ACES: Accelerating Sparse Matrix Multiplication with Adaptive Execution Flow and Concurrency-Aware Cache Optimizations

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SpMM and Sparse Patterns

SpMM is widely used in machine learning and computation fields

- Applications include sparse/compressed deep neural networks, sparse linear algebra, and tensor algebra…
- There is an increasing demand for higher performance and efficiency in SpMM

Sparse Matrices have various sparse patterns

- Various matrix sizes, densities, and distribution of non-zeros
- Significant challenges for conventional cache-based computing architectures

Matrices from SuiteSparse matrix collection

ACES - Motivation

Three common limitations faced by SpMM accelerators:

Tradition: Fixed Execution Flow

- The efficiency of each execution flow is determined by sparse patterns.
- There is inconsistent performance across different sparse matrices

An Adaptive Execution Flow is Needed

ACES - Motivation

Three common limitations faced by SpMM accelerators:

Tradition: Overlook the Importance of Concurrency

- Only focuses on reducing the number of cache misses
- SpMM operations often lead to concurrent cache line demands
- Even a single cache miss can stall the processing chain

Handle the Concurrent Access Demands of SpMM

Tradition: On-Chip Cache does not Incorporate Non-Blocking Features

A single cache miss causes delays in subsequent accesses

Non-Blocking Cache Design in Accelerator

ACES - Adaptive Execution Flow

Condensing degree impacts the execution flow of SpMM

ACES - Adaptive Execution Flow

w/o Condensing Aggressive Condensing Moderate Condensing

Condensing degree impacts the execution flow of SpMM

- Consider four processing elements, each performing scalar-vector multiplication
- Each element (scalar) is taken from Matrix A and is multiplied with the corresponding row (vector) of Matrix B

Detect Sparse Patterns + Select Condensing Degrees

• **Detect Sparse Patterns**

- Indicate sparse pattern changes by row length variations (SPADA [ASPLOS'23])
- Adjacent rows with similar distributions of non-zero elements tend to have a stable row length (number of non-zero elements)
- Partition rows into bands based on changes in row length
- Several bands: rows in the same band have a similar sparse pattern

Detect Sparse Patterns + Select Condensing Degrees

• **Select Condensing Degrees**

- For a large band:
	- Determine the optimal condensing degree via a sampling phase
	- Conduct three sample passes, one for each condensing degree
	- Choose the best condensing degree for the remaining rows in the band
- For a small band:
	- Apply a moderate condensing degree directly

ACES - Concurrency-Aware Cache Replacement (PureFiber)

Locality-Awareness:

- Once the condensation is determined, the demand order of the rows in Matrix B is also determined
- Use the **Next Request Distance (RD)** to capture the **reuse** distance of the rows

Concurrency-Awareness:

- A single miss still stalls the scalar-vector multiplication process
- Use **Fiber Density (FD)** to capture the number of cache lines in the corresponding row

• FD is an indicator of **potential concurrent accesses**

ACES - Concurrency-Aware Cache Replacement (PureFiber)

PureFiber Cache Replacement Policy

- **Pure Fiber** allows all cache lines of a row to be accessed concurrently without any cache misses
- Aim to achieve a high number of **Pure Fibers**
- Select the cache line with the **highest combined sum of RD and FD** for eviction
- Consider both **data locality and concurrency**

ACES - Non-Blocking (NB) Buffer

- Manage concurrent cache miss accesses
- When the global cache has a miss, instead of stalling like a blocking cache, it stores the miss information in the NB buffer
- The NB buffer initiates a fetch for the missing data from the main memory
- **The NB buffer handles multiple outstanding data requests concurrently, allowing the cache to issue new memory requests even when previous ones are still being serviced**

Methodology

Benchmark

Configuration

SuiteSparse

Baselines

- SIGMA [HPCA'20]: Inner-product
- SpArch [HPCA'20]: Outer-product
- SPADA [ASPLOS'22]: Adaptive

Overhead

- Area: 3.5 mm^2
- Power: 2.8 W

ACES - Performance

Comparison among SIGMA, SpArch, SPADA, and ACES

- **ACES** consistently provides **optimal** performance across **all** workloads
- **25.5×** over SIGMA, **8.9×** over SpArch, and **2.1×** over SPADA

ACES vs. ACES-LRU

ACES-LRU:

- Operates with the same workflow as ACES
- Employs an LRU (Least Recently Used) cache replacement policy **ACES** shows a **15.9%** improvement over **ACES-LRU**

ACES vs. ACES w/o NB buffer

ACES w/o NB buffer:

- Operates with the same workflow as ACES
- Does not integrate with the NB buffer
- **ACES** shows a **35.8%** improvement over **ACES w/o NB buffer**

ACES - Summary

ACES features an **adaptive execution flow** that dynamically adjusts to diverse sparse patterns

ACES incorporates **locality-concurrency co-optimizations** within the global cache

ACES integrates a **non-blocking buffer** with the global cache to enhance concurrency

ACES **outperforms** state-of-the-art SpMM accelerators

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