RAMPARTS

RApid Machine-learning Processing Applications and Reconfigurable Targeting of Security

An IARPA-funded seedling exploring ease of use and feasibility of automatic correctness, optimization, and security settings for Fully Homomorphic Encryption

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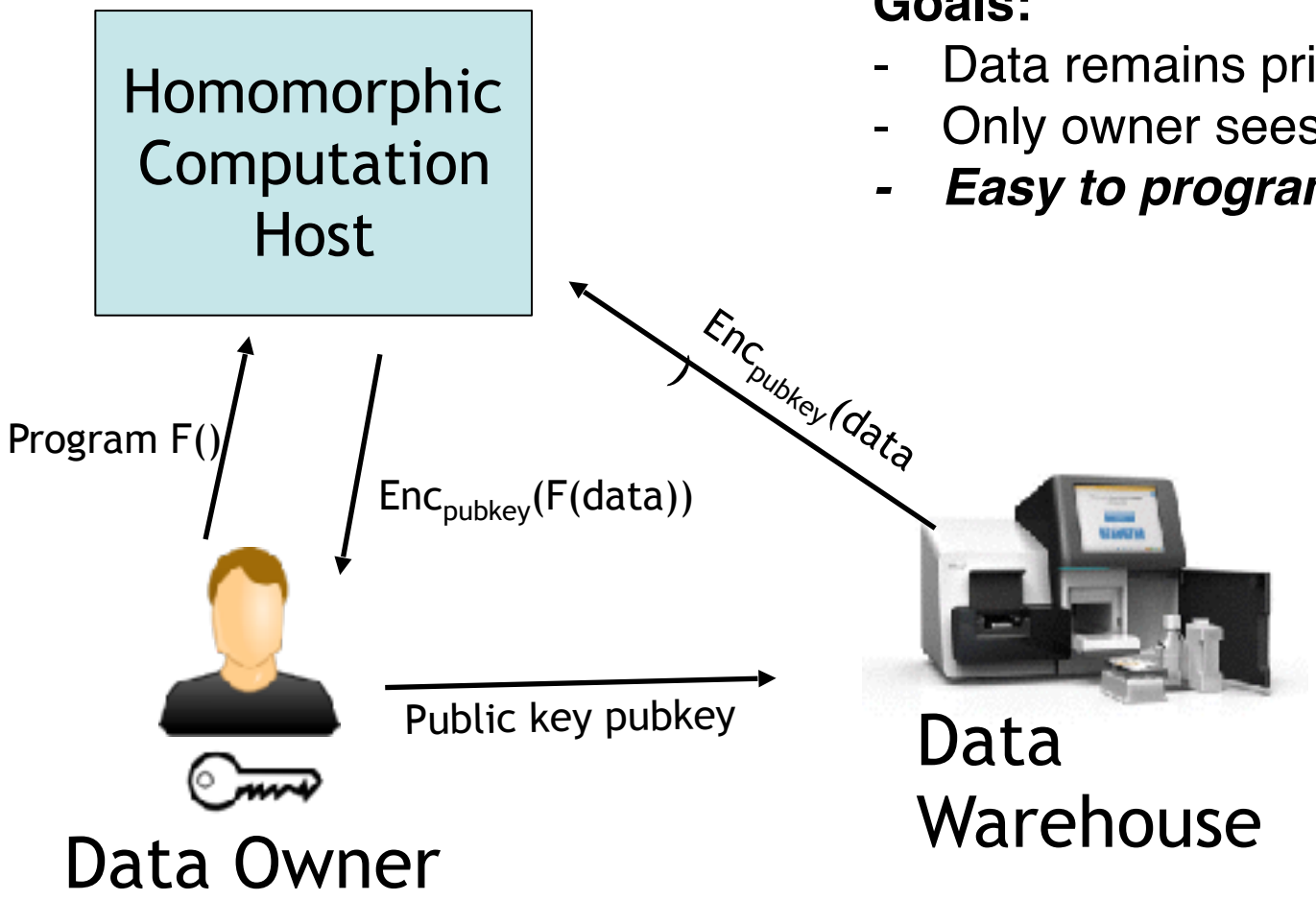
Example FHE Use Case

Goals:

- Data remains private
- Only owner sees result
- ***Easy to program***



Problem: FHE Today is Hard to Use

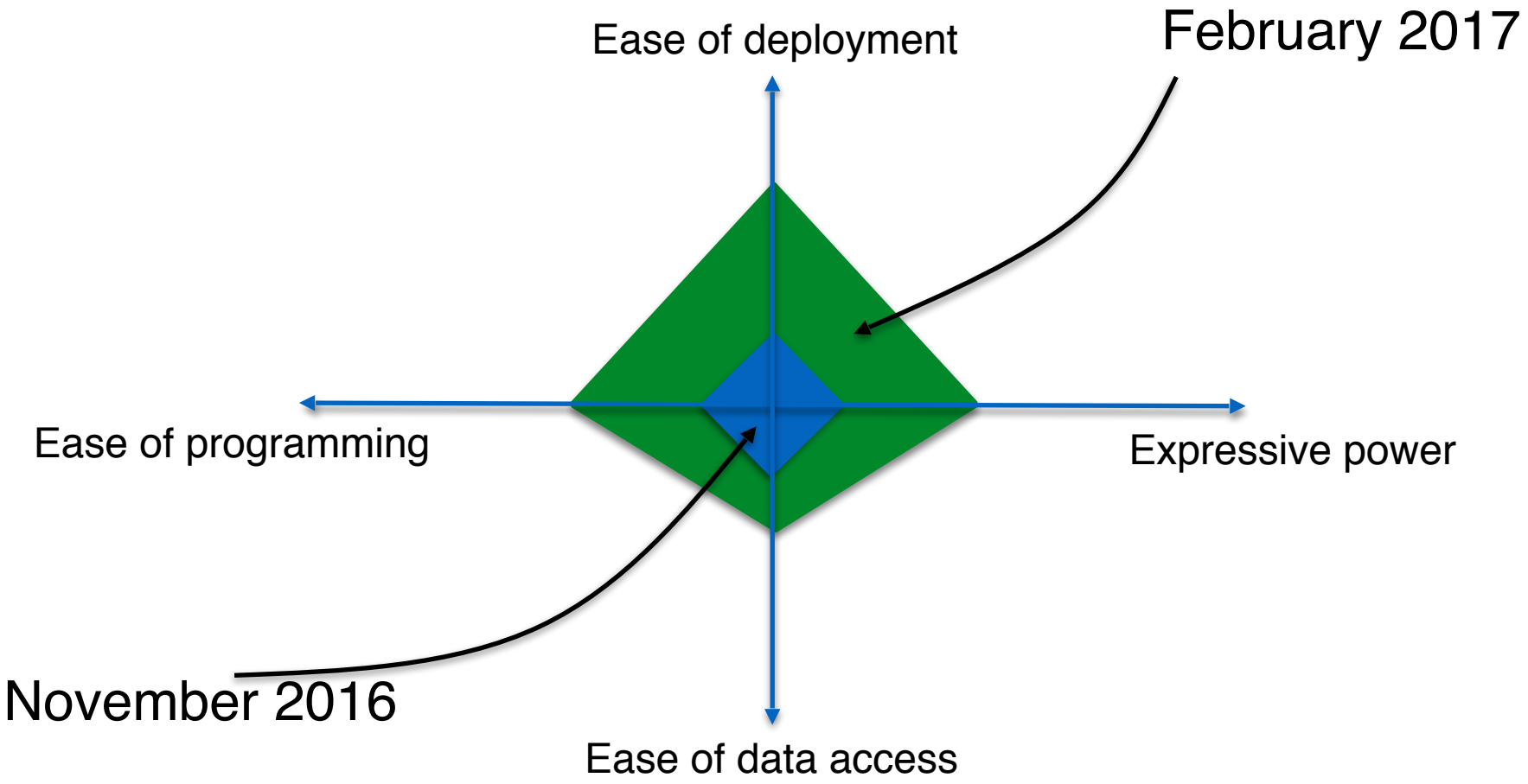
Today: design by hand-tuning and expert knowledge

Challenge: Make FHE easier to use by engineers

Simple Metrics for Ease of Use

- **Expressive power**
  - How much of data analysts' higher level language is supported?
- **Ease of programming**
  - How much do data analysts need to know to use encrypted computing capabilities?
- **Ease of deployment**
  - How easy to setup, install, deploy, re-use and maintain?
- **Ease of data access**
  - How easy is it to encrypt data for FHE use, and how much does it cost to transmit that data to the computation host?

Usability Matrix



November 2016 - the "Front End"

Already substantial improvement on FHE ease of use, but

Only one-liners supported:

Limited expressive power

```
# declare our function, marking with the @fhe macro
# so that the compiler knows that it may be run under FHE
fp = Fhe.@fhe function f(db, pk, sk, a, b, c, d)
  ((a - b) * (a - b)) + ((c - d) * (c - d))
end

# Call the function, currently we have to use dummy data for
# values, this will be improved in future versions
println("Evaluating function on dataset")
res = fp("db", "owner.pk", "owner.sk", 0, 0, 0, 0)
println("Result (FHE): ", res)
```

Special calling convention:

Limited ease of programming

Limited ease of deployment

- Used modified Julia compiler

February 2017: a Better "Front End"

```
# Build crypto context for FHE
ctx = Fhe.CryptoContext("FV")
# Declare our function
function f(db)
  a = db[1] - db[2]
  b = db[3] - db[4]
  return a * a + b * b
end
# Evaluate `f` on encrypted dataset `edb`
res = Fhe.eval(ctx, f, edb)
println("Result (FHE): ", res)
```

Greater function support*:
Better expressive power

Simple interface:
Better ease of programmming

Better ease of deployment

- Uses standard Julia compiler

*: currently in MATLAB, Julia by end of Phase II

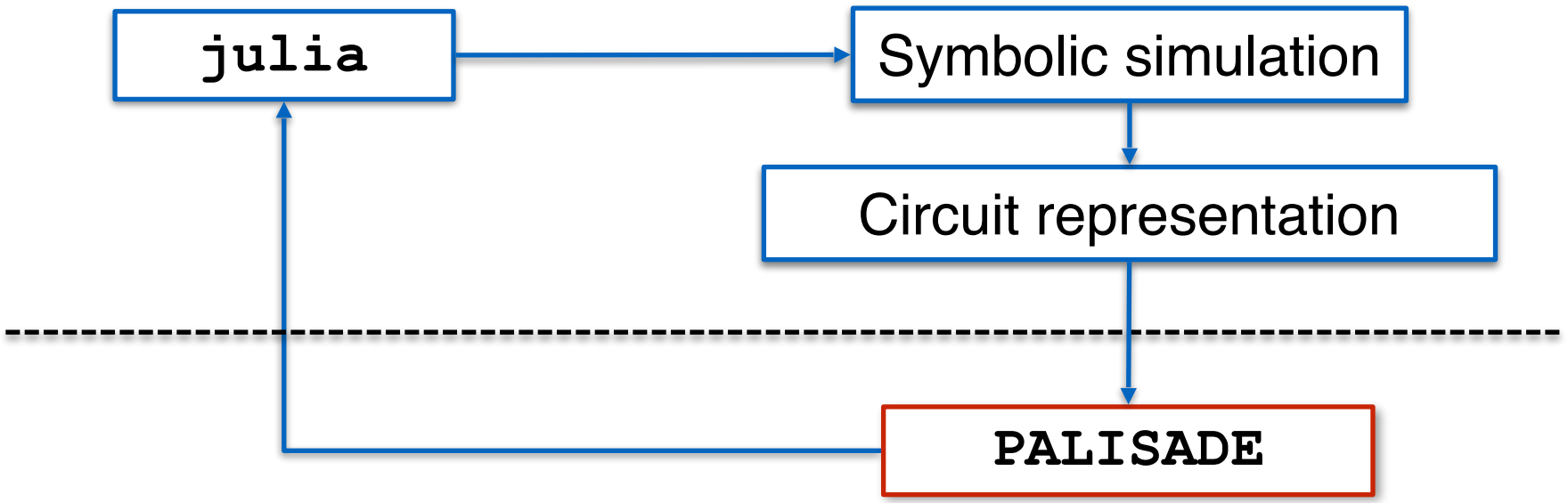
November 2016: the “Back end”

- **Ease of Programming**
  - Integrated NULL and FV scheme support for arithmetic operations
- Ease of Deployment
  - Semi-automated configuration of FHE protocols
  - Wrapper for high-level usage

February 2017: A Better “Back End”

- Ease of Data Access
  - More data types supported
    - Ex: Matrices and Rationals
- **Ease of Programming**
  - Support for custom optimized FHE circuits.
    - Ex: Vectorized operations
    - Ex: Linear regression
  - Circuit estimator framework
    - Functional and performance estimator

Goal: From Julia Function to FHE



Why Symbolic Execution?

- FHE uses circuits statically configured *before* execution

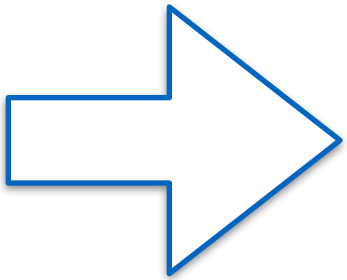
But…

- (Imperative) programs dynamically configured *during* execution

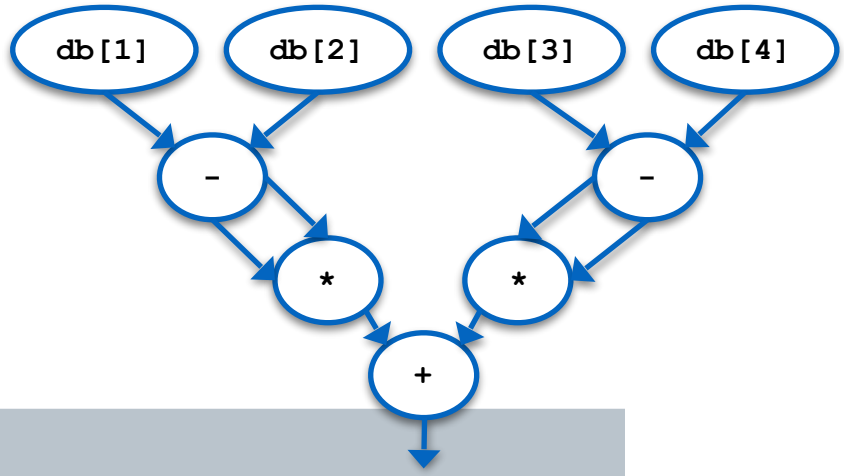
To cross evaluation gap, use *symbolic execution*

- ***Interpret*** (almost) all execution paths in the program
- ***Express*** program values symbolically rather than concretely
- ***Encode*** terminal expressions for values as logic or arithmetic circuits

```
a = db[1] – db[2]
b = db[3] – db[4]
return a*a + b*b
```



Symbolic simulation



Demonstrations, February 2017

Linear Regression

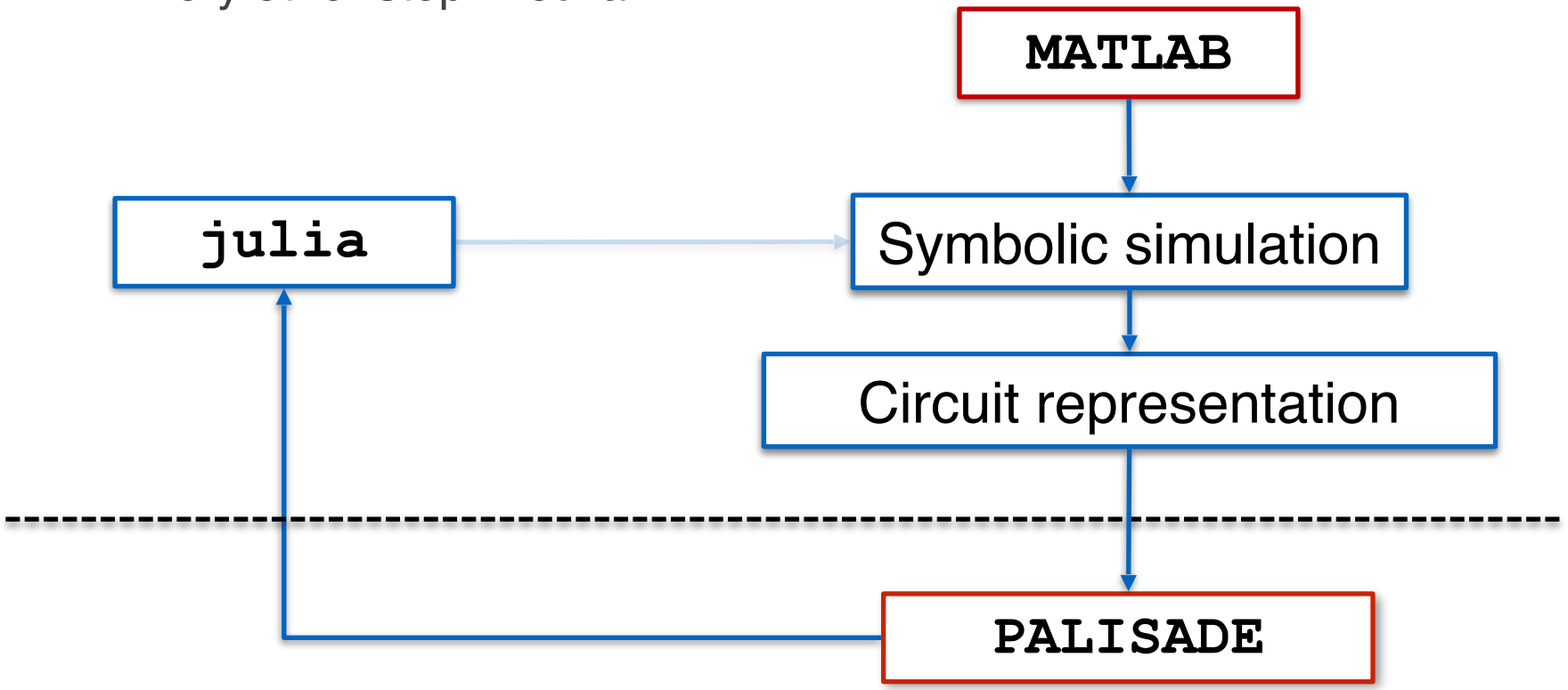
- Implemented in Julia/MATLAB
  - For functions written in “native” language without expertise
- Implemented in PALISADE
  - For functions written in “assembly” language to incorporate expert knowledge

Circuit Estimation

- Shows ability to estimate FHE circuit properties for compiler use

Demonstration: Linear Regression

- For demo, use MATLAB (vs. Julia) as language for compiling circuit
  - Pre-existing capabilities for MATLAB to symbolic simulator input
- Every other step in Julia



Conclusions

- RAMPARTS focuses on ease of use and efficiency for practical FHE
  - Expressive power that's easy to program
  - Simplicity of deployment
  - Simplicity of accessing data sets
  - Competent optimization of functions in FHE
- RAMPARTS prototypes are making novel contributions and progress in all of these areas
  - Symbolic execution generates FHE-ready circuits from analytic programs
  - Integrated FHE capability makes user experience match analyst expectations
  - Extensible FHE library allows for continuous enhancement of performance and capability
- RAMPARTS may offer a useful model for standardization of MPC interfaces beyond FHE alone