Dense Dynamic Blocks: Optimizing SpMM for Processors with Vector and Matrix Units Using Machine Learning Techniques

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Multiplying Matrices

IBM POWER10 Matrix-Multiply Assist instructions (MMA)

- Successfully utilized for dense matrix multiply operations in ML domain
- Functional unit rich processors

Sparse Matrix Dense Matrix Multiply

- Building block for many complex applications
  - Linear solvers, graph neural networks, recommender systems
- Many of these applications are iterative
  - SpMM consumes many execution cycles
- Irregular, unpredictable sparsity structure
  - Hard to utilize matrix-multiply capabilities

Our Approach

Our target: Functional unit rich processors with vector and matrix units

Dense Dynamic Blocks (DDB)

- Utilizes matrix and vector units synergistically to maximize floating-point throughput

A performance prediction tool (SpMM-OPT) capable of selecting

- Functional unit strategy
- Register reuse and cache optimization strategies

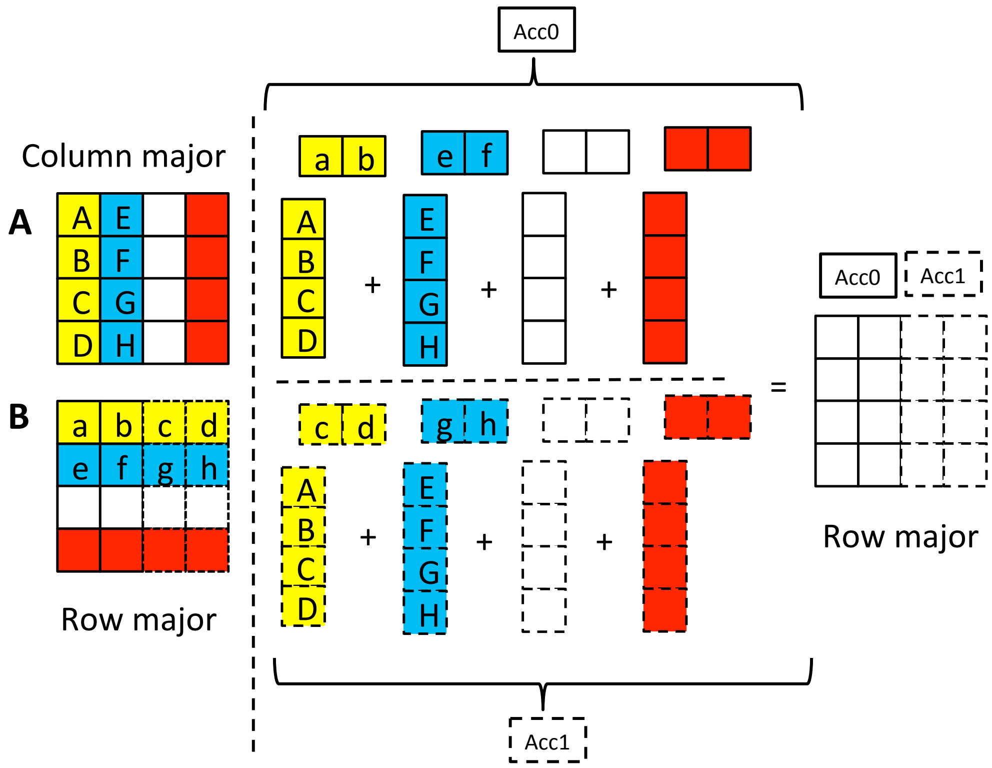
In This Talk

- **POWER10 Matrix Multiply Facilities (MMA)**
- **Dense Dynamic Blocks to utilize POWER10 MMA units**
- **SpMM-Optimizer for selecting SpMM strategy**
- **Conclusions**

POWER10 Matrix Multiply Assist (MMA)

Provides double (single) precision
- 4 × 2 (4 × 4) outer product operations
- Eight 4 × 2 (4 × 4) accumulators

Operation of MMA:
- Execute a sequence of outer product instructions



Blocking the Sparse Matrix for SpMM

Previously blocking the sparse matrix

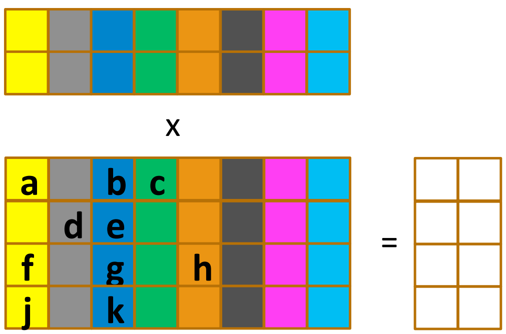
- $r \times c$ blocks to improve the irregular accesses → Hard to obtain
- Introduces zero padding, underutilizes matrix-multiply units

Our proposal for POWER10: Dense Dynamic Blocks (DDB)

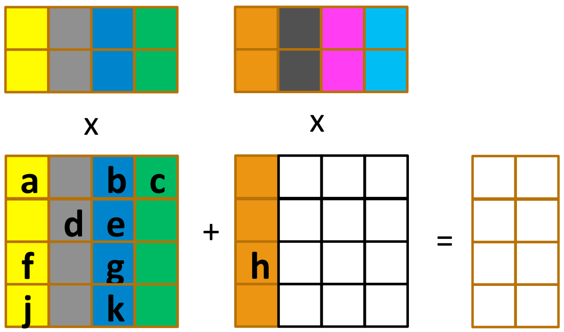
- Form dynamic blocks from $r \times 1$ blocks
- Utilizes matrix and vector units synergistically to maximize floating-point throughput

Using 4x4 Blocks

- Creating 4 × 4 blocks
- 128 FLOPs executed (only 40 FLOPs are necessary)

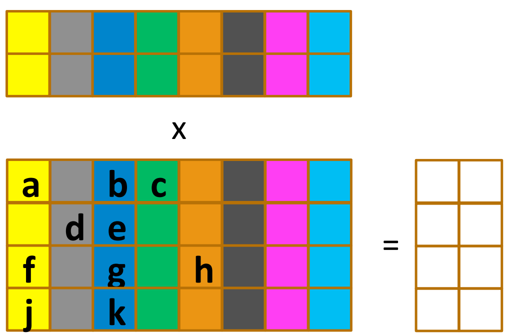


Example 4x8 Sparse Matrix

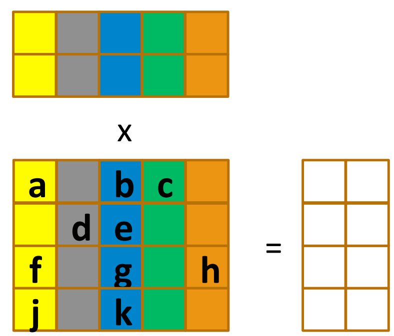


Dense Dynamic Blocks (DDB-MM)

- DDB-Matrix Multiply (DDB-MM): Ignore c and create 4 × 1 blocks
- 80 FLOPs executed (only 40 FLOPs are necessary) → 38% reduction



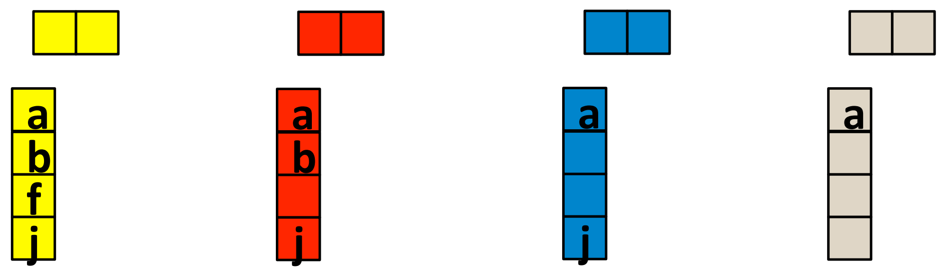
Example Sparse Matrix



Not All Blocks Are Equal

MMA Throughput

- Double precision 32 Flops/cycle



Effective FP Throughput with MMA | 32 Flops/cycle | 24 Flops/cycle | 16 Flops/cycle | 8 Flops/cycle

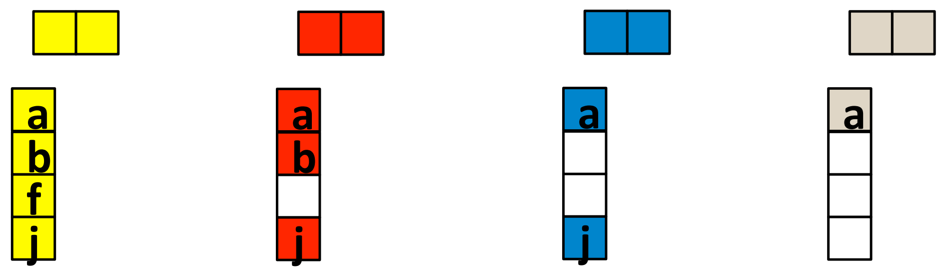
Not All Blocks Are Equal

MMA Throughput

- Double precision 32 Flops/cycle

VSX Throughput

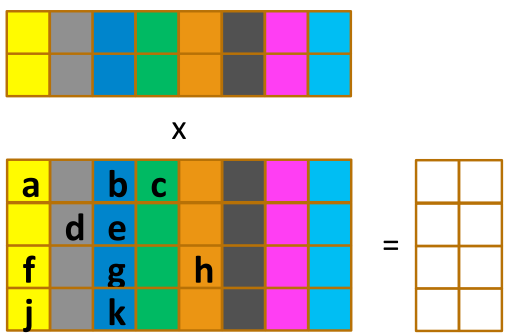
- Double precision 16 Flops/cycle



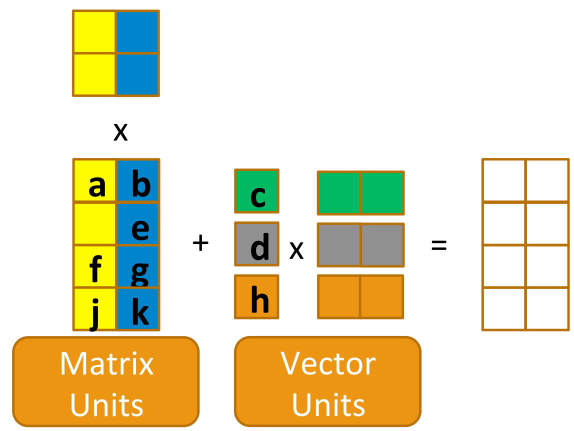
Effective FP Throughput with MMA	32 Flops/cycle	24 Flops/cycle	16 Flops/cycle	8 Flops/cycle
Effective FP Throughput with VSX	16 Flops/cycle	16 Flops/cycle	16 Flops/cycle	16 Flops/cycle

Dense Dynamic Blocks (DDB-HYB)

- DDB-Hybrid(DDB-HYB): Utilize both matrix and vector units
- 44 FLOPs executed, only 40 FLOPs are necessary



Example Sparse Matrix



Performance of DDB for SpMM

Tested on IBM POWER10 with 30 SMT4 cores

440 matrices from SuiteSparse

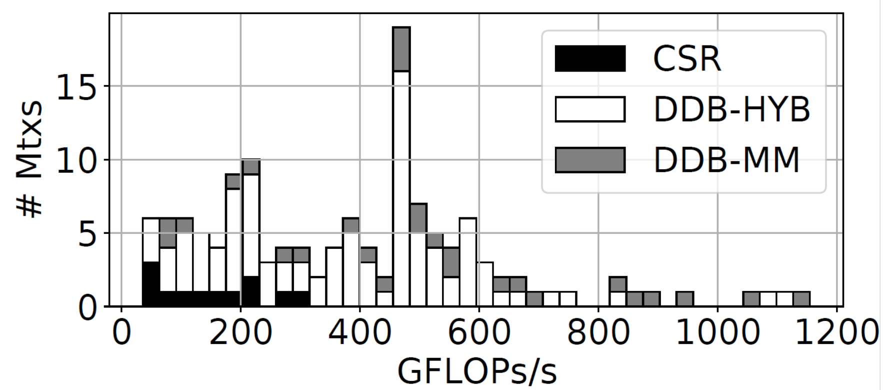
Maximum FLOPs/s

- 1.15 TFLOPs/s for double-precision (DP)
- 2.5 TFLOPs/s for single-precision (SP)

DDB-HYB fastest for 247 of the matrices for DP

DDB-MM fastest for 211 of the matrices for SP

FP throughput distribution with method breakdown (Double Precision)



Other SpMM Optimizations

$C = A \times B \rightarrow A$ (sparse), B and C (dense)

Improving reuse for A or C

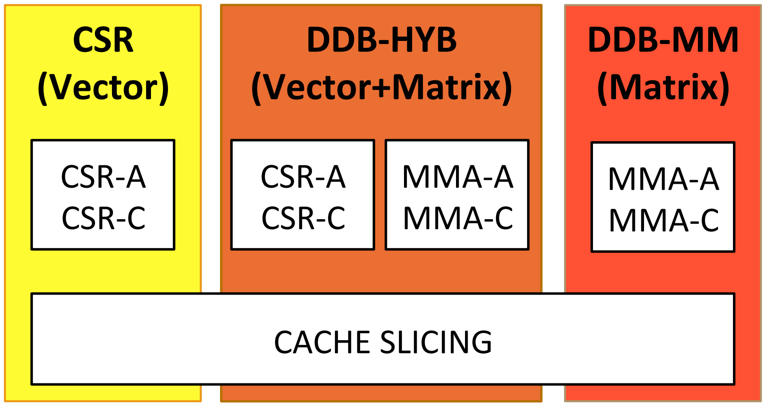
- For compressed portion: CSR-A and CSR-C
- For blocked portion: MMA-A and MMA-C

Cache slicing

- Execute $C = A \times B$ in multiple phases
- 64 columns C and B can be sliced into 16 columns slices

SpMM Optimizations Search Space

1) Choosing vector or matrix units
   - FU St: The functional unit strategy
     - {CSR, DDB-HYB, DDB-MM}
2) Improving reuse for A or C
   - Reuse approach for the blocked portion
     - {MMA-A, MMA-C}
   - Reuse strategy for the compressed portion
     - {CSR-A, CSR-C}
3) Cache slicing
   - The slicing factor
     - {16, 32, 64, 128, 256}



SpMM-Optimizer

SpMM-Optimizer: An ML-based approach to select best SpMM strategy

- *Functional unit, reuse, slicing* strategies for a sparse matrix
- **Detecting Sparse Matrices with High and Low Potential for MMA utilization**
  - Average floating-point throughput (AFT) metric
- **Features to summarize matrix characteristics**
  - Size, locality, and blocking characteristics
- **Machine learning models**
  - Separate models for High and Low Potential matrices with different # cols in dense matrices
  - 10 different models : {High Potential , Low Potential} × {16, 32, 64, 128, 256}
  - Each model uses Support Vector Machines with the linear kernel

Average Floating-Point Throughput (AFT)

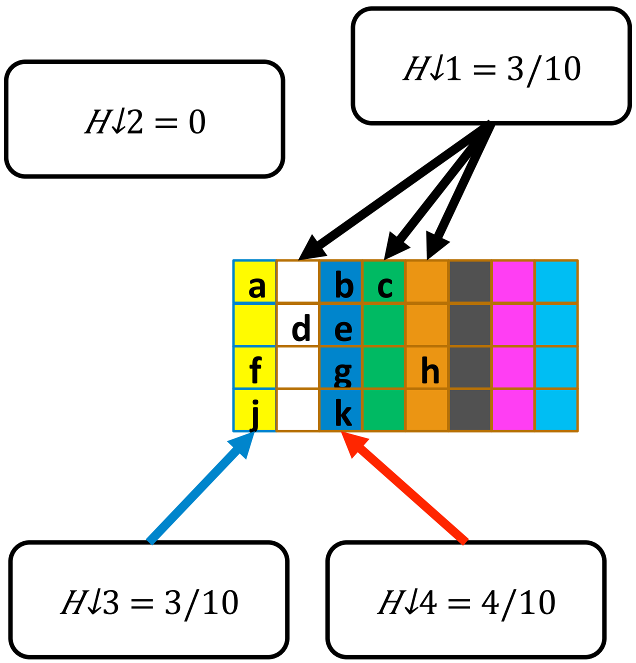
Calculate the potential to utilize MMA for a given sparse matrix

What would be the average FLOP throughput for the matrix?

Breakdown matrices into **High Potential** and **Low Potential** groups

- Experimentally selected threshold 20

AFT Example



AFT: Estimate the throughput per nnz

- H_i : Fraction of nonzeros in a block with i nonzeros
- T_i : Effective throughput for i element block
  - $T_4 = 32,\ T_3 = 24,\ T_2 = 16,\ T_1 = 16$ FLOPS/cycle
  - Blocks with 1 nnz assumed → On Vector Units

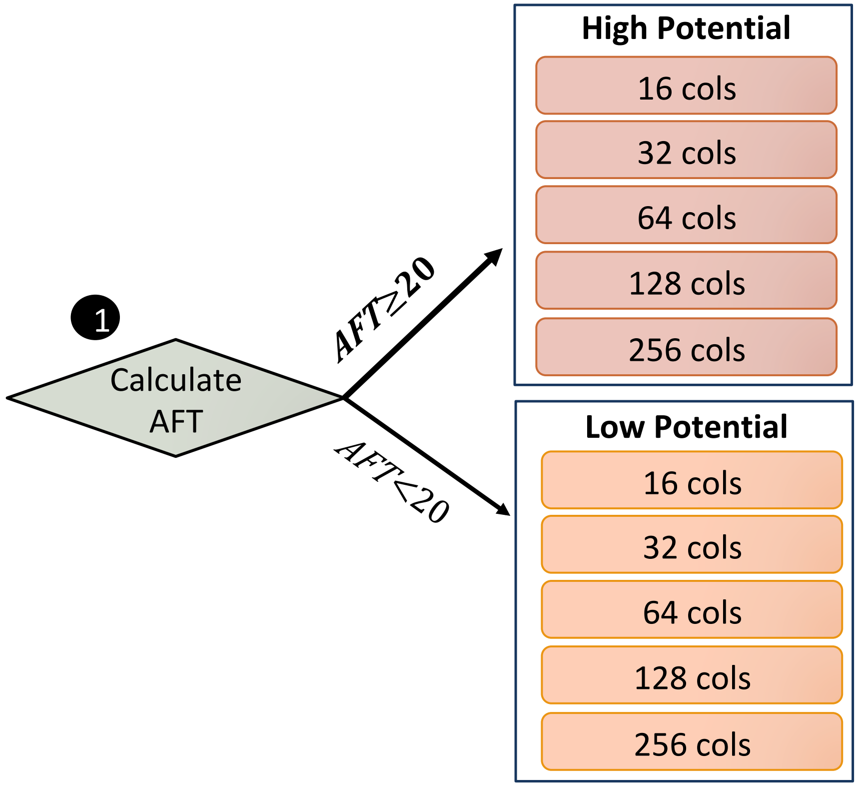
$$AFT = \sum_i (T_i \times H_i)$$

Example Matrix: $AFT = 24.8$ → High Potential

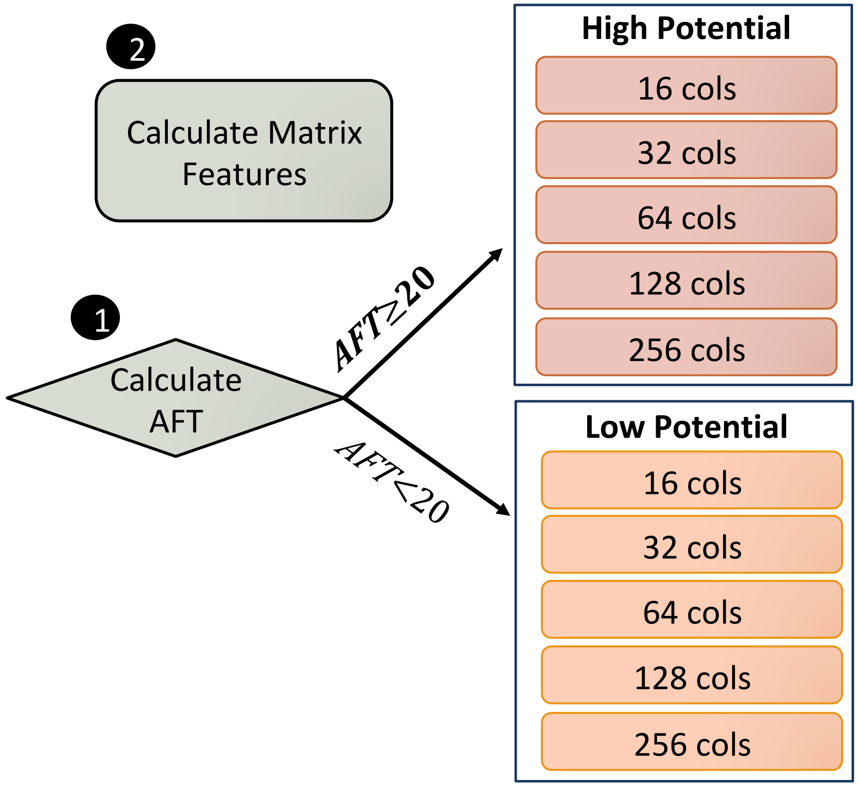
ML System Features

- **Size Characteristics**
  - # rows, # nonzeros: Encode the size characteristics of the matrix
- **Blocking Characteristics**
  - Distribution of nonzeros to 4x1 dense blocks
- **Locality Characteristics**
  - Memory access characteristics of 4x1 blocks created
  - Memory access characteristics for a chunk of the sparse matrix assigned to a thread

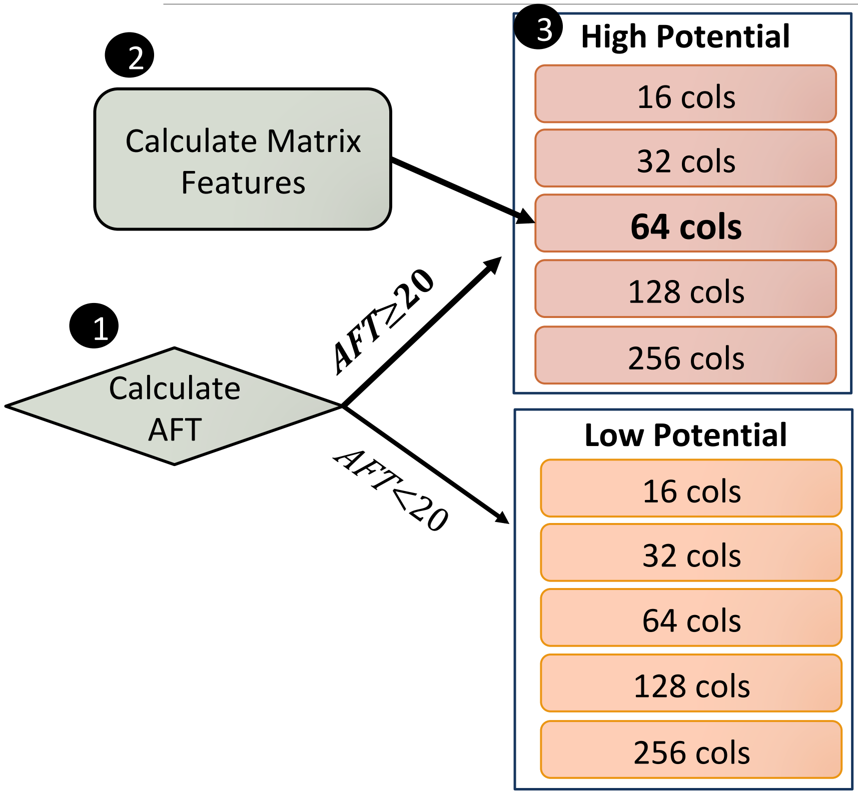
Putting it All Together



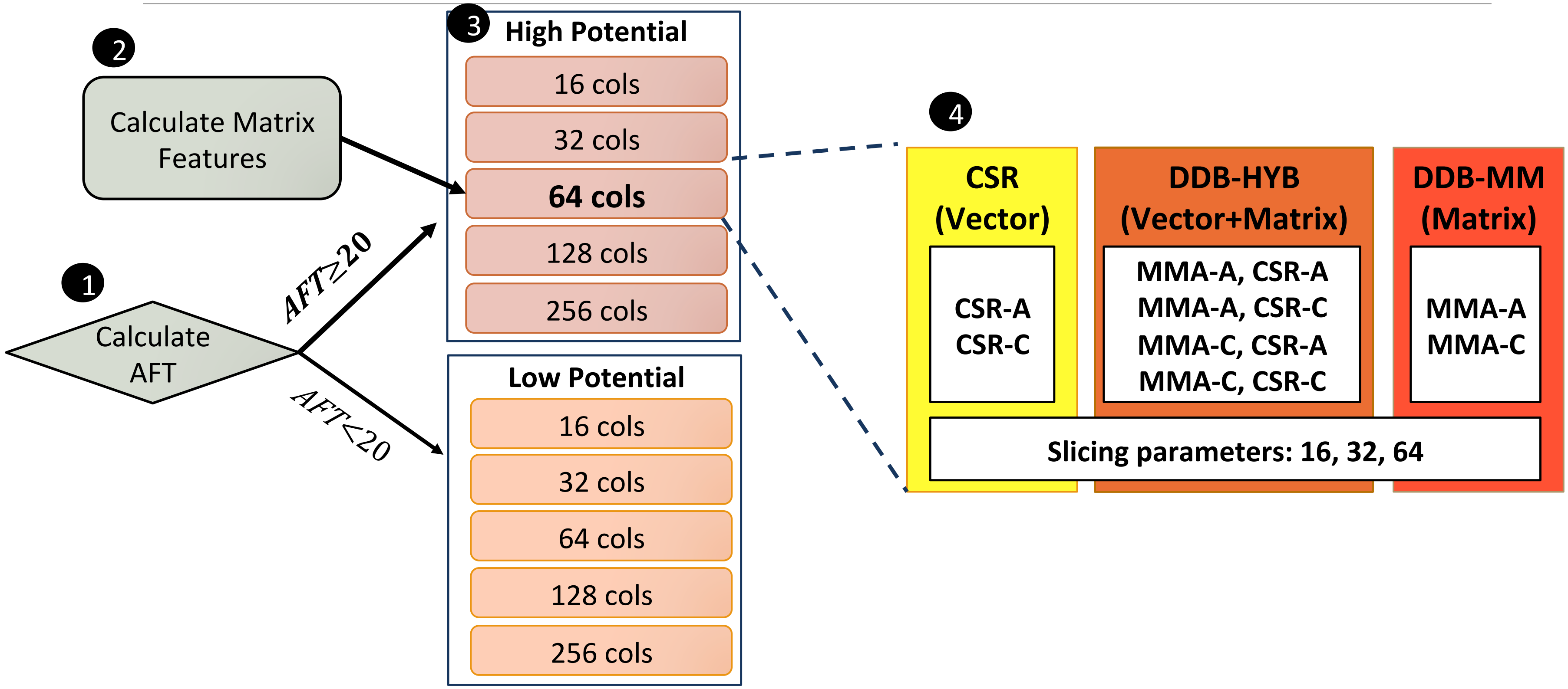
Putting it All Together



Putting it All Together



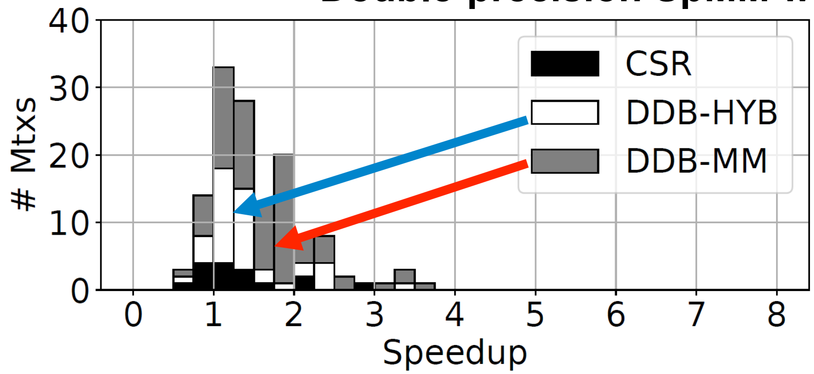
Putting it All Together



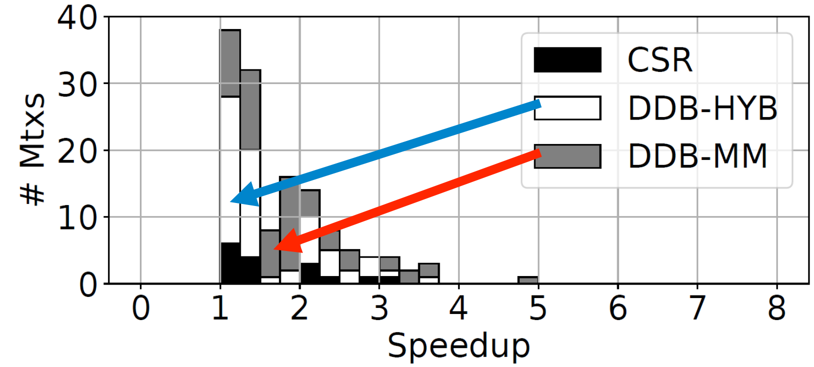
SpMM-OPT for High Potential Matrices

- ***Oracle*** and ***SpMM-OPT*** select: *Functional unit, reuse, slicing* strategies for a sparse matrix
- ***SpMM-OPT*** can achieve 1.55× average speedup
- ***oracle*** delivers 1.76× average speedup
- ***DDB-HYB*** and ***DDB-MM*** generally achieve the highest performance

Distribution of speedup for oracle method and SpMM-OPT
Double-precision SpMM with 64 columns dense matrices



SpMM-Optimizer

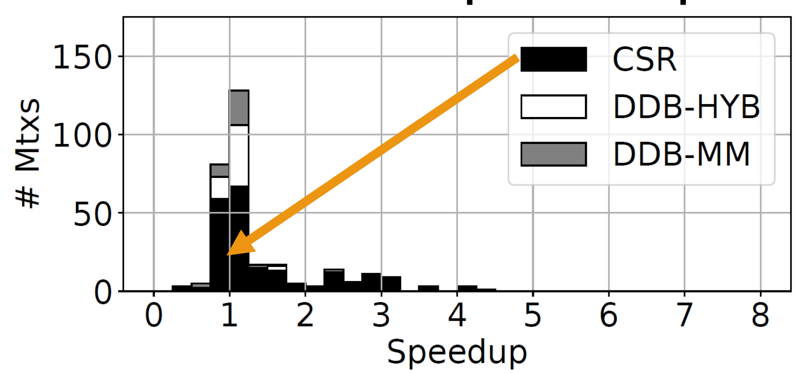


Oracle

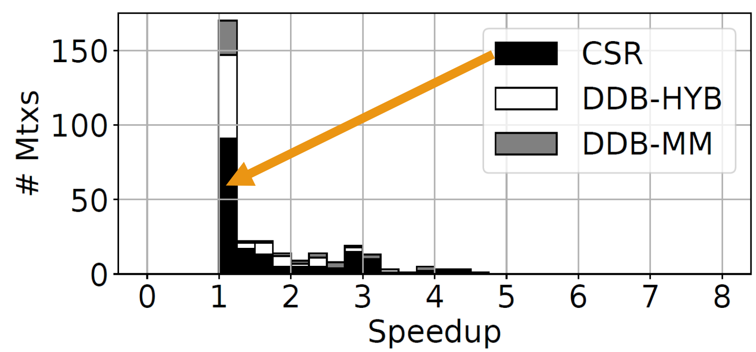
SpMM-OPT for Low Potential Matrices

- ***Oracle*** and ***SpMM-OPT*** select: *Functional unit, reuse, slicing* strategies for a sparse matrix
- ***SpMM-OPT*** can achieve 1.3× average speedup
- ***oracle*** delivers a 1.64× average speedup
- ***Slicing*** is the key to achieve high speedups for Low Potential matrices

Distribution of speedup for oracle method and SpMM-OPT
Double-precision SpMM with 64 columns dense matrices



SpMM-Optimizer



Oracle

More details in the paper

Detailed descriptions of register reuse and cache slicing optimizations

Detailed description of DDB and SpMM-Optimizer

Experiments with 16-256 columns dense matrices

Discussion on effect of slicing

Conclusions

- Optimizing SpMM on processors with vector and matrix units
- Dense Dynamic Blocks
  - A hybrid approach to utilize vector and matrix units for SpMM
  - Observed up to 1.1 TFLOPS/s for DP, 2.5 TFLOPS/s for SP SpMM
- SpMM-Optimizer
  - An ML method to navigate the optimization search space for SpMM
  - An average speedup of up to 2x compared to an optimized CSR baseline

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