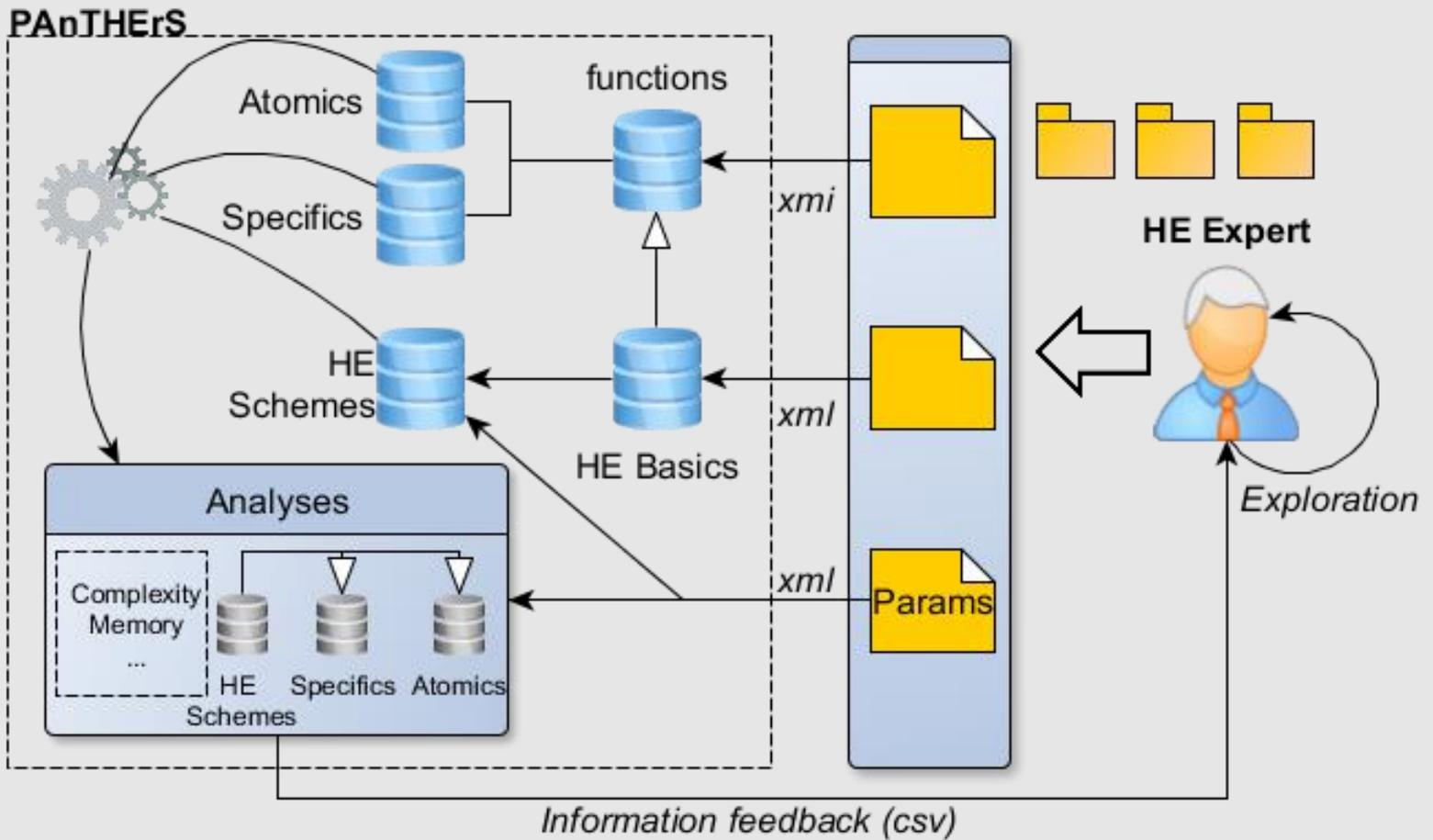
PAnTHERs usage



PAnTHERs usage



PAnTHERs usage



V – Results

1. FV and YASHE complexity
2. FV and YASHE memory cost
3. FV and YASHE depth

Results – *FV and YASHE complexity*

$$R = \mathbb{Z}[x]/\Phi_d(x), \quad n = \varphi(d)$$

$$R_q = R/qR$$

Integer base w

$$\text{Plaintext space : } R_t = R/tR$$

n	1024	2048	4096	8192
max. $\log_2(q)$	46	88	174	348

Ref : Migliore, V., Bonnoron, G., and Fontaine, C. (2017). Determination and exploration of practical parameters for the latest Somewhat Homomorphic Encryption (SHE) schemes. *Working paper or preprint.*

Results – *FV* and *YASHE* complexity

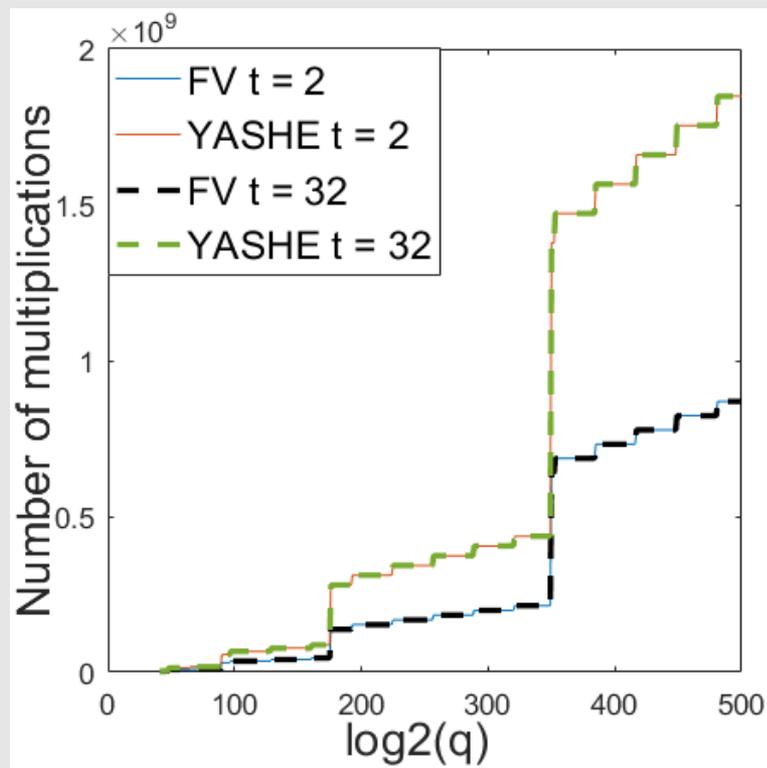
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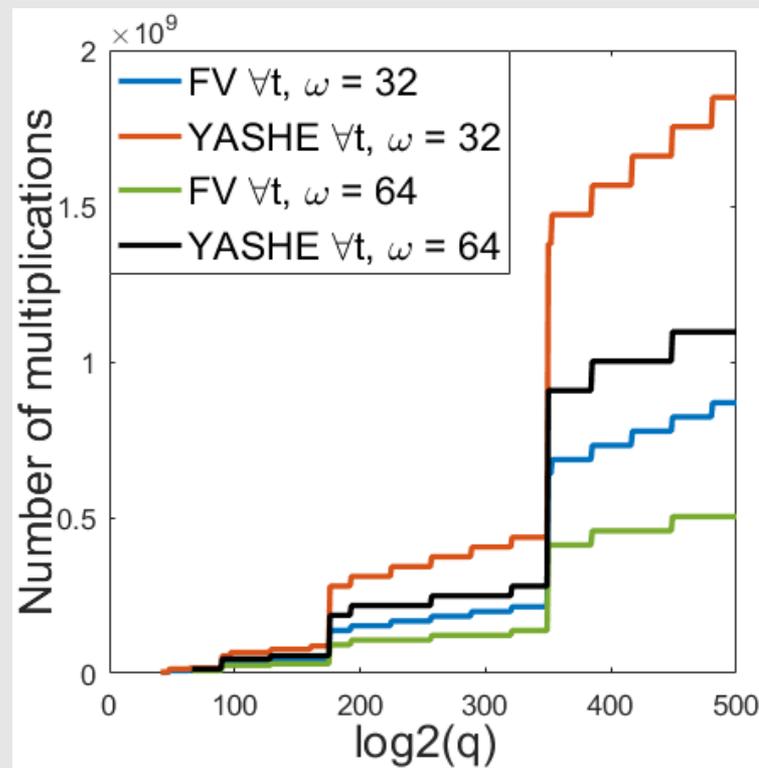
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Fixed parameter: $\log_2(w) = 32$



Here, $\omega = \log_2(w)$

Results – *FV* and *YASHE* memory cost

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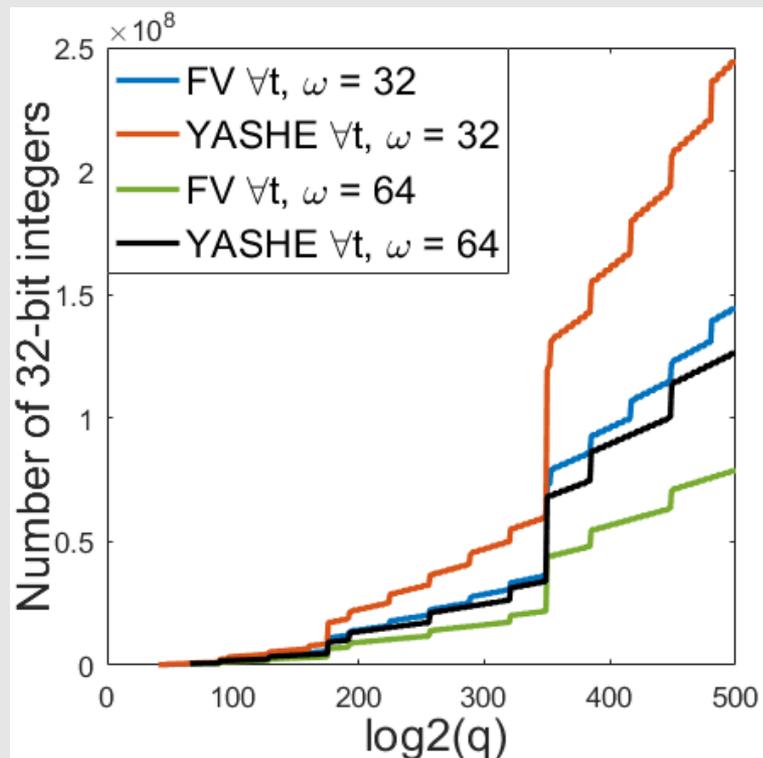
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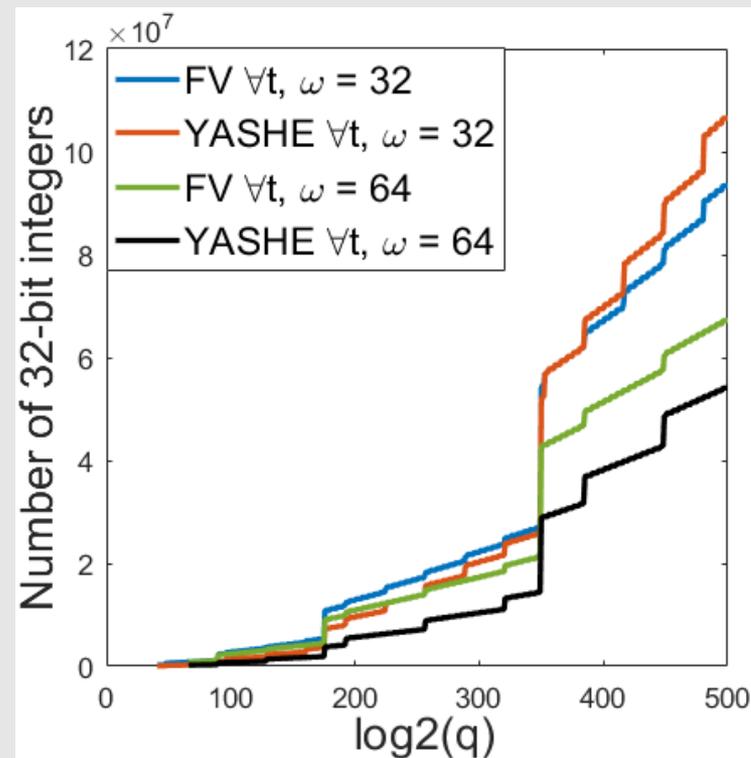
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KeyGen function



Mult function

Results – *FV* and *YASHE* depth

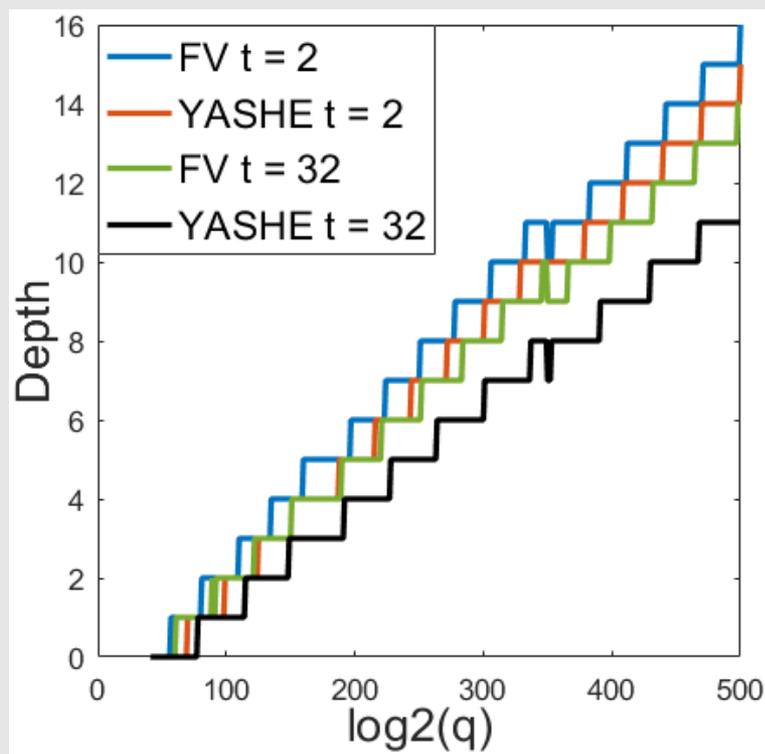
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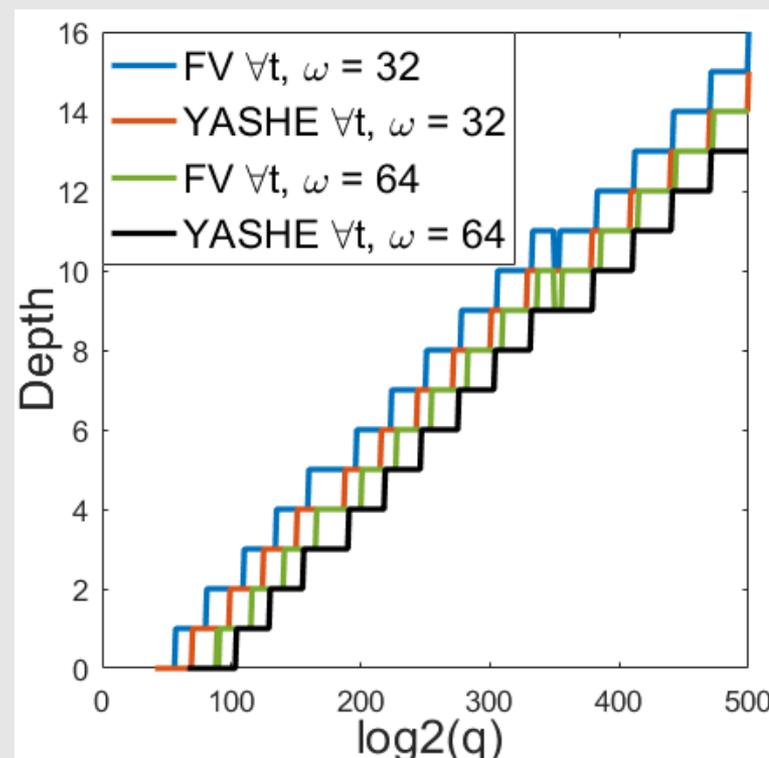
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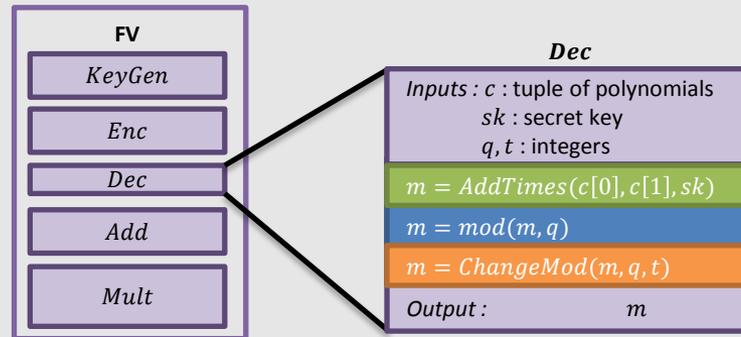
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VI – Conclusion & future work

Conclusion

HE scheme modeling :

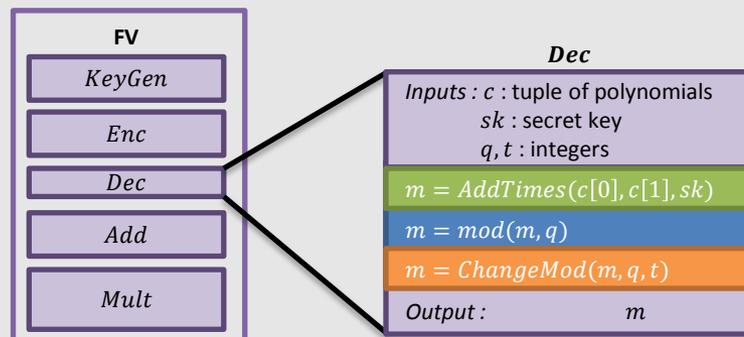
5 HE basic functions composed of Atomic and Specific functions.



Conclusion

HE scheme modeling :

5 HE basic functions composed of Atomic and Specific functions.



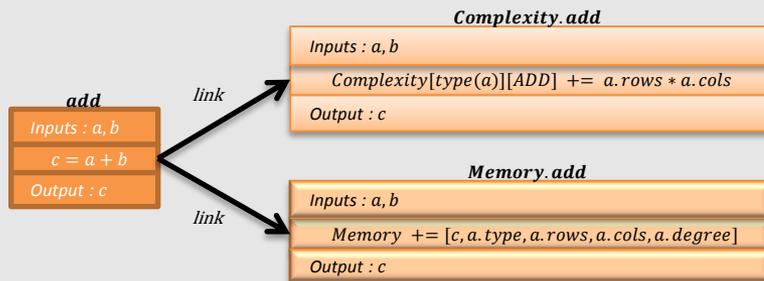
Filling the library implies **faster** modeling for new HE schemes.



Conclusion

Atomic , specific & HE basic functions analysis:

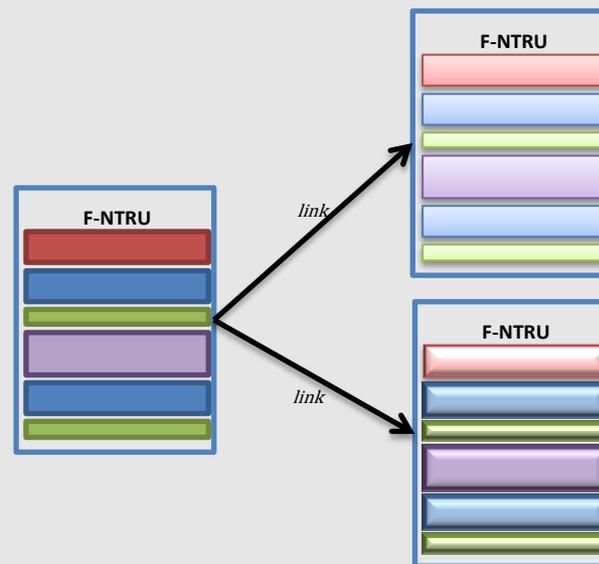
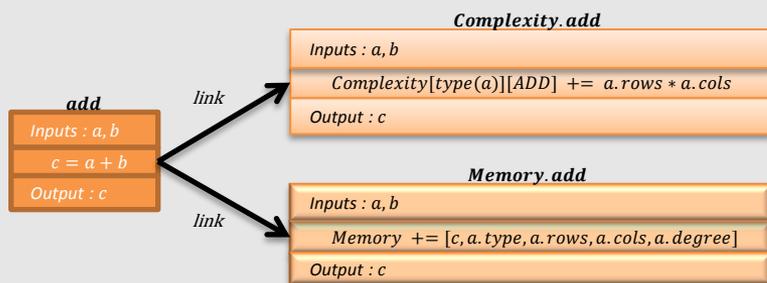
Atomic, specific & HE basic functions are linked to their complexity and memory cost analysis functions.



Conclusion

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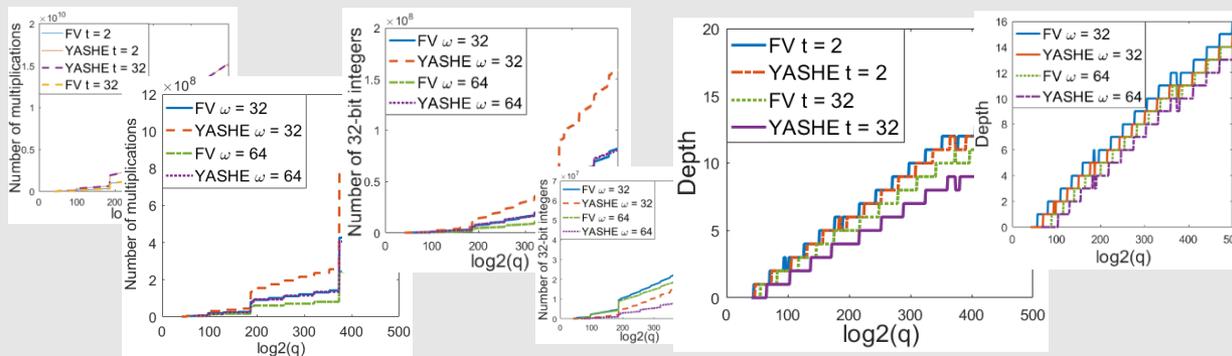
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Automated generation of HE scheme analysis functions.

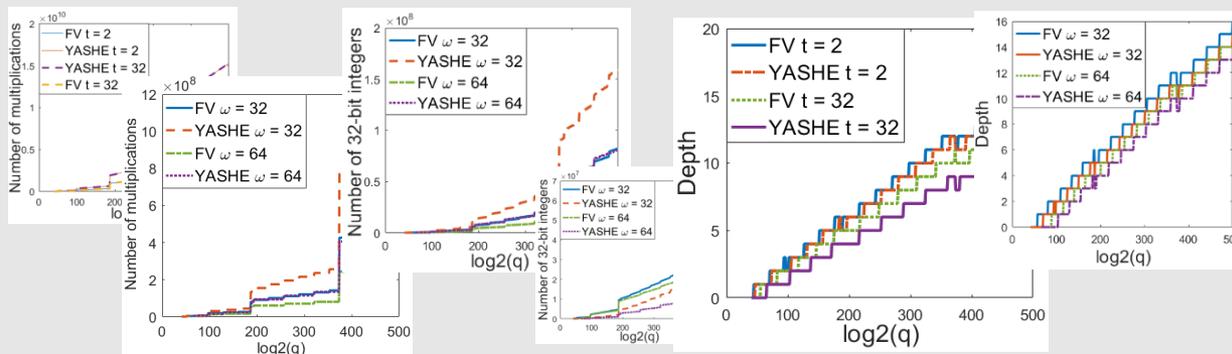
Conclusion

By varying input parameters, PAnTHERS provides memory, complexity and depth results.



Conclusion

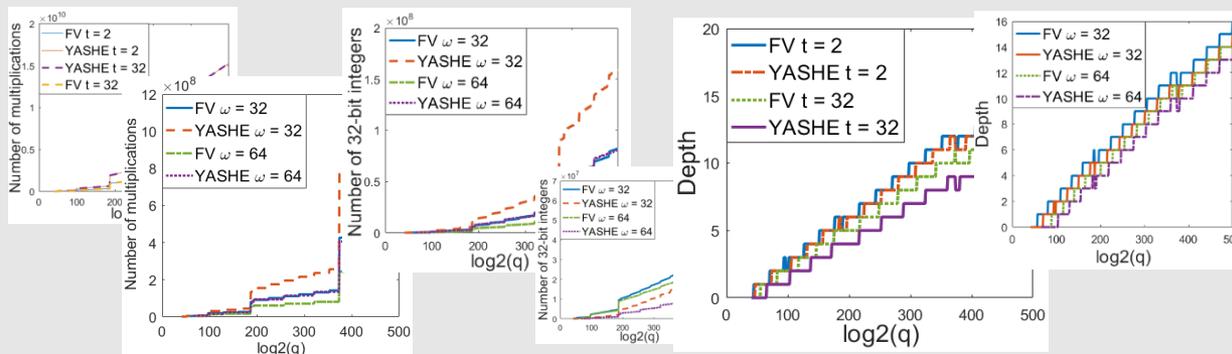
By varying input parameters, PAnTHERs provides memory, complexity and depth results.



HE expert interprets PAnTHERs data...

Conclusion

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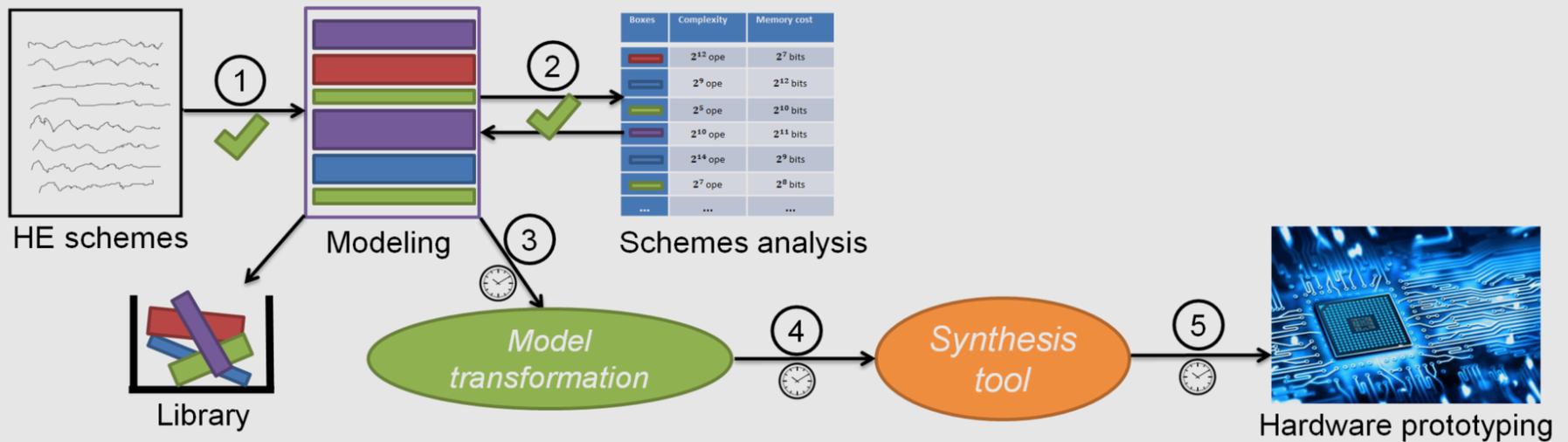


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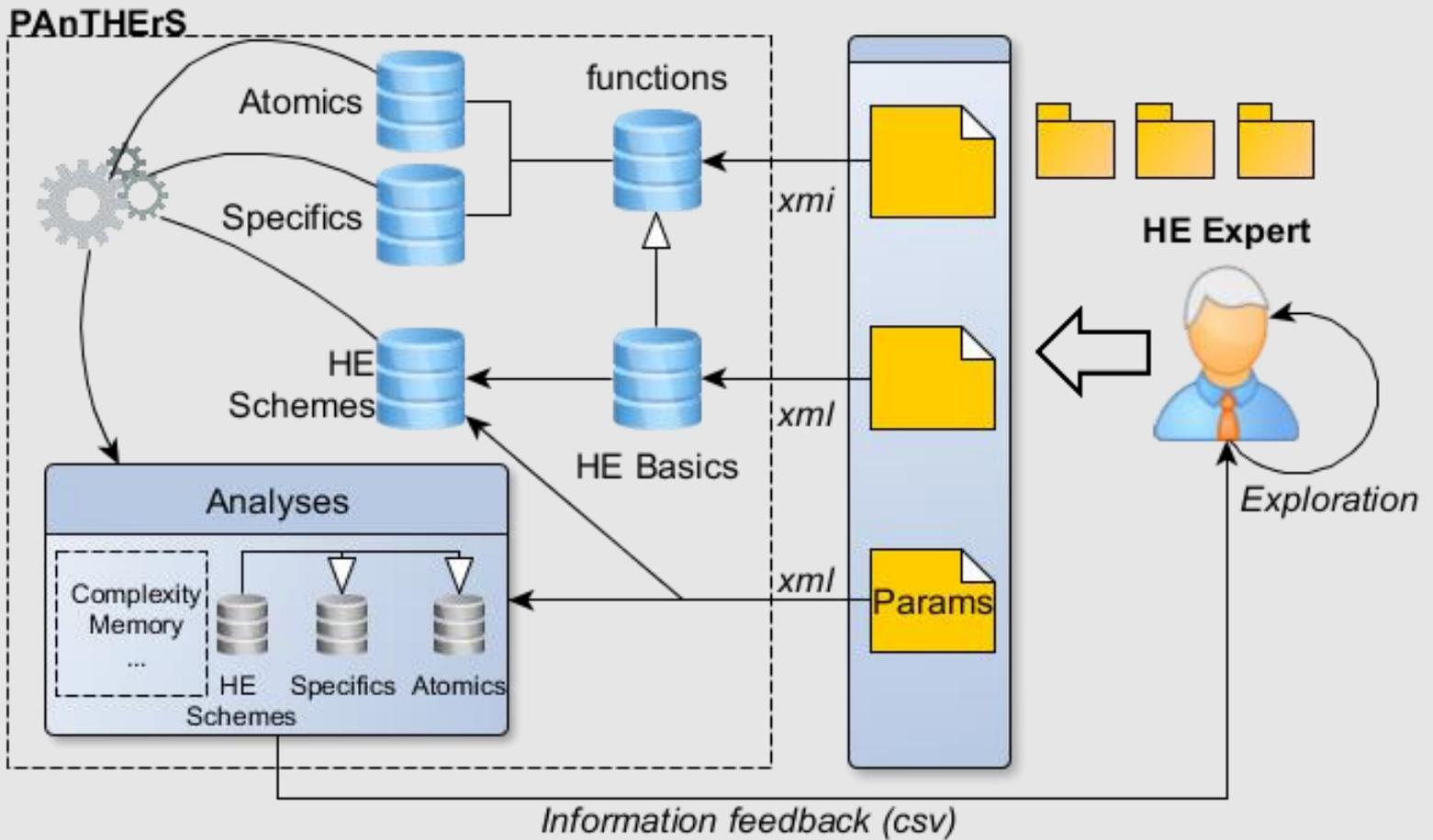
...to select the scheme which fits better his application.



Future work



Future work



Thanks

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Loïc LAGADEC

Vianney LAPOTRE



ENSTA
Bretagne



References :

- [1] Migliore, V., Bonnoron, G., and Fontaine, C. (2017). Determination and exploration of practical parameters for the latest Somewhat Homomorphic Encryption (SHE) schemes. *Working paper or preprint*.
- [2] Doröz, Y. and Sunar, B. (2016). Flattening NTRU for evaluation key free homomorphic encryption. *IACR Cryptology ePrint Archive*, 2016:315.
- [3] Fan, J. and Vercauteren, F. (2012). Somewhat Practical Fully Homomorphic Encryption. *IACR Cryptology ePrint Archive*, 2012:144.
- [4] Gentry, C., Sahai, A., and Waters, B. (2013). Homomorphic Encryption from Learning with Errors: Conceptually-Simpler, Asymptotically-Faster, Attribute-Based. In *Proc. CRYPTO*, pages 75–92, Santa Barbara, CA, USA.
- [5] Khedr, A., Gulak, P. G., and Vaikuntanathan, V. (2016). SHIELD: scalable homomorphic implementation of encrypted data-classifiers. *IEEE Trans. Computers*, 65(9):2848–2858.
- [6] Bos, J.W., Lauter, K. E., Loftus, J., and Naehrig, M. (2013). Improved Security for a Ring-Based FHE Scheme. In *Proc. Cryptography and Coding IMA*, pages 45–64, Oxford, UK.