TerseCades: Efficient Data Compression in Stream Processing

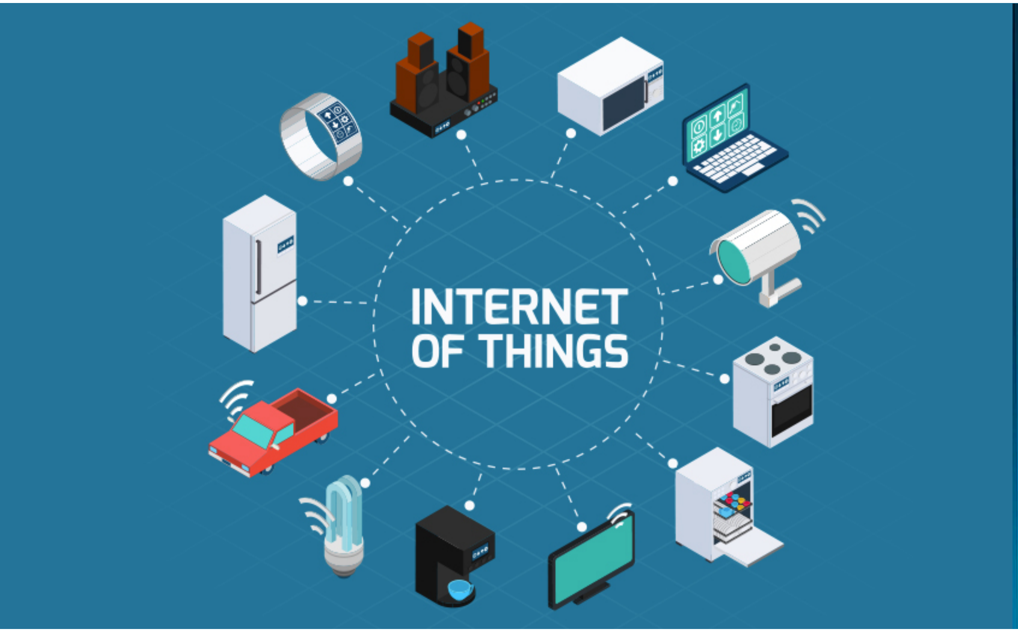
Gennady Pekhimenko

Chuanxiong Guo, Myeongjae Jeon, Peng Huang, Lidong Zhou

Microsoft Research

UNIVERSITY OF TORONTO

JOHNS HOPKINS WHITING SCHOOL of ENGINEERING




IoT **Clouds** **Big Data**

Huge volumes of streaming data with real-time processing requirements

Enormous pressure on the capacity and bandwidth of servers' main memory

Is Data Compression Useful for Streaming?

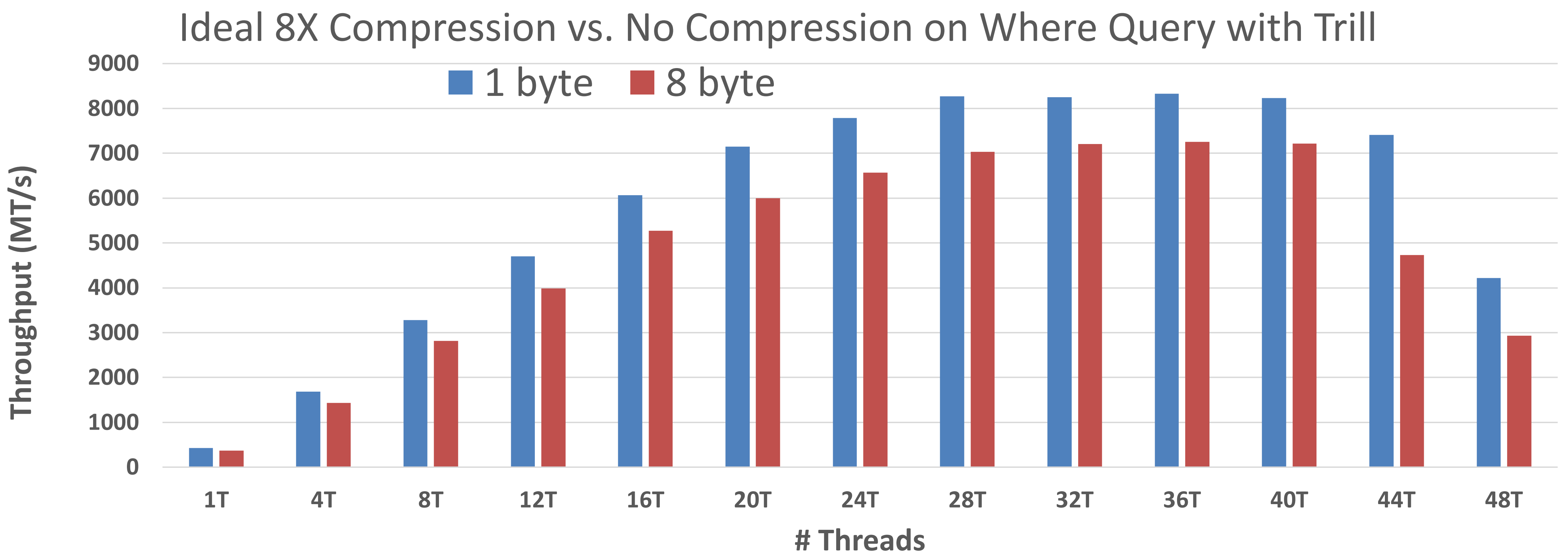
- Intuitively, streaming with simple operators should be **bandwidth-bottlenecked**: either network or memory bandwidth

- Simple single node experiment with the state-of-the-art streaming engine, **Trill**, with the ***Where*** query over large one column 8-byte field:

```
E.g., Where (e => e.errorCode != 0)
```

- Expectation: observe **memory bandwidth** as a major bottleneck

Compressibility ≠> Performance Gain



Only 10%-15% performance improvement with 8X compression

What Went Wrong?

- Memory allocation overhead:

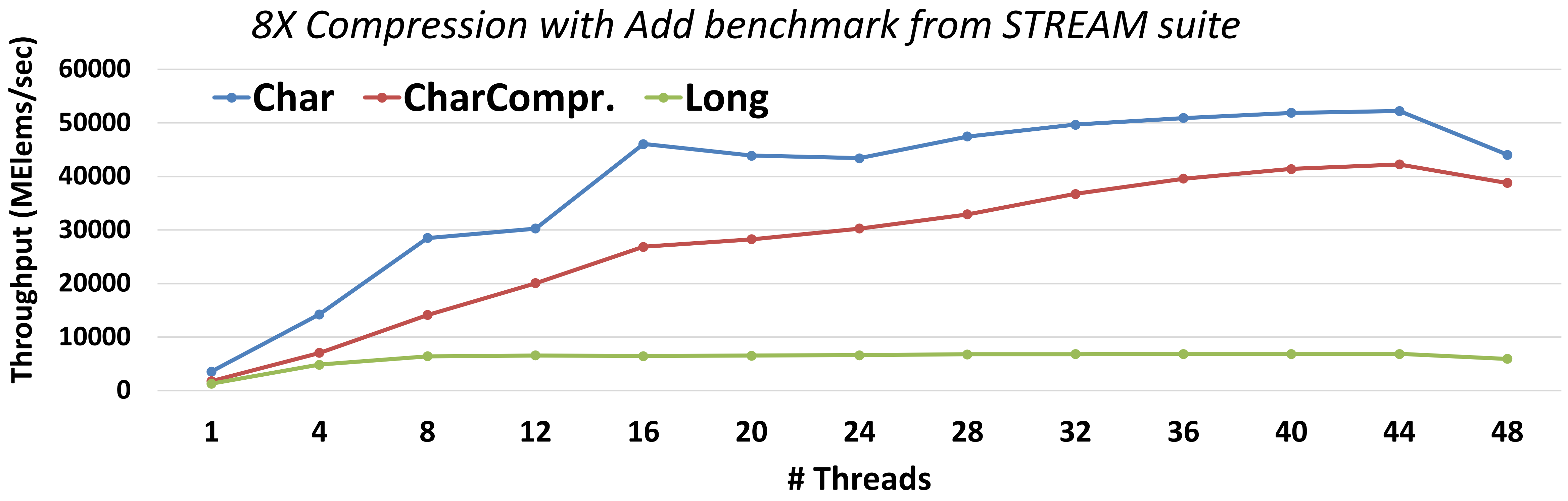
  just-in-time copy of payloads to create a streameable event

- Memory copying and reallocation:

  enables flexible column-oriented data batches

- Inefficient bit-wise manipulation
- Hash tables manipulations

Compressibility => Performance Gain



Up to 6.1X speedup with realistic compression algorithm: Base-Delta Encoding

If no artificial bottlenecks: performance improvement is close to compression ratio (7.6X speedup with 8X compression)

Prerequisites for Efficient Data Streaming

✓ ***Fixed Memory Allocation***

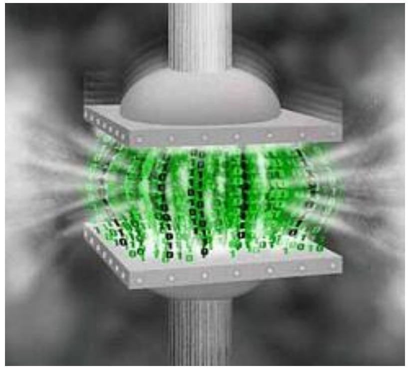
✓ ***Efficient HashMap Primitives***

✓ ***Efficient Filtering Operations (bit-wise manipulations)***

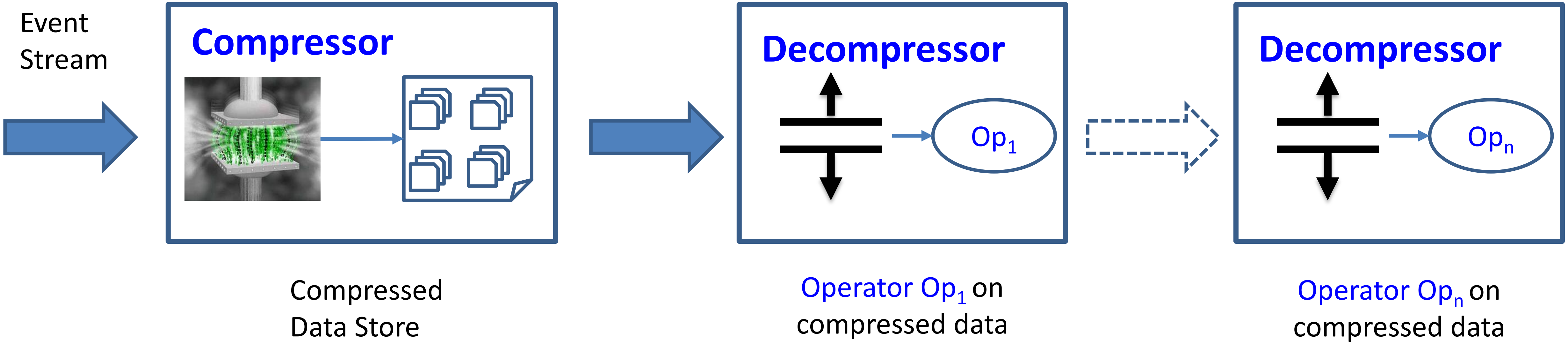
Key Observations

- **Memory bandwidth** becomes the ***major bottleneck*** if streaming is properly optimized

- Dominant part of the data is ***synthetic*** in nature and hence has a lot of **redundancy**
  - Can be exploited through efficient **data compression**



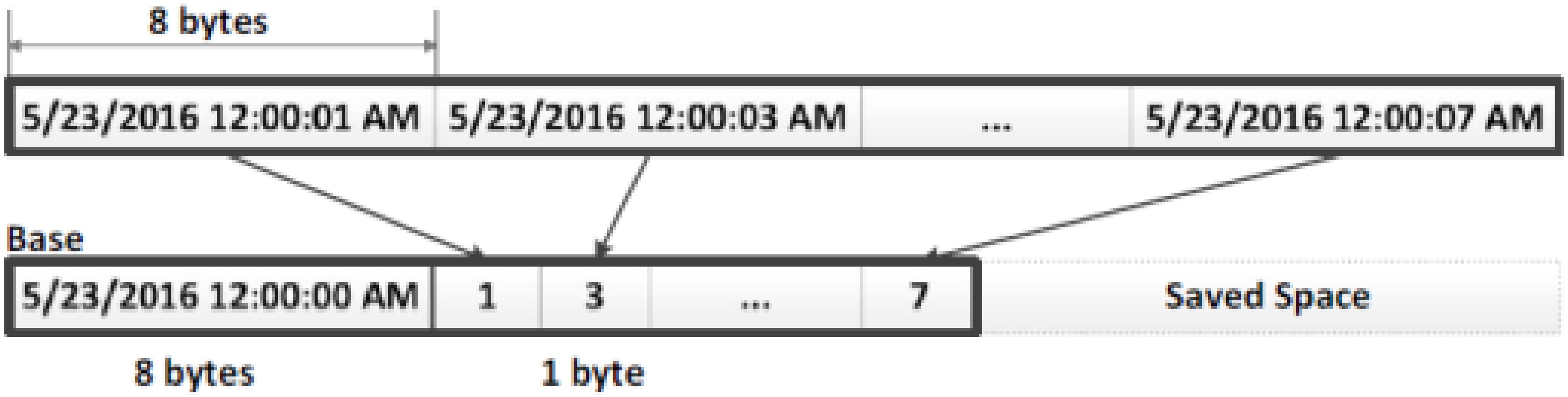
TerseCades: Baseline System Overview



Key Design Choices and Optimizations

- ✓ ***Lossless Compression***
  - ✓ ***Arithmetic vs. Dictionary-based Compression***
  - ✓ ***Decompression is on the critical path***
- ✓ ***Lossy Compression without Output Quality Loss***
  - ✓ ***Integers and floating points***
- ✓ ***Reducing Compression/Decompression Cost***
  - ✓ ***Hardware-based acceleration: vectorization, GPU, FPGA***
- ✓ ***Direct Execution on Compressed Data***

Lossless Compression: Base-Delta Encoding



✓ **Fast Decompression:** vector addition

✓ **Simple SW/HW Implementations:** arithmetic and comparison

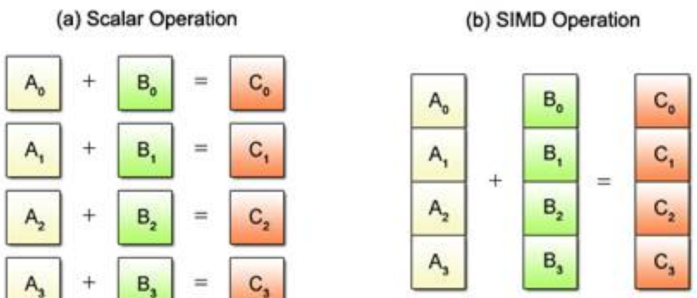
✓ **Effective:** good compression ratio

Lossy Compression Without Output Quality Loss

- Base-Delta Encoding modification
  - Truncate deltas when full precision not required

- ZFP floating point compression engine
  - Equivalent of BD in floating point domain with controlled precision

Reducing Compression Overhead



SIMD/Vectorization

Intel Xeon with 256-bit SIMD

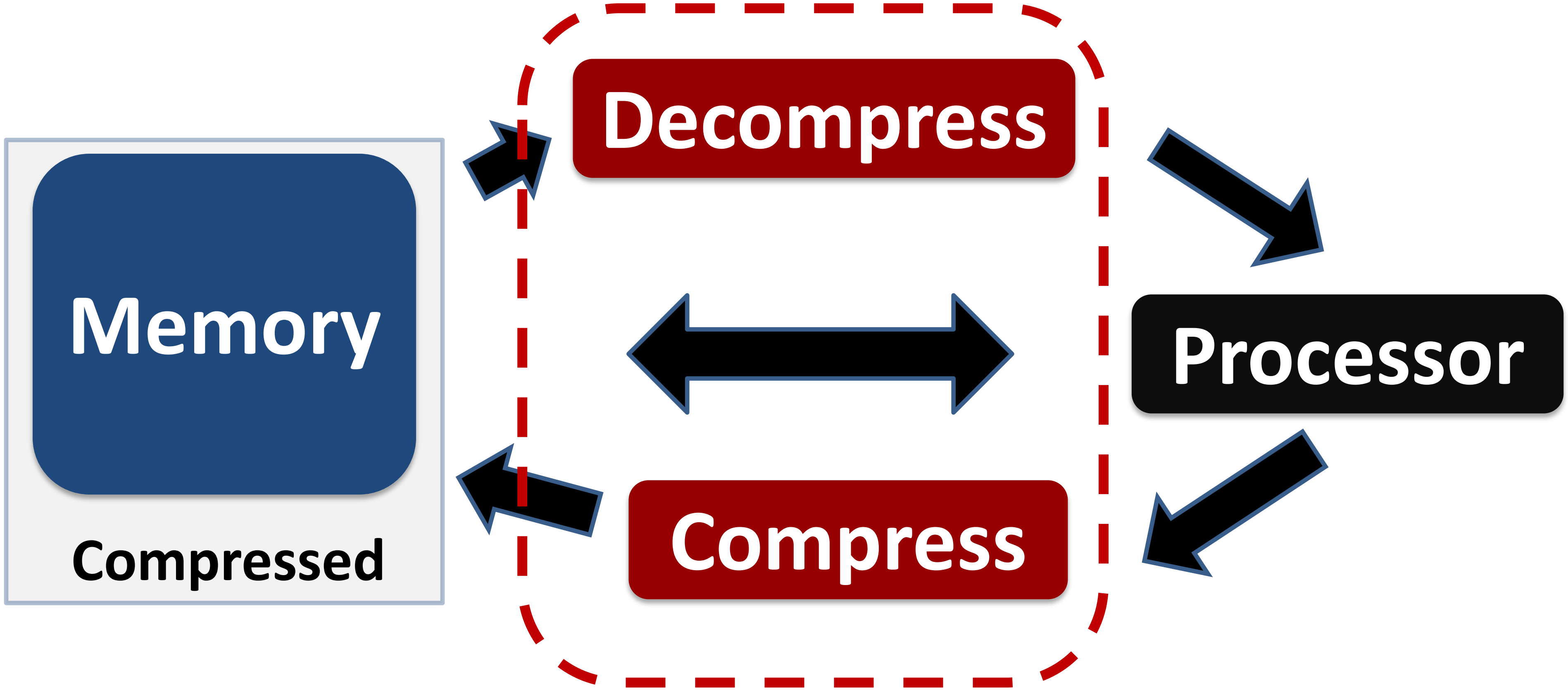
GPU

NVIDIA 1080Ti

FPGA

Altera Stratix V

Execution on Compressed Data

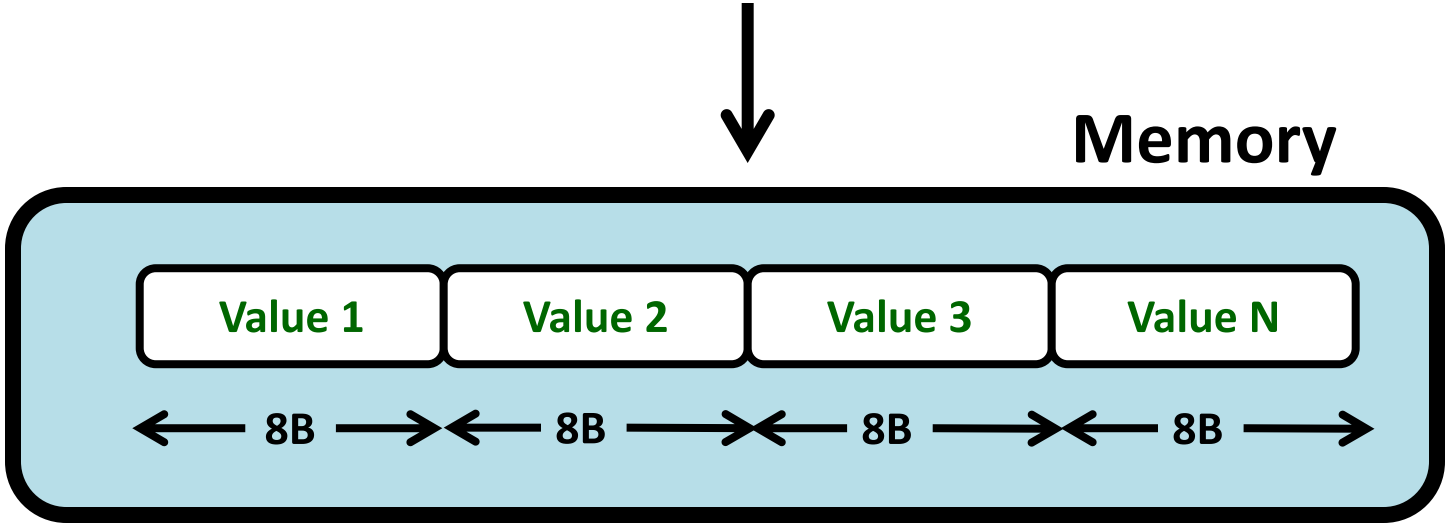


- ✘ *Incurs decompression and compression latency*
- ✘ *High energy overhead*

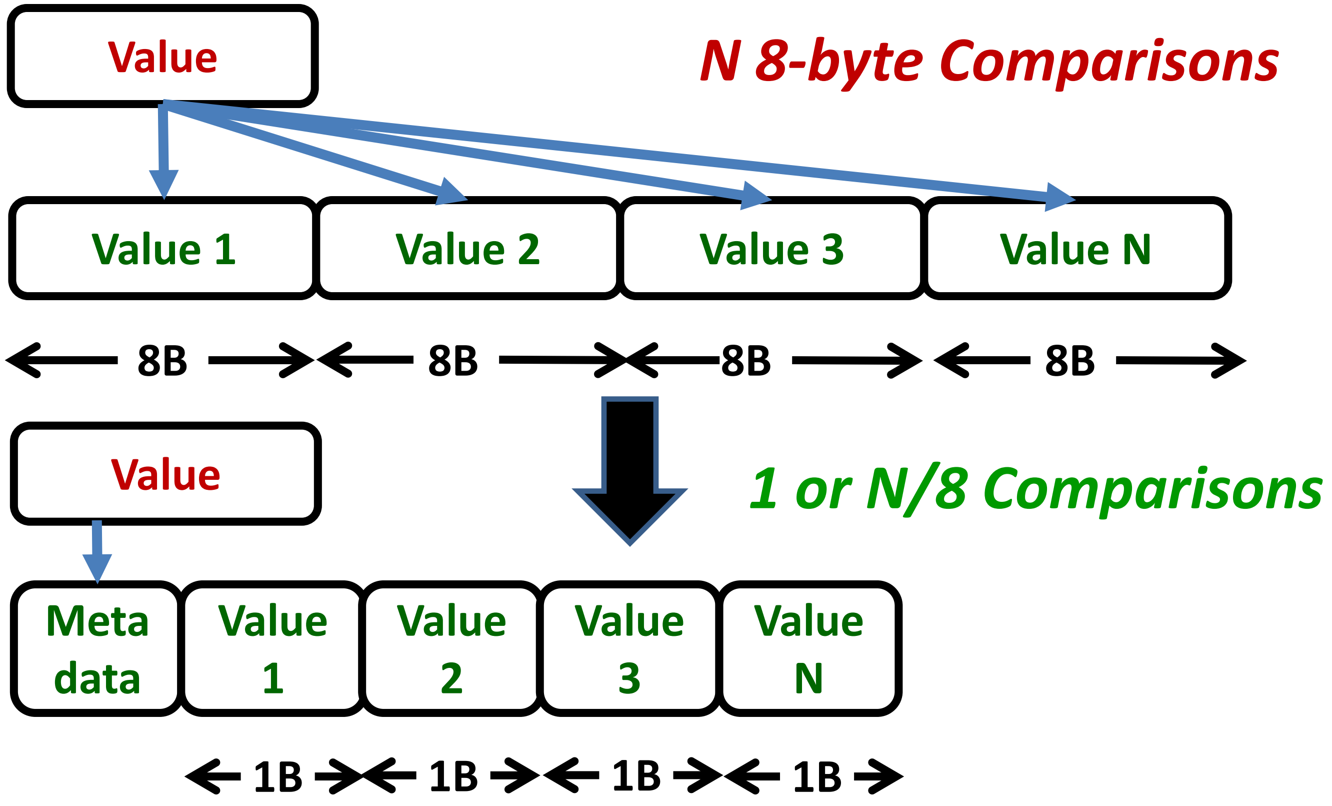
Can we leverage data being in a condensed form?

Execution on Compressed Data

Key 1	Value 1
Key 2	Value 2
Key 3	Value 3
Key N	Value N



Execution on Compressed Data



✓ ***Low Latency***

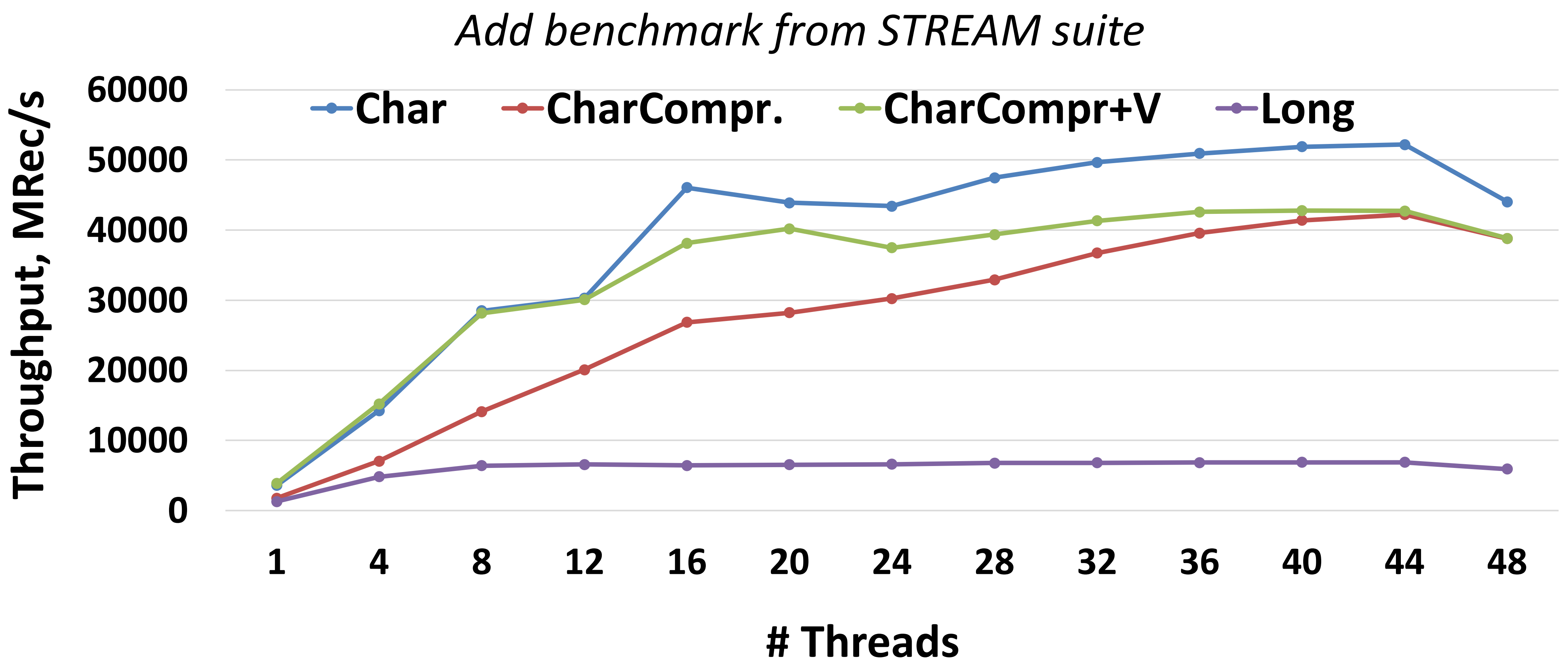
✓ ***Single Comparison***

✓ ***Narrower Operations***

Evaluation: Methodology

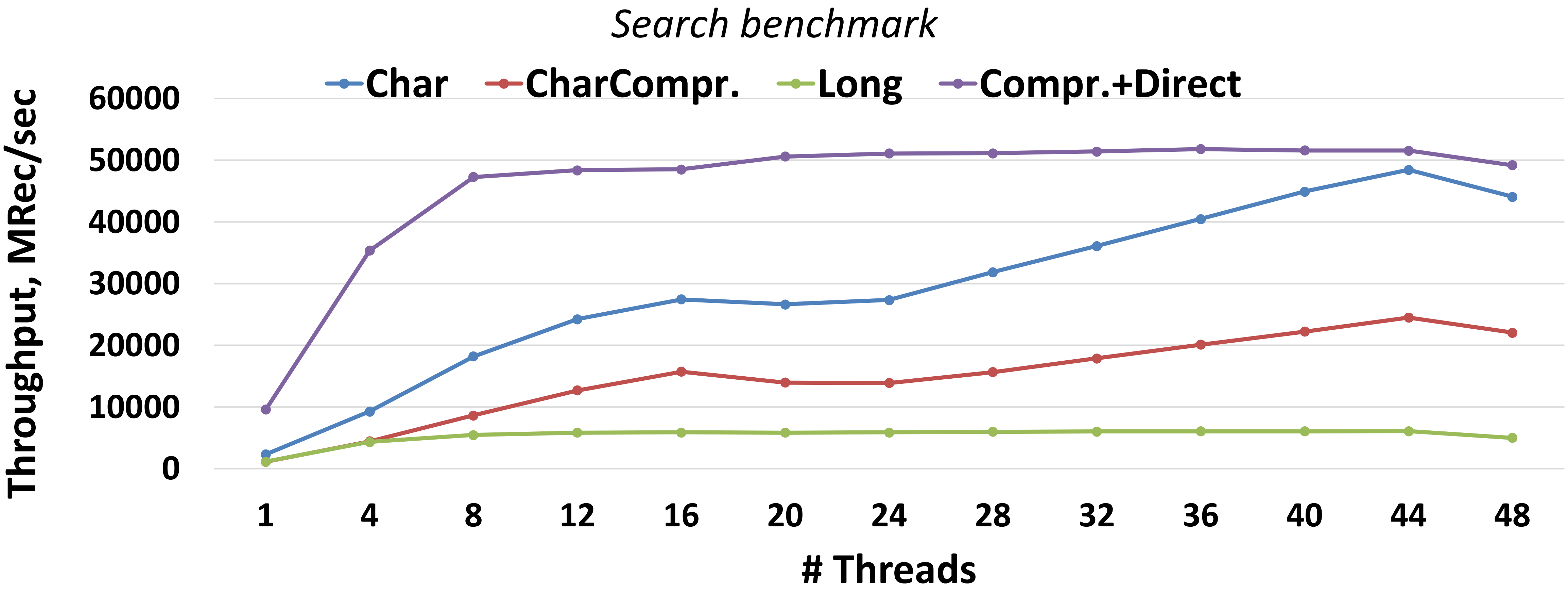
- CPU: 24-core system based on Intel Xeon CPU E5-2673, 2.40GHz with SMT-enabled, and 128GB of memory
- GPU: NVIDIA GeForce GTX 1080 Ti with 11GB of GDDR5X memory
- FPGA: Altera Stratix V FPGA, 200MHz

STREAM Benchmark Results



Vectorization further reduces compression/decompression overhead, especially for smaller number of threads

STREAM Benchmark Results (2)



When direct execution is applicable, it can significantly improve performance as it reduces the total computation

Monitoring and Troubleshooting: PingMesh

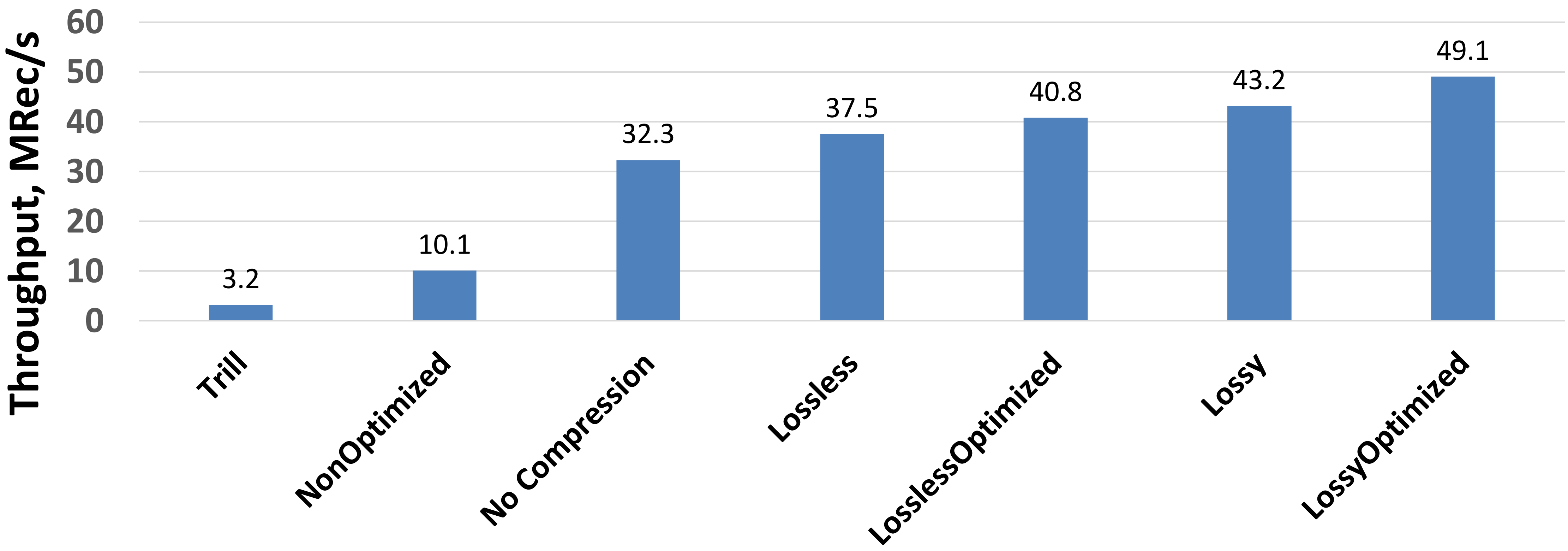
```
C2cProbeCount = Stream
.HopWindow(windowSize, period)
.Where(e => e.errorCode != 0
       && e.rtt >= 100)
.GroupApply((e.srcCluster,
             e.dstCluster))
.Aggregate(c => c.Count())

T2tProbeCount = Stream
.HopWindow(windowSize, period)
.Where(e => e.errorCode != 0
       && e.rtt >= 100)
.Join(m, e => e.srcIp, m => m.ipAddr,
(e,m) => {e, srcTor=m.torId})
.Join(m, e => e.dstIp, m => m.ipAddr,
(e,m)=> {e, dstTor=m.torId})
.GroupApply((srcTor, dstTor))
.Aggregate(c => c.Count())
```

TimeStamp (8, BD)	ErrorCode (4, EN+BD)	SrcCluster (4, HS+BD)
DstCluster (4, HS+BD)	RoundTripTime (4, BD)	

BD – Base+Delta encoding
HS – String hashing
EN – Enumeration

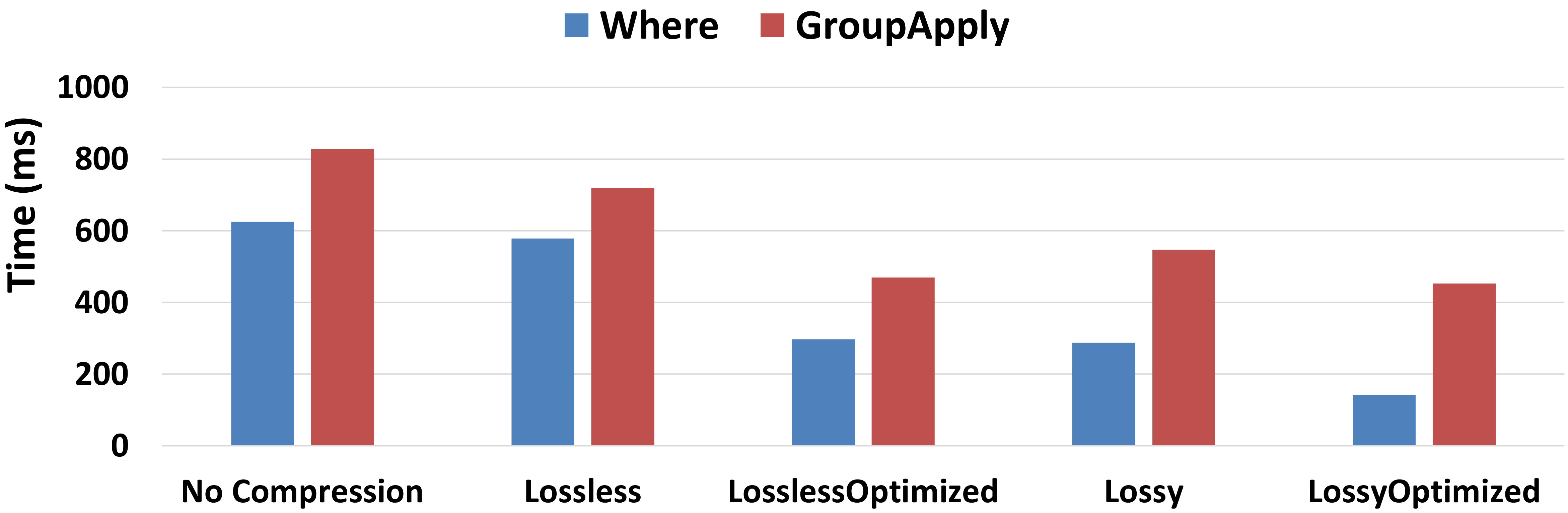
Number in parenthesis – number of bytes before compression

PingMesh C2cProbeCount Results



Total of more that 15X improvement in throughput due to data compression with efficient optimizations

Performance of Individual Operators



The highest performance benefits are for operators where direct execution is applicable (e.g., Where)

IaaS VM Performance Counters

TimeStamp (8, BD)	Cluster (11, HS)	VmID (36, HS)	SampleCount (4, BD)	MinValue (8, ZFP)
MaxValue (8, **ZFP**)	CounterName (15, EN)	NodeId (10, HS)	Datacenter (3, HS)	AverageValue (8, **ZFP**)

BD – Base+Delta encoding; HS – String hashing; EN – Enumeration;
ZFP – efficient floating point compression (lossy with controlled accuracy)

Number in parenthesis – number of bytes before compression

Upto 6X compression with ZFP lossy compression algorithm

IoT Datasets

- **Geolocation data** (GPS coordinates from GeoLife project):
  - 4.5X average compression ratio
  - Less than 10^{-6} loss in accuracy

TimeStamp (8, BD)	Latitude (8, ZFP)
Longtitude (8, ZFP)	Altitude (4, BD)

- **Weather data** (Hurricane Katrina in 2005)
  - 3X-4X compression ratios for 18 metrics used in the data set

Comparison to Prior Work

- Compression in databases
  - Succinct, NSDI'15: execution on compressed **textual** data, complete redesign of data storage in memory
  - Abadi, SIGMOD'06: compression in column-oriented data stores; uses conventional compression algorithms **not applicable to streaming**
- Generic memory compression
  - Execution on compressed data is **not** supported
  - **Lower** compression ratios due to generality of algorithms chosen

Summary

- Q: Can **data compression** be effective in stream processing?
- A: **Yes**, our TerseCades design is the proof-of-concept
  - Properly optimize the baseline system
  - Use light-weight data compression algorithms + HW acceleration
  - **Directly execute** on compressed data
- Results on troubleshooting workload used in production allowed to replace 16 servers with just one!

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