Accelerating Approximate Data Analysis with Parallel Processors

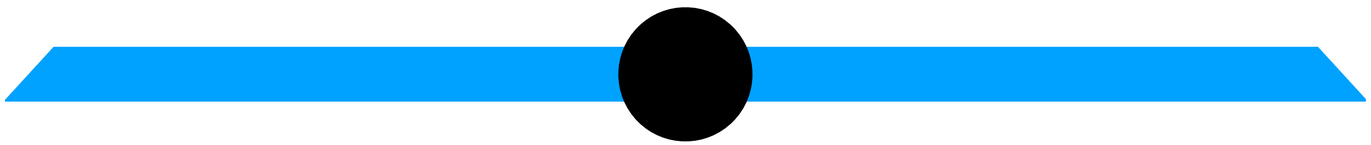
Martin Kiefer

PhD Defense

2.2.2023

Approximate Data Analysis

Trading accuracy for faster / cheaper results



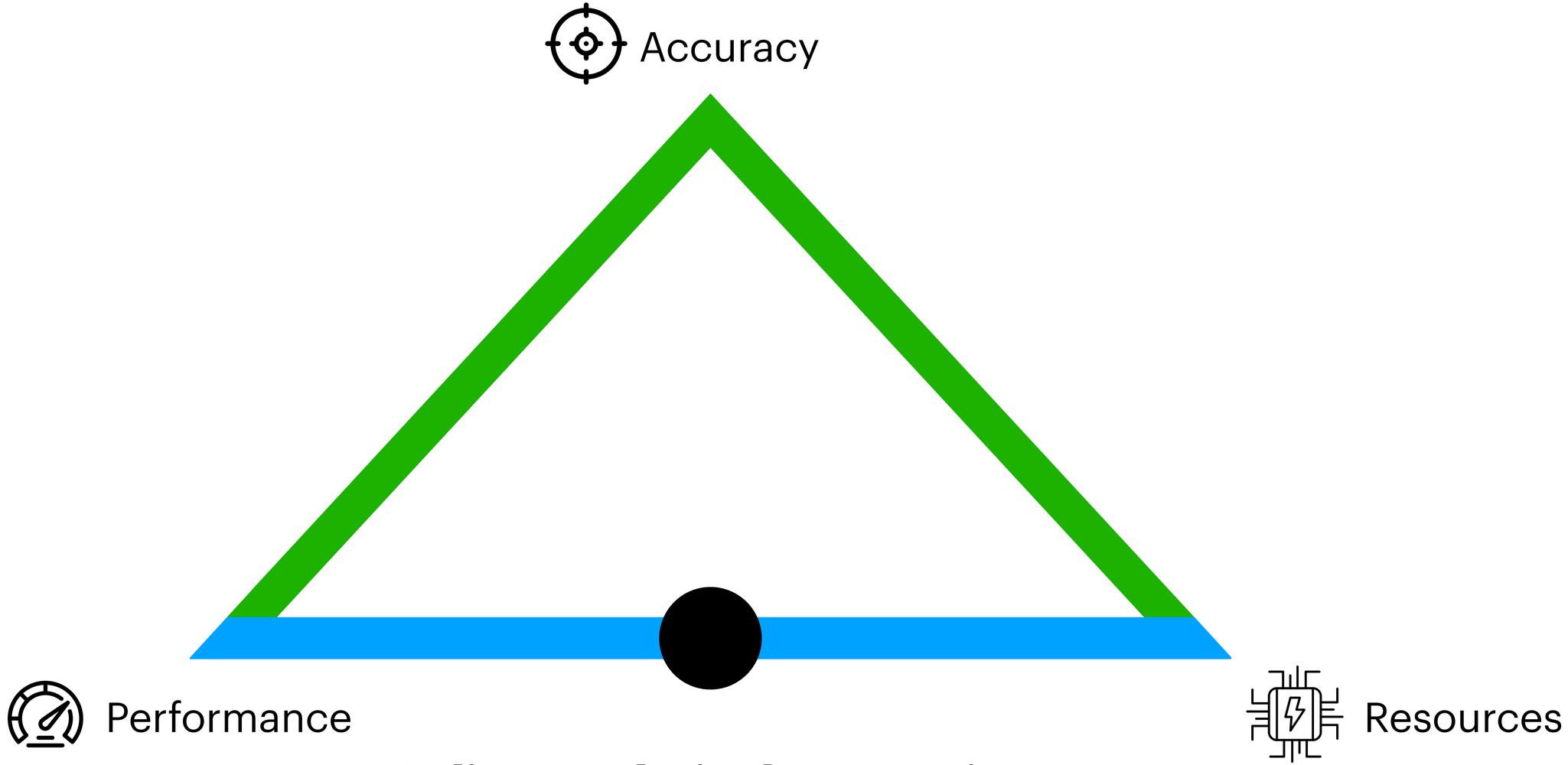
Performance

Resources

Online Analytical Processing

Approximate Data Analysis

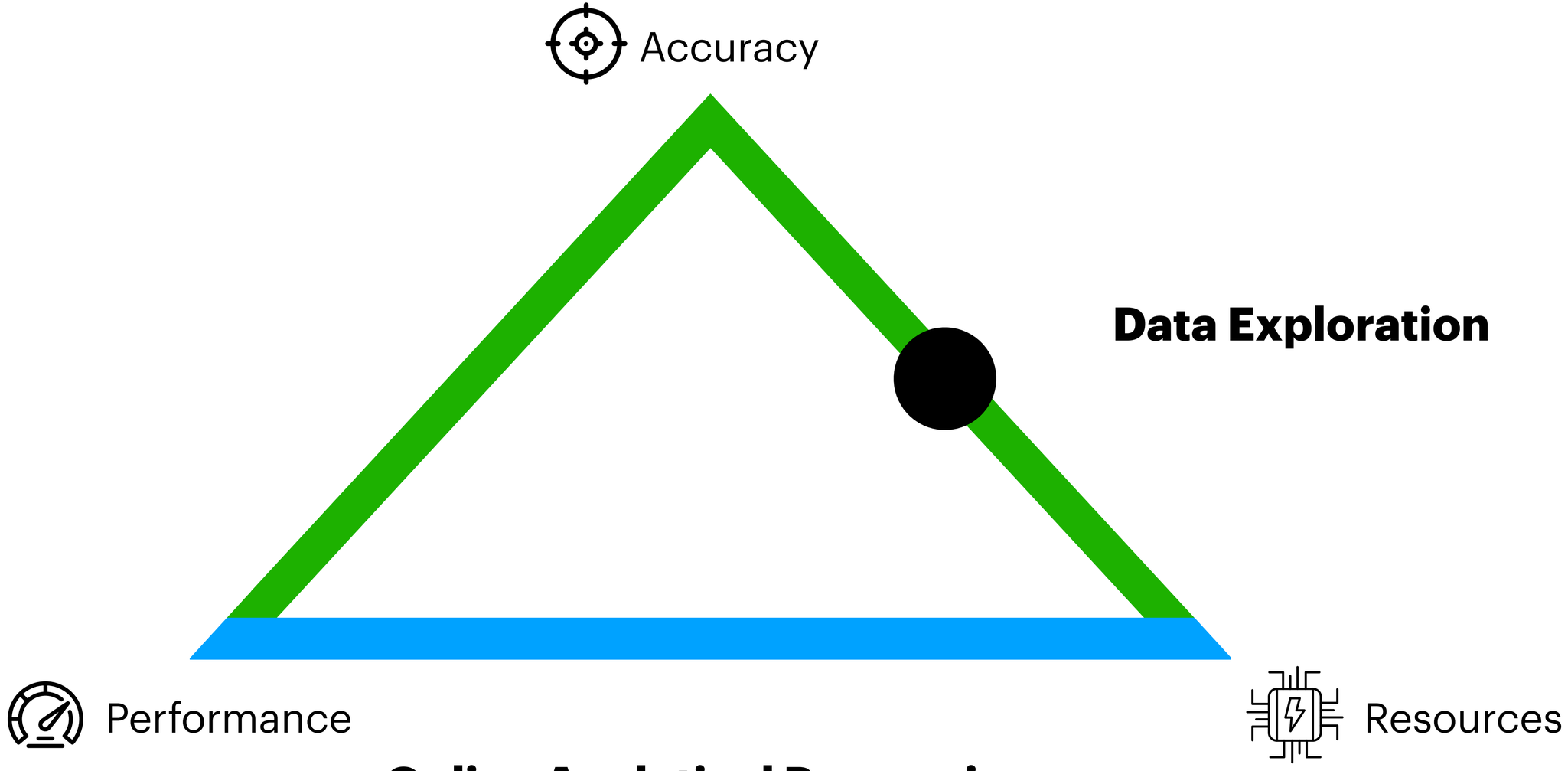
Trading accuracy for faster / cheaper results



Online Analytical Processing

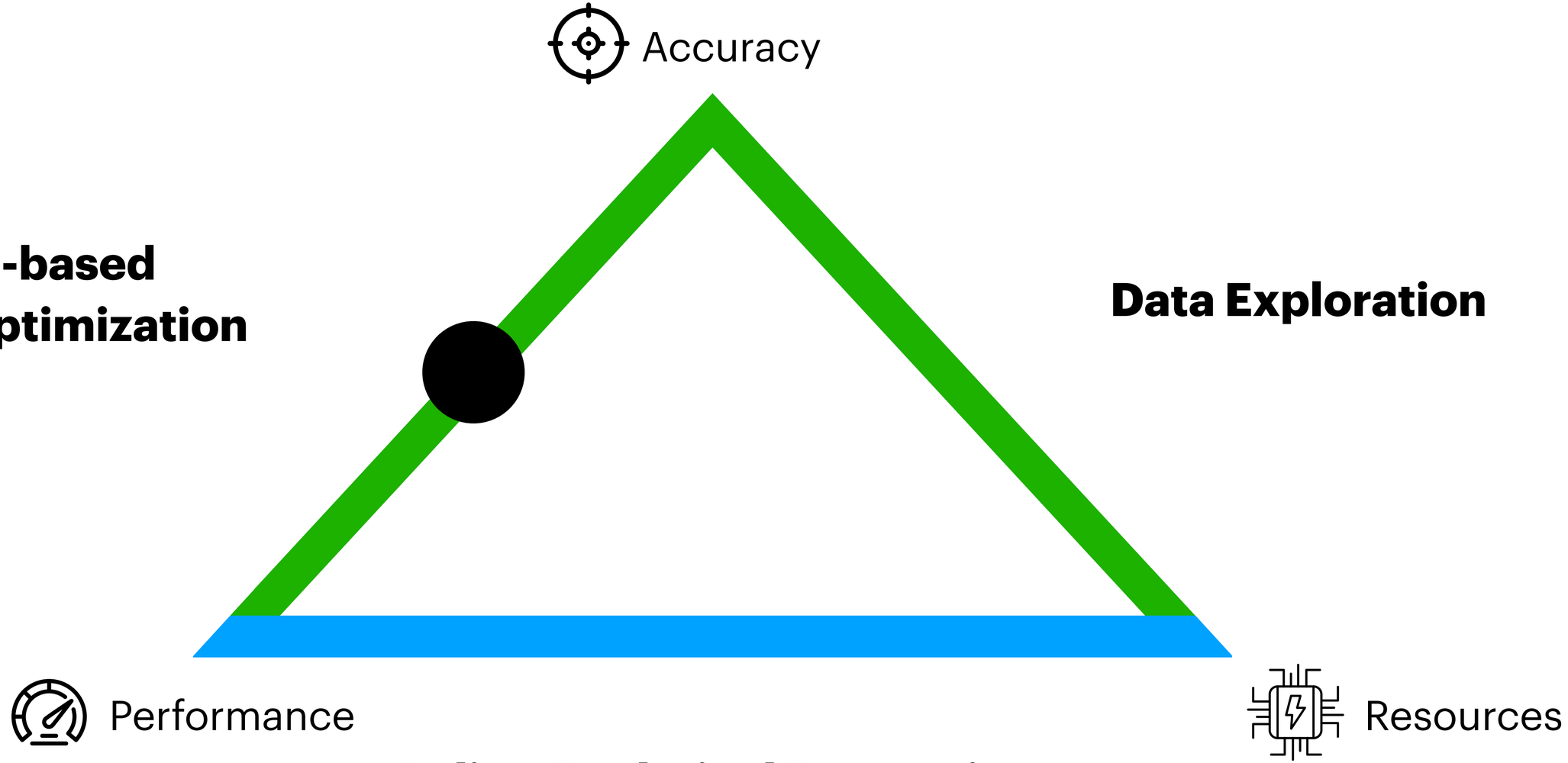
Approximate Data Analysis

Trading accuracy for faster / cheaper results



Approximate Data Analysis

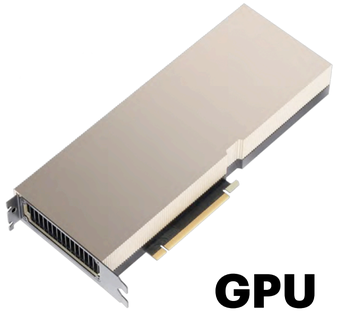
Why go for approximations?



Specialized Parallel Processors

Highest efficiency for certain computations

- **Graphics Processing Unit**
  - Thousands of parallel threads
  - Throughput optimized



GPU

- **Field-Programmable Gate Array**
  - Parallelism in custom circuits
  - Reprogrammable ressources

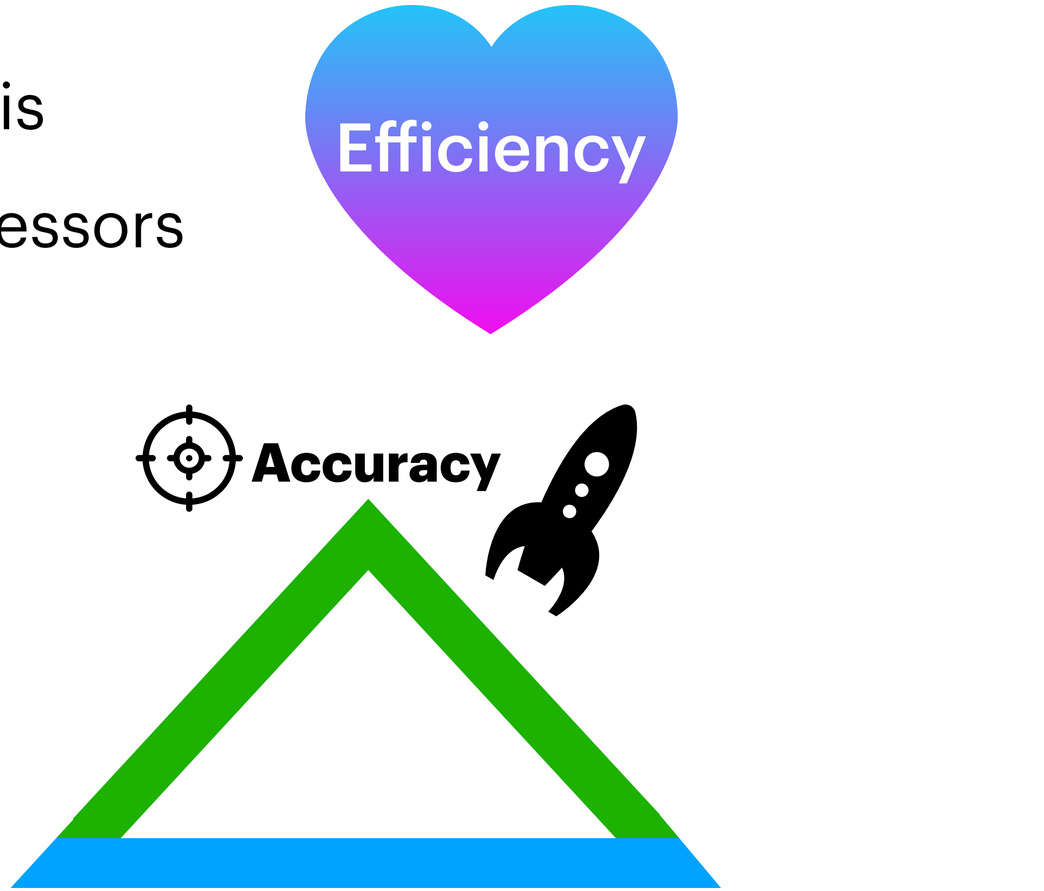
FPGA

- Higher performance, lower energy consumption
- Embrace parallelism, properties, programming models

Approximate Data Analysis + Parallel Processors

Efficiency beyond the approximation trade-off

- Approximate data analysis
- Specialized parallel processors



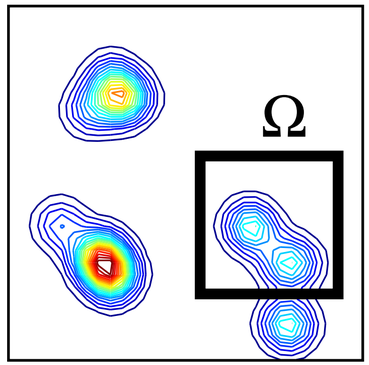
Approach
2 Use Cases, 2 Goals

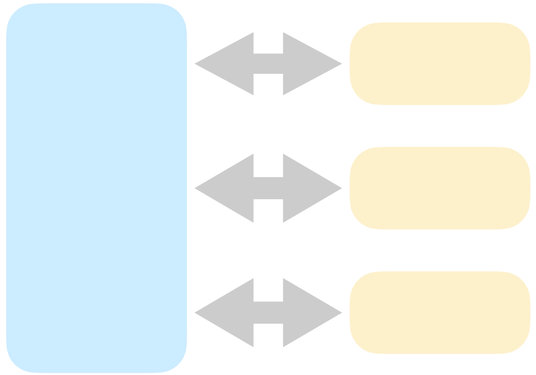
- For two relevant use cases, we
  - generalize existing approaches
  - hide the complexity of the processor

- **We solve problems limiting the applicability of the approaches**

Overview

Use Case #1: GPU-Accelerated Selectivity Estimation





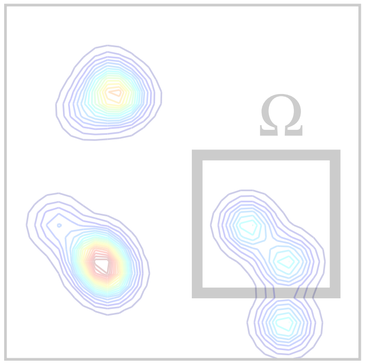
Estimating Join Selectivities using Bandwidth-Optimized Kernel Density Models

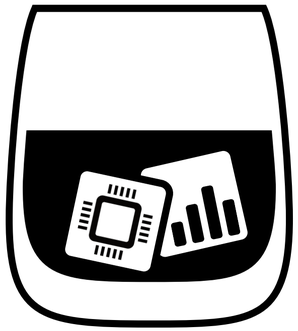
Martin Kiefer, Max Heimel, Sebastian Breß, Volker Markl

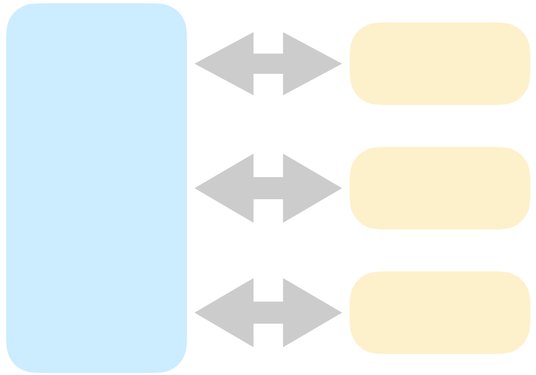
PVLDB, 10 (13), 2017

Overview

Use Case #2: FPGA-Accelerated Sketching







Scotch: Generating FPGA Accelerators for Sketching at Line Rate

Martin Kiefer, Ilias Poulakis, Sebastian Breß, Volker Markl

PVLDB, 14 (3), 2021

Overview

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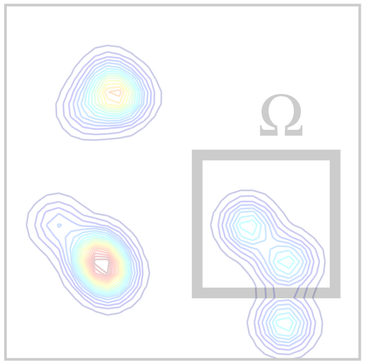
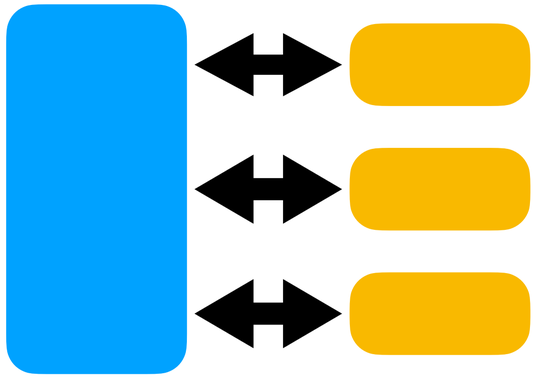




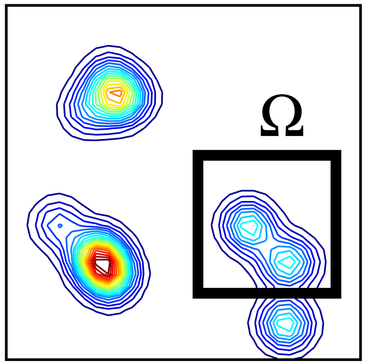
Optimistic Data Parallelism for FPGA-Accelerated Sketching

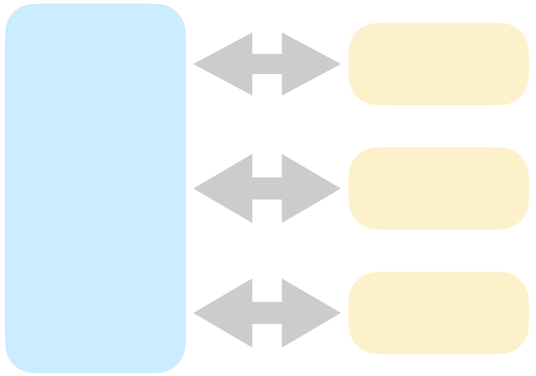
Martin Kiefer, Ilias Poulakis, Eleni Tzirita Zacharatou, Volker Markl

PVLDB, 16 (5), 2023

GPU-Accelerated Selectivity Estimation

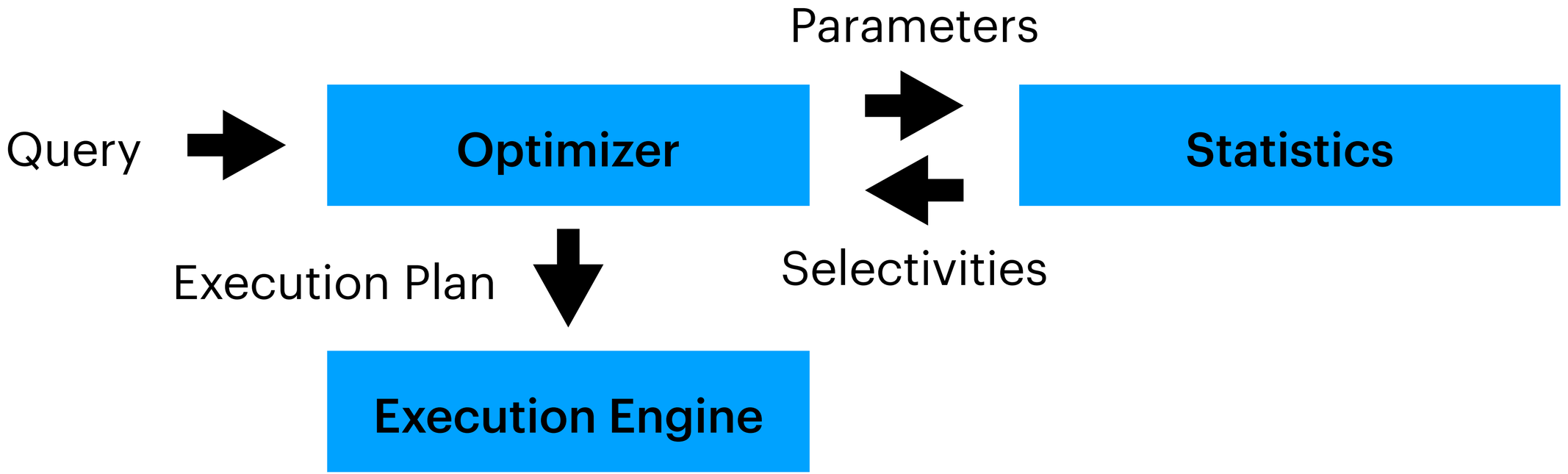
Use Case #1





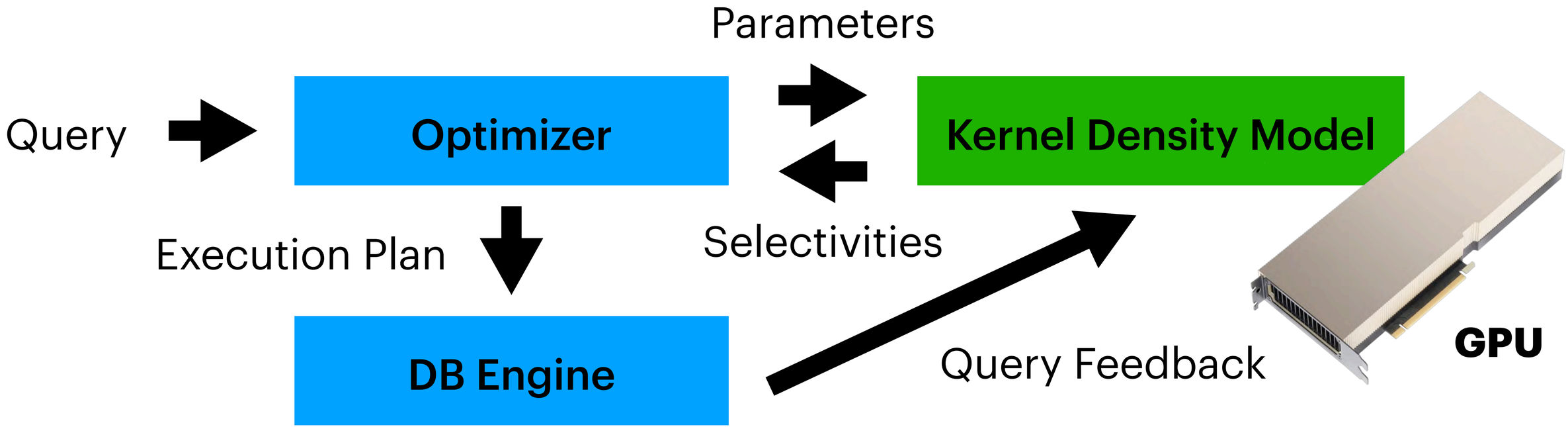
Use Case 1: GPU-Accelerated Selectivity Estimation

Statistical Coprocessing in Relational Databases



Use Case 1: GPU-Accelerated Selectivity Estimation

Statistical Coprocessing in Relational Databases



Problem: Limited operator support, no joins

Self-Tuning, GPU-Accelerated Kernel Density Models for Multidimensional Selectivity Estimation. Max Heimel, Martin Kiefer, Volker Markl. SIGMOD'15.

Estimating Join Selectivities using Bandwidth-Optimized Kernel Density Models

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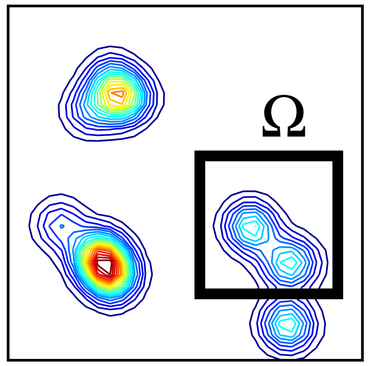
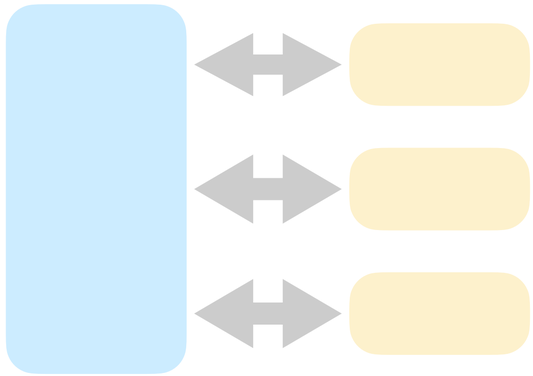
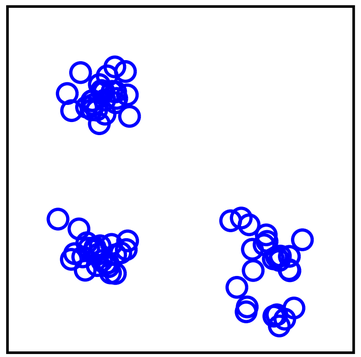




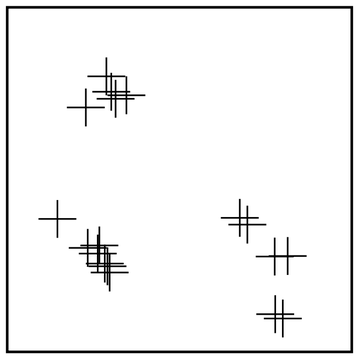
Kernel Density Estimation

Sampling meets histogram

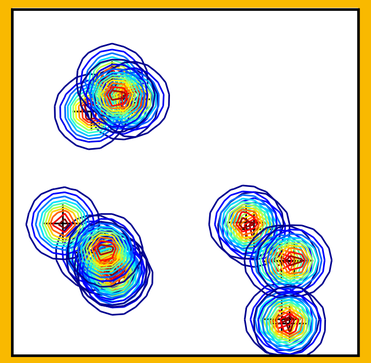
$$\hat{P}(\vec{x}) = \frac{1}{|S|} \sum_{i=1} K_H(\vec{s}_i - \vec{x})$$



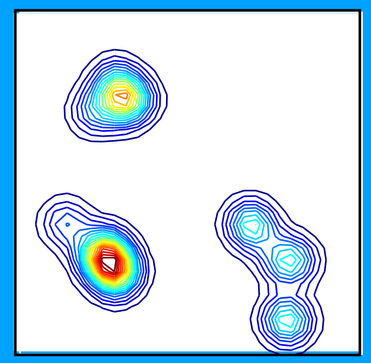
Dataset



Sample



Kernels K_H

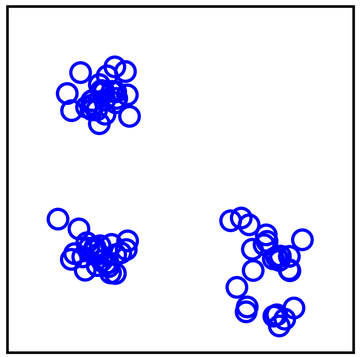


Estimate P_H

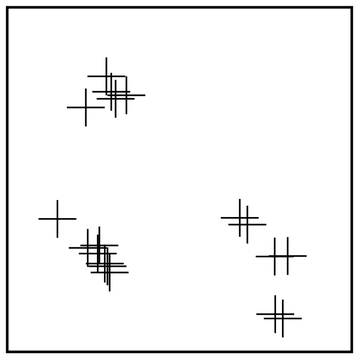
Kernel Density Estimation

Estimating the selectivity of a region Ω

$$\hat{P}(\vec{x}) = \frac{1}{|S|} \sum_{i=1} \int_{\Omega} K_H(\vec{s}_i - \vec{x})$$



Dataset



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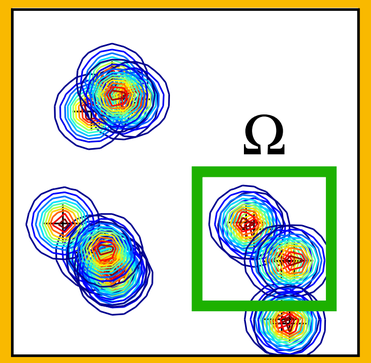
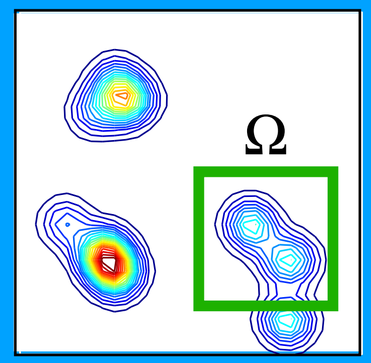


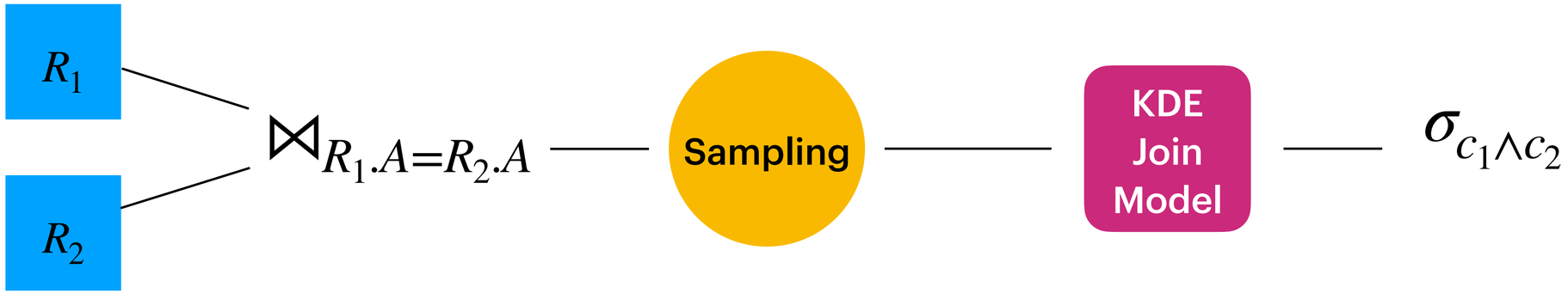
Kernels K_H



Estimate P_H

Sampling from the Join Result

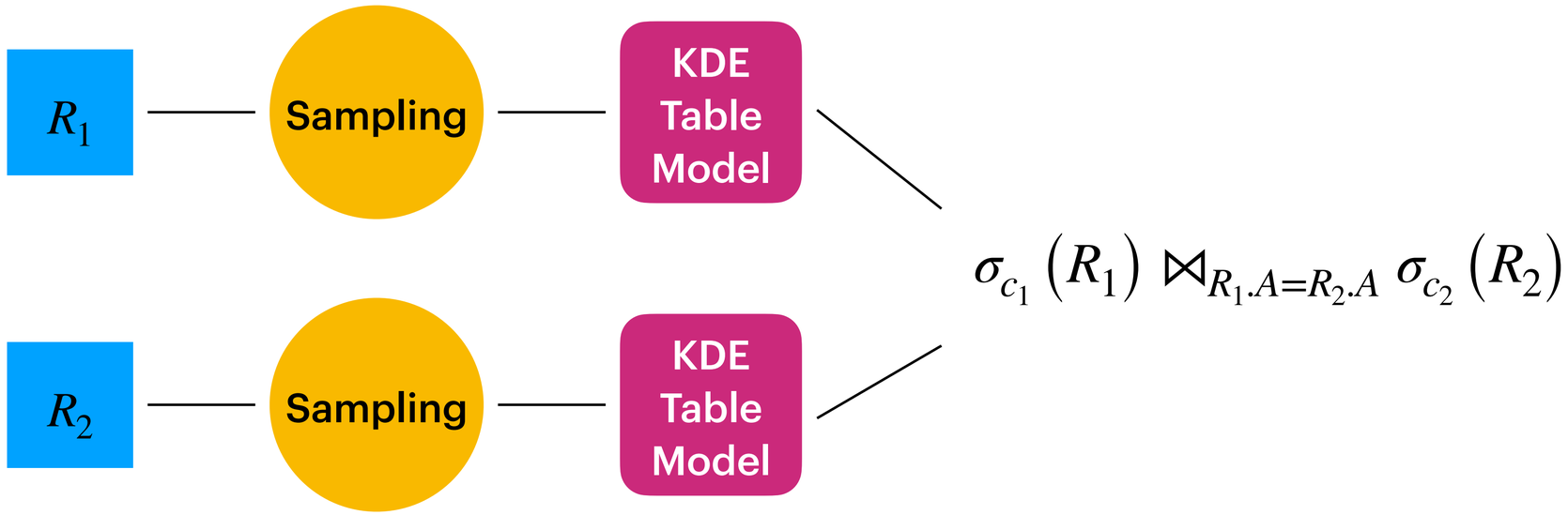
Just treat the join like a base table



- **Benefits**
  - Accurate model, no modifications required
- **Drawbacks**
  - KDE model tailored to one particular join

Combining Base Table Models

Modeling the join explicitly



- **Benefits**
  - Models can handle both base selections and joins
- **Drawbacks**
  - The join has to be applied explicitly on the estimated distribution

Computing joins over KDE models

Avoiding cross products

Sum over cross product

$$\sum_{i=1,j=1}^{s_1,s_2} \hat{p}_1{}^{(i)}(c_1) \cdot \hat{p}_2{}^{(j)}(c_2) \cdot \hat{J}_{i,j}$$

Computing joins over KDE models

Invariant Contributions

Sum over cross product

$$\sum_{i=1,j=1}^{s_1,s_2} \hat{p}_1^{(i)}(c_1) \cdot \hat{p}_2^{(j)}(c_2) \cdot \hat{J}_{i,j}$$

Invariant Contributions

(Effect of selections, depend on individual samples)

Filter samples by invariant contributions

(Predicate pushdown)

Computing joins over KDE models

Cross contributions

Sum over band join

$$\sum_{i=1,j=1}^{s_1,s_2} \hat{p}_1{}^{(i)}(c_1) \cdot \hat{p}_2{}^{(j)}(c_2) \cdot \underbrace{\hat{J}_{i,j}}$$

Cross Contributions

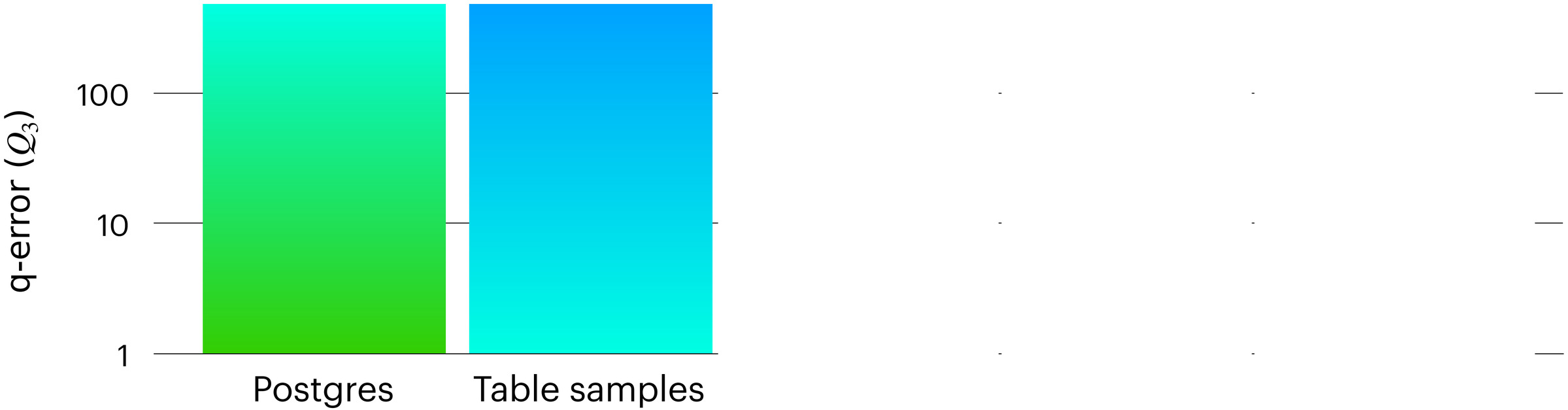
(Effect of the join, similarity function)

Join only sufficiently close tuples

(Binary Search Band Join)

Evaluation: Estimator Accuracy

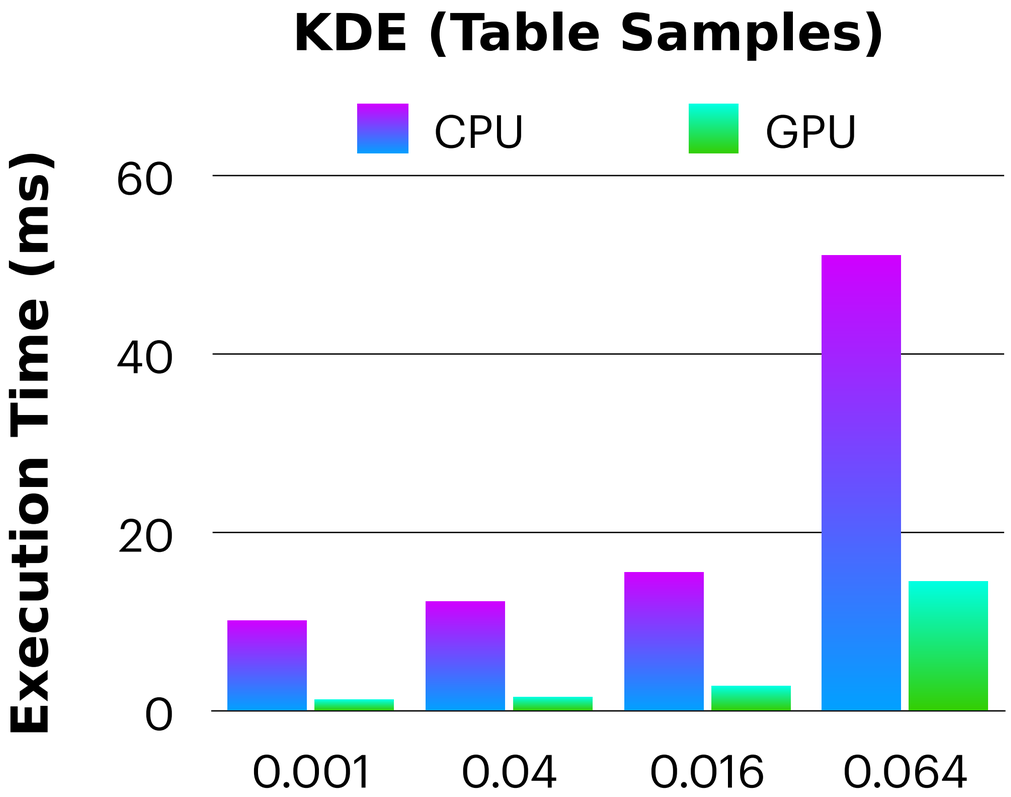
KDE prevents reduces severe misestimations



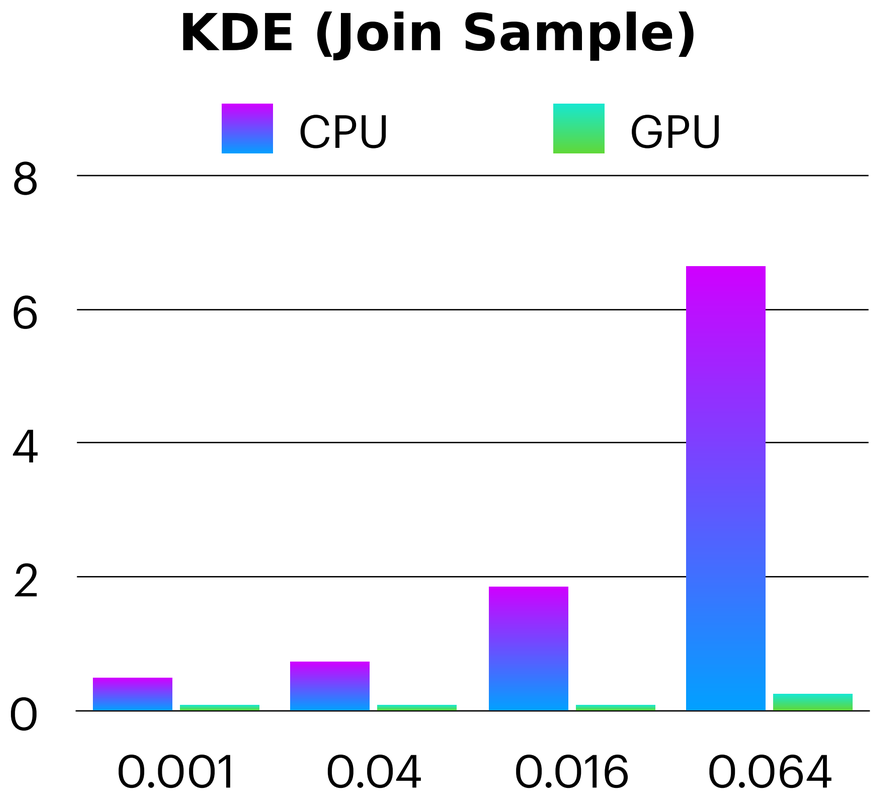
DMV, Distinct Workload, 3 joins, 8 selections, 300 Training Queries, 100 Test Queries, 1% sample size

Evaluation: Estimator Accuracy

KDE prevents reduces severe misestimations



GPU: 4x - 40x larger model sizes



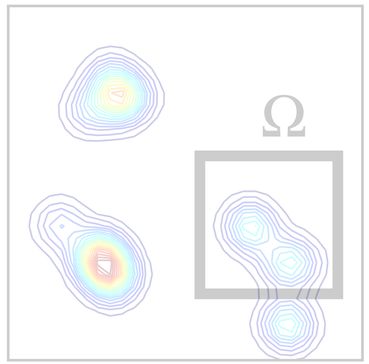
GPU: 30x - 140x larger model sizes

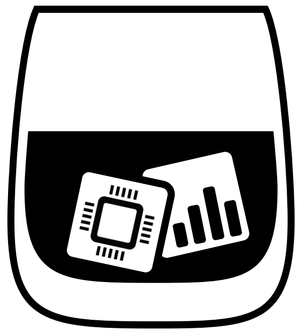
IMDb, 3 joins, 6 selections, 300 Training Queries, 50 KB - 6 MB

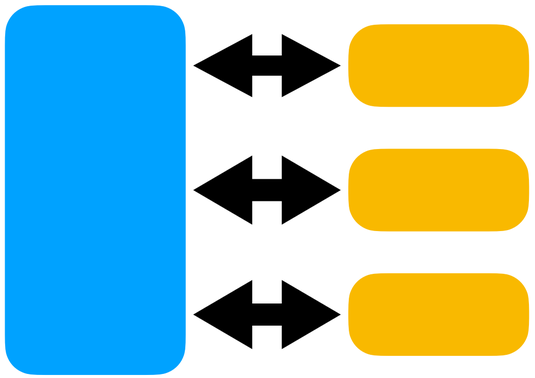
GPU: Nvidia V100, CPU: 2x Intel Xeon Gold 5115

FPGA-Accelerated Sketching

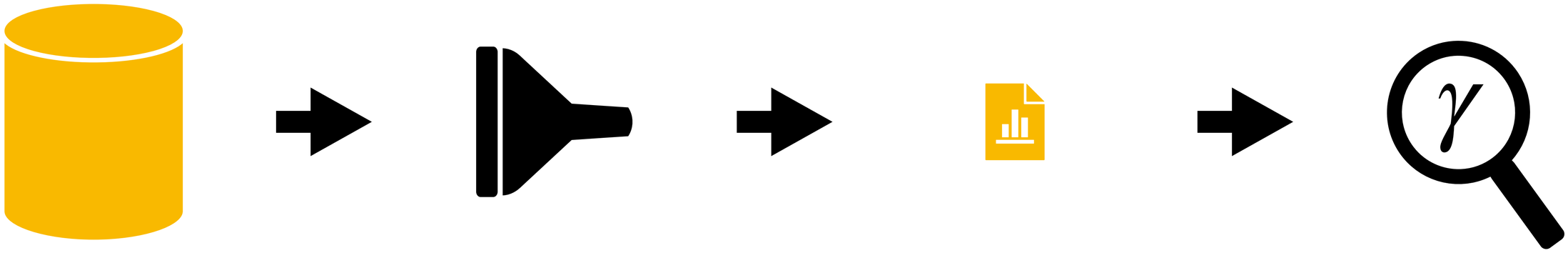
Use Case #2





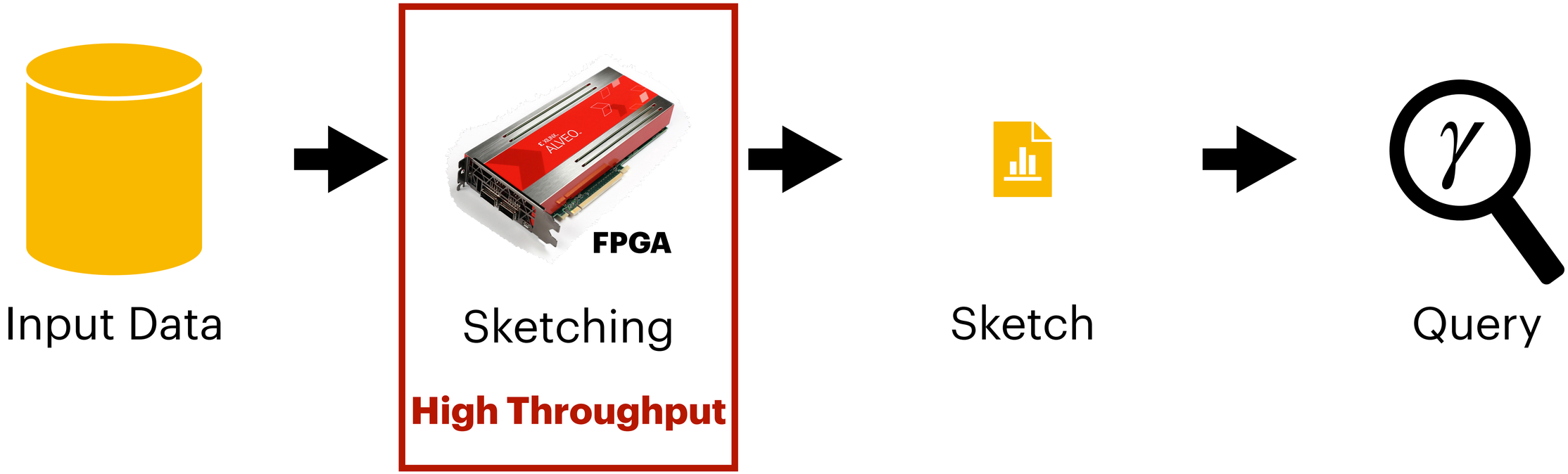


FPGA-Accelerated Sketching
for Approximate Query Processing



Use Case 2: FPGA-Accelerated Sketching

for Approximate Query Processing



Problem 1: An FPGA expert is required

Problem 2: High resource consumption for replicated data parallelism

Scotch: Generating FPGA Accelerators for Sketching at Line Rate

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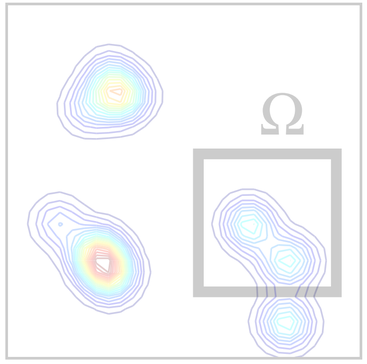
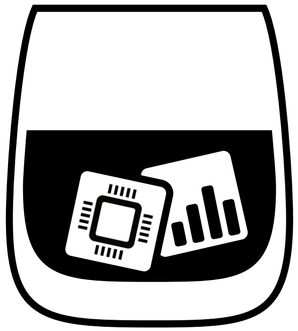
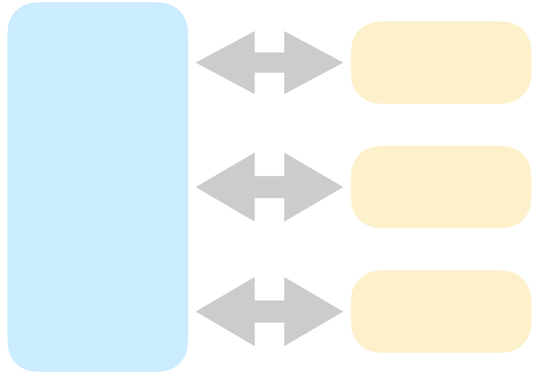
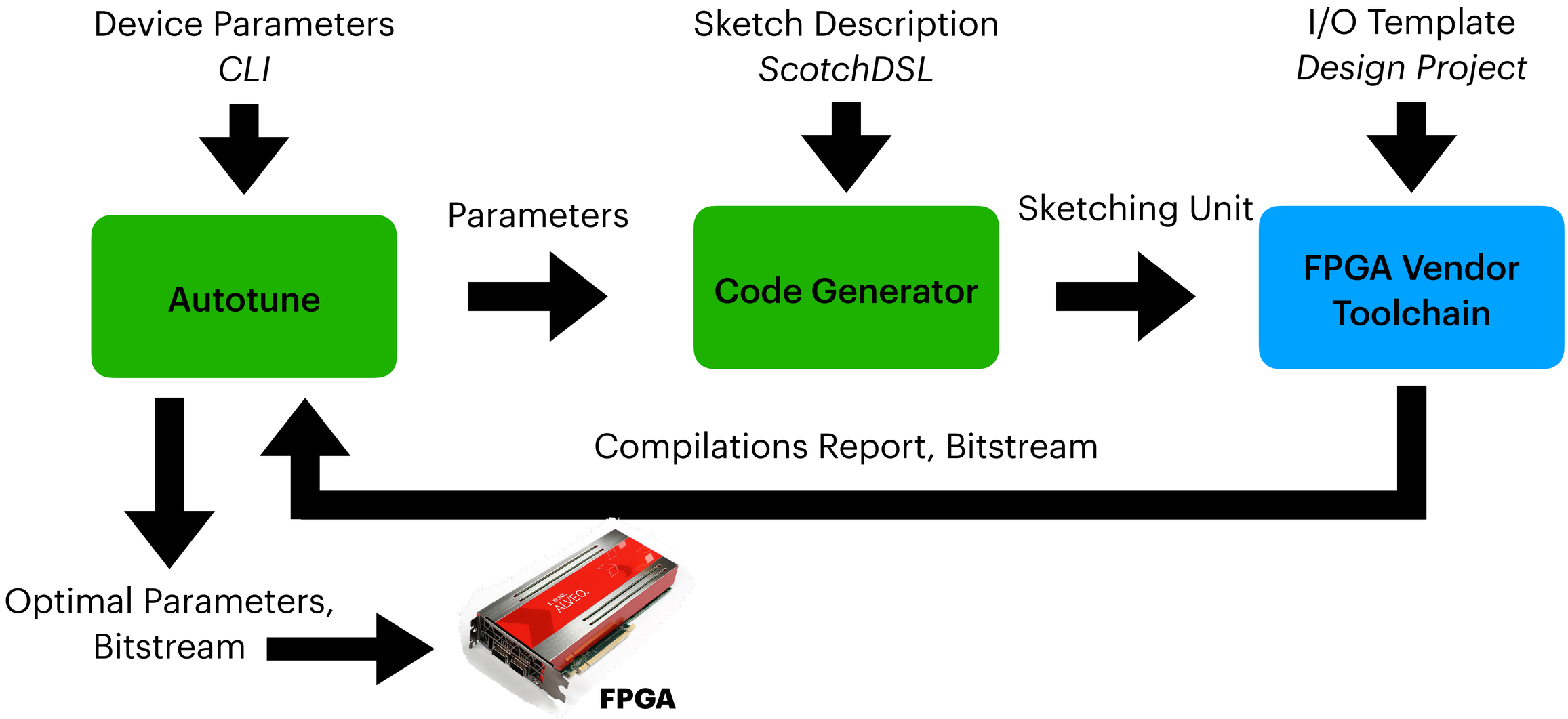






Scotch System Architecture

Generating and optimizing in a feedback-loop



Scotch System Architecture

Generating and optimizing in a feedback-loop

Device Parameters
CLI

Sketch Description
ScotchDSL

I/O Template
Design Project

Autotune

Parameters

Code Generator

Sketching Unit

FPGA Vendor Toolchain

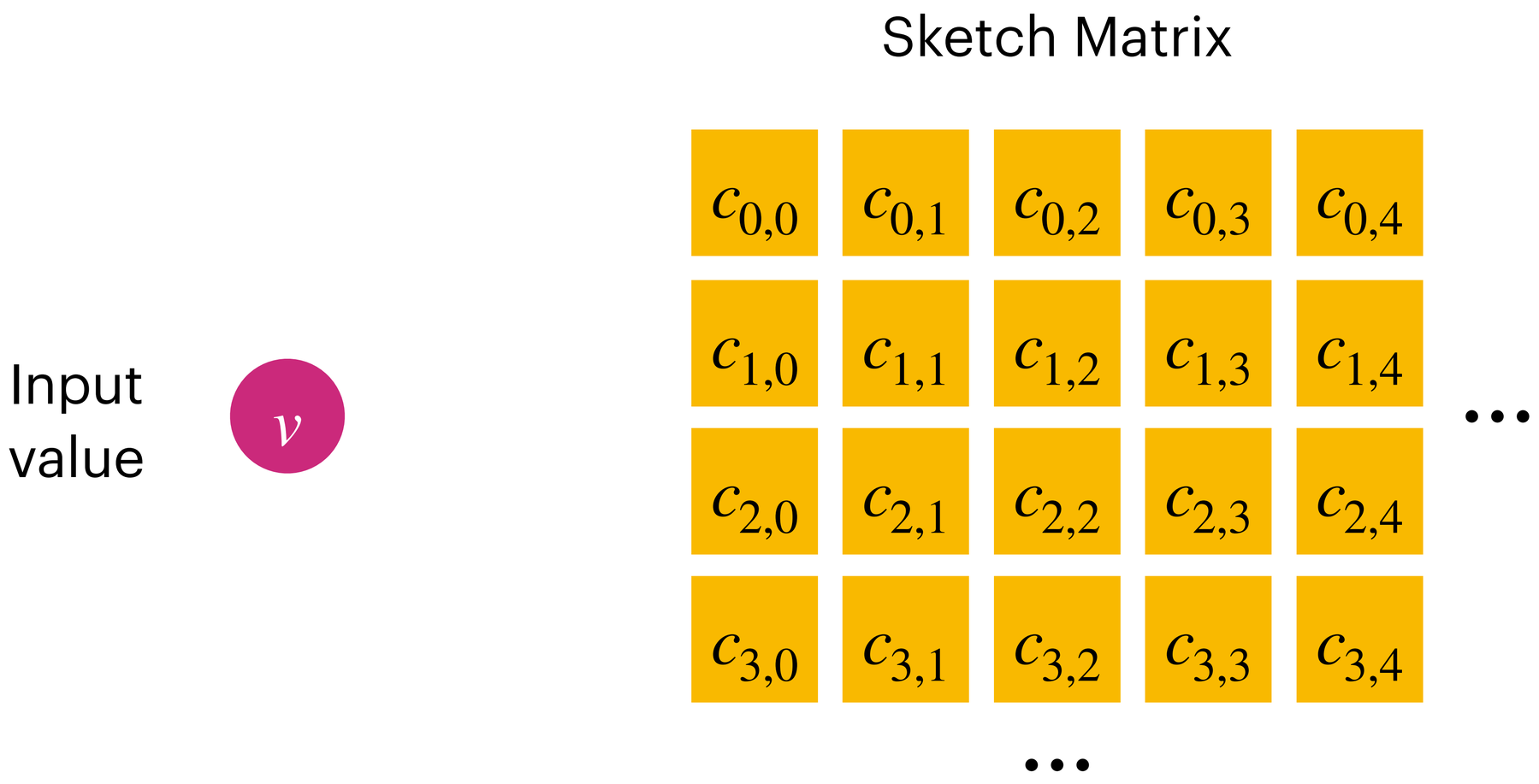
Compilations Report, Bitstream

Optimal Parameters,
Bitstream

FPGA

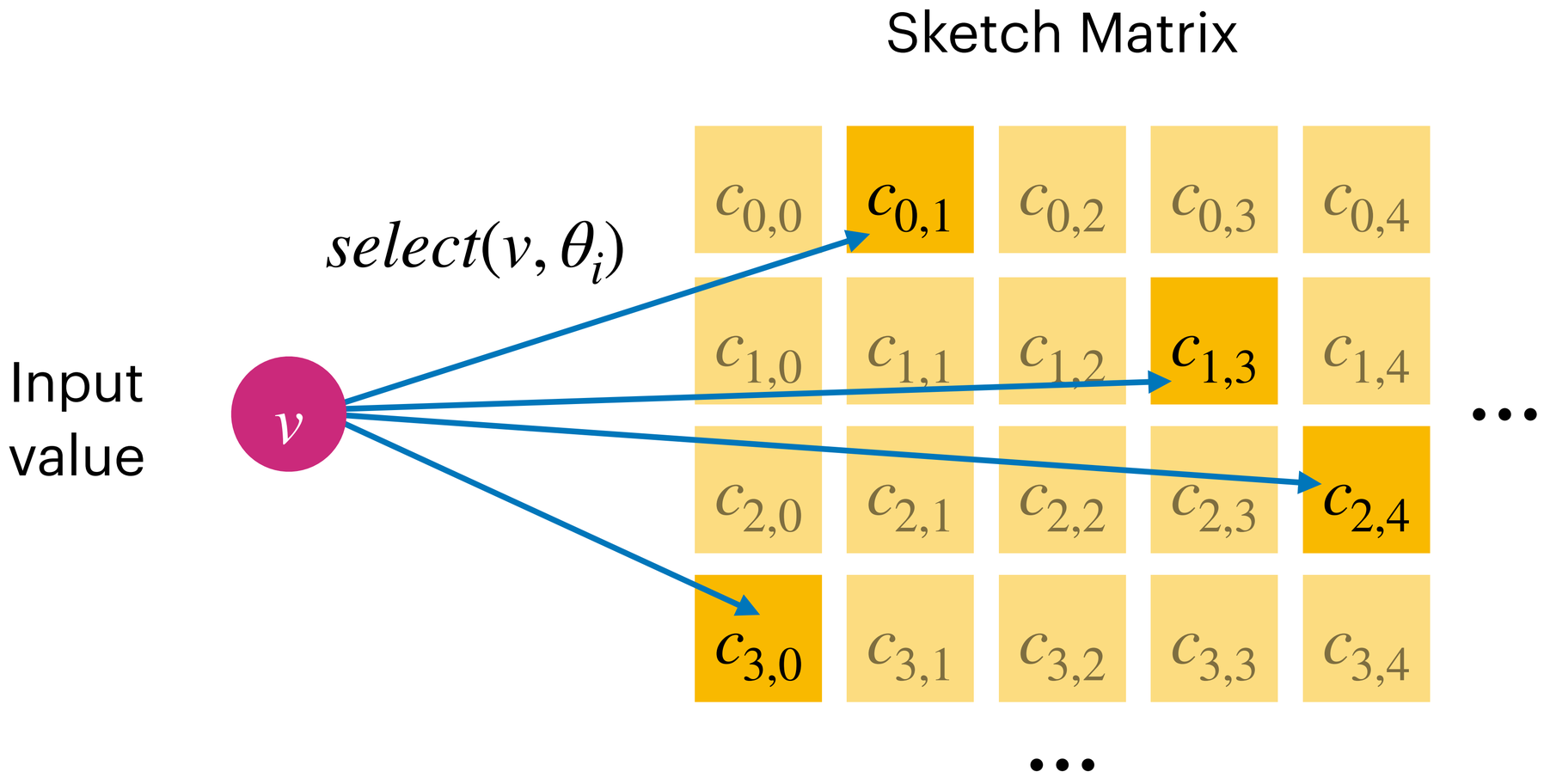
Select-Update Model

Lightweight sketch specification



Select-Update Model

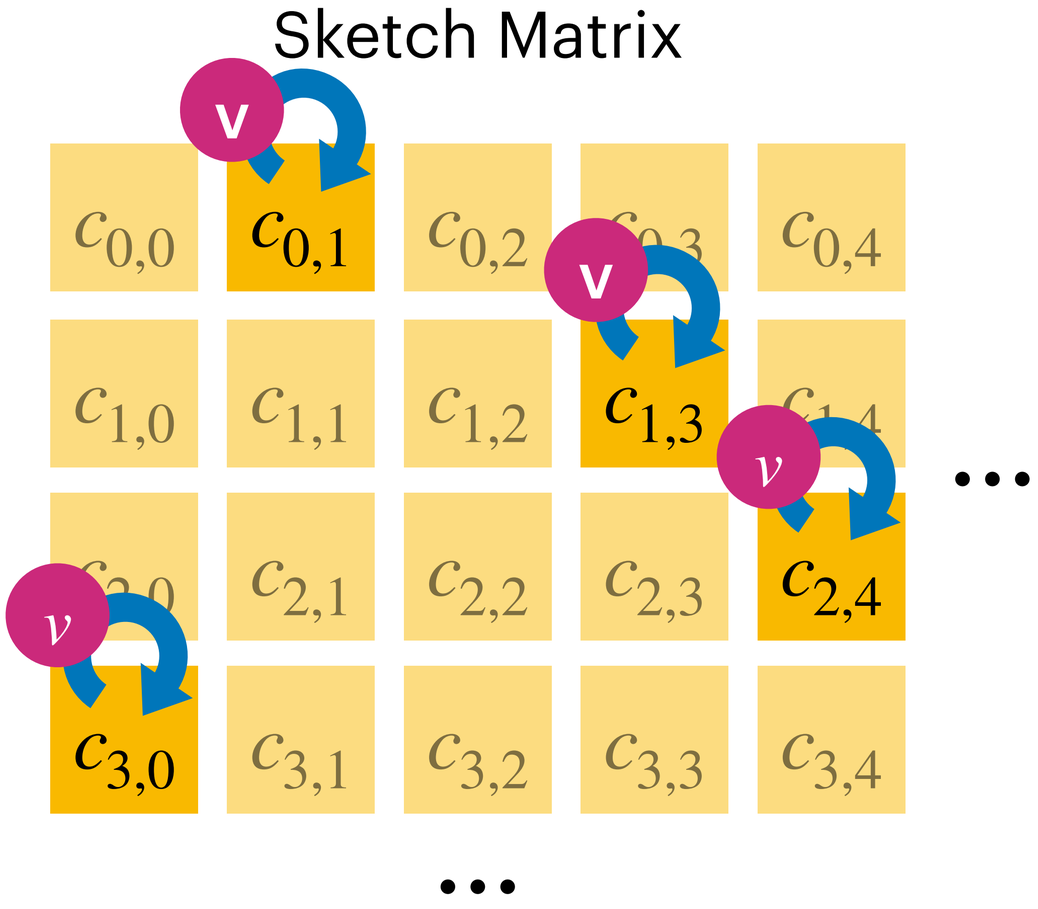
Select one entry in each row



Select-Update Model

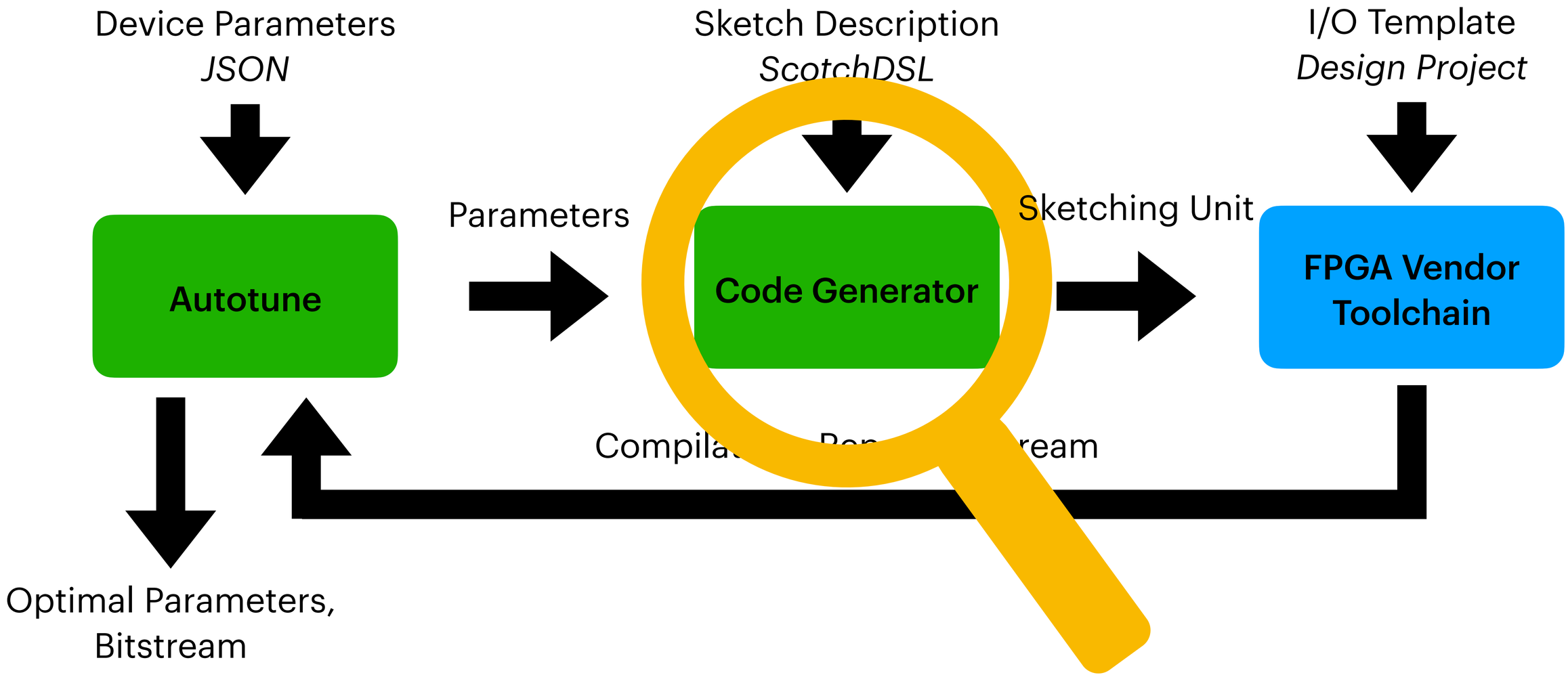
Update the selected entry

$update\ (v, \theta_i, c_{0,1})$



Scotch System Architecture

Generating and optimizing in a feedback-loop



High-Level RTL Architecture

Processing at line-rate

For each row:

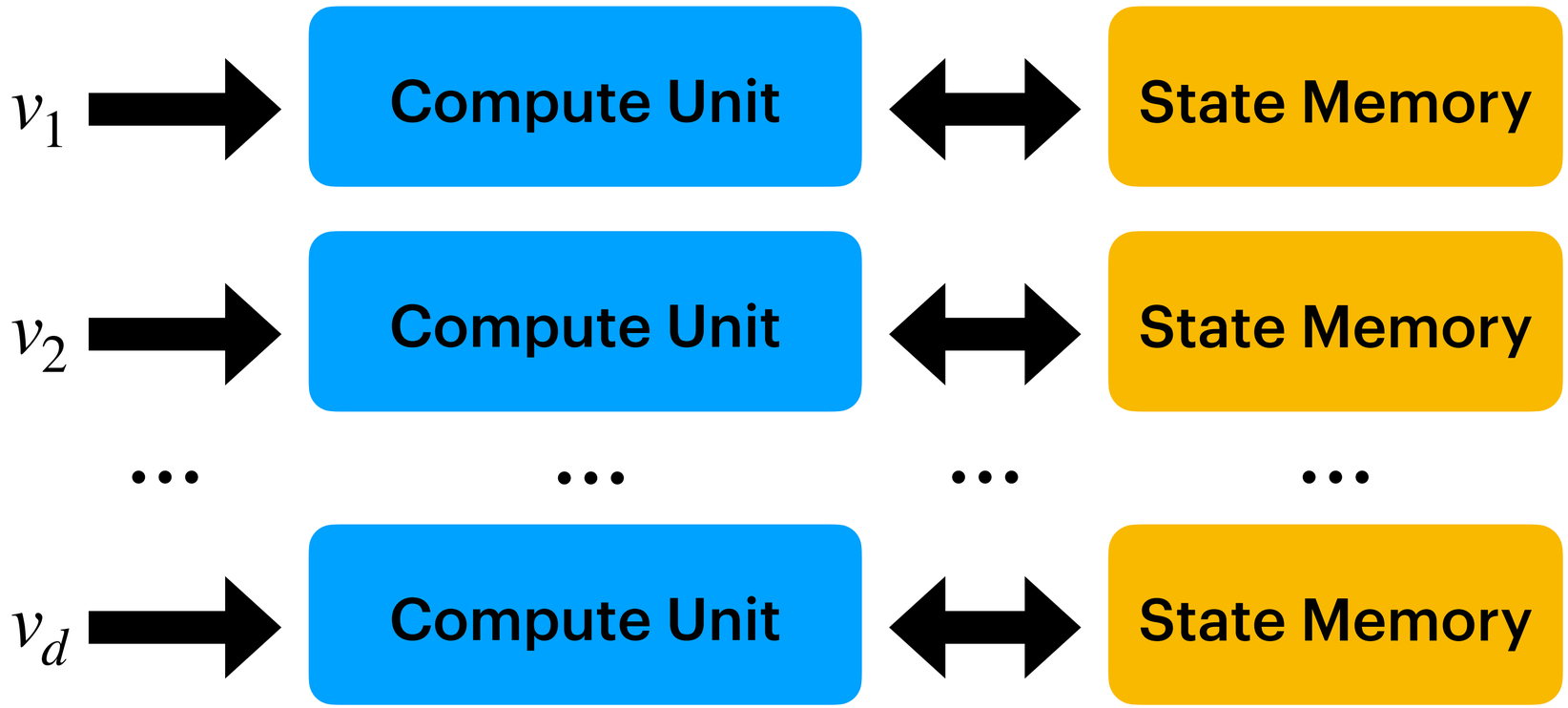
- Computes evaluates select/update
- One input value per cycle

- Pipelined random access memory
- One read & write operation per cycle

Data Parallelism

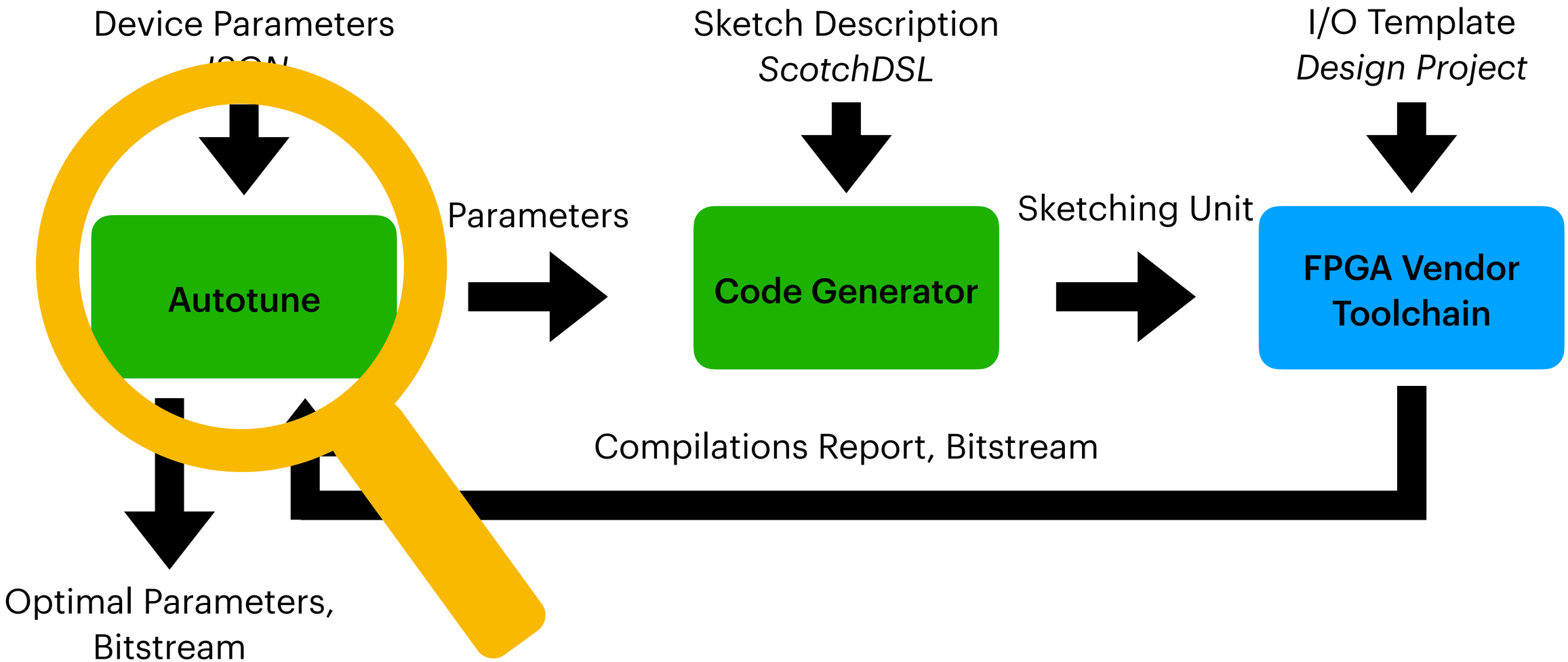
General Approach: Processing at line-rate via full replication

For each row:



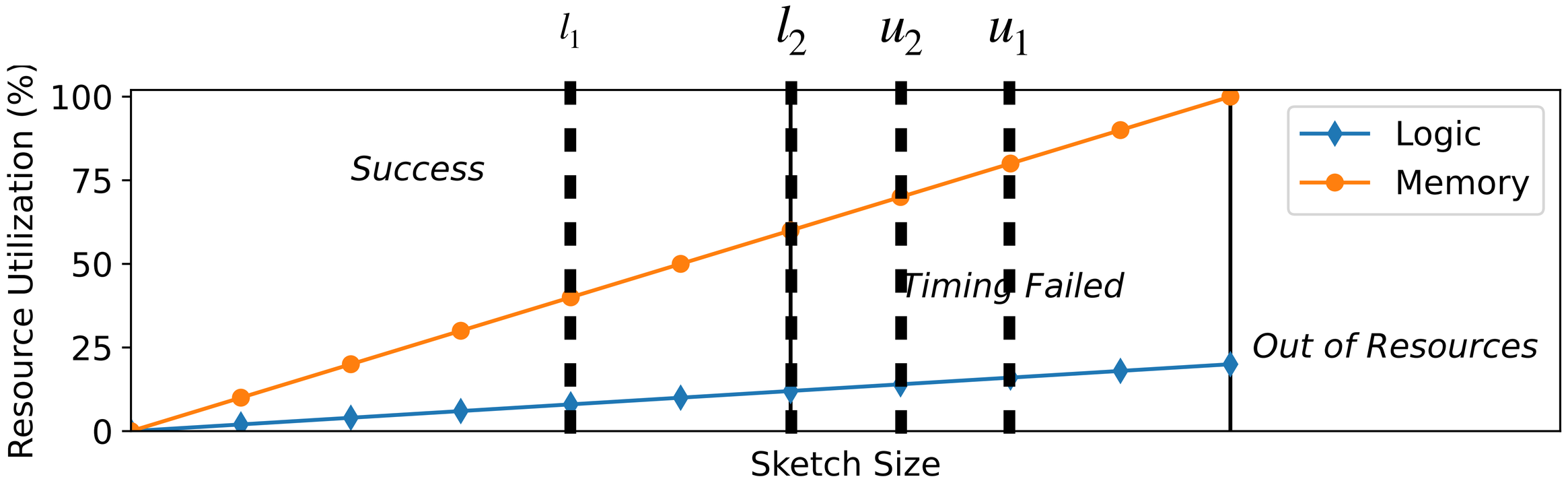
Scotch System Architecture

Generating and optimizing in a feedback-loop



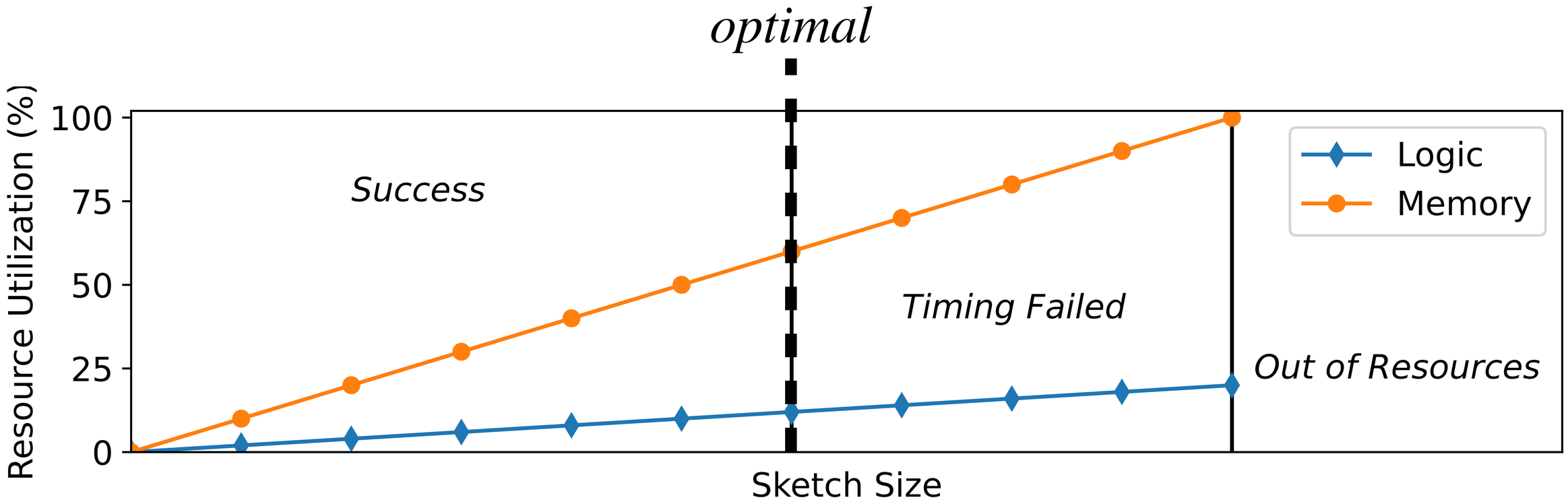
Automated Tuning

Finding the largest sketch size that works



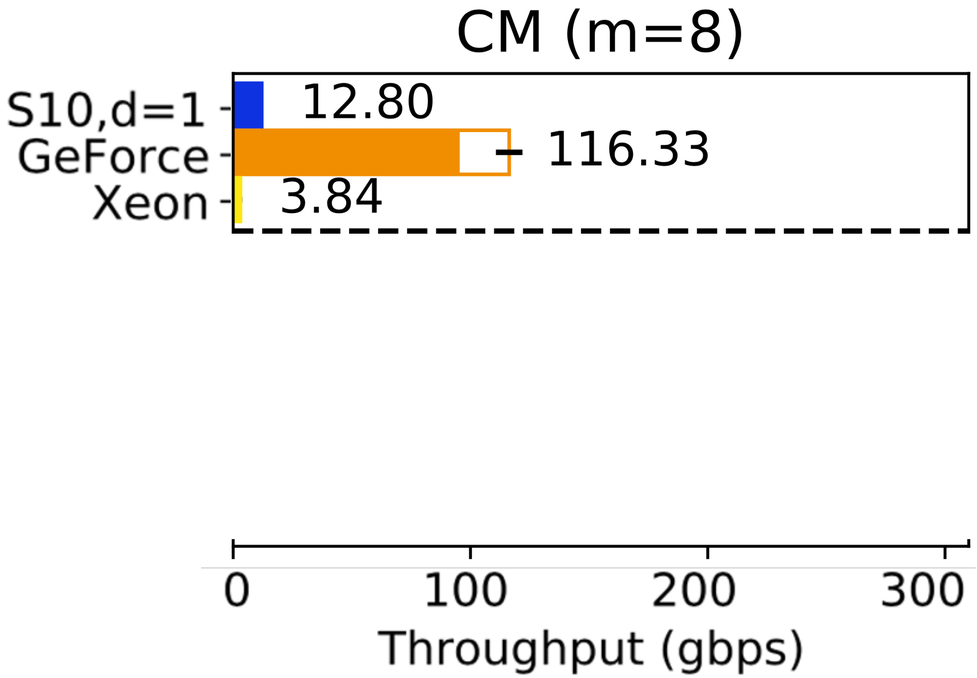
Automated Tuning

A binary search for optimal parameters



Evaluation: Throughput

Matrix sketch (m=8 rows)

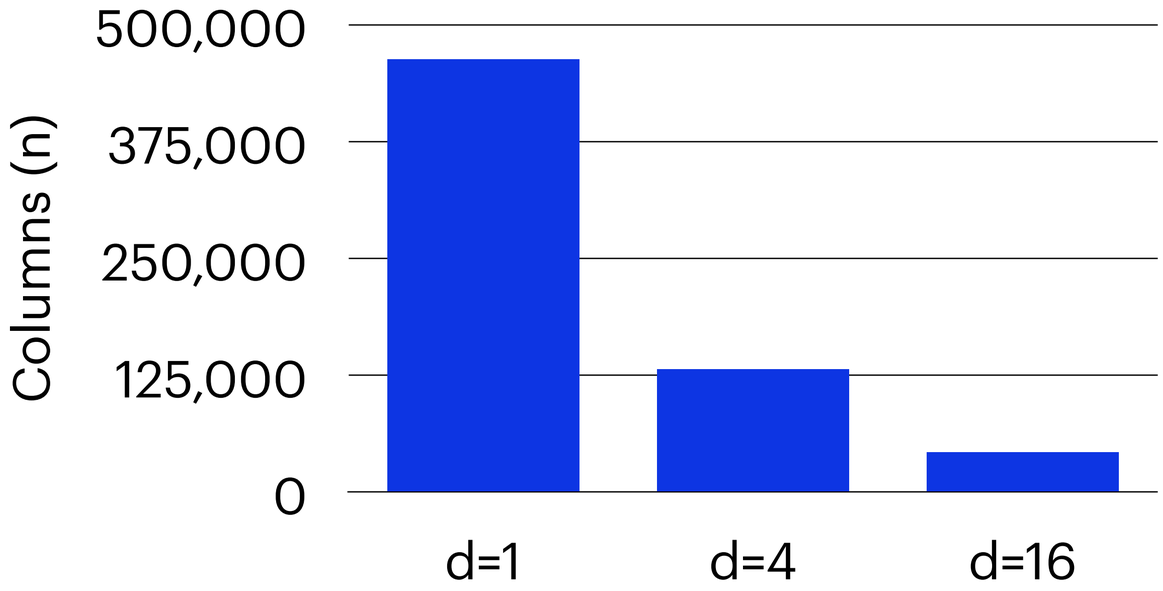


- Data parallelism is crucial for high throughput

Stratix 10 GX 2800, 400MHz | Nvidia GeForce RTX 2080 | 2x Intel Xeon Silver 4214 | 32 Bit State & Input | Uniform Data

Evaluation: Sketch Size

Matrix sketch (m=8 rows)



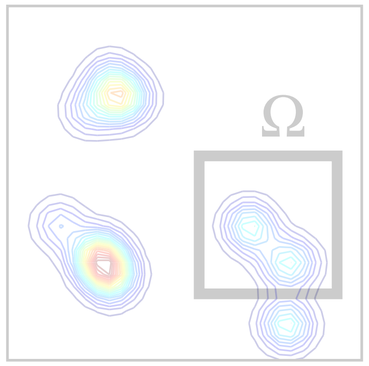
- Summary size reduces proportionate to number of inputs d

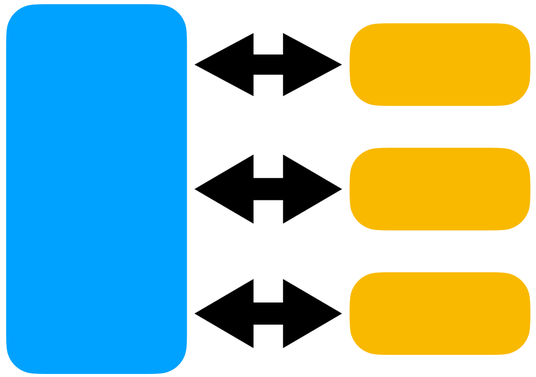
Stratix 10 GX 2800, 400MHz | Nvidia GeForce RTX 2080 | 2x Intel Xeon Silver 4214 | 32 Bit State & Input | Uniform Data

Optimistic Data Parallelism for FPGA-Accelerated Sketching

Martin Kiefer, Ilias Poulakis, Eleni Tzirita Zacharatou, Volker Markl

Proceedings of the VLDB Endowment, 16 (5), 2023

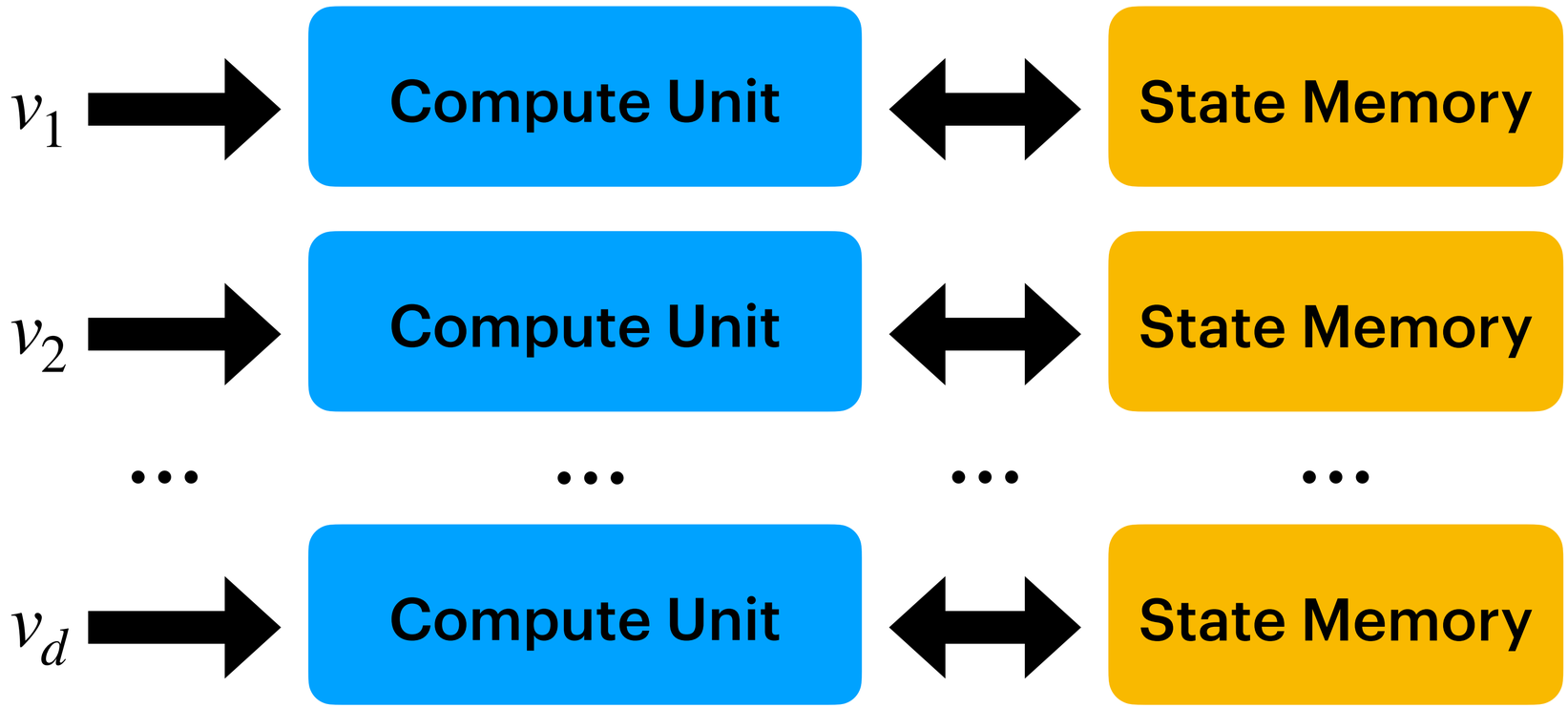




Pessimistic Data Parallelism

Guaranteed processing rates at the

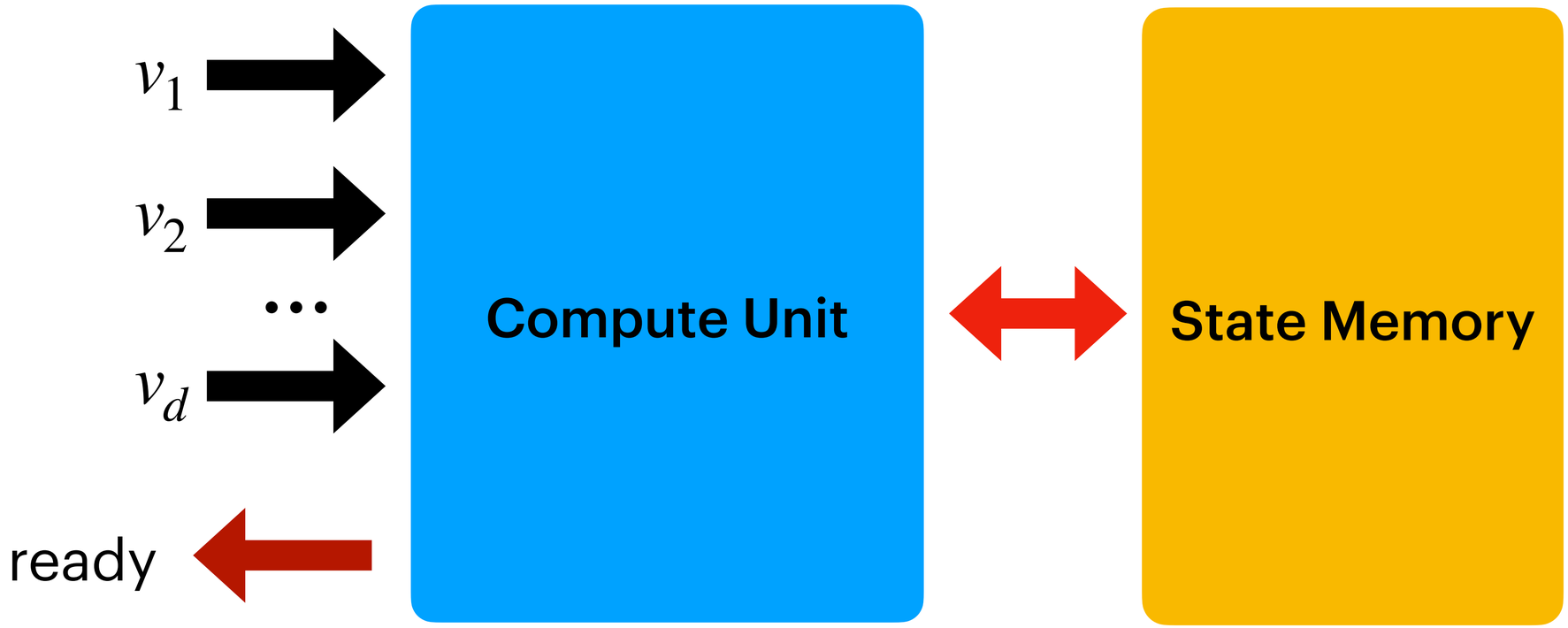
For each row:



Sharing the State Memory

Sharing the state memory across input values

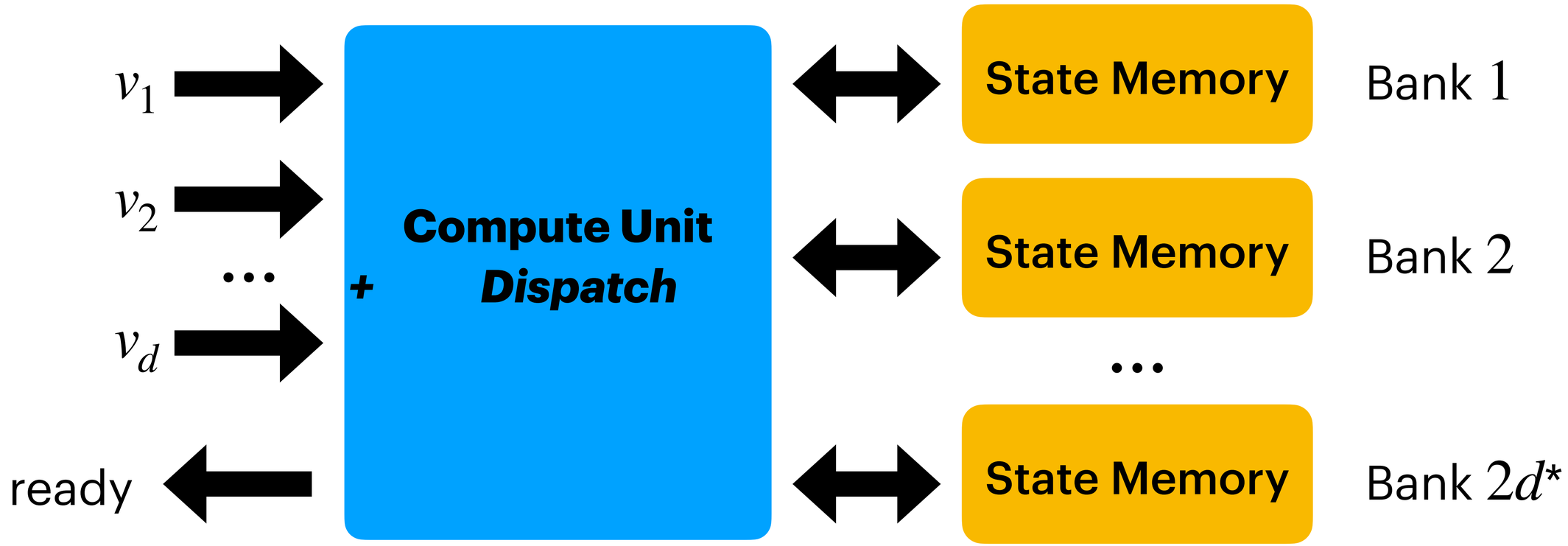
For each row:



Optimistic Architecture

Split the state memory into multiple banks

For each row:

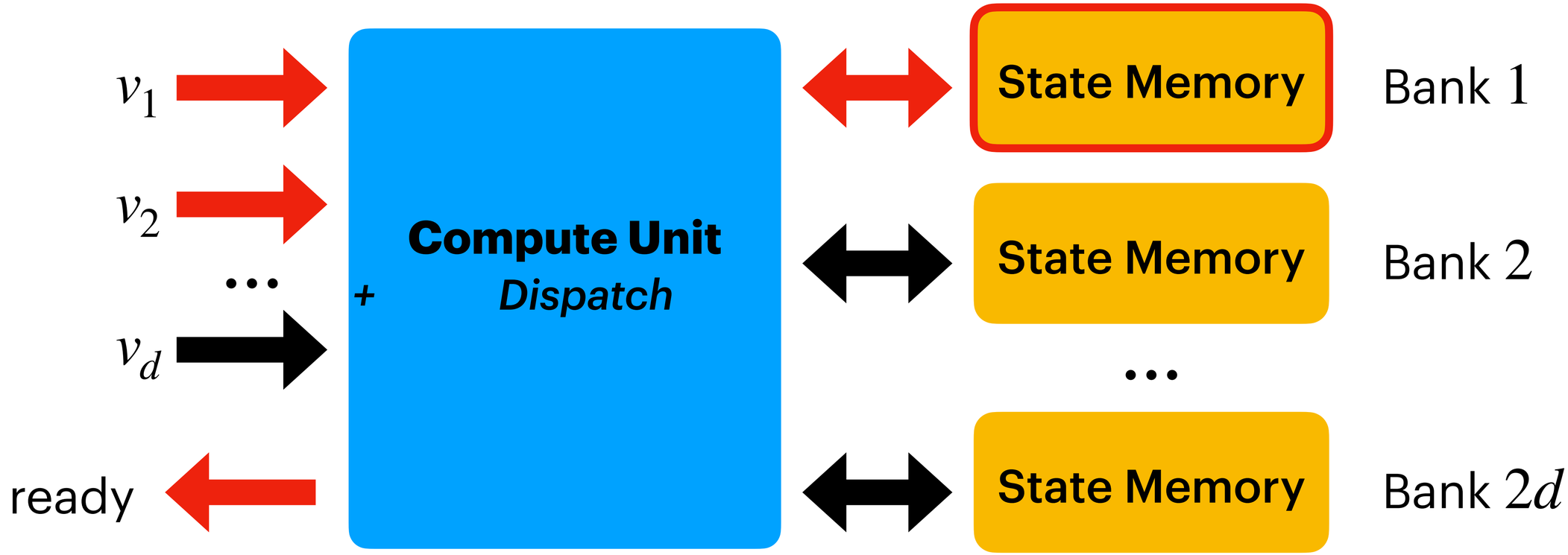


*** Oversubscribed Configuration**

Optimistic Architecture

Problem: Resource congestion + uniform data

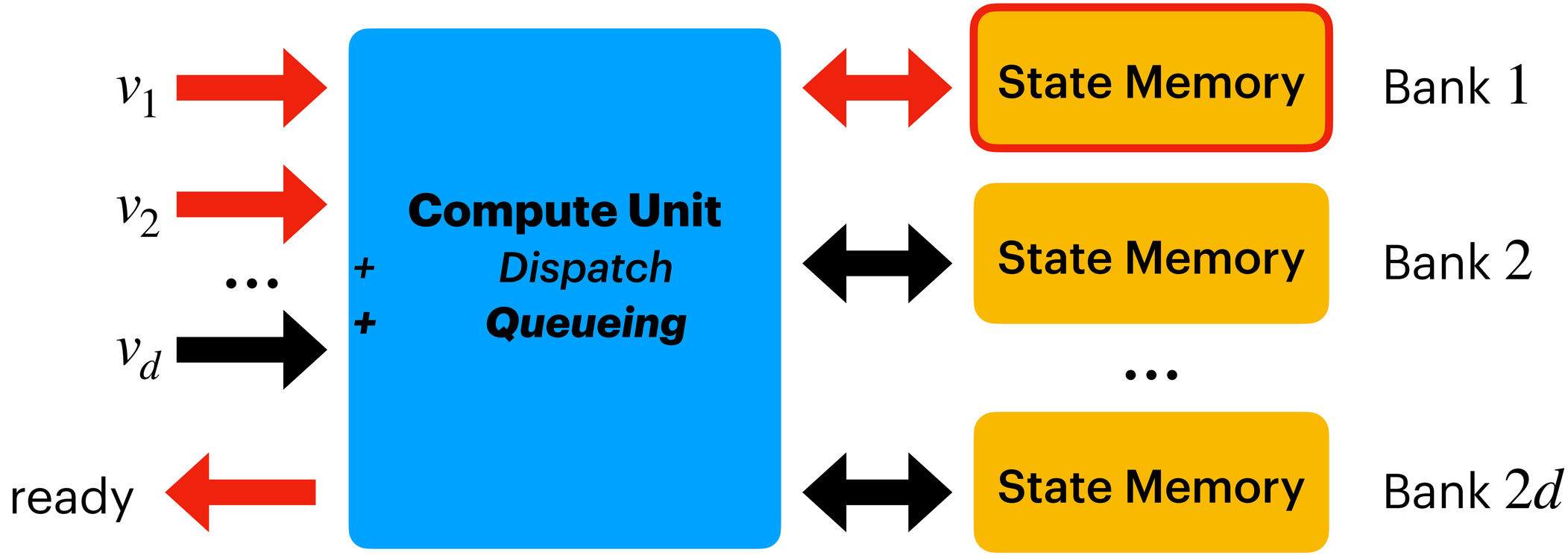
For each row:



Optimistic Architecture

Problem: Resource congestion + uniform data

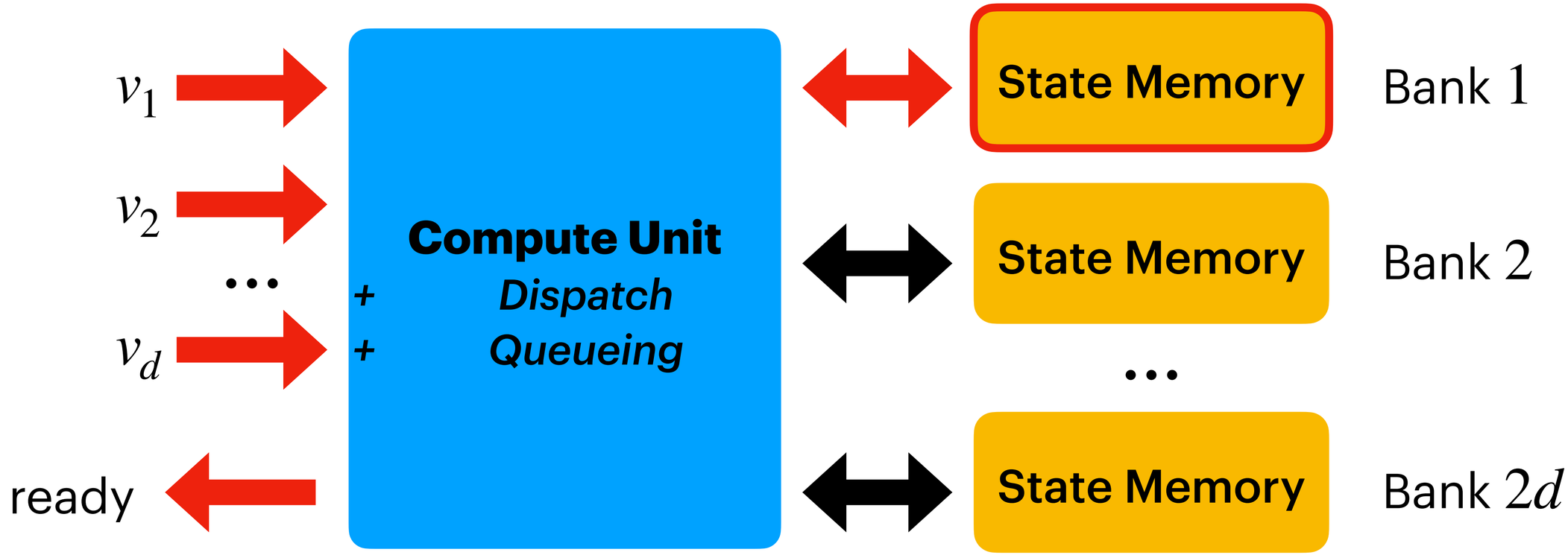
For each row:



Optimistic Architecture

Problem: Resource congestion + skewed data

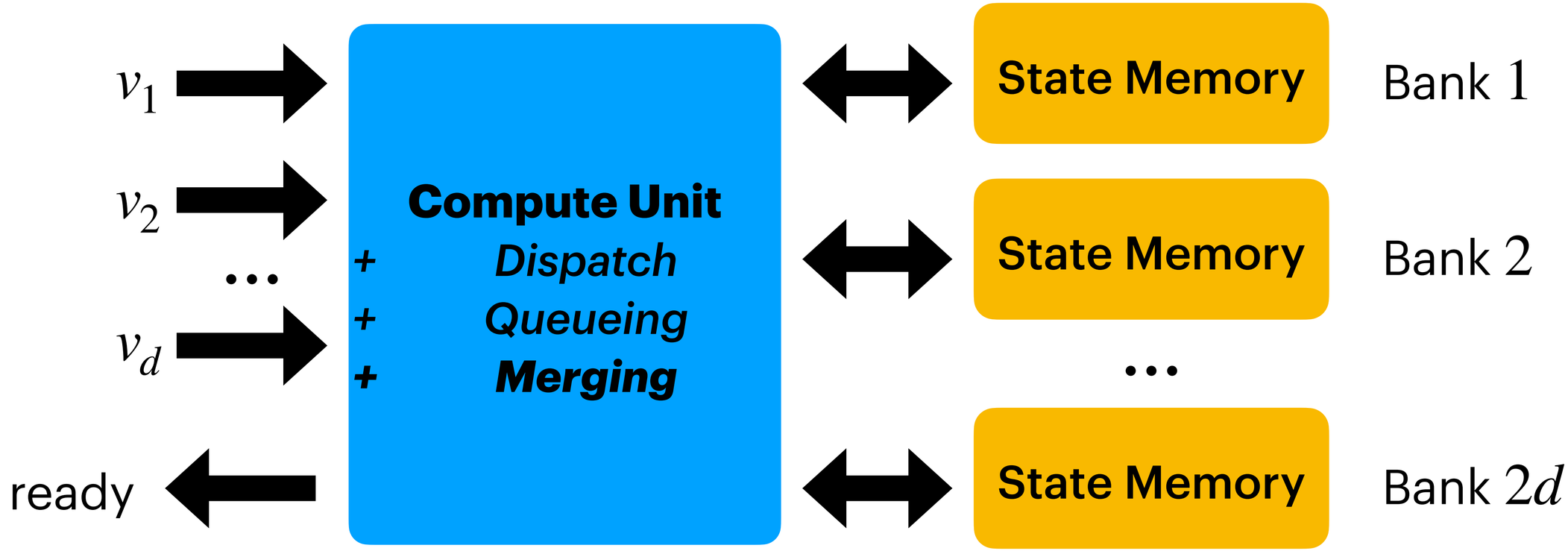
For each row:



Optimistic Architecture

Banking + Queues + Mergers

For each row:

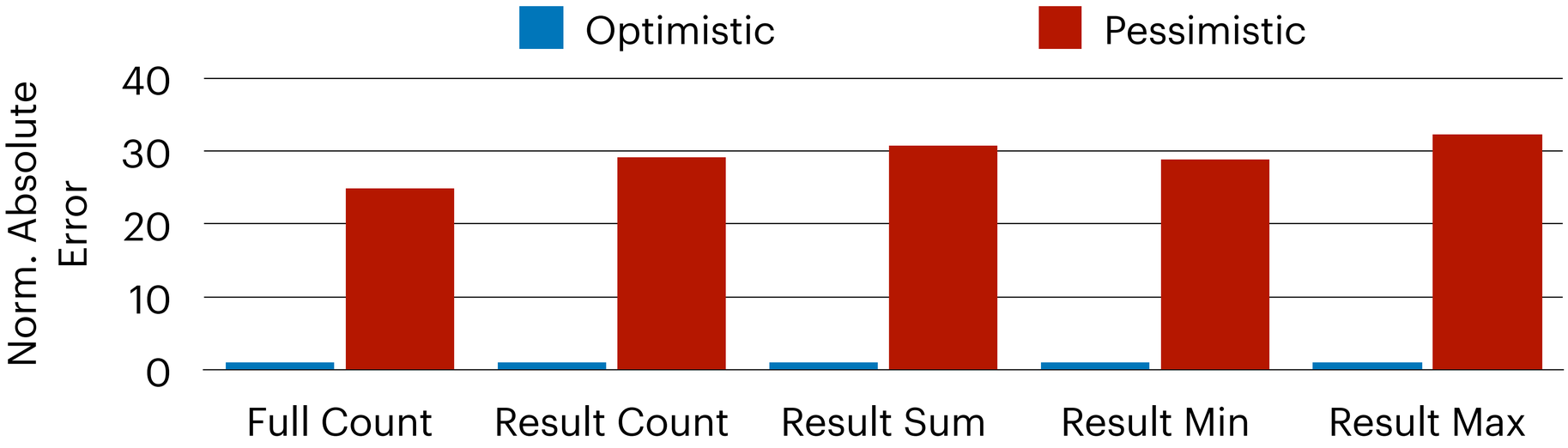


Evaluation: Sketch Size & Accuracy

Approx. Query Processing: Optimistic vs. Pessimistic

- Maximum sketch size
  - Pessimistic: $n = 2,\ m = 4096 \cdot \mathbf{5}$
  - Optimistic: $n = 2,\ m = 4096 \cdot \mathbf{32}$

$6.4x$
larger sketches



$25 - 32x$
better estimates

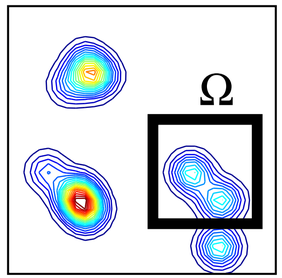
Queue Size = 64, NYT Dataset, Vertical Merging + Horizontal Merging h=2

Conclusion

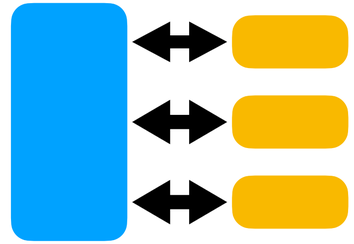
Summary

Approximate data analysis with parallel processors

- **Highly efficient approximate analyses in two use cases**
  - Selectivity estimation & sketching



- **Generalizations and abstractions**
  - Join support for KDE models
  - *M*odels & generators for sketching on FPGAs

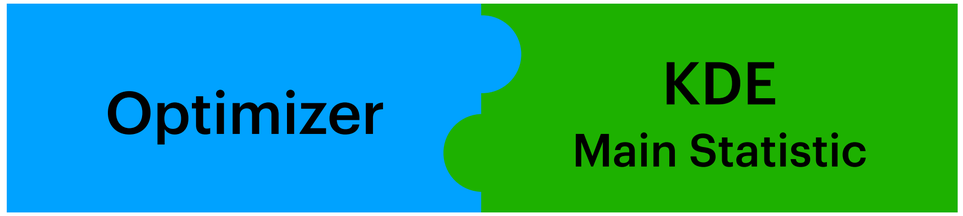


- **Hiding the complexity of parallel processors**
  - GPU hidden behind the query optimizer
  - Autotune & code generator perform expert tasks

Conclusion

The bigger picture: Applicability

- **KDE for selectivity estimation**
  - Towards a general framework
  - Sampling + histograms + ML
  - Statistical coprocessing



- **FPGA-accelerated sketching**
  - Accessible to systems engineers
  - Statistics collection in the data path