Integrating Fully Homomorphic Encryption Into the MLIR Compiler Framework

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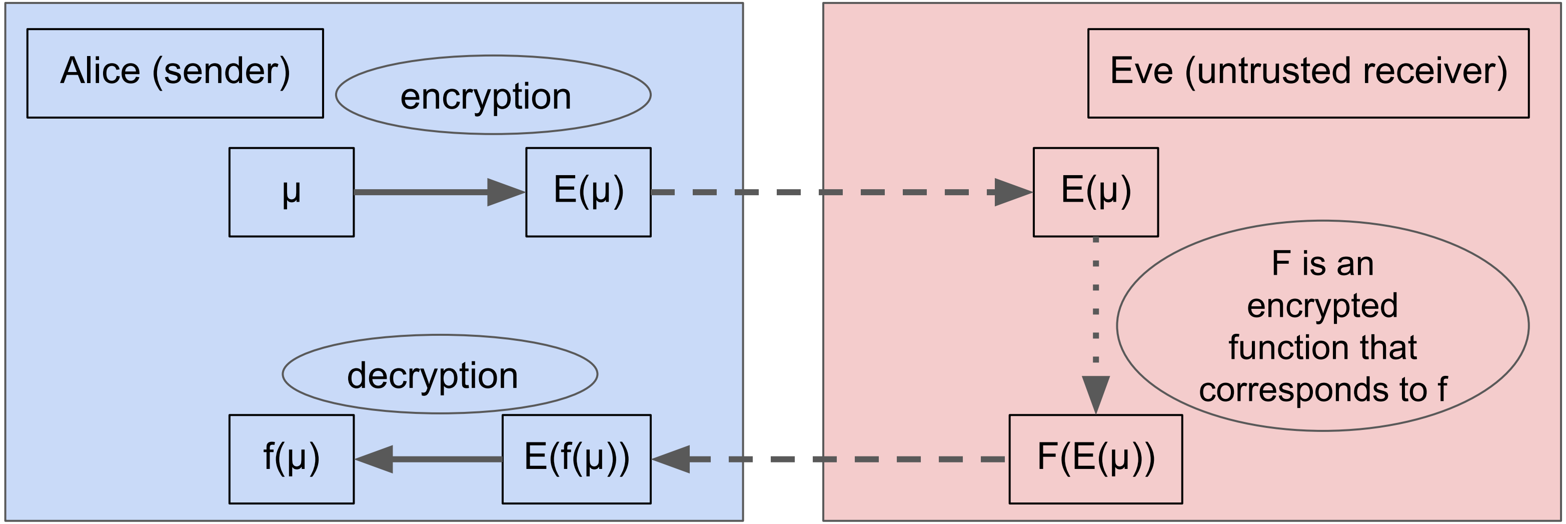
Fully Homomorphic Encryption

Run arbitrary functions on private data

Applications: medical, security, cloud computing, etc.



FHE: $F(E(\mu)) = E(f(\mu))$

Pros and Cons of Fully Homomorphic Encryption

- At no point is your data known to anyone except yourself
- At no point are your results known to anyone except for yourself
- At no point is the computation known to anyone except the receiver
- Theoretically, ability to translate any existing program into an encrypted program

- FHE libraries are unwieldy and complicated to learn and use
- Not as widespread as other encryption methods
- Tools for fully homomorphic encryption (FHE) still in early stages
- Homomorphically encrypted programs must be constructed from primitives like binary gates, addition, and multiplication
- Very slow compared to other encryption methods because of the need for high-level and low-level optimizations (scheduling etc.)

The Current State of FHE Libraries

- Currently popular libraries: SEAL, HELib, PALISADE
- FHE operations are called using library functions, one primitive at a time
- Different libraries for different schemes
- No cross-operation optimization
  - PRIMES project last year: enabled cross-operation optimization in the GSW (2013) scheme using Halide
  - Still difficult to write complicated functions
  - Limited to bit-wise optimizations

MLIR

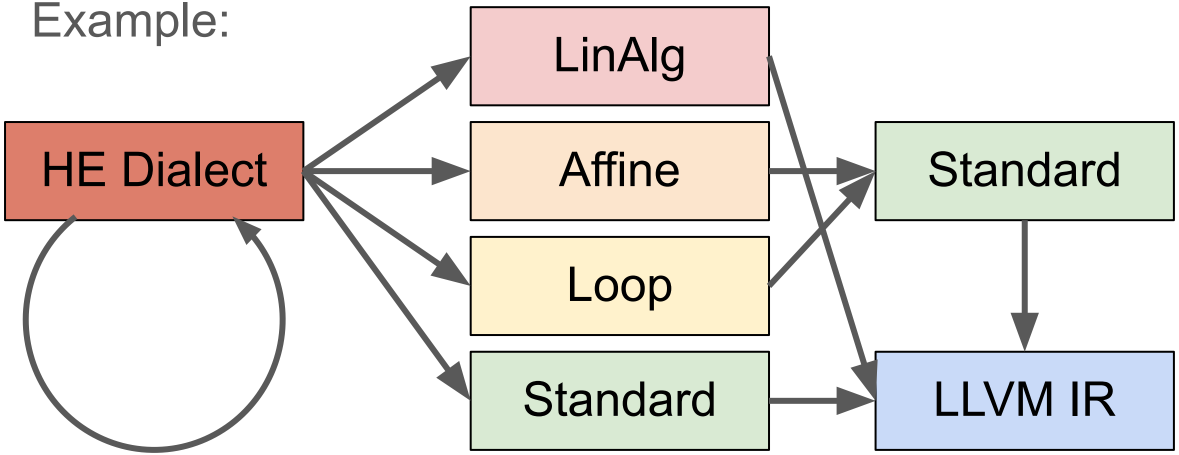
- A compiler, not a library
- An SSA-based ***M***ulti-***L***evel ***I***ntermediate ***R***epresentation that sits on top of the LLVM IR
- A multi-level optimizer
- Language-independent
- Language-specific

Levels of Optimization

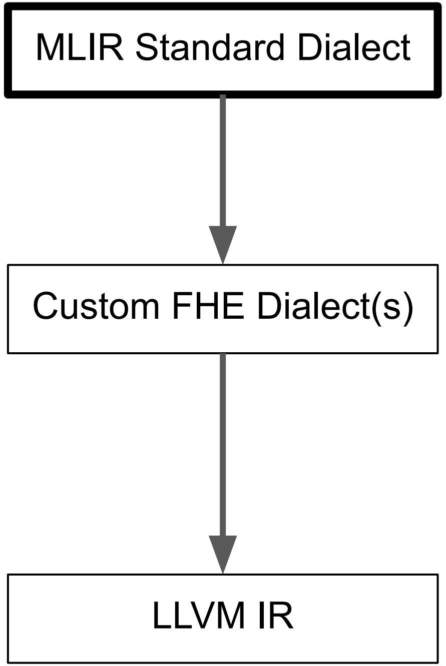
- Normal compiler optimizations (incl. language-specific)
- DAG rewrites (highly language- and scheme-specific)
- Loop scheduling
- Parallelization
- Overall, three levels: syntax/high level, HE level, low (scheduling) level

How Does MLIR Work?

- Opaque operations, not instructions
- Dialects: sets of operations at a similar level
- Progressive lowering: translating from a higher-level dialect to a lower-level dialect (lowest is LLVM IR) and optimizing along the way
- Can mix and match dialects within a single MLIR module
- Example:



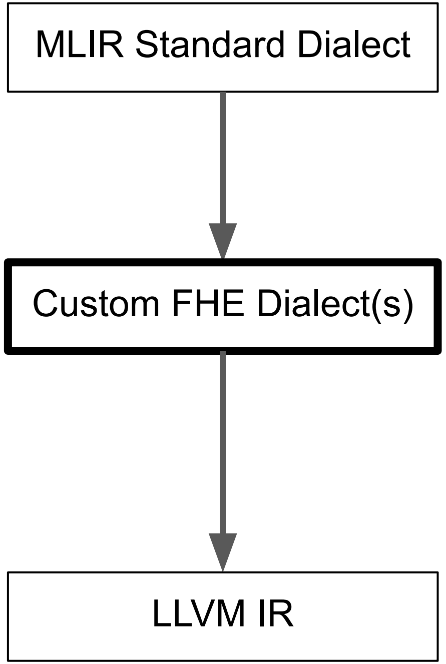
High Level (Input Code)




```
// add x + x, unoptimized
func @add(%x : i64) -> i64 {
    %0 = addi %x, %x : i64
    return %0
}

// add x + x, optimized
// x + x = x << 1
func @add_opt(%x : i64) -> i64 {
    %cst_1 = constant 1 : i64
    %0 = shift_left %x, %cst_1 : (i64, i64) -> i64
    return %cst_1
}
```

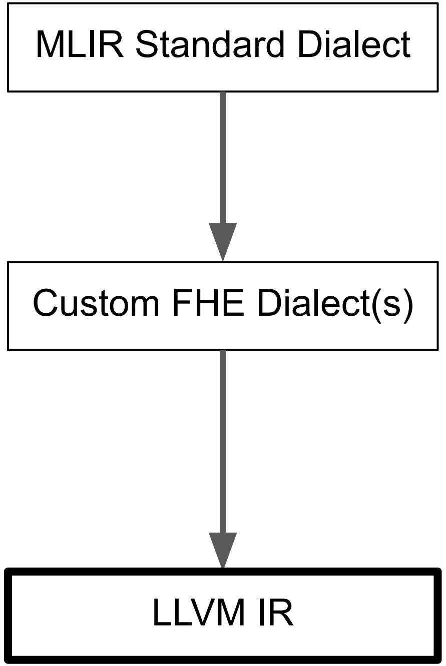
Mid Level (FHE)




```
// Take the NAND of a ciphertext with itself
func @self_nand(%input : memref<20x20xi128>) {
    "HE.NAND" (%input, %input, %input) {mod = 11 :
i128} : (memref<20x20xi128>, memref<20x20xi128>,
memref<20x20xi128>) -> ()
    return
}

// optimized: NAND(a, a) = NOT(a)
// removes two unnecessary operations under the hood
// (aka 1 modular matrix multiplication)
func @self_nand_opt(%input : memref<20x20xi128>) {
    "HE.NOT" (%input, %input) {mod = 11 : i128} :
(memref<20x20xi128>, memref<20x20xi128>) -> ()
    return
}
```

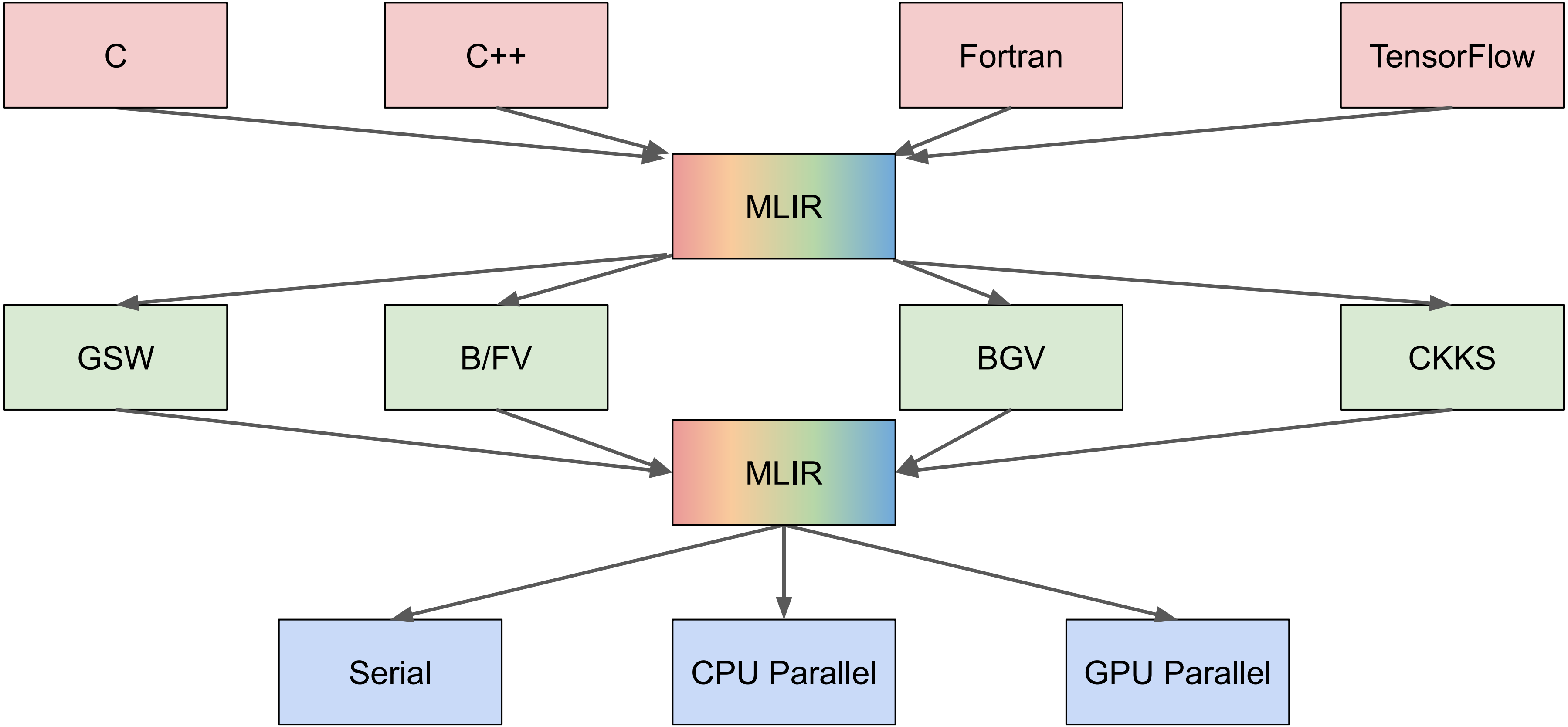
Low Level (Scheduling)




```
// regular loop nest
func @regular() {
  ...
  ...
  loop.for %arg0 = %c0 to %c200 step %c1 {
    loop.for %arg1 = %c0 to %c200 step %c1 {
      loop.for %arg2 = %c0 to %c200 step %c1 {
        %3 = load %1[%arg2, %arg1] : memref<200x200xi128>
        %4 = load %0[%arg0, %arg2] : memref<200x200xi128>
        %5 = muli %4, %3 : i128
        %6 = load %2[%arg0, %arg1] : memref<200x200xi128>
        %7 = addi %6, %5 : i128
        store %7, %2[%arg0, %arg1] : memref<200x200xi128>
      }
    }
  }
  return
}

// GPU loop nest
func @gpu {
  ...
  ...
  gpu.launch blocks(%arg0, %arg1, %arg2) in (%arg6 = %3, %arg7 = %c1_0, %arg8 = %c1_0) threads(%arg3,
%arg4, %arg5) in (%arg9 = %4, %arg10 = %c1_0, %arg11 = %c1_0) {
    %5 = addi %c0, %arg0 : index
    %6 = addi %c0, %arg3 : index
    loop.for %arg12 = %c0 to %c200 step %c1 {
      %7 = load %1[%arg12, %6] : memref<200x200xi128>
      %8 = load %0[%5, %arg12] : memref<200x200xi128>
      %9 = muli %8, %7 : i128
      %10 = load %2[%5, %6] : memref<200x200xi128>
      %11 = addi %10, %9 : i128
      store %11, %2[%5, %6] : memref<200x200xi128>
    }
    gpu.terminator
  }
  return
}
```

Language, Scheme, Hardware-Independent



Current Work & Results

- GSW (2013) and B/FV (2012) FHE schemes: custom dialects and lowering implemented
  - Custom dialects allow for highly optimized, custom high-level operations such as “HE.identity_minus”, “HE.flatten”, and “BFV.ntt”
- Optimizations across operations, including DAG rewrites: building off my previous work with Walden Yan
- Language- and scheme-specific optimizations, e.g. removing redundant flatten’s and NTT’s

Future Work

- Write dialects and lowering for more FHE schemes such as BFV RNS and CKKS
- Implement “raising” step for all Standard dialect operations - this will allow encryption of any arbitrary program with just one or two compiler flags
- Implement parallelization / multithreading

Conclusion

- The MLIR compiler framework can be used to easily encrypt any program in any compatible programming language by simply passing a flag
- MLIR also provides a powerful framework for language-specific optimizations - we can take advantage of this to speed up FHE
- The entire system is modular, allowing you to swap out the FHE scheme that you use, the set of lowering passes, and/or the architecture that you are targeting

Acknowledgements

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Sources

- Gentry, Sahai, and Waters (2013): https://eprint.iacr.org/2013/340.pdf
- Fan and Vercauten (2012): https://eprint.iacr.org/2012/144.pdf
- Optimizations for B/FV (2016): https://eprint.iacr.org/2016/504.pdf
- MLIR (2020): https://arxiv.org/abs/2002.11054

Questions?