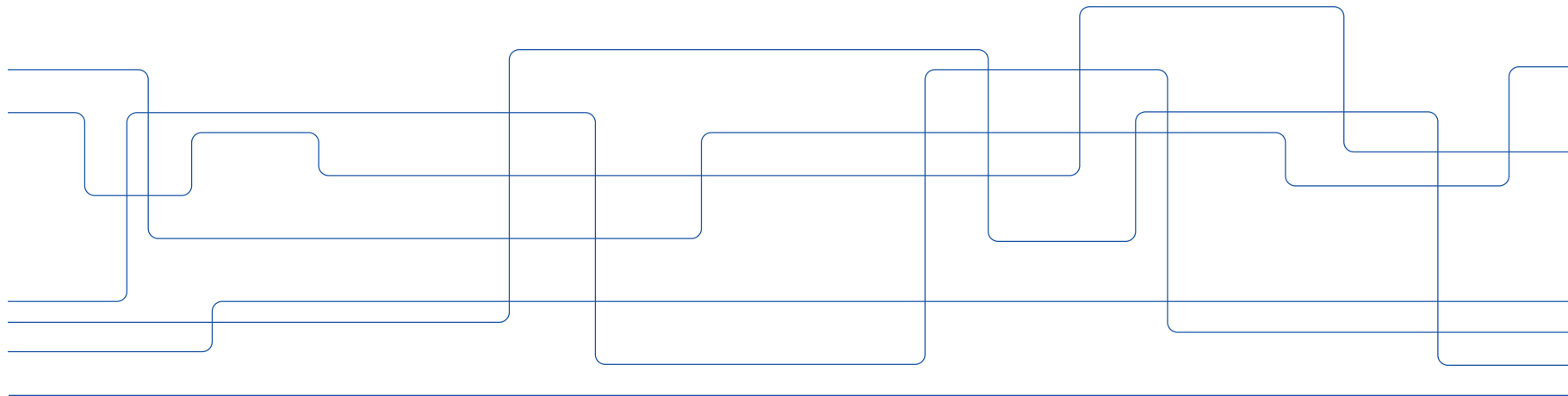




High Performance FFT Code Generation through MLIR Linalg Dialect and Micro-kernel

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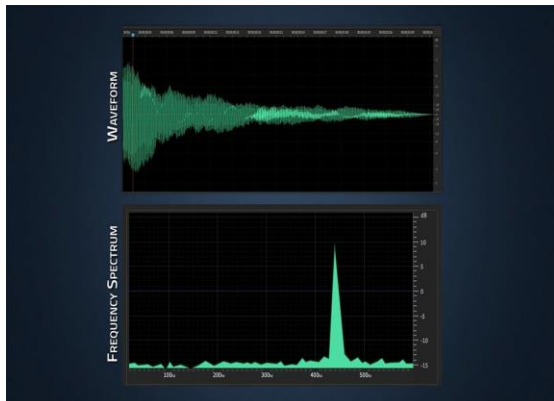
Outline

- Motivation
- Background
- Methodology
- Insights
- Future Work

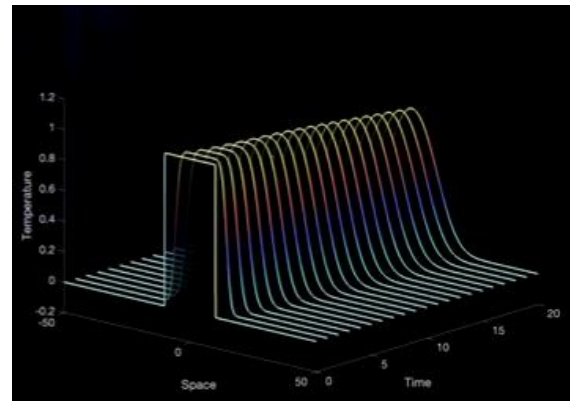
Motivation: Importance of Fast Fourier Transform

- Applications

Signal
processing



Partial
Differential
Equations(PDE)



- Libraries for FFT:

FFTW



heFFTe



CUFFT

Background: FFT Algorithm in Matrix-Formalism

$\mathcal{O}(n^2)$

$$DFT_{N_{m,n}} = (\omega_N)^{mn}, \quad \text{where } \omega_N = \exp(-2\pi i/N) \quad \text{for } 0 \leq m, n < N.$$



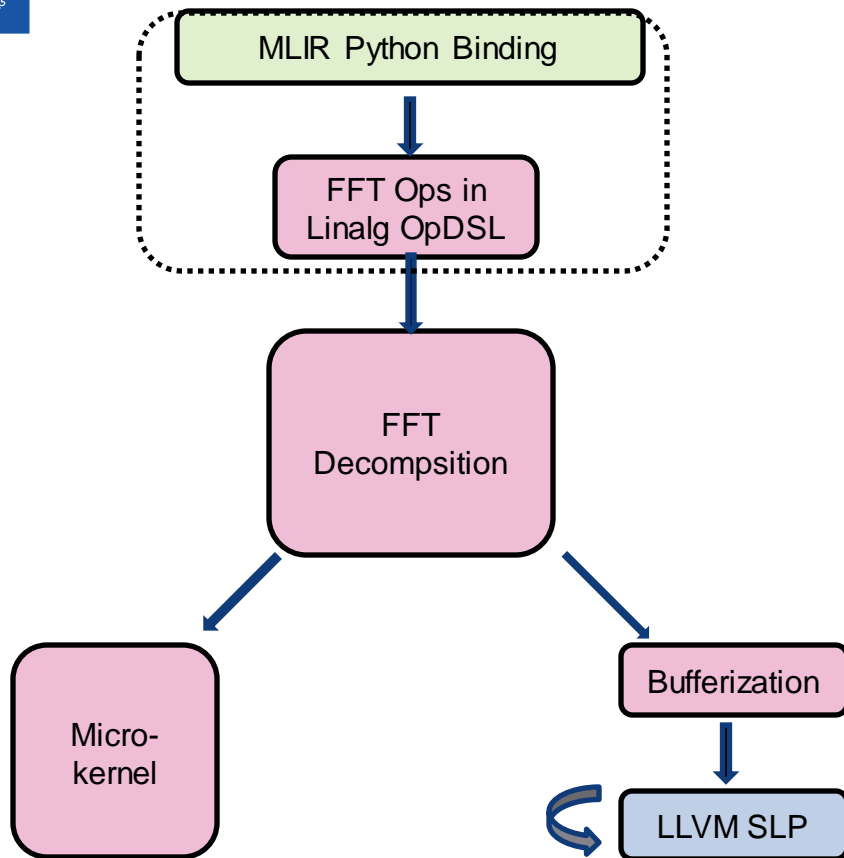
$$DFT_N = (DFT_K \otimes I_M) D_M^N (I_K \otimes DFT_M) \Pi_K^N \quad \text{with } N = MK.$$



$\mathcal{O}(n \log n)$

$$\begin{bmatrix} 1 & 1 & 1 & 1 \\ 1 & -i & -1 & i \\ 1 & -1 & 1 & -1 \\ 1 & i & -1 & -i \end{bmatrix} = \underbrace{\begin{bmatrix} 1 & & & \\ & 1 & & \\ & & -1 & \\ & & & -1 \end{bmatrix}}_{DFT_2 \otimes I_2} \begin{bmatrix} 1 & & & \\ & 1 & & \\ & & 1 & \\ & & & -i \end{bmatrix} \underbrace{\begin{bmatrix} 1 & & & \\ & 1 & & \\ & & 1 & 1 \\ & & 1 & -1 \end{bmatrix}}_{I_2 \otimes DFT_2} \begin{bmatrix} 1 & & & \\ & 1 & & \\ & & 1 & \\ & & & 1 \end{bmatrix}.$$

Implementation: Compilation Pipeline



Complex Arithmetic not supported well in MLIR/LLVM

Python friendly

- Generate MLIR from Python Binding
- Pass manager in Python

JIT:

- Input/output as Python array

AOT:

- Implemented as a C library
- Input/output as C buffer

Implementation Linalg: Utilize Sparsity in FFT Computation

FFTC DSL Pattern	Sparse Fusion	Bufferization
$Y = (A_m \otimes I_n) \cdot X$	FusedMKIV(A, n, X)	for($i = 0$; $i < n$; $i++$) $Y[i : n : i + m * n - n] =$ $A * (X[i : n : i + m * n - n])$
$Y = (I_m \otimes A_n) \cdot X$	FusedIKMV(A, n, X)	for($i = 0$; $i < m$; $i++$) $Y[i * n : 1 : i * n + n - 1] =$ $A * (X[i * n : 1 : i * n + n - 1])$
$(\Pi_m^{mn} \otimes I_k) \cdot X$	FusedPKIV(m, mn, k, X)	for($i = 0$; $i < m$; $i++$) for($j = 0$; $j < n$; $j++$) $Y[k * (i + m * j) : 1 : k * (i + m * j)] =$ $X[k * (n * i + j) : 1 : k * (n * i + j)]$
$D_m^n \cdot X$	Mul(TwiddleCoe, X)	for($i = 0$; $i < m$; $i++$) $Y[i] = D_m^n[i] * X[i]$
$\Pi_m^{mn} \cdot X$	Permute(m, mn, X)	for($i = 0$; $i < m$; $i++$) for($j = 0$; $j < n$; $j++$) $Y[i + m * j : 1 : i + m * j] =$ $A * (X[n * i + j : 1 : n * i + j])$

Source: He, Yifei, Artur Podobas, and Stefano Markidis. "Leveraging MLIR for Loop Vectorization and GPU Porting of FFT Libraries." *arXiv e-prints* (2023): arXiv-2308.

Implementation Linalg: FFT Operations in MLIR Linalg OpDSL

$$Y = (A_m \otimes I_n) \cdot X$$

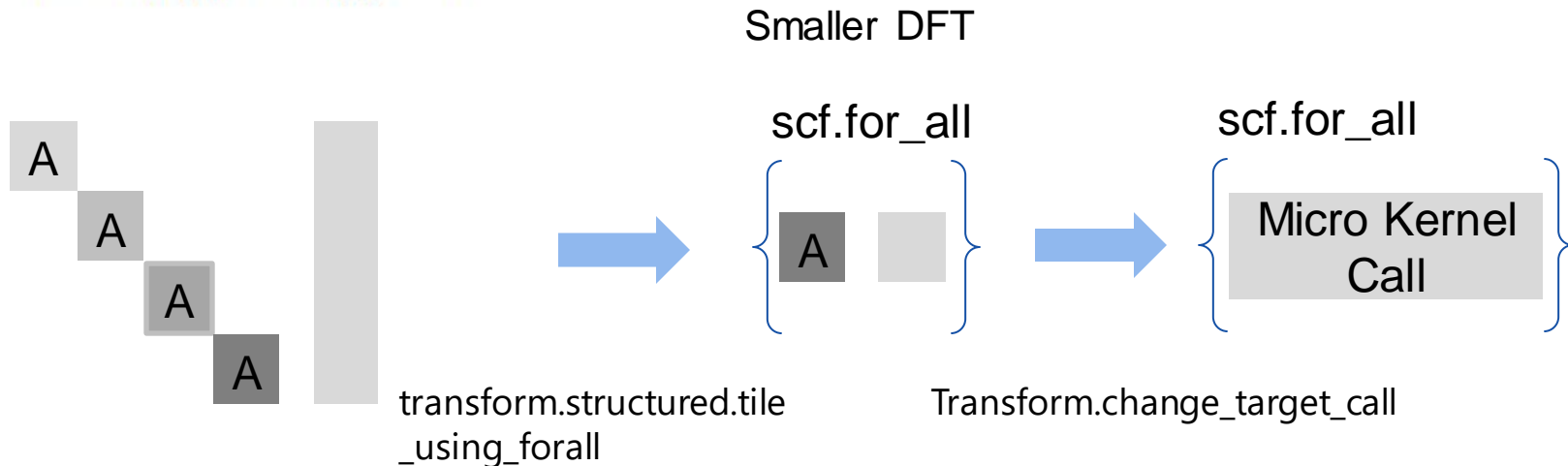
```
@linalg_structured_op
def AKI_x(
    K=TensorDef(T1, S.KN, index_dims=[D.kn]),
    A=TensorDef(T1, S.M, S.N),
    B=TensorDef(T1, S.N * S.KN),
    C=TensorDef(U, S.M * S.KN, output=True),
    strides=IndexAttrDef(S.SM, default=[1]),
    cast=TypeFnAttrDef(default=TypeFn.cast_signed),
):
    domain(D.kn, D.m, D.n)
    C[D.kn + D.m * S.SM] += cast(U, A[D.m, D.n]) *
    | cast(U, B[D.kn + D.n * S.SM])
```

FFT patterns not supported well in OpDSL:

- Work around: Redundant tensor to specify iteration domain dimension

Implementation Linalg: Map to micro-kernel with transform dialect

$$Y = (I_m \otimes A_n) \cdot X$$

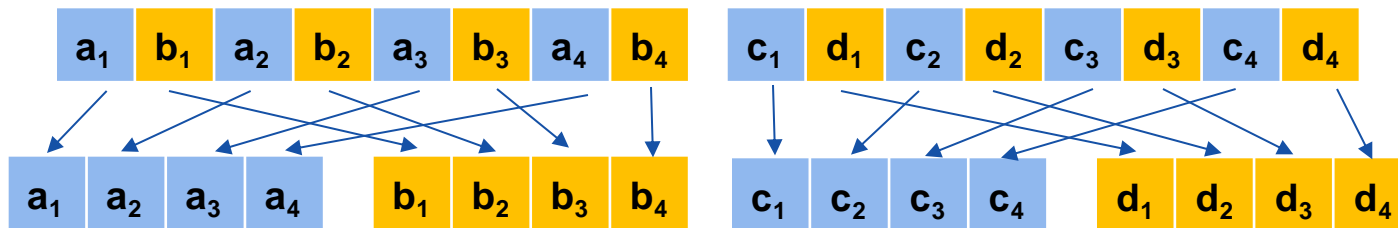


Implementation Micro-kernel: Data layout

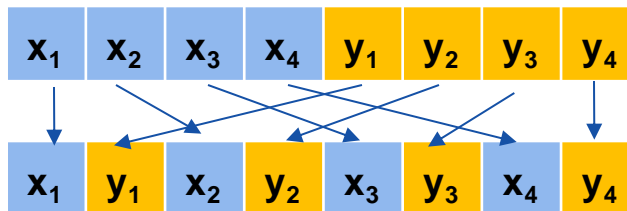
SIMD friendly Data Layout for Complex Arithmetic

$$(a+bi) * (c+ di) = ac-bd + (ad+bc)i$$

Interleaved



$$(a+bi) * (c+ di) = ac-bd + (ad+bc)i$$



Source: Popovici, Doru T., Franz Franchetti, and Tze Meng Low. "Mixed data layout kernels for vectorized complex arithmetic." *2017 IEEE High Performance Extreme Computing Conference (HPEC)*. IEEE, 2017.

Implementation Micro-kernel: Data layout

SIMD friendly Data Layout for Complex Arithmetic

$$(a+bi) * (c+ di) = ac-bd + (ad+bc)i$$

Block-interleaved



$$(a+bi) * (c+ di) = ac-bd + (ad+bc)i$$



Source: Popovici, Doru T., Franz Franchetti, and Tze Meng Low. "Mixed data layout kernels for vectorized complex arithmetic." *2017 IEEE High Performance Extreme Computing Conference (HPEC)*. IEEE, 2017.

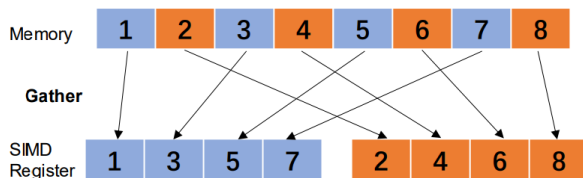


Implementation Micro-kernel: Other optimizations

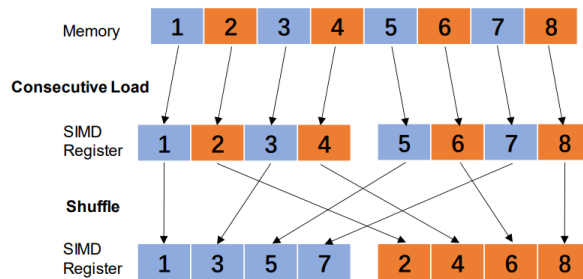
- Memory access optimization for strided permute
 - Multiple iterations of in-register shuffle to implement blocked & strided memory access pattern
 - 10x speed up compared with gather/scatter
- Loop unroll to enable vectorization for small loop trip count
 - Require extra shuffle, can not be done by auto-vectorizer
- Software prefetching
- Pre-computed constants
 - DFT matrix, Twiddle factor

Implementation Code Generation: Auto Vectorization on Complex Array with LLVM SLP Vectorizer

Interleaved memory access optimization for complex array



(a) Directly Load Complex Data Using Gather Instructions



(b) Optimized Interleaved Memory Access

Source: He, Yifei, Artur Podobas, and Stefano Markidis. "Leveraging MLIR for Loop Vectorization and GPU Porting of FFT Libraries." *arXiv e-prints* (2023): arXiv:2308.



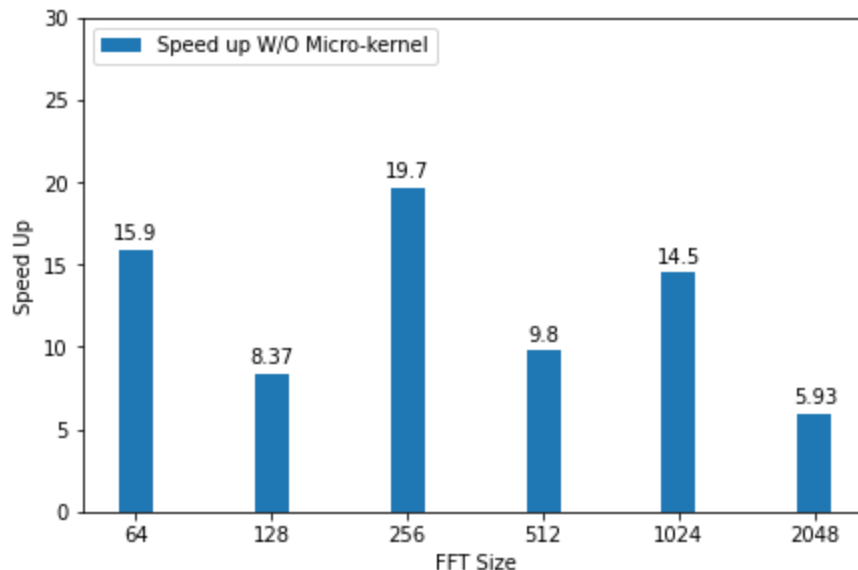
Our Contribution:

- **FFT Representation & Transformation in MLIR Python binding and OpDSL**
 - FFT-specific ops in Linalg
 - FFT decomposition to smaller size
 - > Cache friendly
 - > Reduce computation complexity
 - > Change inner most kernel to micro-kernel call
- **Optimize complex arithmetic in micro-kernel:**
 - Complex values not supported well in MLIR/LLVM
 - Complex arithmetic specific optimization not available in general purpose auto-vectorizer
 - > SIMD friendly data layout
 - > Memory access optimization

Future Work

- Overhead in buffer allocation & function call between MLIR&C
- Constant propagation
- Currently C++ intrinsics, better register allocation & instruction scheduling with assembly
- Enable complex value vectorization in MLIR
- Enable complex value vectorization in MLIR

Initial results (In progress)





Thanks!

Q&A