NANYANG TECHNOLOGICAL UNIVERSITY
SINGAPORE

Parallelizing Data-Intensive Applications and Systems

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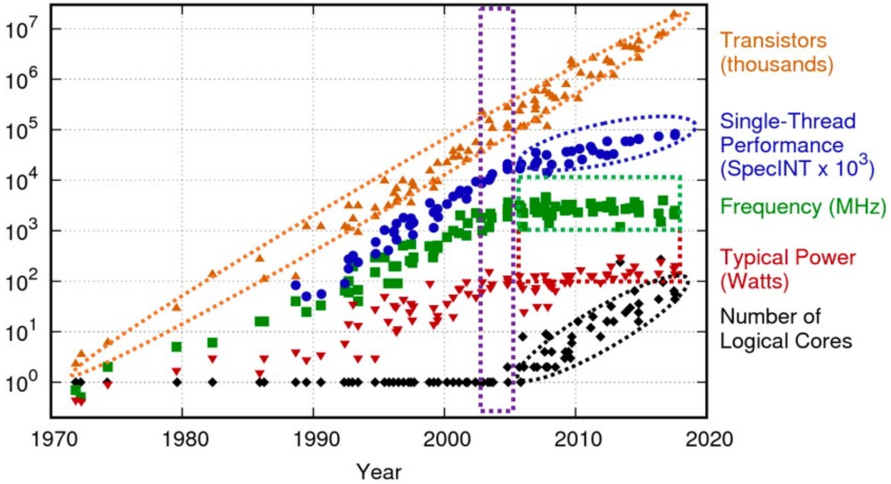
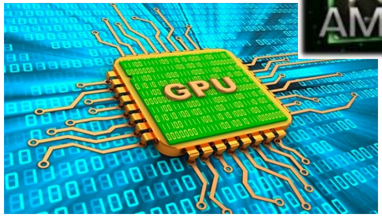
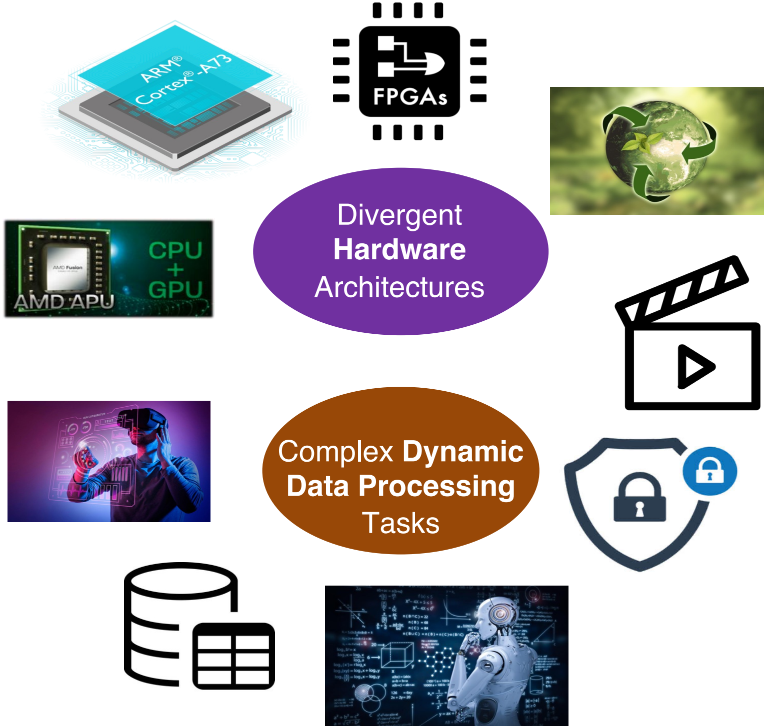
Introduction





Source: BACKUS: Comprehensive High-Performance Research Software Engineering Approach for Simulations in Supercomputing Systems, 2019

Motivation



Data Challenges:

- Volume: Massive datasets
- Velocity: Rapid data streams
- Variety: Diverse data types

Our past focus

Traditional Architecture Limits:

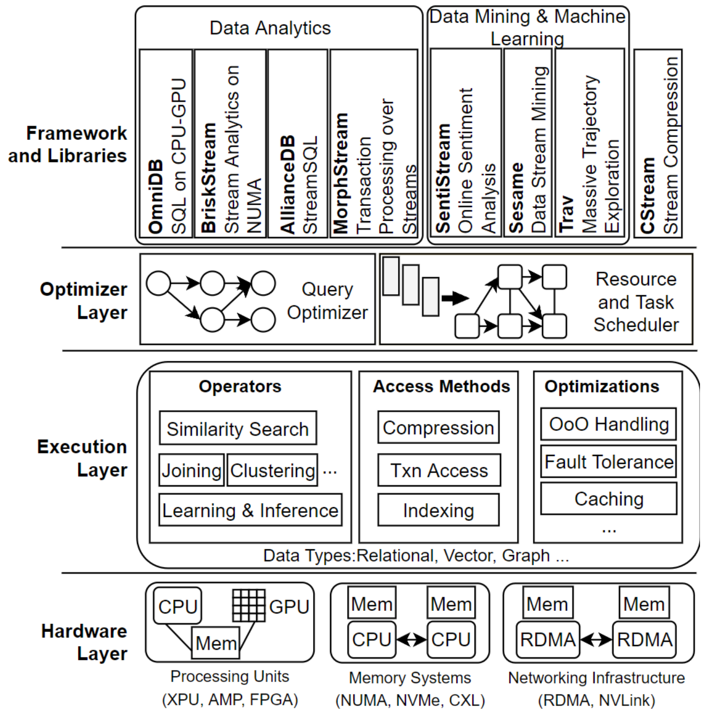
- Scalability
- Efficiency
- Flexibility

Modern Hardware Solutions:

- Processors: Multicore CPUs, GPUs, FPGAs, ASICs
- Memory: NVRAM, HBM
- Network: RDMA

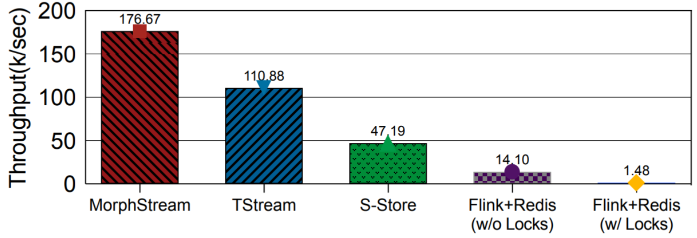
Our Research Contributions

- **Journal**
  IEEE TPDS '16/ '17/ '21, IEEE TKDE '21, ACM SIGMOD Rec. '19, VLDBJ '22/'23
- **Conference**
  SIGMOD '19/ '21/ '23(x2)/ '24(x2), ICDE '17(x2)/ '20/ '23(x3), VLDB '13, EMNLP'23, SC '16, IJCAI '20, USENIX ATC '20, DEBS '23 (vision)
- **System demo and Workshop**
  VLDB '13, IEEE BIGMM '19, VLIoT '20, ICDE'24
- **Code distribution**
  - BriskStream - First authored patents registered in USA
  - MorphStream
  - ...

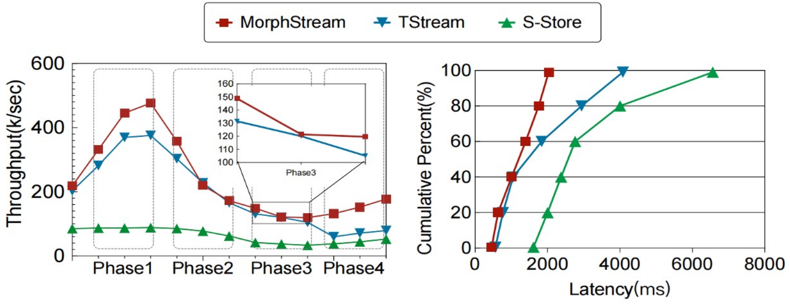


System Development and Optimization

intellistream / MorphStream lines 108.7k Public

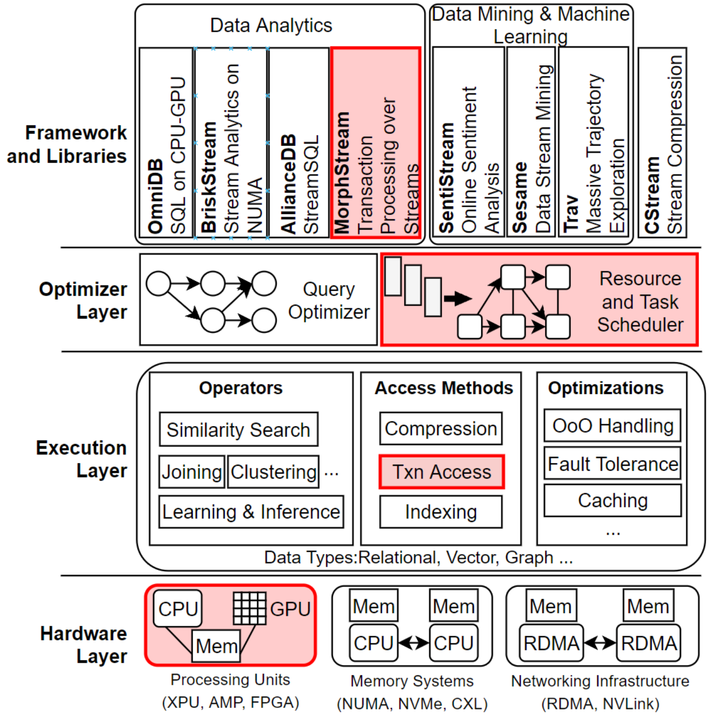


100x performance improvement



(a) Throughput (b) Latency

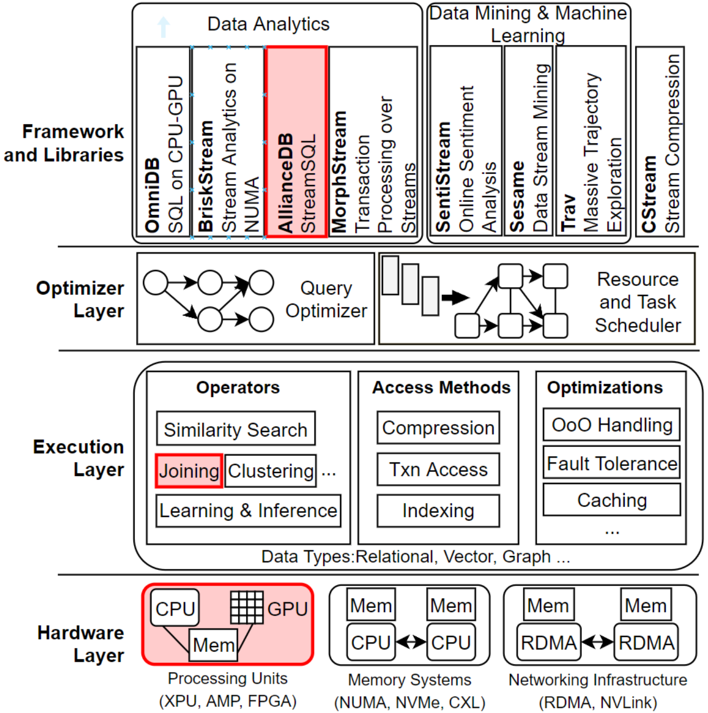
Always select a better-performing scheduling strategy under changing workloads

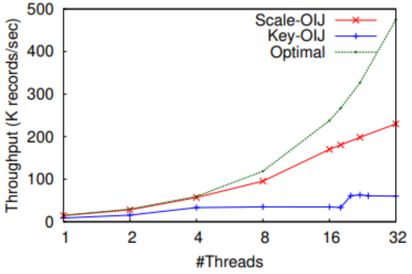


Yancan Mao, Jianjun Zhao, Shuhao Zhang, Haikun Liu, and Volker Markl. 2023. MorphStream: Adaptive Scheduling for Scalable Transactional Stream Processing on Multicores. Proc. ACM Manag. Data 1, 1, Article 59 (May 2023), 26 pages.

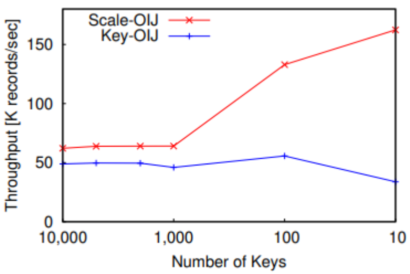
Algorithmic Innovations

AllianceDB lines 103.2k Public

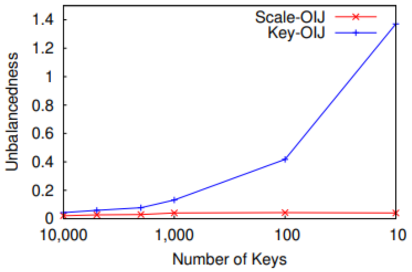




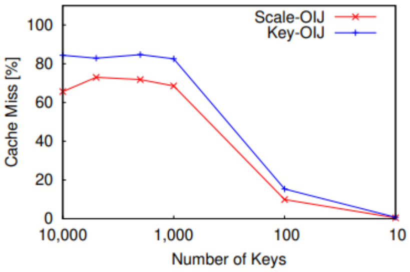
(a) Scalability under 10 Unique Keys



(b) Throughput



(c) *unbalancedness*

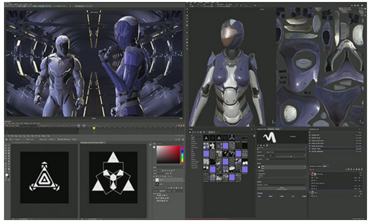


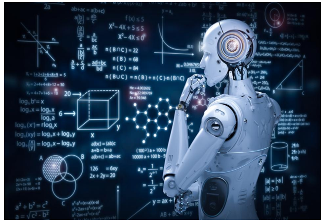
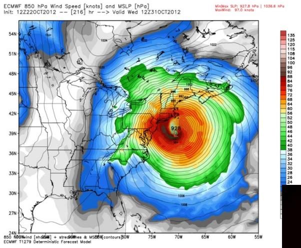
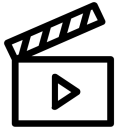
(d) LLC Load Miss

H. Zhang, X. Zeng, S. Zhang, X. Liu, M. Lu and Z. Zheng, "Scalable Online Interval Join on Modern Multicore Processors in OpenMLDB," 2023 IEEE 39th International Conference on Data Engineering (ICDE), Anaheim, CA, USA, 2023, pp. 3031-3042, doi: 10.1109/ICDE55515.2023.00232.

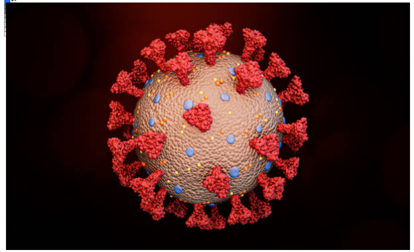
Real-world Applications

- ❑ Stream Compression on Drone [ICDE’23]
- ❑ Accelerating On-line decision augmentation (OLDA) [ICDE’23, SIGMOD’24]
- ❑ Video Database View Materialization [SIGMOD’24]
- ❑ Sentiment Analysis in Data Streams [EMNLP’23]
- ❑ …







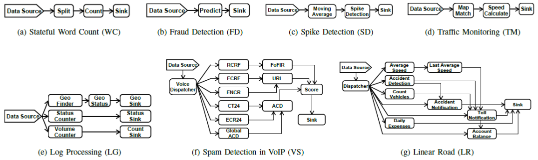
Current Research Direction: System-Wise

Data Management on New Hardware (DaMoN)

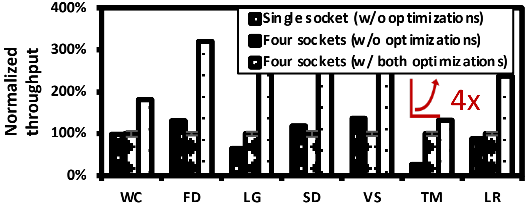
A) Profiling and benchmarking: to understand the gaps between new hardware and current DB algos & systems

B) Algorithm Optimization: Optimizing data processing algorithms, e.g., Join, Aggregation, Clustering on modern hardware

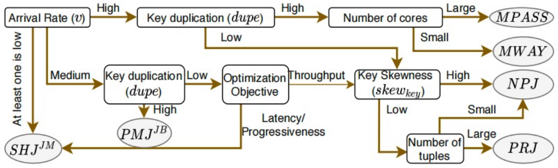
C) System Optimization: Optimizing data processing systems, e.g., MapReduce, DB, Stream engine on modern hardware



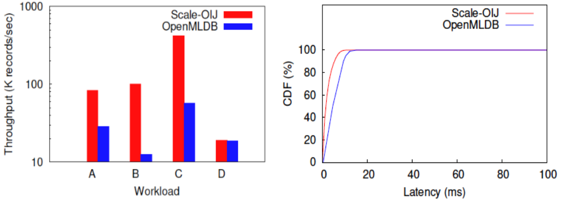
Our own public benchmark sets



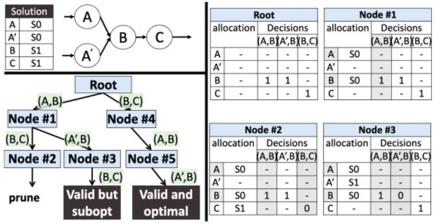
Discovered major issues of open-sourced stream processing systems



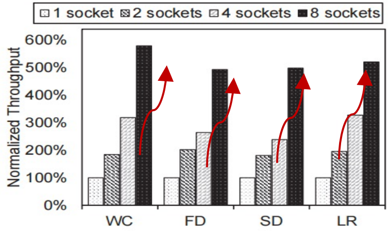
Decision Model for Join over Streams on Multicores



Improves commercial database system (OpenMLDB) with 8x higher throughput



NUMA-aware Query Planner



Almost linearly scalable on NUMA architecture

Current Research Direction: App-Wise

Database meets Artificial Intelligence (DB4AI & AI4DB)

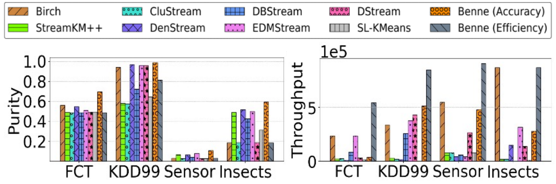
A) Benchmarking: to understand the gaps among current DB algos & systems and AI applications and new hardware

B) DB4AI: bring (HW-accelerated) database system technologies into AI to enhance their training and/or inferring efficiency

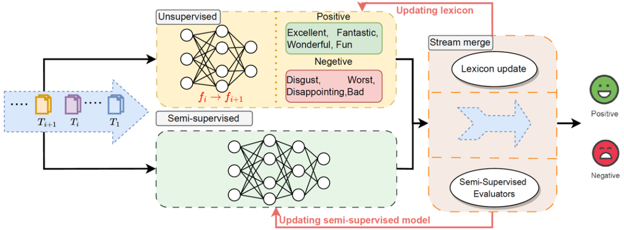
C) AI4DB: bring AI into (HW-accelerated) DB to enhance their processing capabilities on complex situations that can be hardly handled with simple models

Algorithm	Year	Summarizing Data Structure		Window Model	Outlier Detection	Offline Refinement
		Name	Catalog			
BIRCH [37]	1996	CFT	Hierarchical	LandmarkWM	OutlierD	NoRefine
CluStream [5]	2003	MCs	Partitional	LandmarkWM	OutlierD-T	Refine
DenStream [11]	2006	MCs	Partitional	DampedWM	OutlierD-BT	Refine
DStream [13]	2007	Grids	Partitional	DampedWM	OutlierD-T	NoRefine
StreamKM++ [4]	2012	CoreT	Hierarchical	LandmarkWM	NoOutlierD	Refine
DBStream [19]	2016	MCs	Partitional	DampedWM	OutlierD-T	Refine
EDMStream [18]	2017	DPT	Hierarchical	DampedWM	OutlierD-BT	NoRefine
SL-KMeans [9]	2020	AMS	Partitional	SlidingWM	NoOutlierD	NoRefine

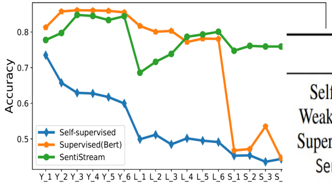
Decomposing Stream clustering algorithms into 4 dimension



Discovered reconfigurable algorithm to meet dynamic requirements

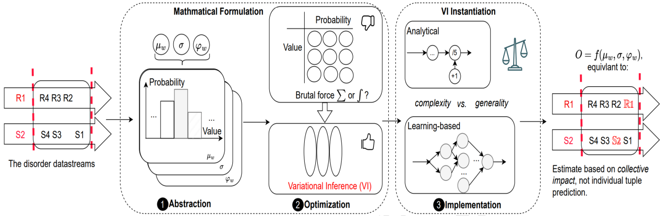


Bring stream pipeline to NLP

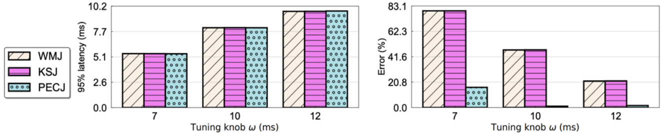


Method	Latency(ms)	Throughput
Self-supervised	2.43	409
Weakly-supervised	584.75	9
Supervised (BERT)	53.17	162
SentiStream	**0.67**	**1471**

High accuracy (**80%**), high performance ($l = 0.7ms, Tpt = 1.4K$) self-learning systems



Bring learning-based variational inference to DB



(a) 95% latency of Q1

(b) Relative error of Q1

Low processing latency with ~1% marginal error when handling disordered data streams

Challenges and Future Directions

Things are getting complicated…

REQUIREMENT

HARDWARE

APPLICATION

- ❑ **Scalability:** Keeping up with data growth.
- ❑ **Complexity:** Managing diverse data types and processing demands.
- ❑ **Energy Efficiency:** Reducing the carbon footprint.

Conclusion and Q&A

Emphasis on **Modern Hardware** for data processing challenges.

Innovative Techniques in execution plan optimization and state management.

Real-World Applications showcasing our research impact.

Future Directions highlighting unexplored areas and potential advancements.

Call for Collaboration to push the boundaries further.

Thank You

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