

Relational Memory:

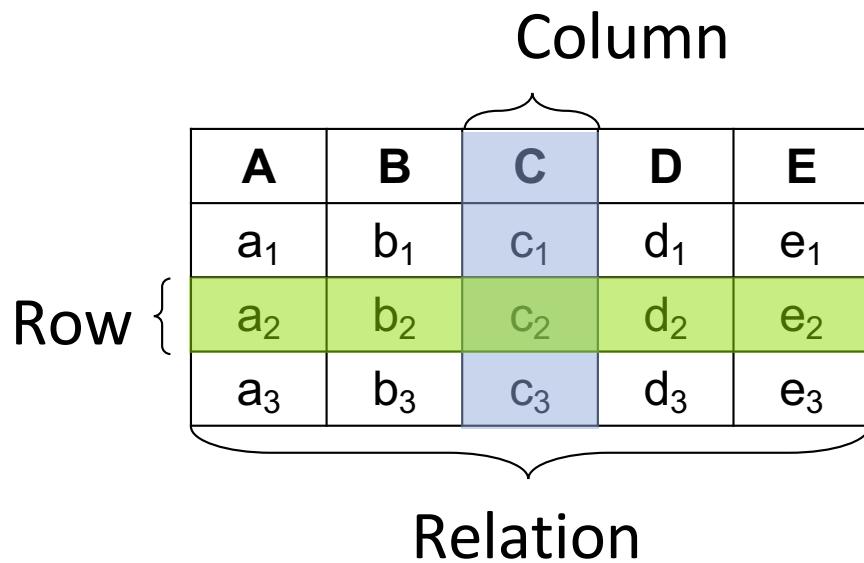
Native In-Memory Accesses on Rows and Columns

Ju Hyoung Mun



Red Hat

Relational Databases are everywhere



ORACLE®
D A T A B A S E

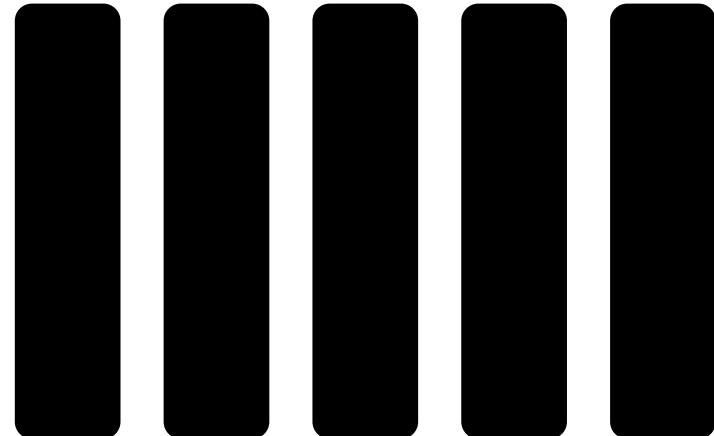


Data Layouts

row-stores



column-stores

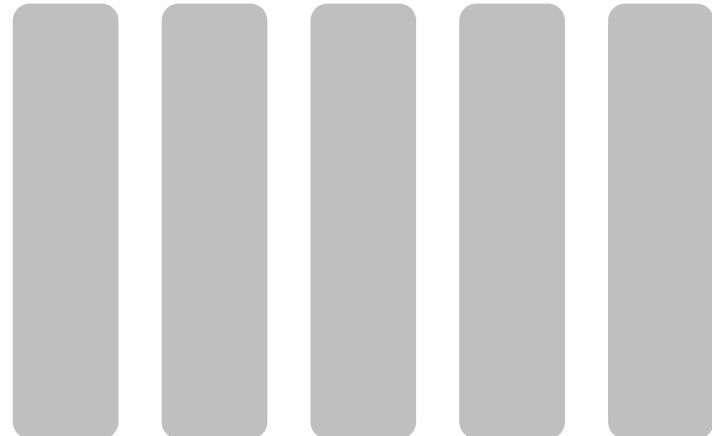


Data Layouts

row-stores



column-stores



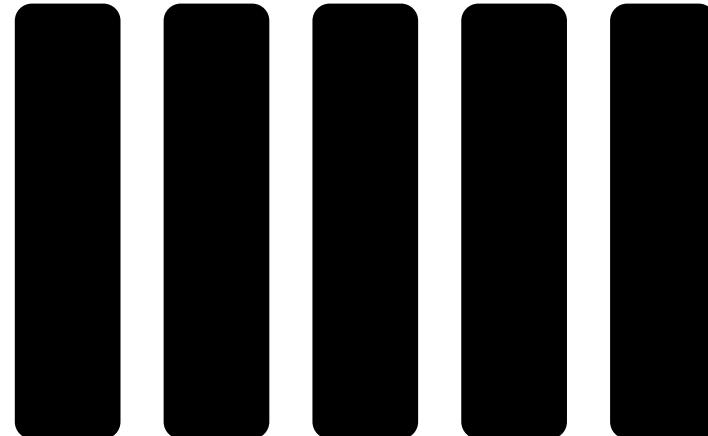
Transactional

Data Layouts

row-stores

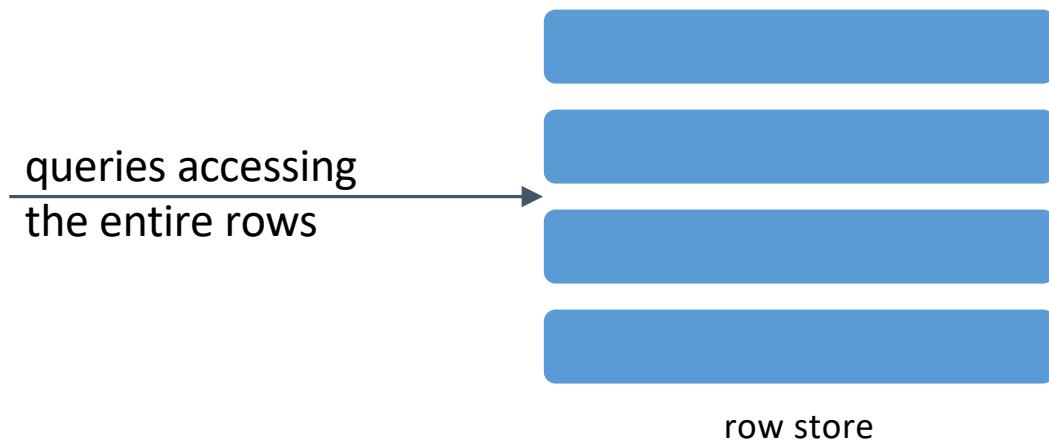


column-stores



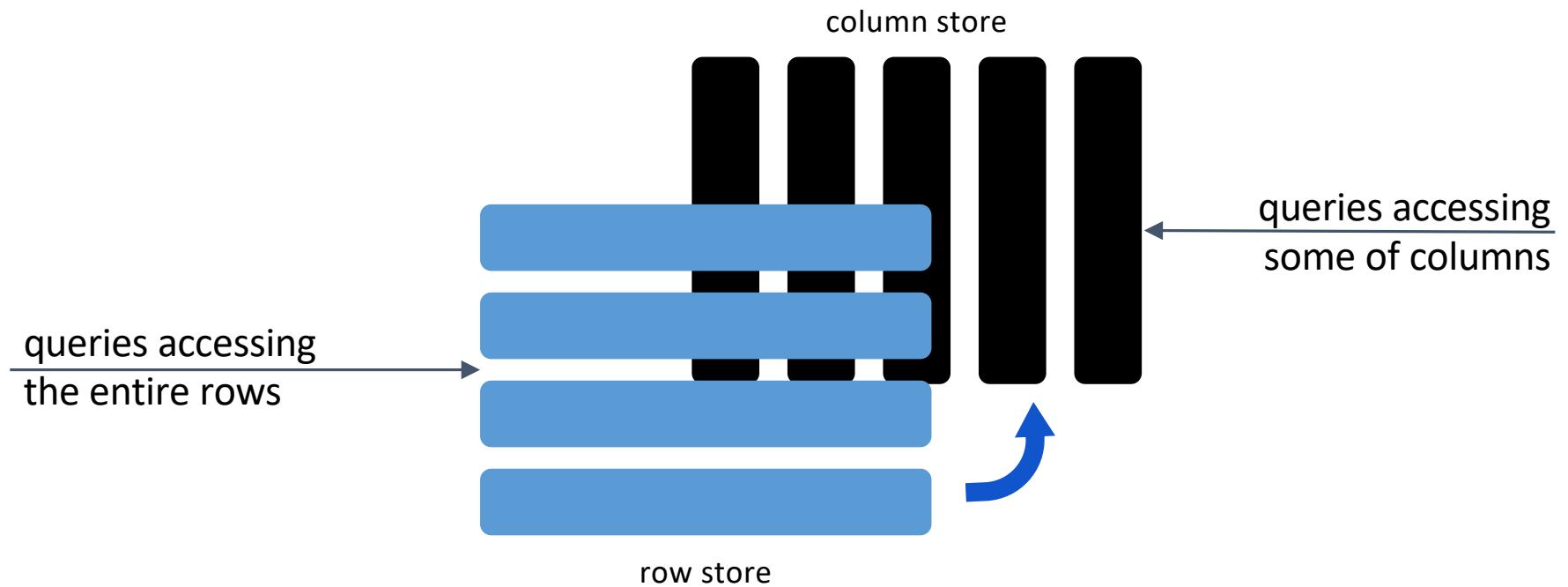
Analytical

Adaptive layout



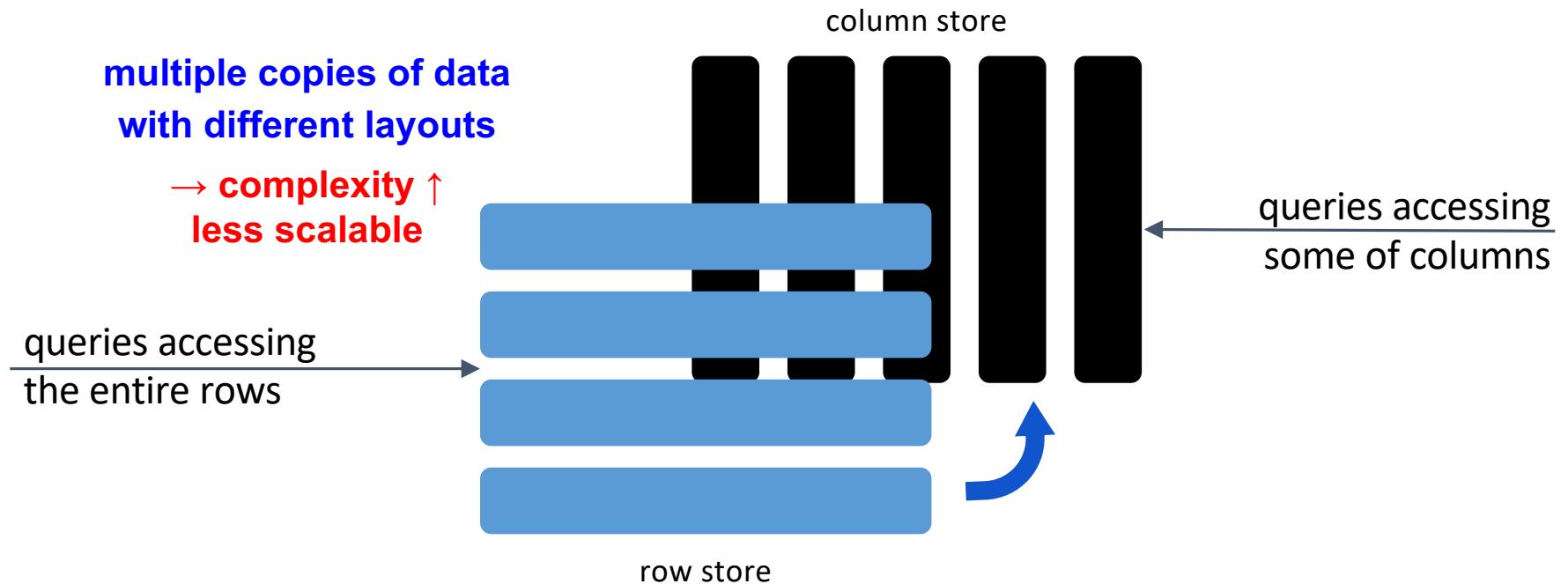
E.g., H2O (ACM SIGMOD, 2014), HyPer (IEEE ICDE , 2011), Peloton (ACM SIGMOD, 2016), OctopusDB (CIDR, 2011)

What are the disadvantages of the adaptive layout?



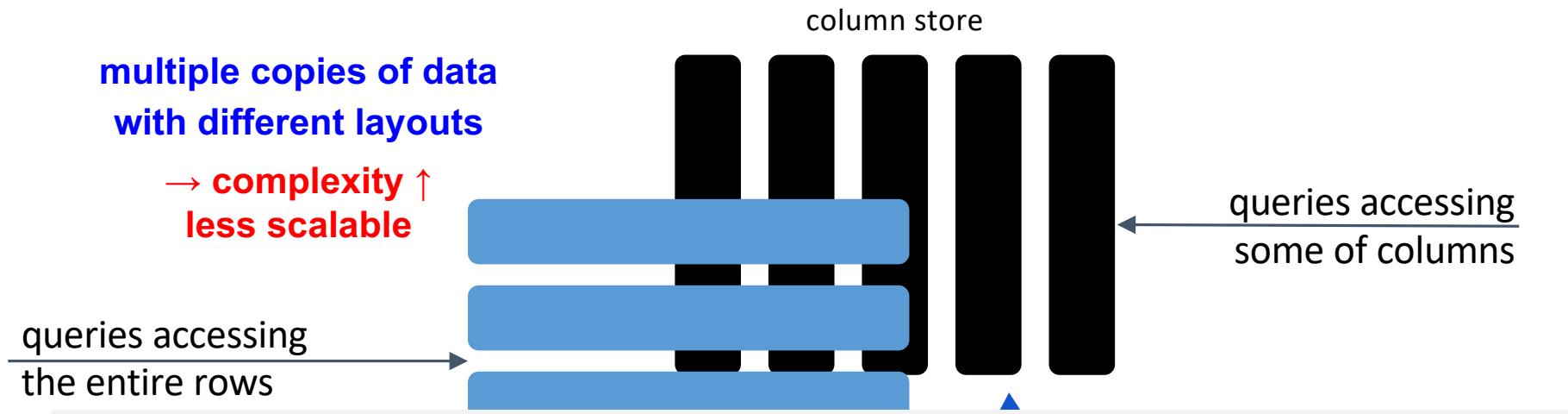
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Adaptive layout



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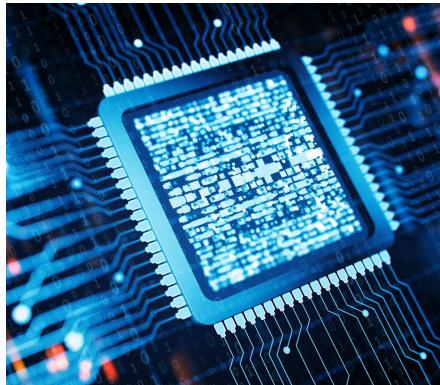
Adaptive layout



What if there is a shift over columns?

E.g., H2O (ACM SIGMOD, 2014), HyPer (IEEE ICDE , 2011), Peloton (ACM SIGMOD, 2016), OctopusDB (CIDR, 2011)

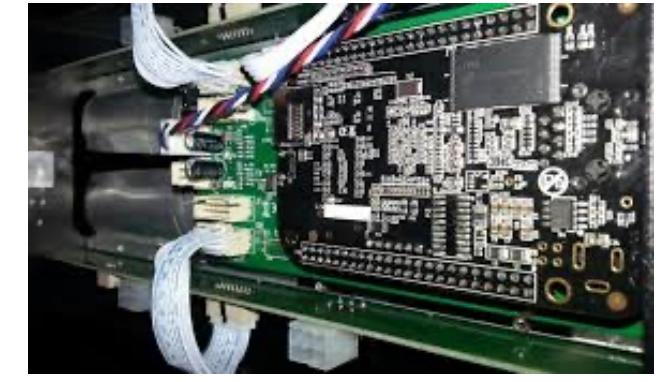
How can we access
only the desired columns
without storing or maintaining
multiple copies of data?



a novel hardware design
for data transformation
Relational Memory

What is Hardware?





Application-Specific Integrated Circuits (ASICs)

Advantages of Hardware Accelerators

Advantages

- Speedup
- Reduced power consumption
- Lower latency
- Increased parallelism and bandwidth
- Better utilization of area and functional components available on an integrated circuit

Advantages of Hardware Accelerators

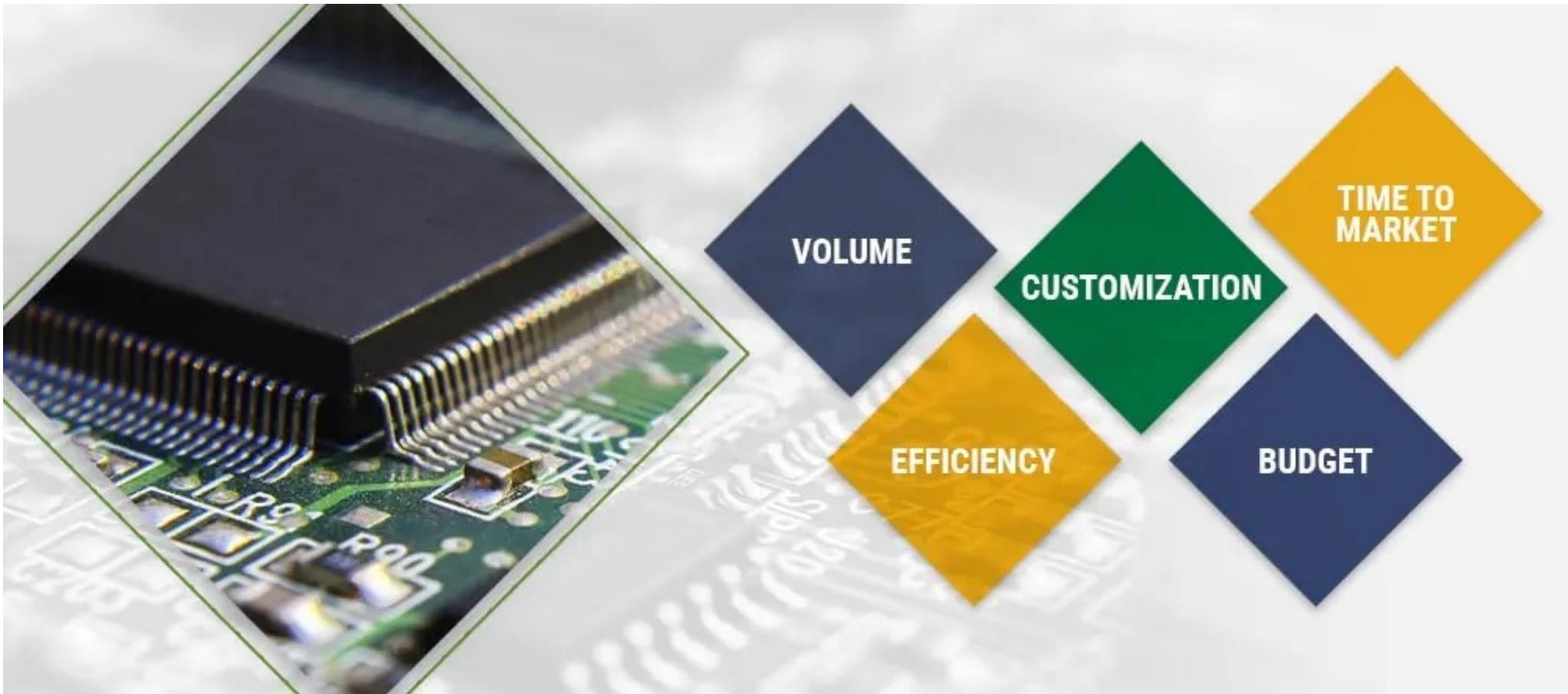
Advantages

- Speedup
- Reduced power consumption
- Lower latency
- Increased parallelism and bandwidth
- Better utilization of area and functional components available on an integrated circuit

Disadvantages

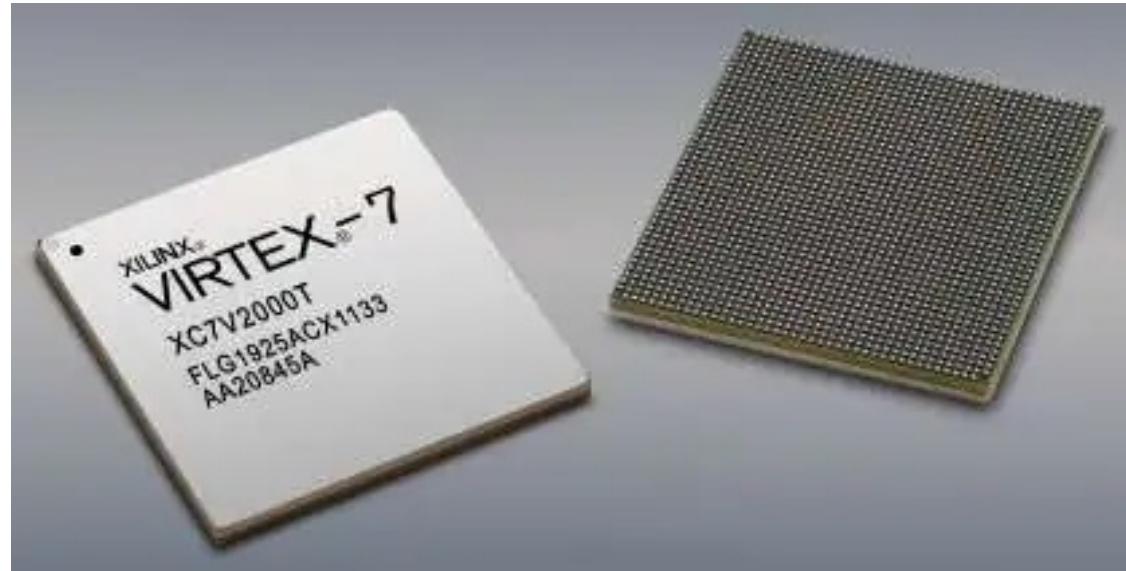
- Lower flexibility
- Higher costs of functional verification and times to market

ASICs

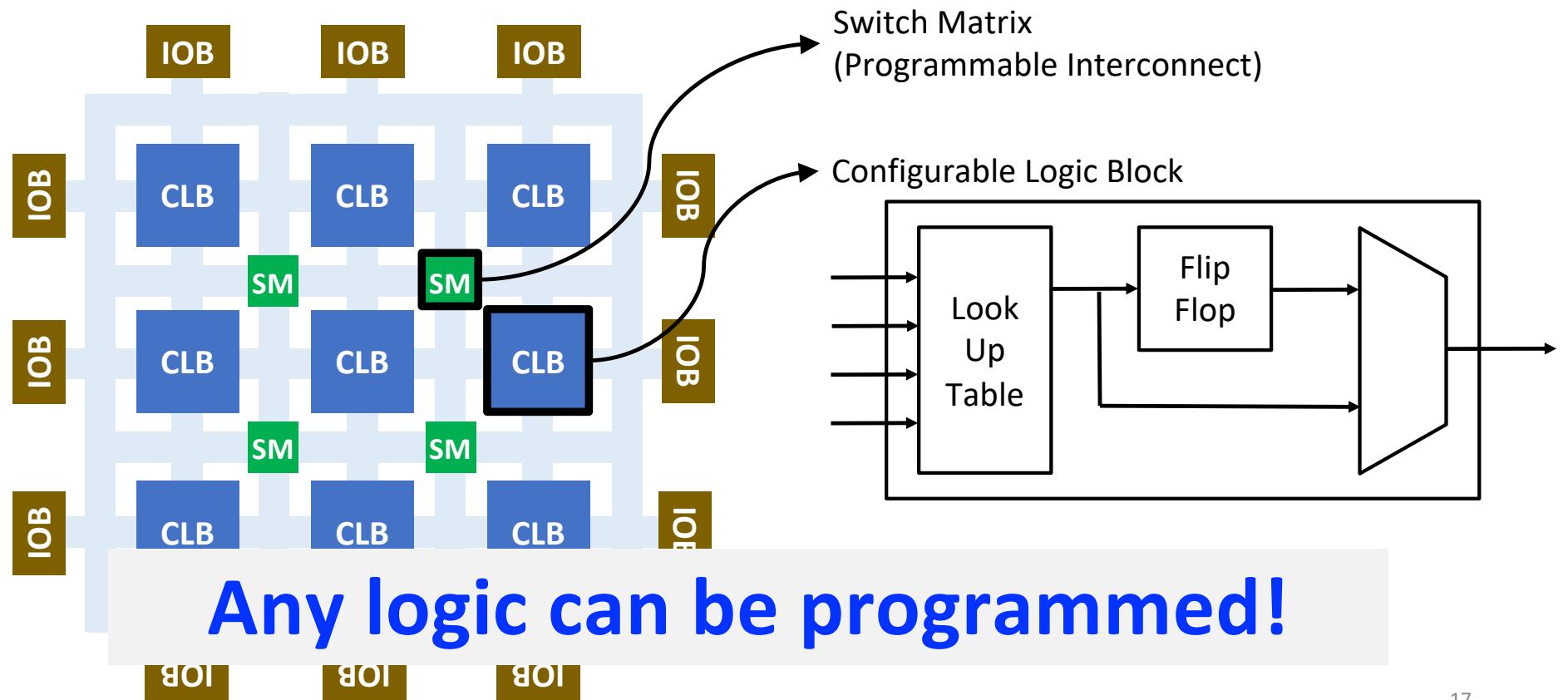


Programmable Logic

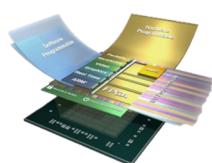
Field Programmable Gate Arrays (FPGAs)



Architecture of Programmable Logic

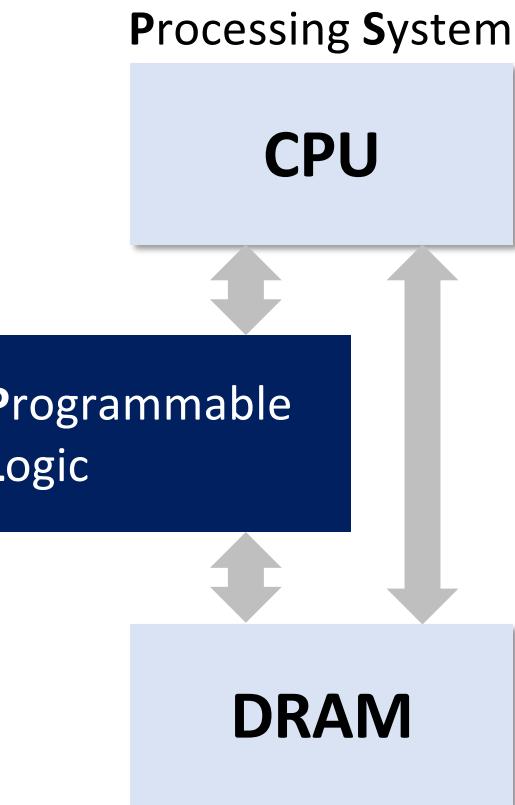


PS-PL Platforms

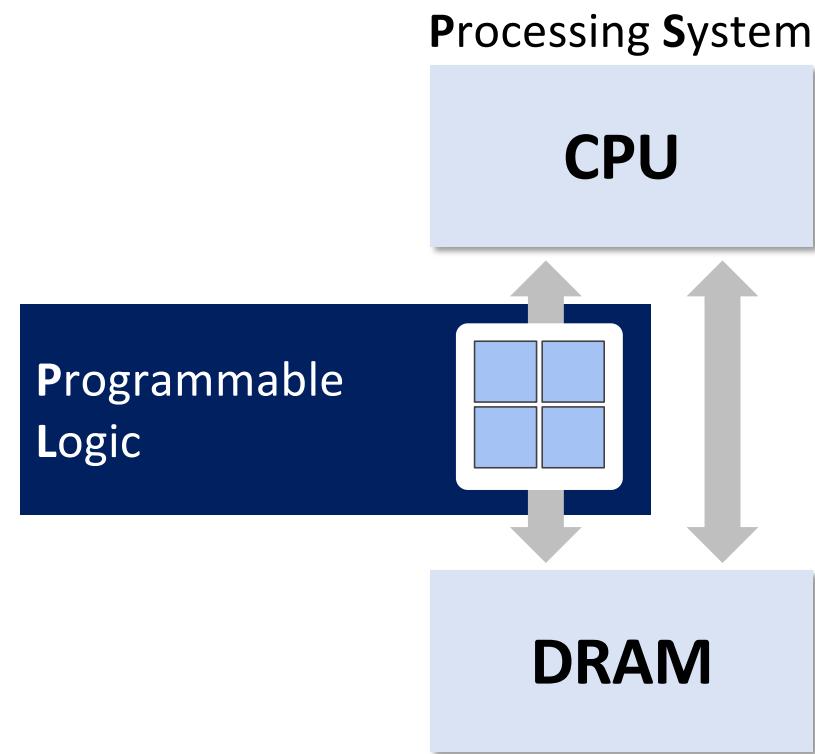


AMD
XILINX
UltraScale+ 

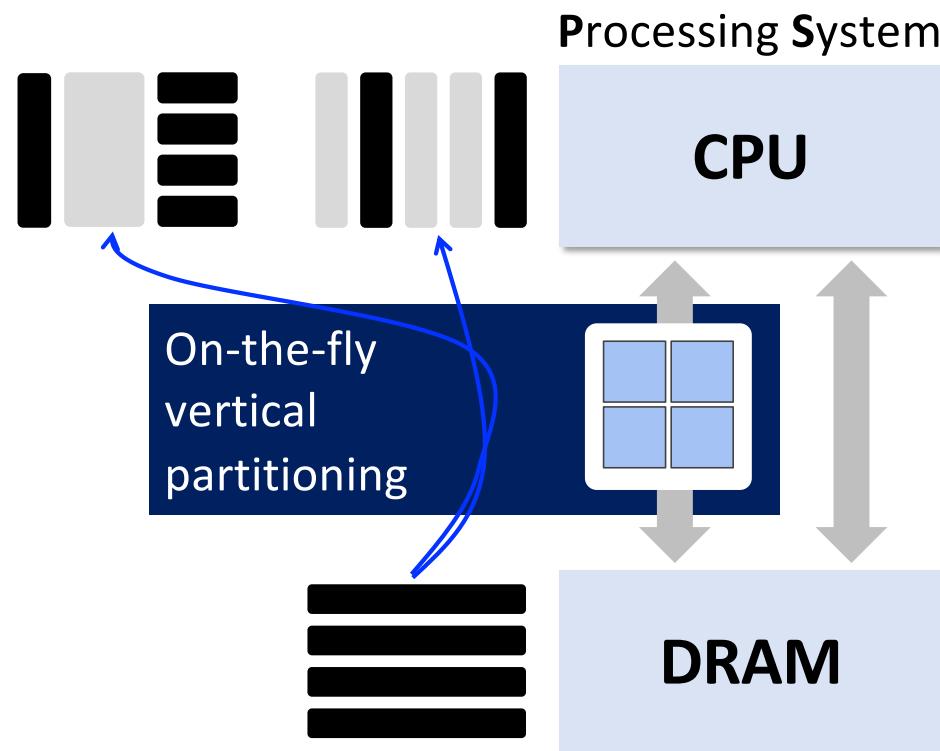
intel.
AGILEX™



Relational Memory Engine



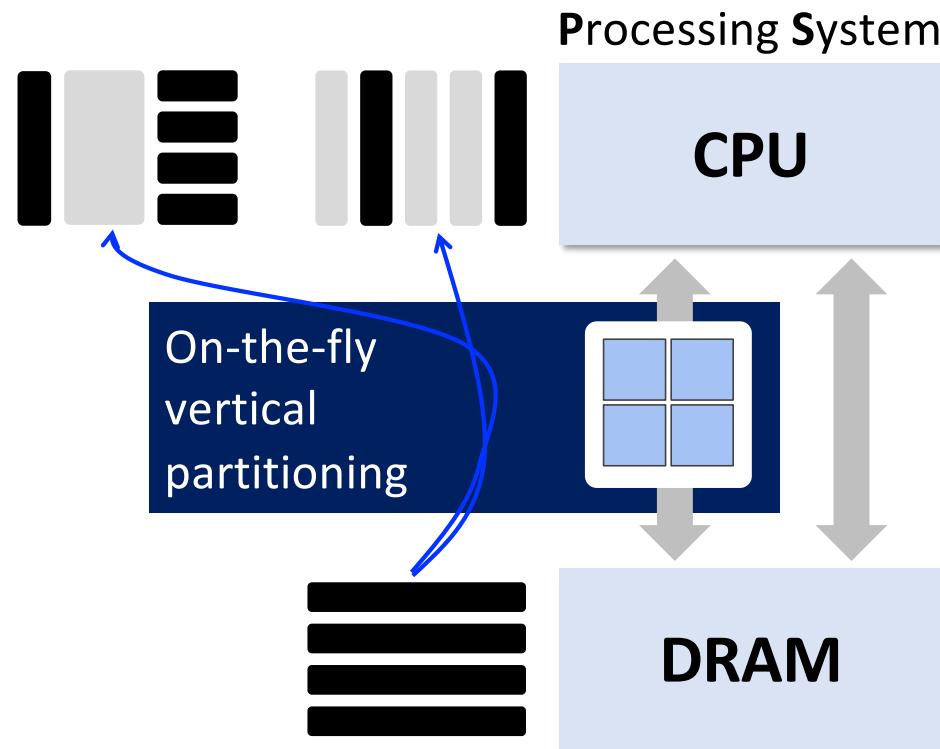
Relational Memory Engine



Q1: how to build?

Q2: how to use?

Relational Memory Engine



ephemeral variable

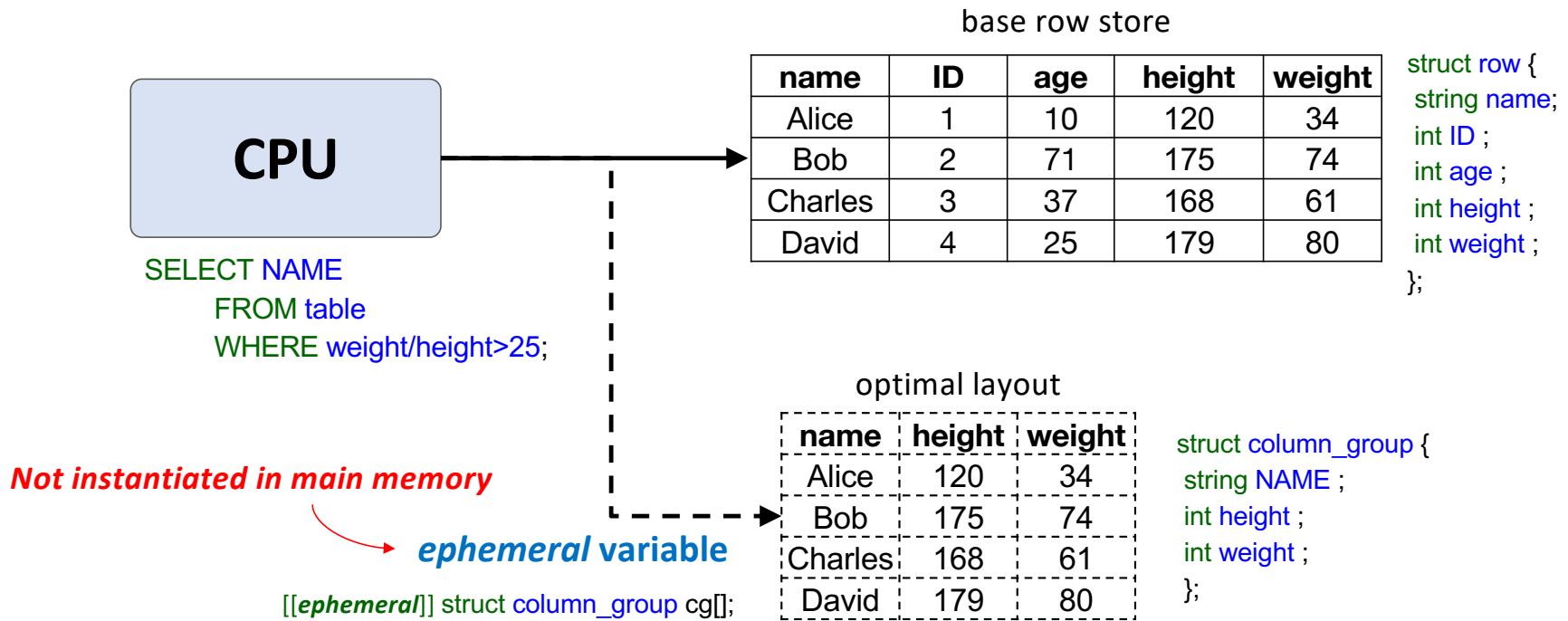
a simple, lightweight programming abstraction
to use Relational Memory

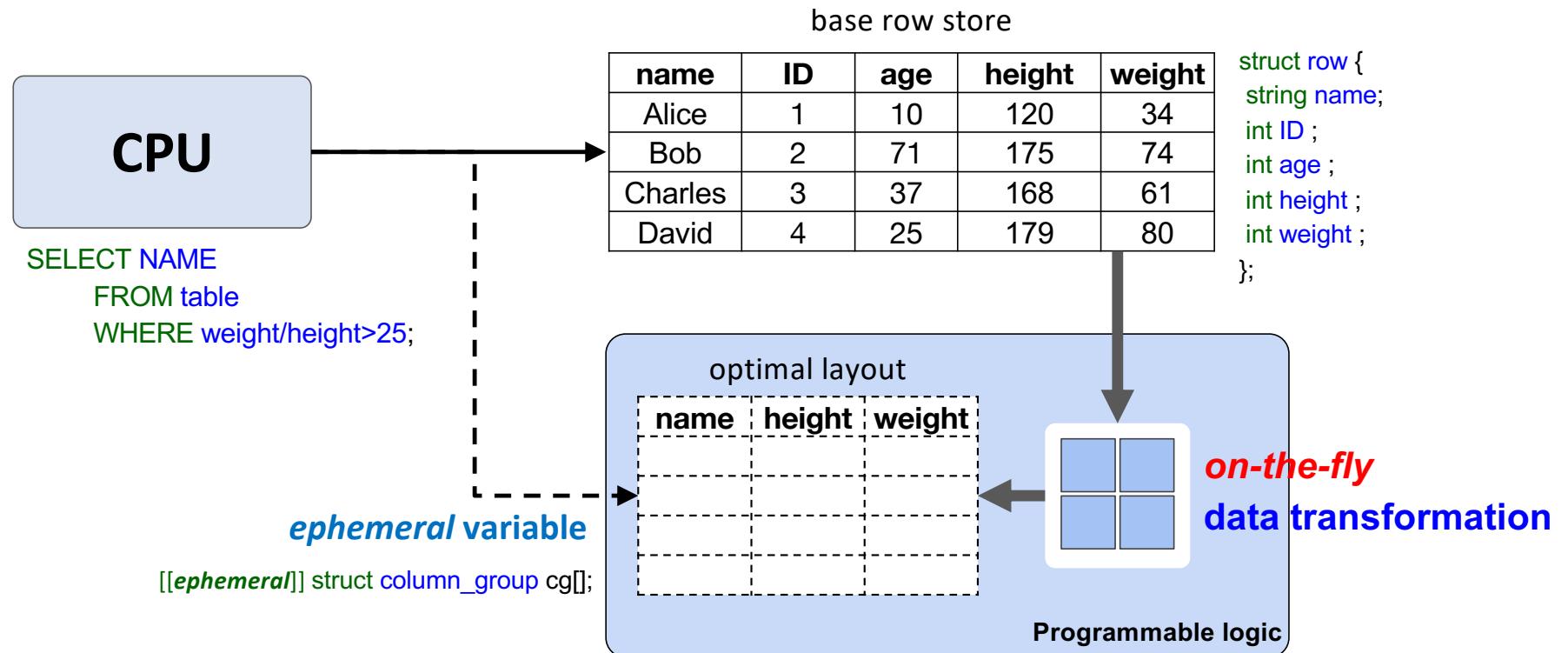
leads to normal memory accesses

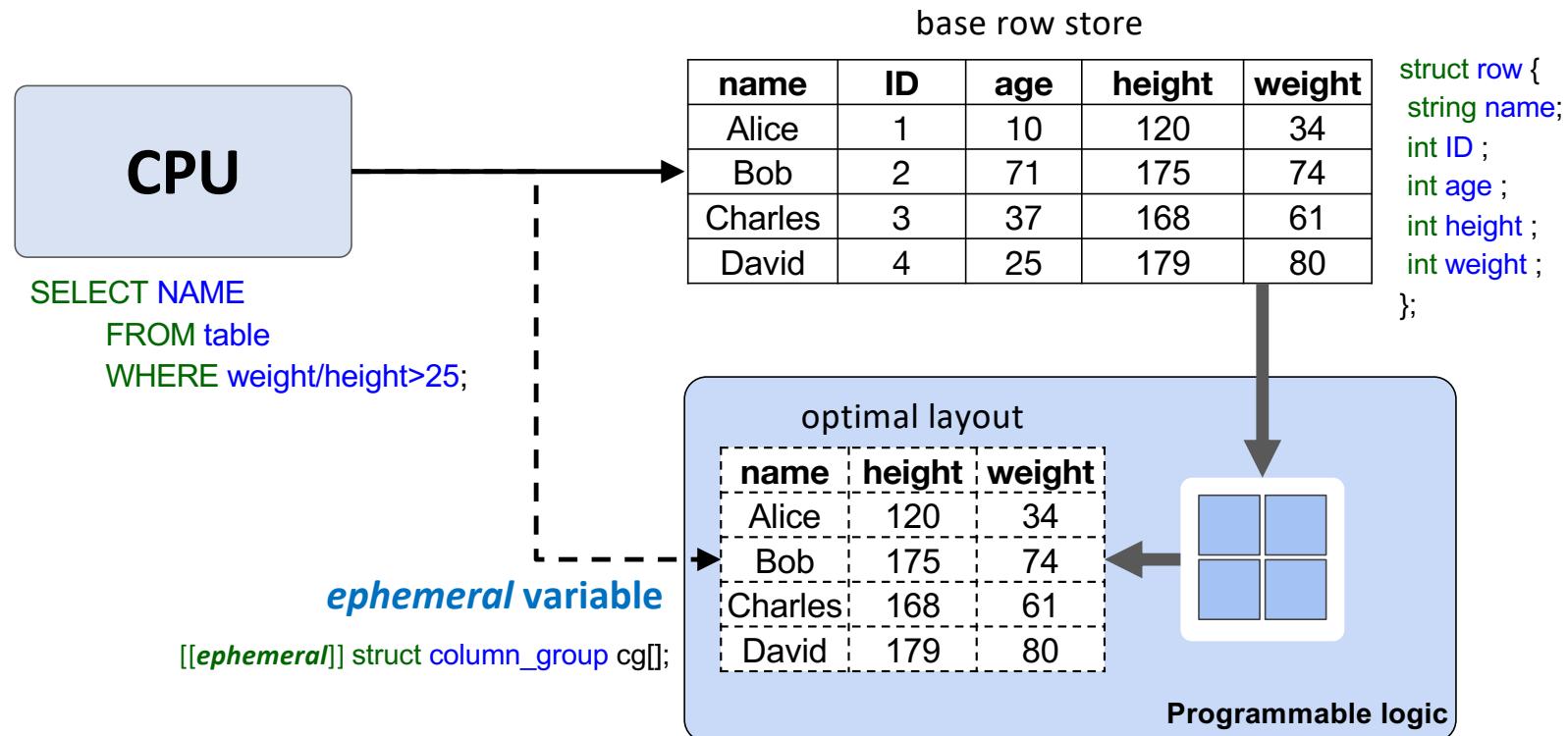
struct row_table[];

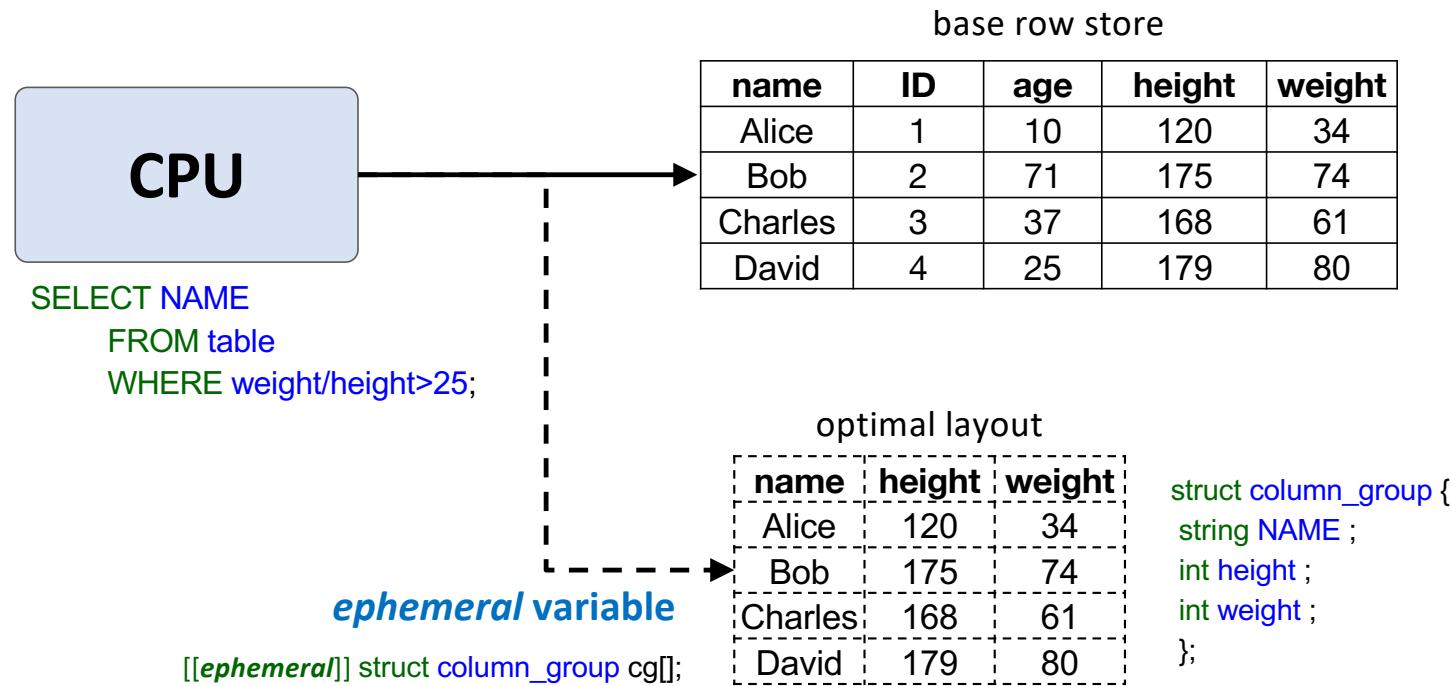
[[*ephemeral*]] struct col_group cg[];

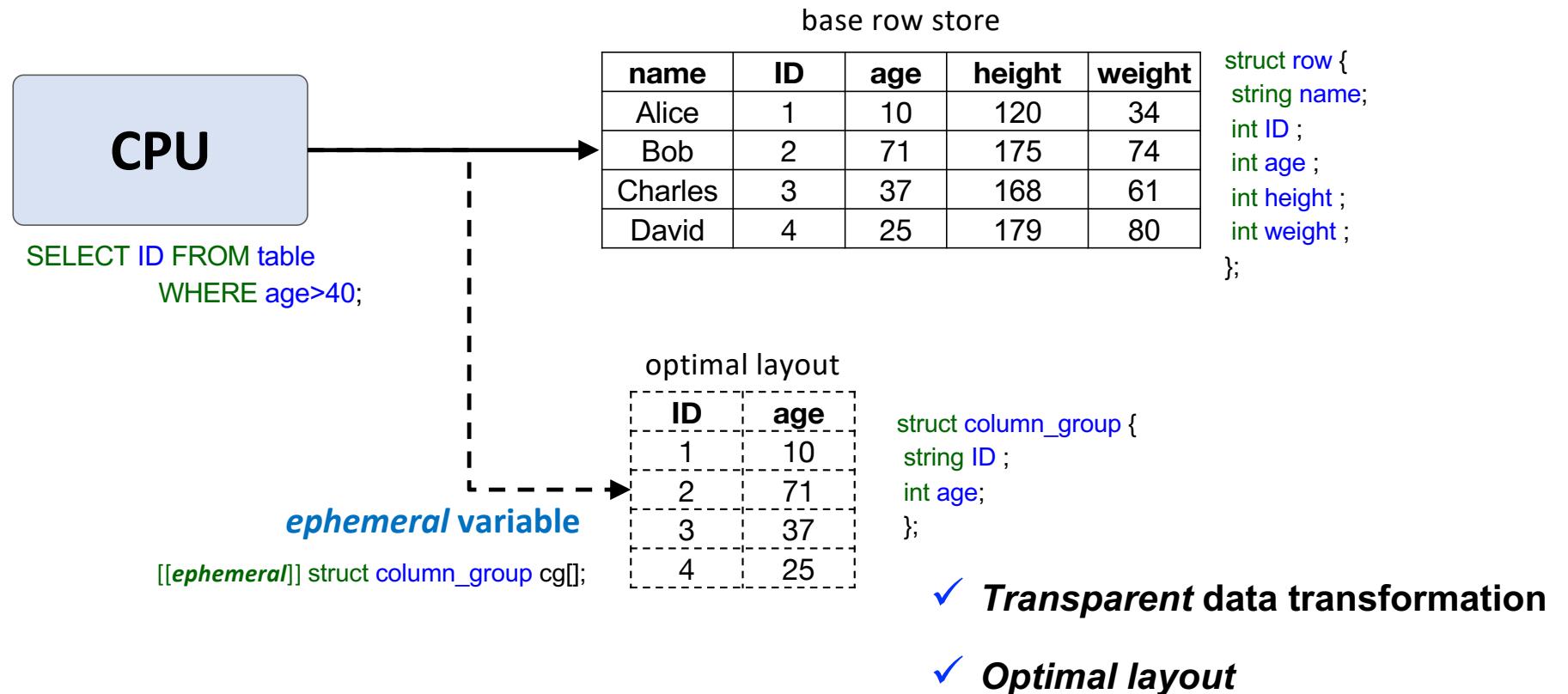
fake address that CPU thinks it exists
intercepted by RME







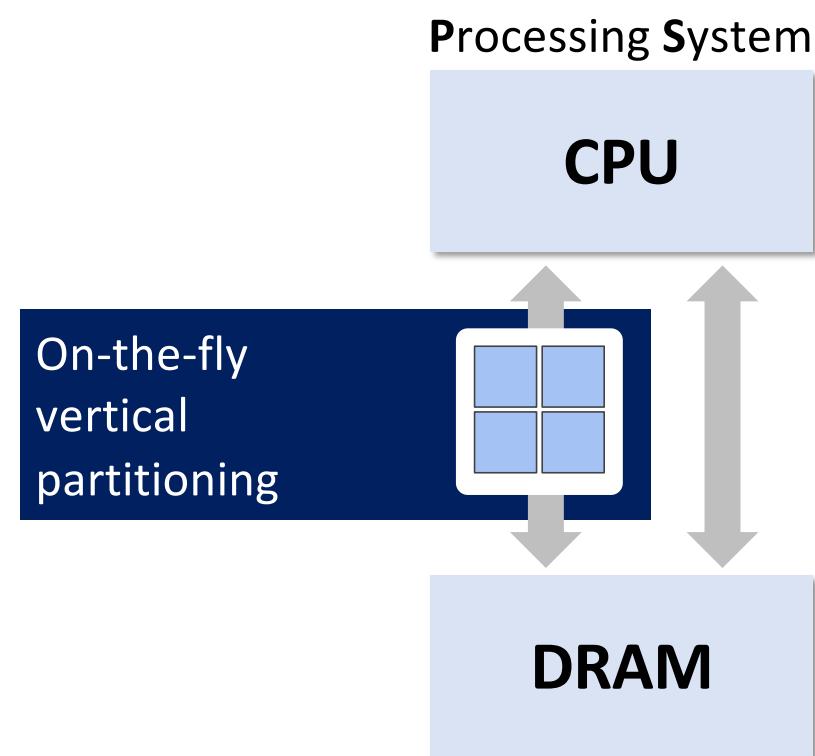




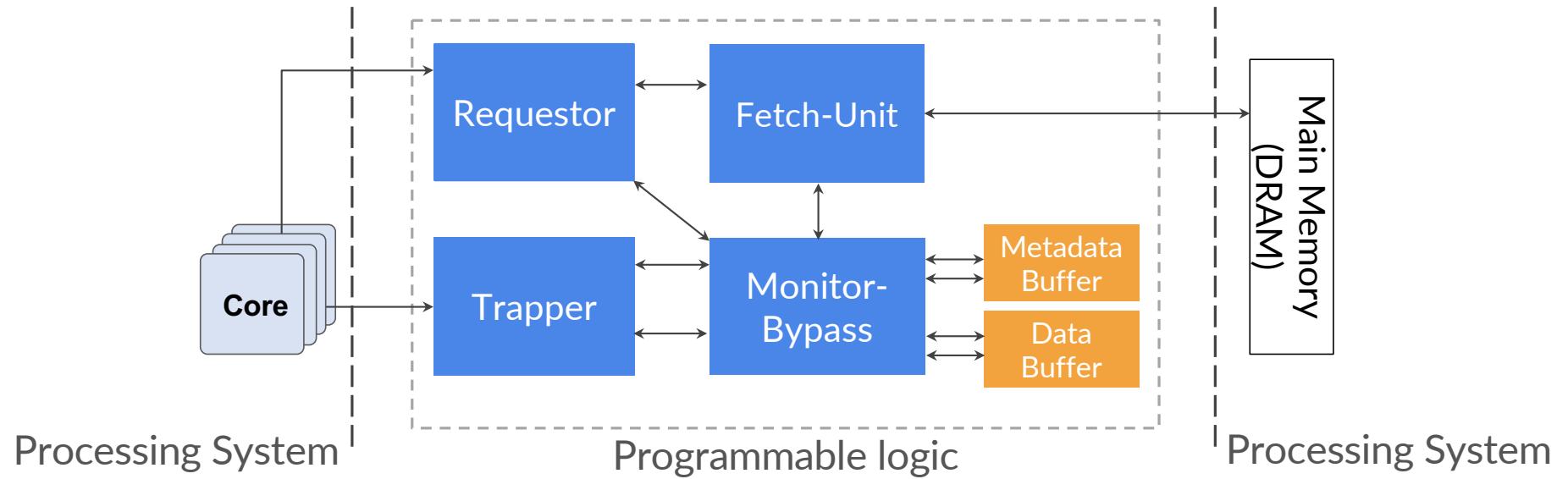
Q1: how to build?

Q2: how to use?

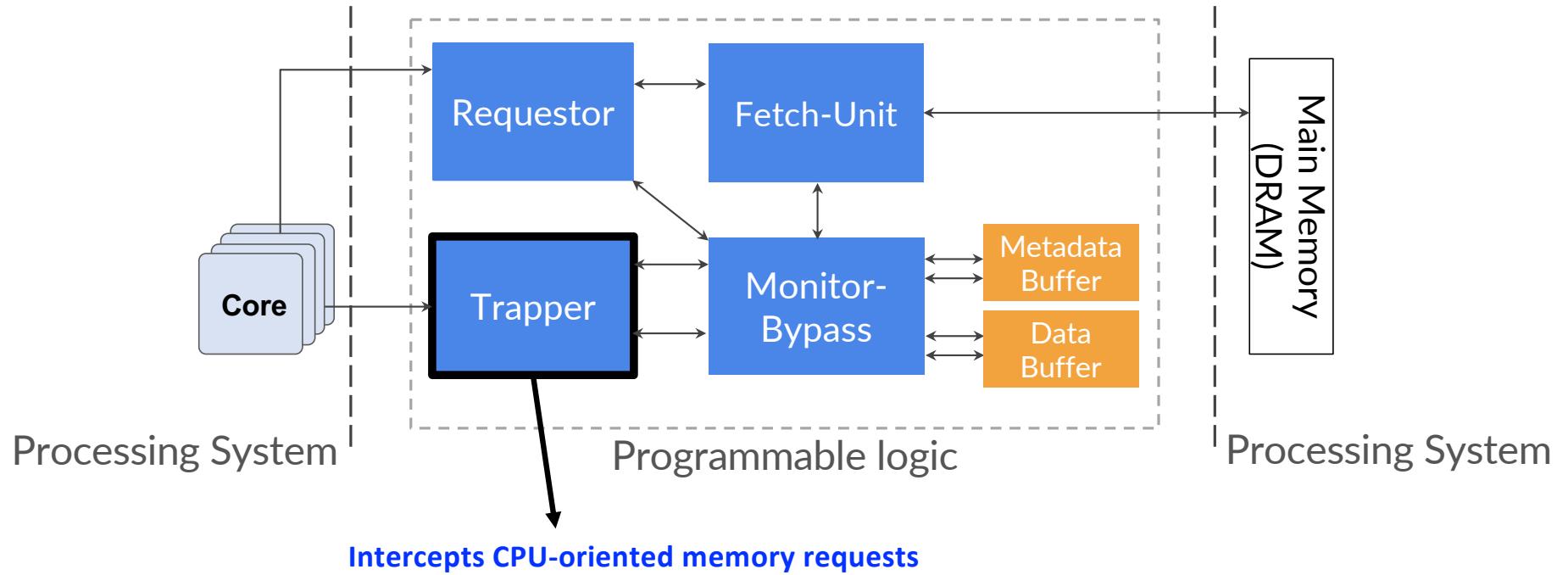
Relational Memory Engine



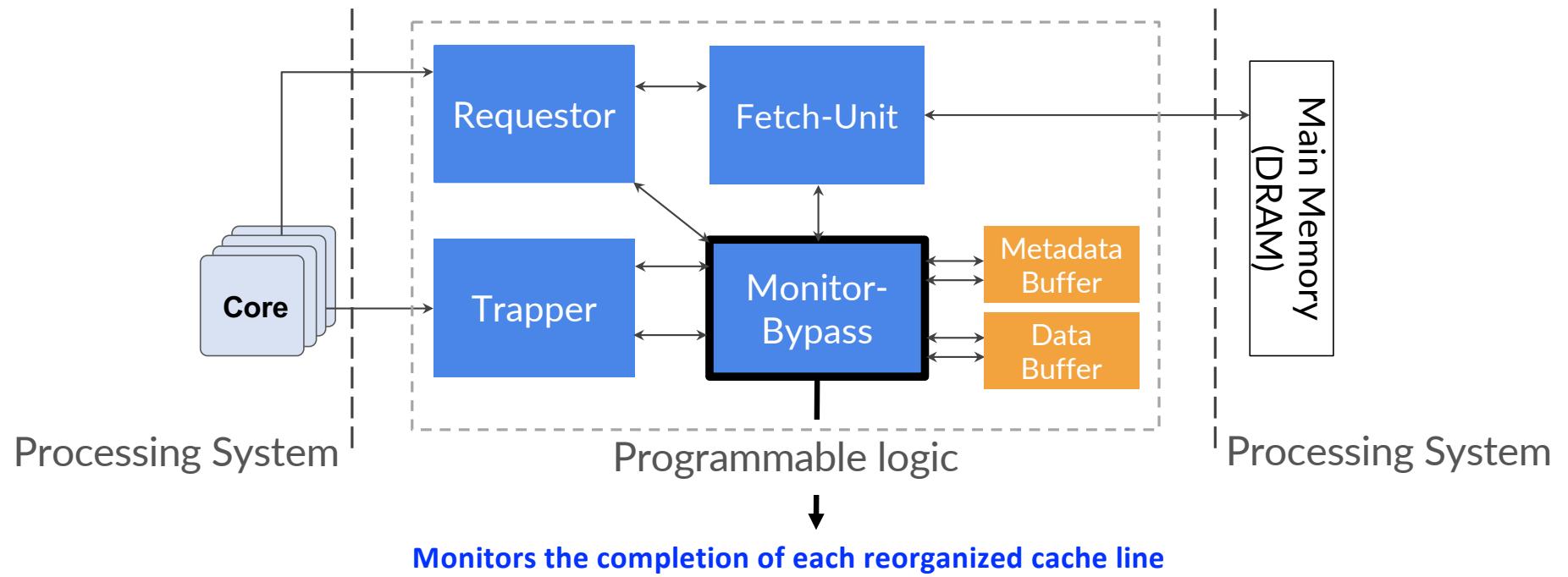
Relational Memory Engine



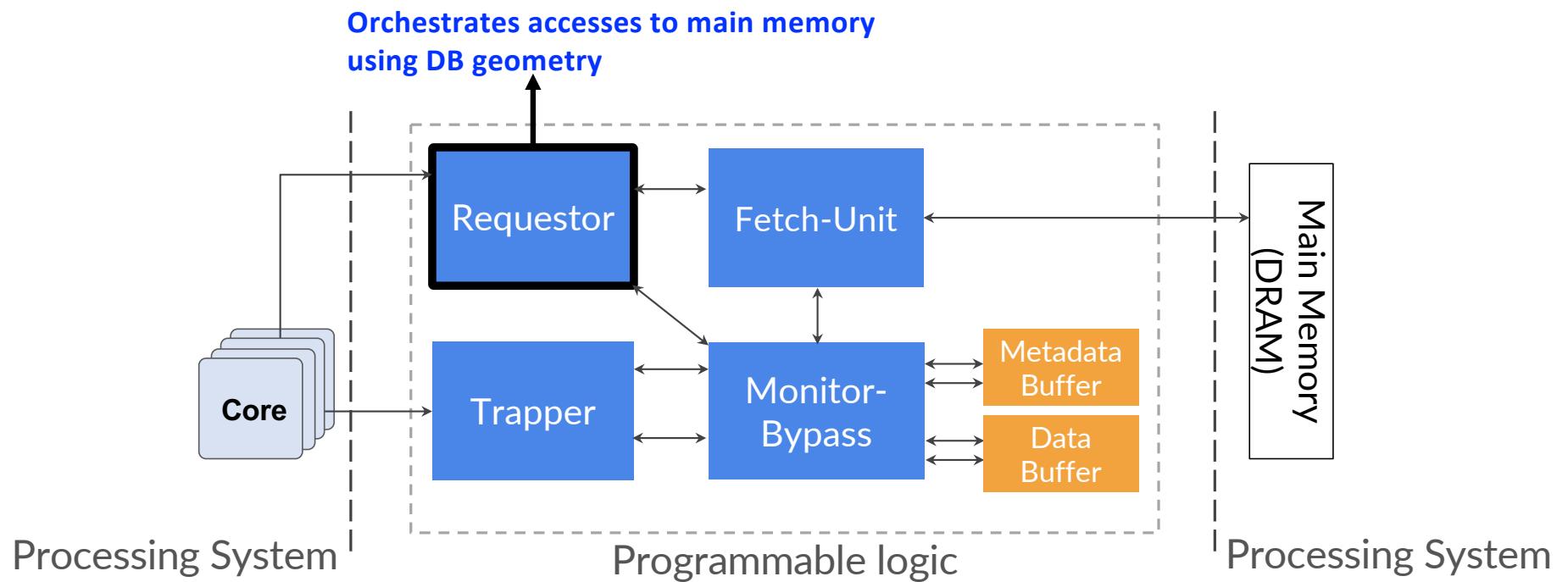
Relational Memory Engine



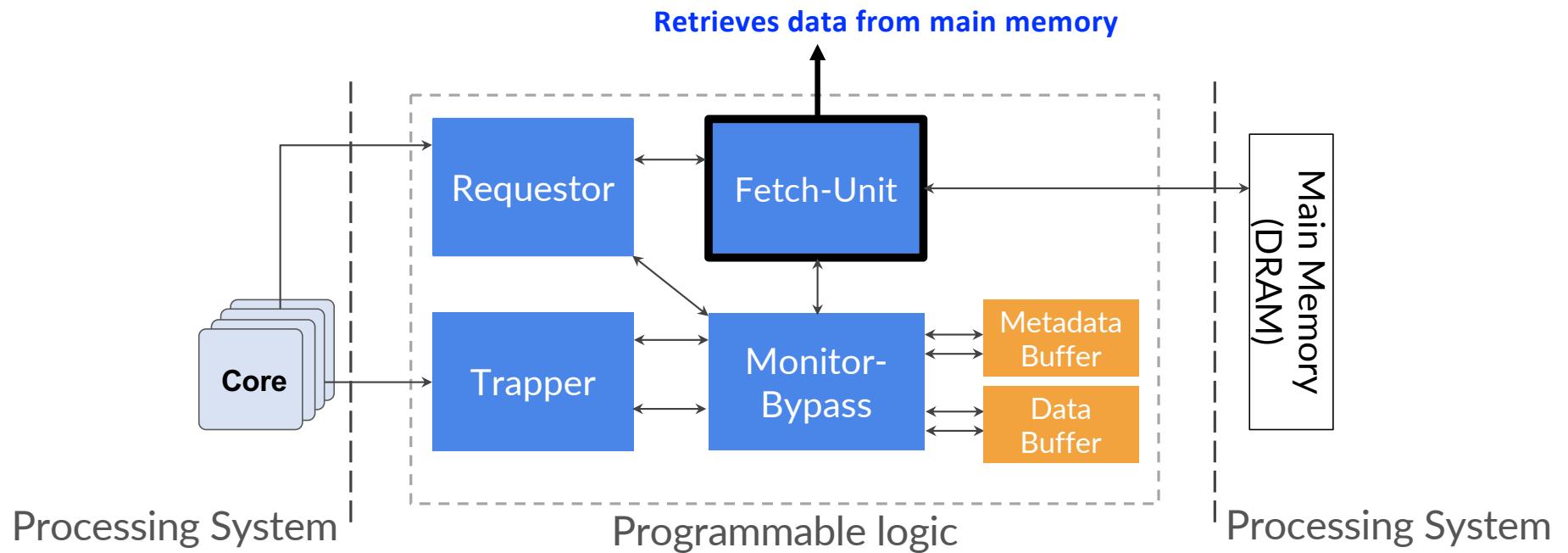
Relational Memory Engine



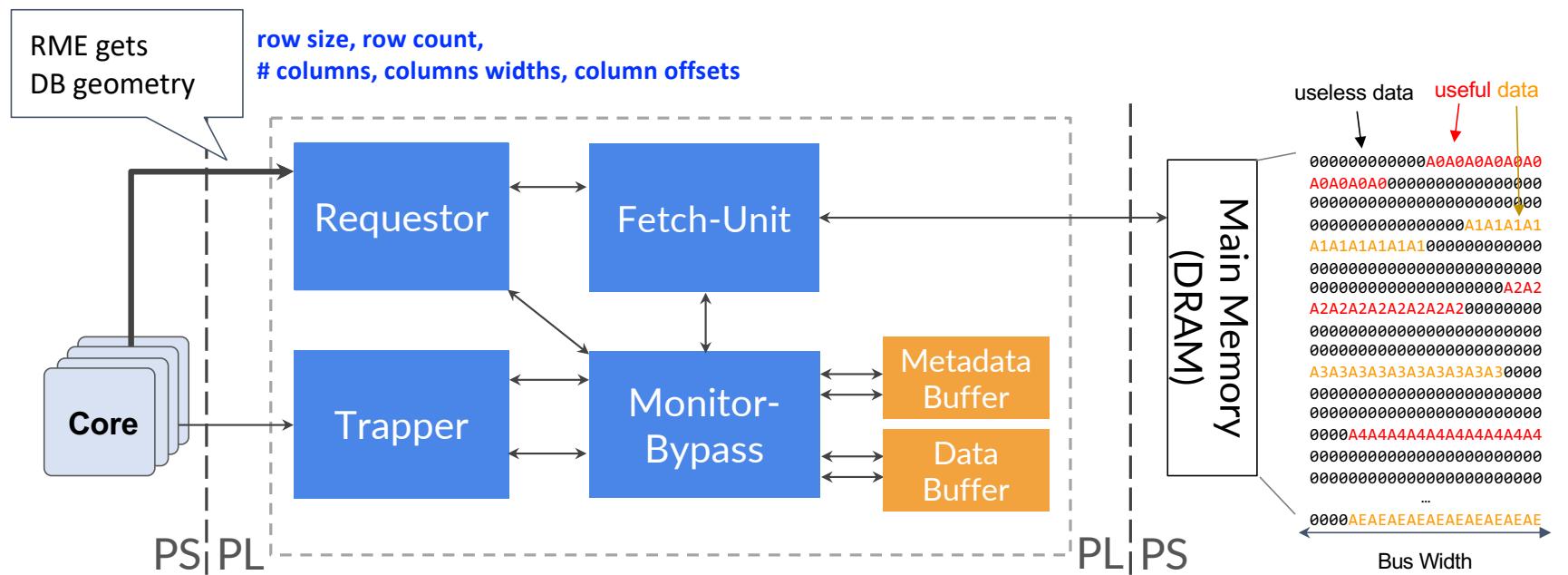
Relational Memory Engine



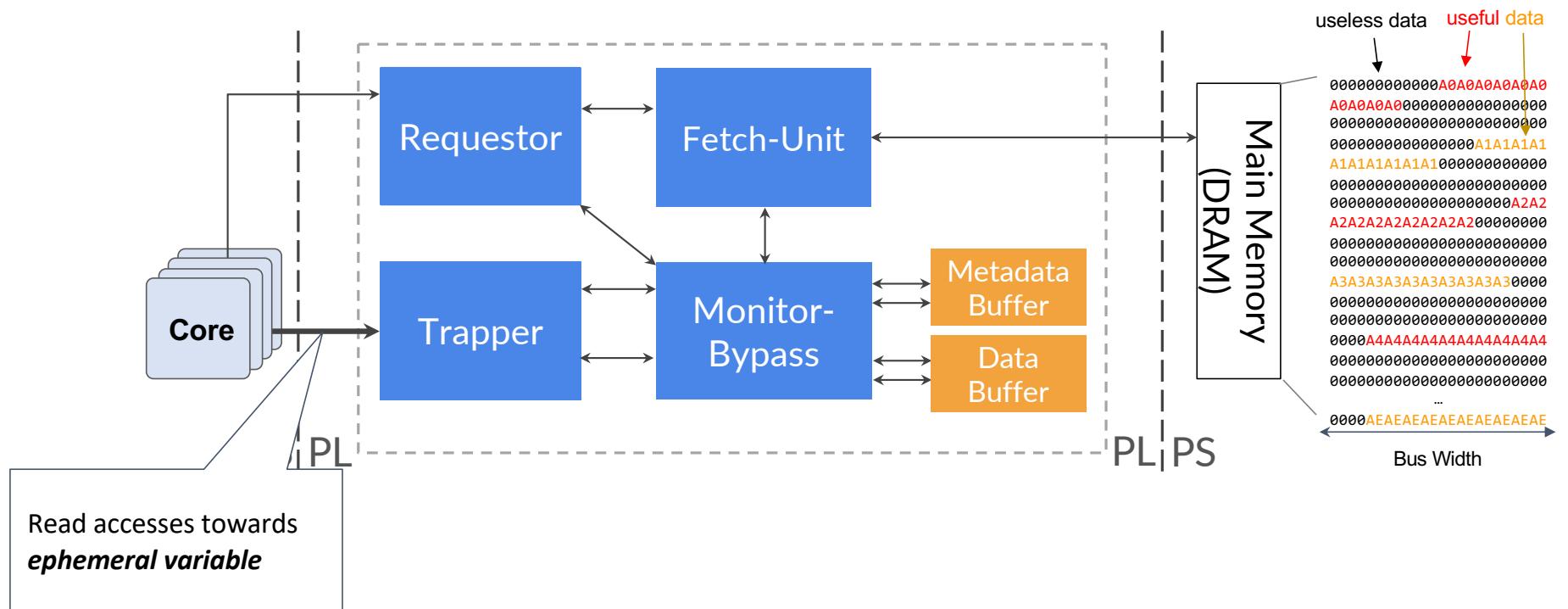
Relational Memory Engine



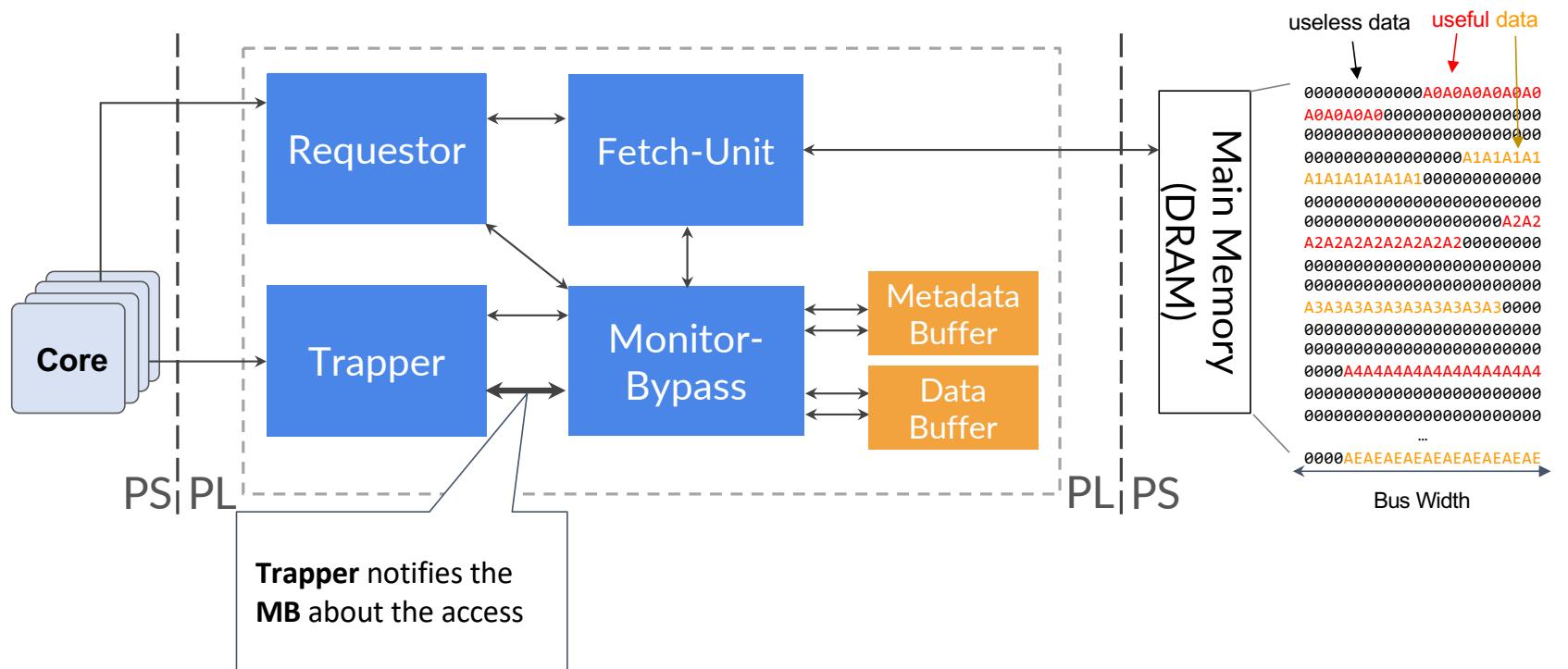
Relational Memory Engine



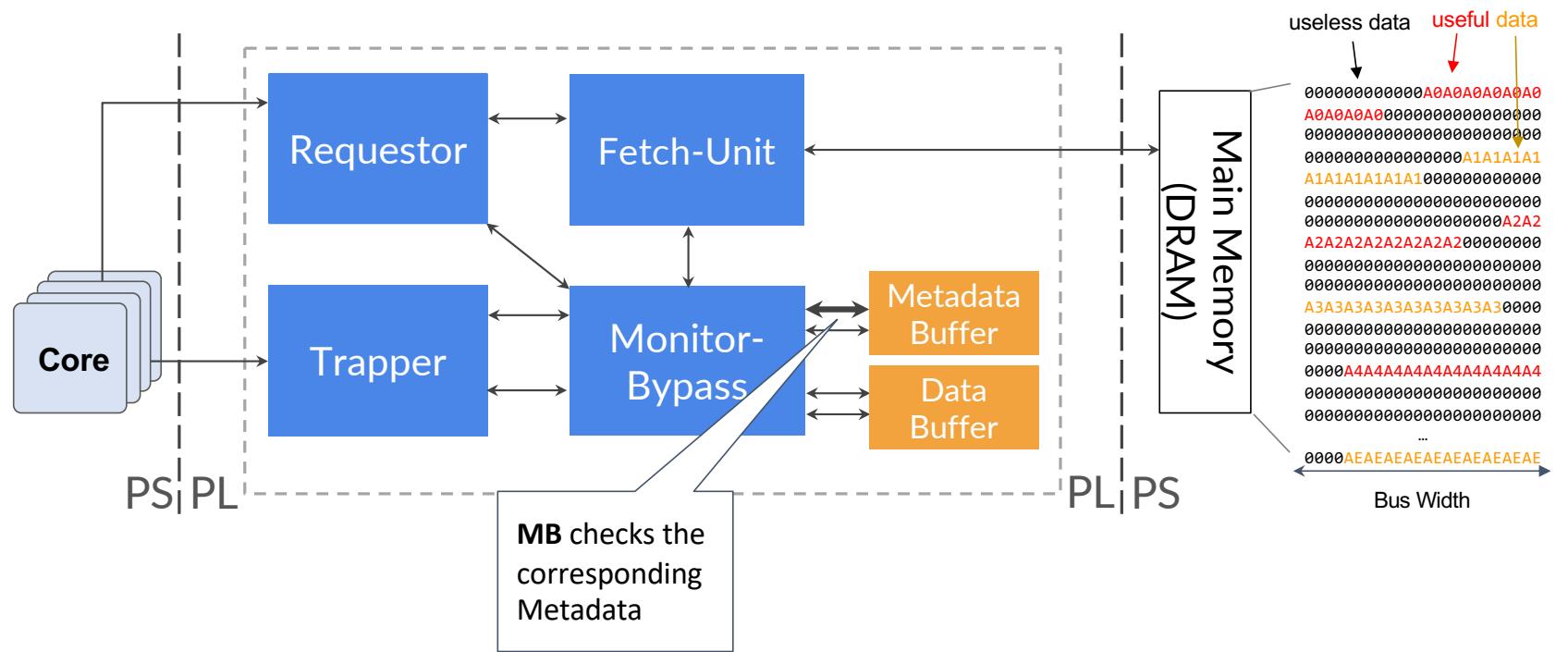
Relational Memory Engine



Relational Memory Engine

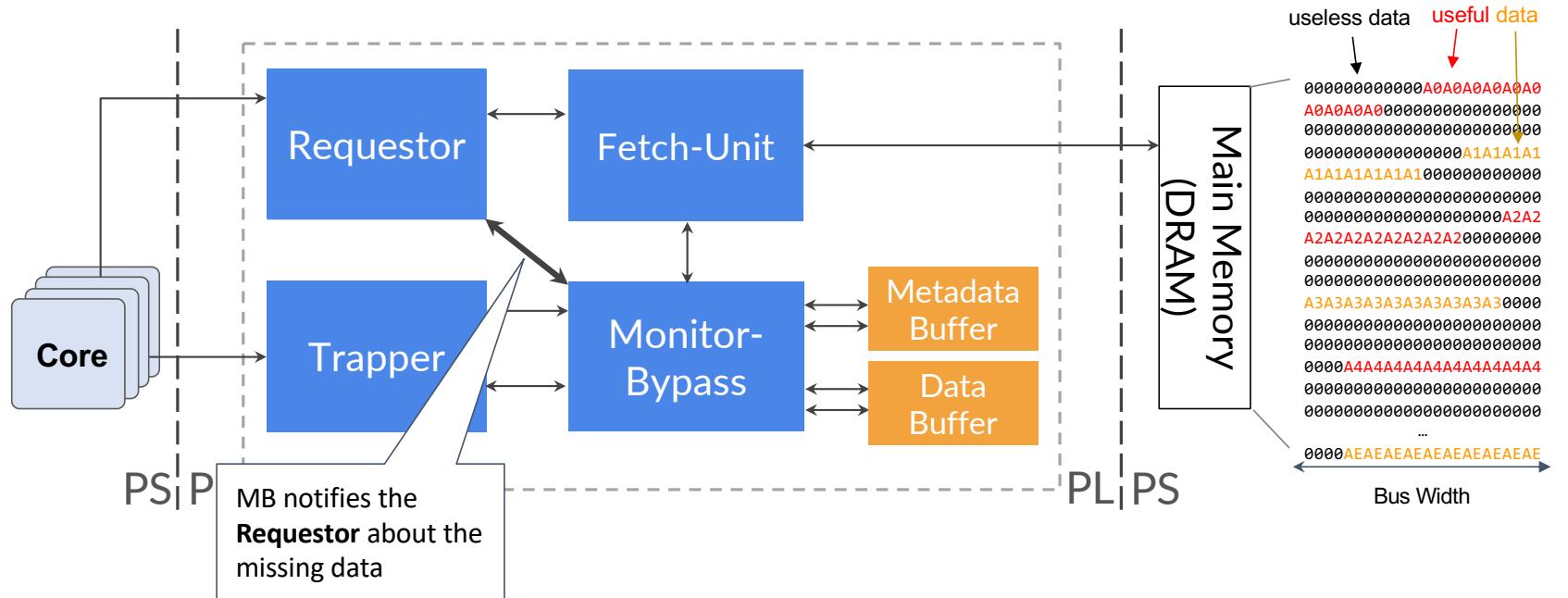


Relational Memory Engine



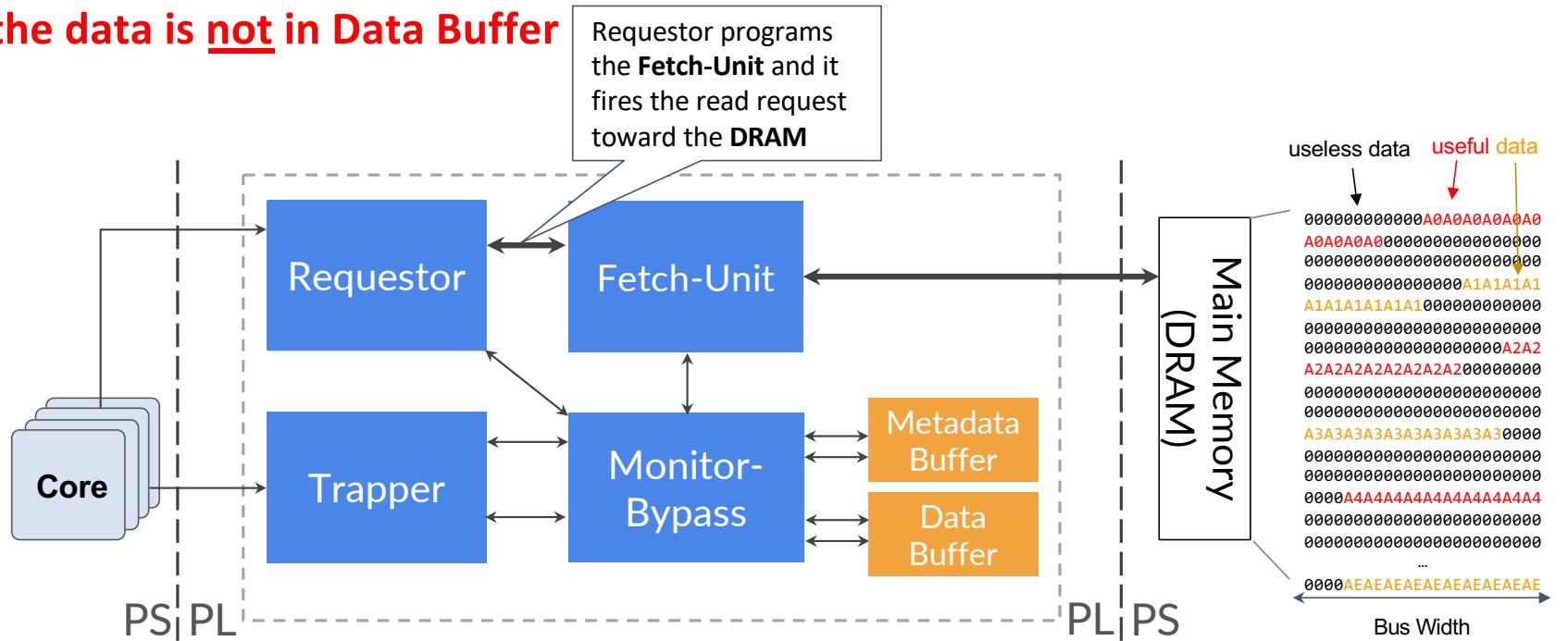
Relational Memory Engine

When the data is not in Data Buffer



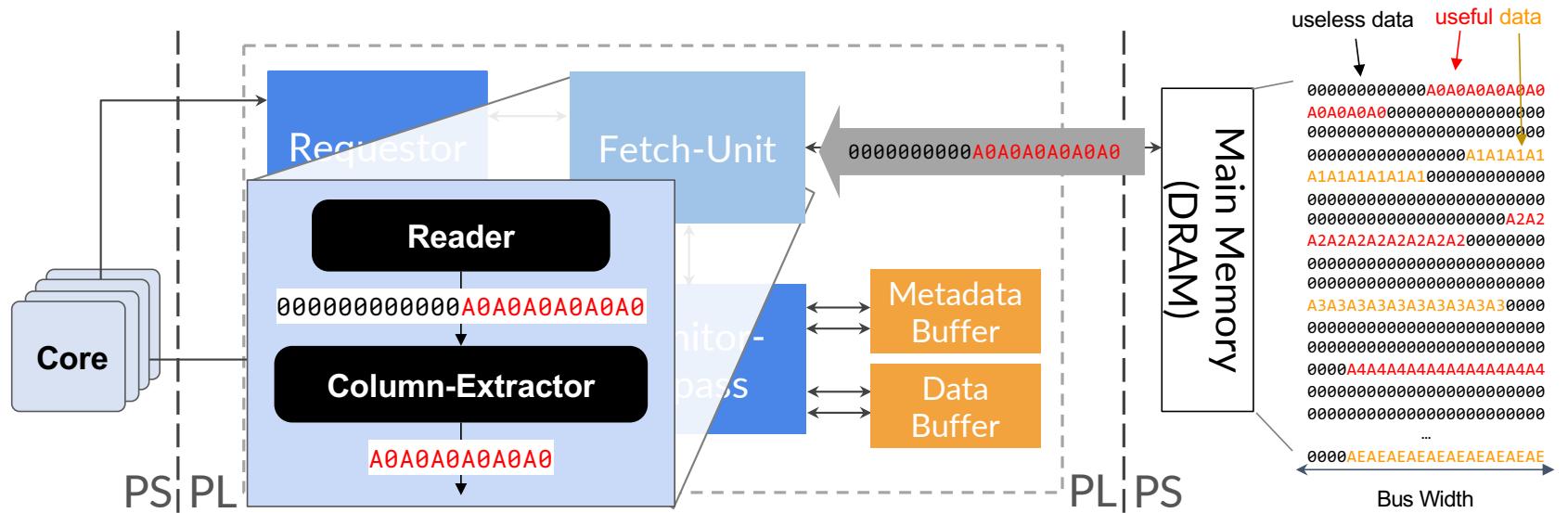
Relational Memory Engine

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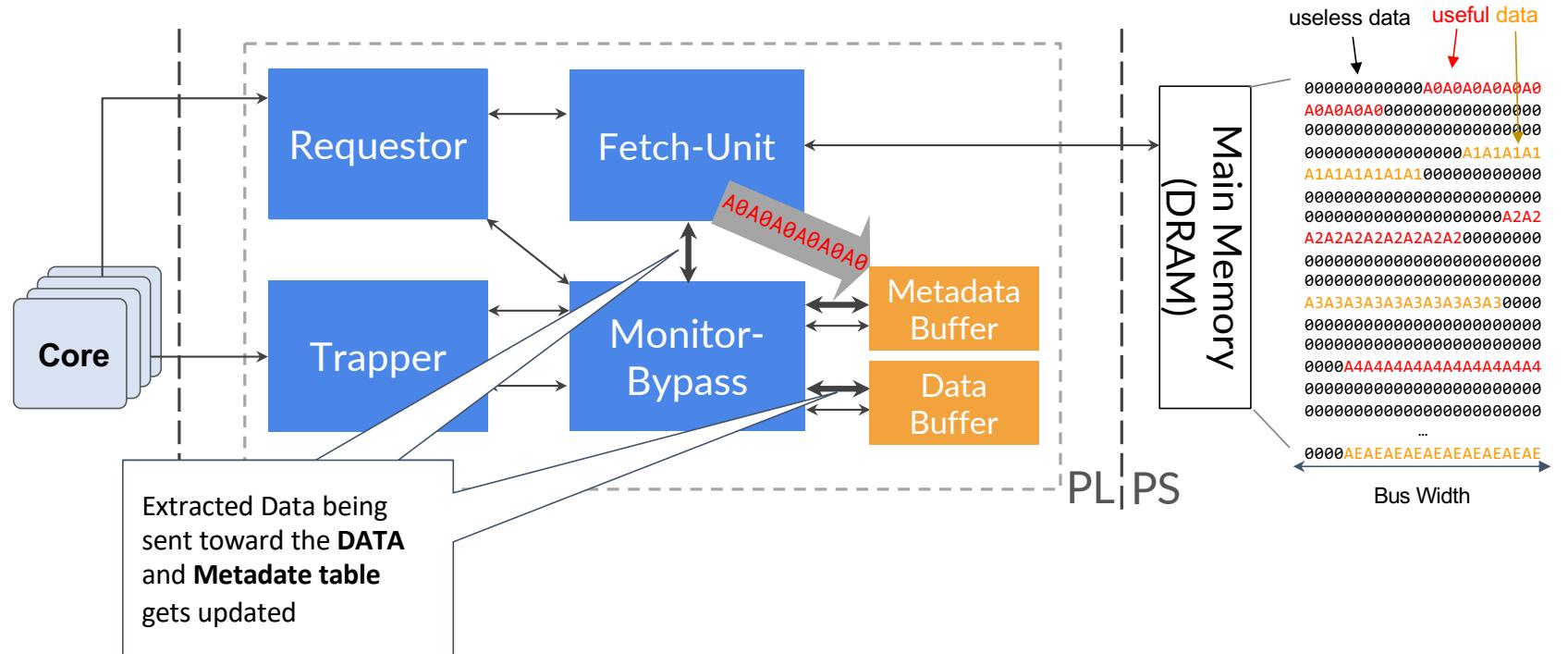
Relational Memory Engine

When the data is not in Data Buffer



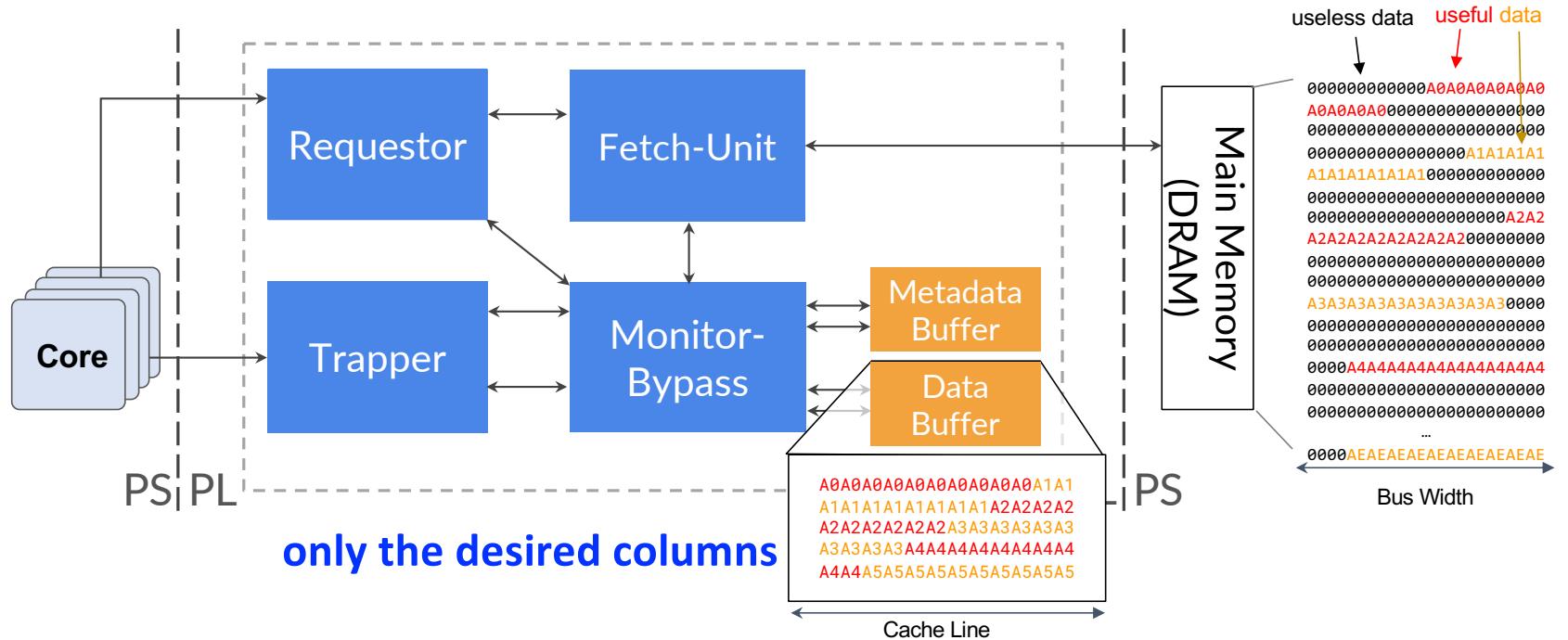
Relational Memory Engine

When the data is not in Data Buffer



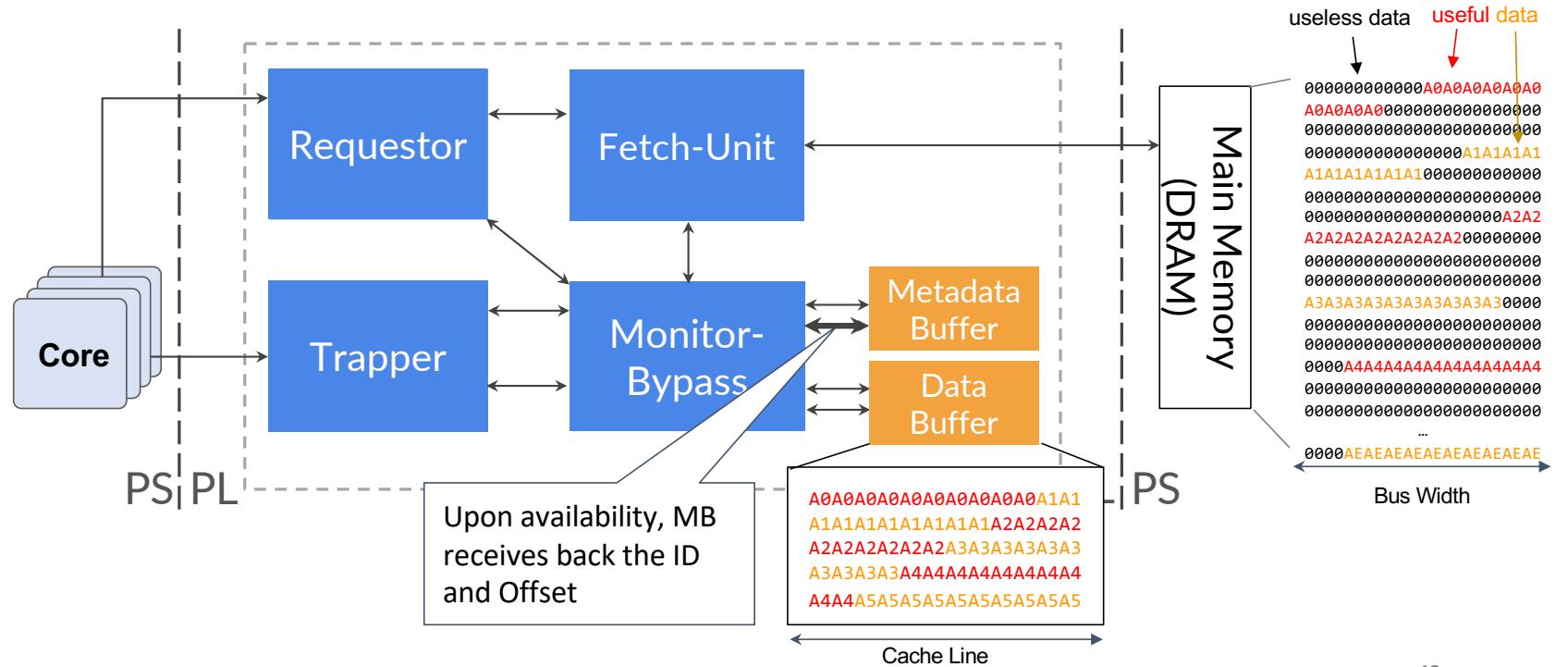
Relational Memory Engine

When the data is not in Data Buffer



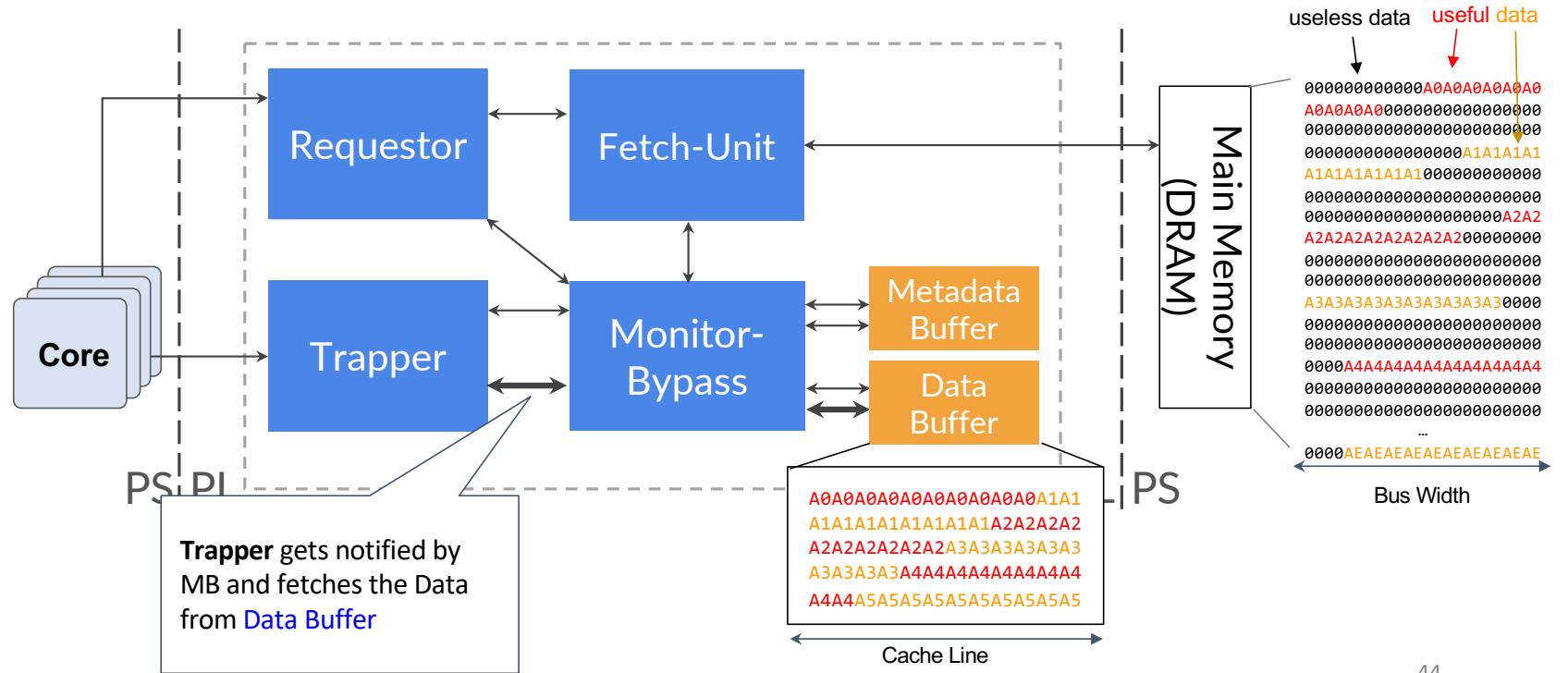
Relational Memory Engine

When the data is already in Data Buffer

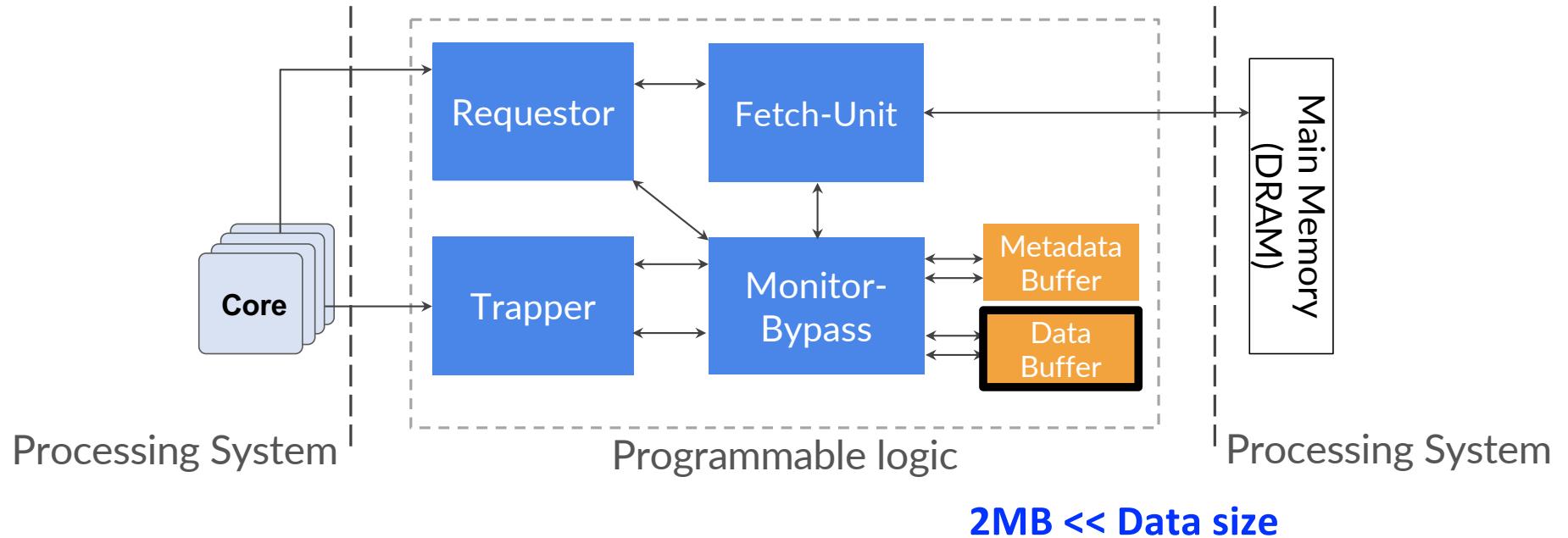


Relational Memory Engine

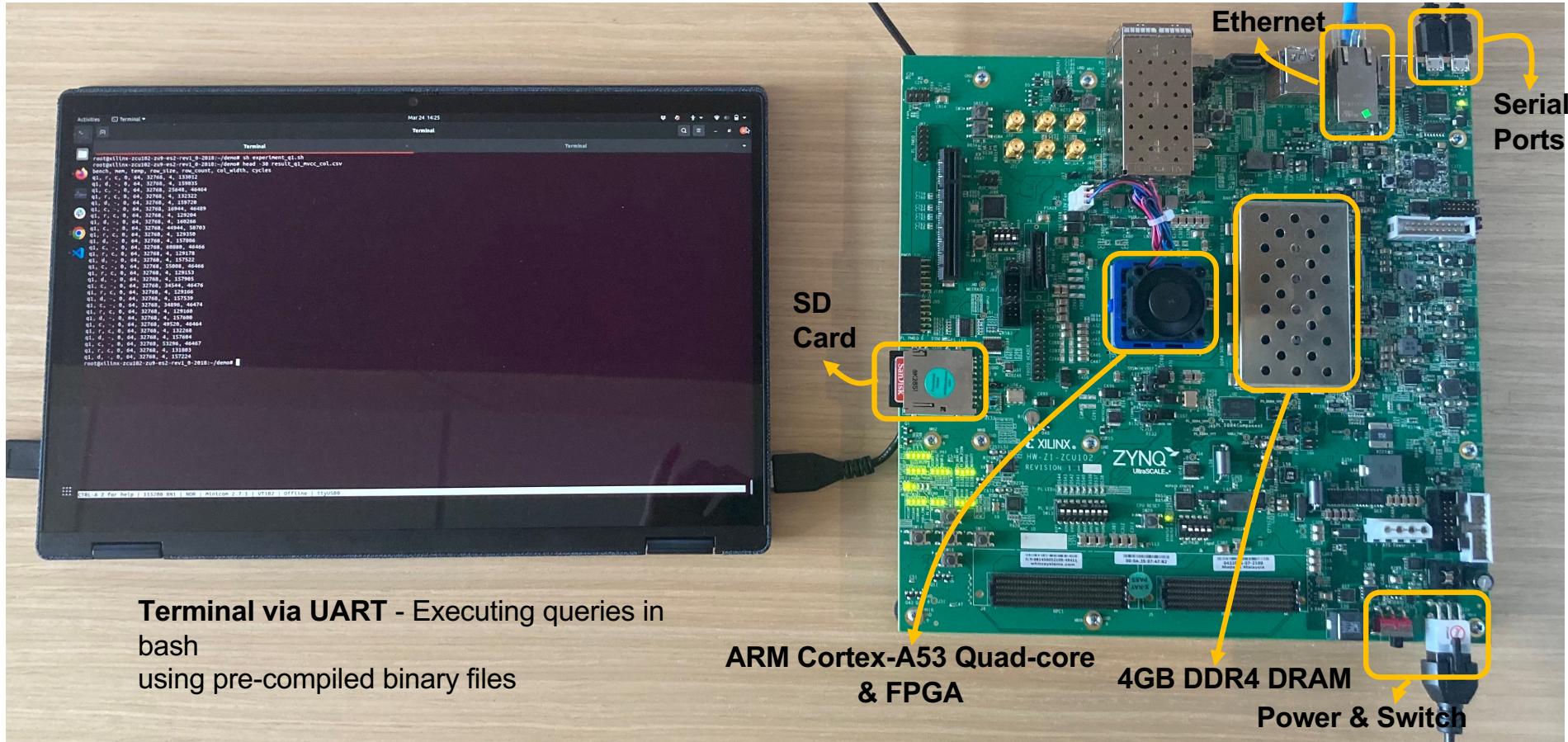
When the data is already in Data Buffer



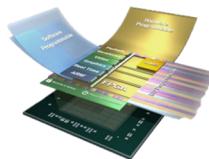
Relational Memory Engine



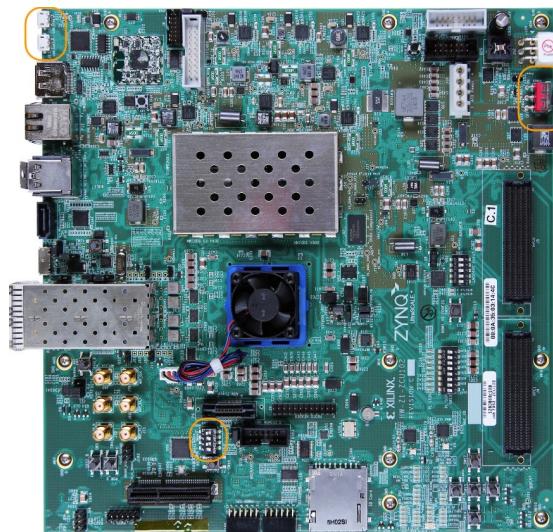
Target Platform



Target Platform



AMD XILINX
UltraScale+
ZCU102 platform



- CPUs : 4x ARM Cortex-A53
- L1/L2 Cache : 32+32KB I+D / 1 MB
- PS Frequency : 1.5 GHz
- PL Frequency : 100MHz

Resources	Utilization (%)
LUT	2.78
FF	0.68
DSP	0.08
BRAM	60.69

area utilization
less than 3%

Relational Memory Benchmark

Q1: SELECT A₁ , A₂ , ... , A_k FROM S;  projection

Q2: SELECT A₁ , A₂ , ... , A_k FROM S WHERE C₁, C₂, ... , C_i;  both projection & selection

Q3: SELECT AVG (A₁) FROM S WHERE A₃ < k GROUP BY A₂;  group by

Q4: SELECT S.A₁ , R.A₃ FROM S JOIN R ON S.A₂ = R.A₂;  join over two tables

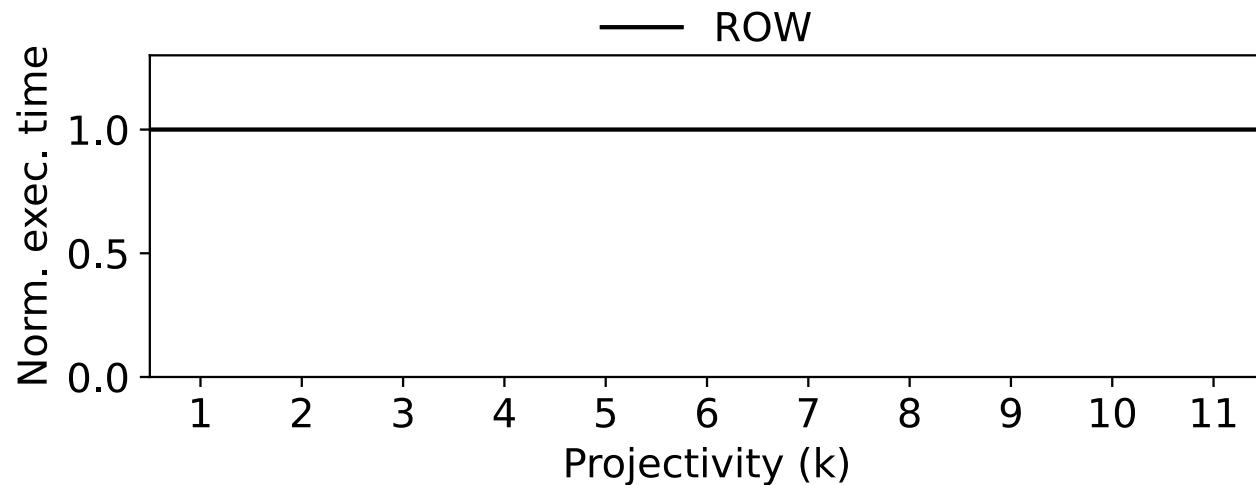
Approach tested

ROW : Direct row-wise access
COL : Direct columnar access  Processing System

RME : using Relational Memory Engine → **Slow FPGA (100MHz)**

Queries Varying Projectivity

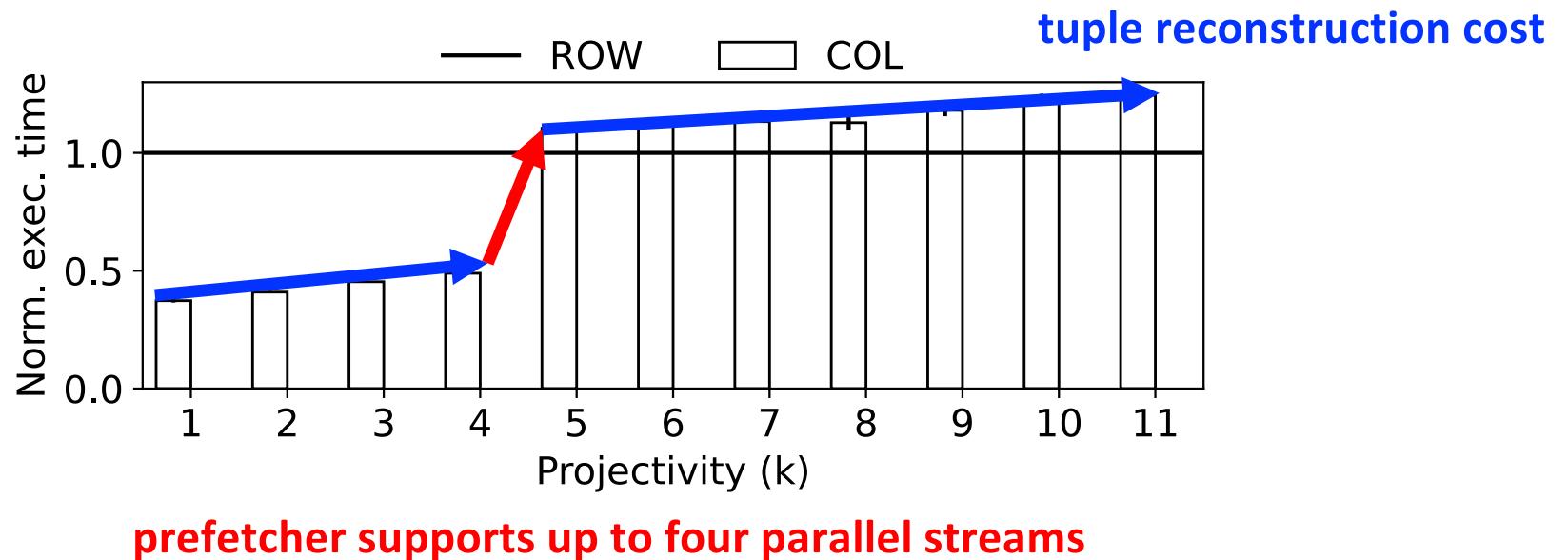
Q1: `SELECT A1 , A2 , ... , Ak FROM S;`



Row size: 64 Bytes, Column size: 4 Bytes

Queries Varying Projectivity

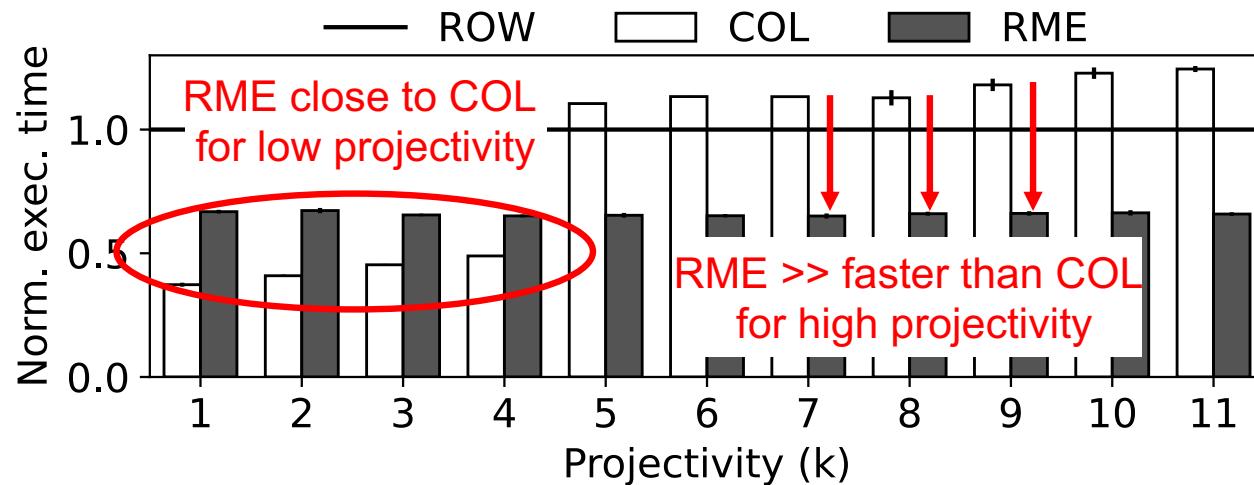
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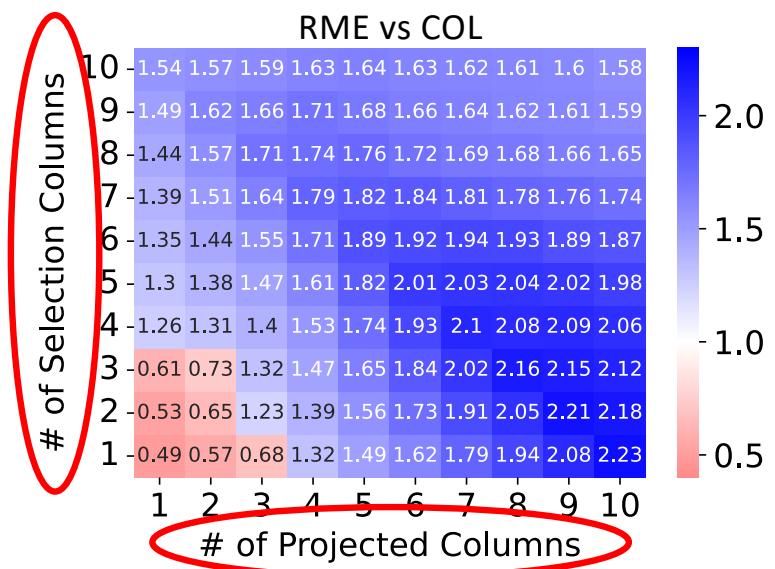


RME provides stable performance irrespectively of projectivity

Row size: 64 Bytes, Column size: 4 Bytes

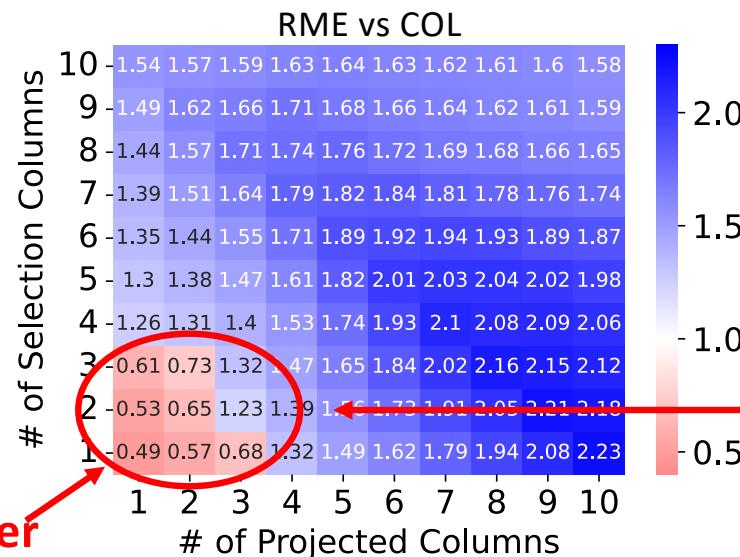
RME for Multiple Selection and Projection Attributes

Q3: `SELECT A1 , A2 , ... , Ak FROM S WHERE C1, C2, ... ,Ci;` Row size: 64 Bytes, Column size: 4 Bytes



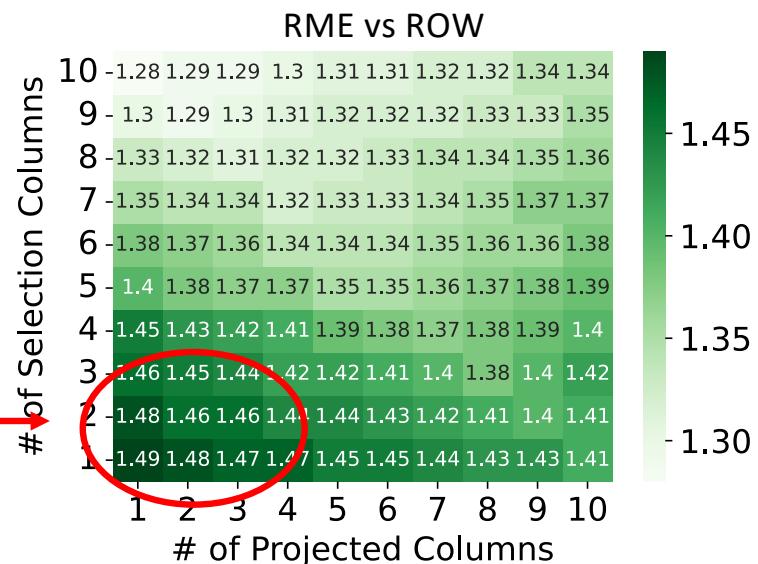
RME for Multiple Selection and Projection Attributes

Q3: `SELECT A1 , A2 , ... , Ak FROM S WHERE C1, C2, ... ,Ci;` Row size: 64 Bytes, Column size: 4 Bytes



COL faster

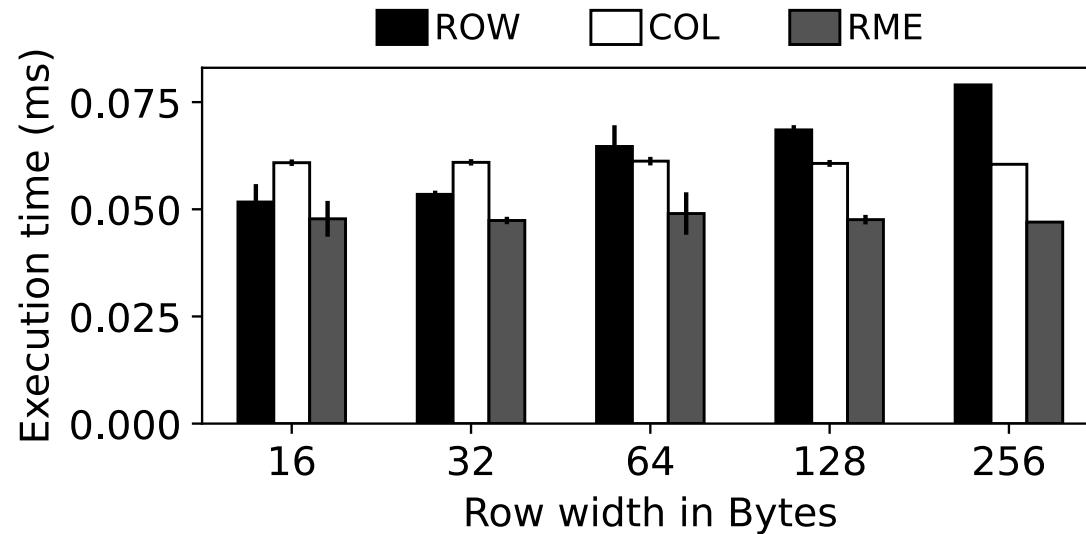
RME can be up to 2.23× faster than columnar access



RME always outperforms row access by being 1.3 – 1.5× faster

Group by

Q4: `SELECT AVG (A1) FROM S WHERE A3 < k GROUP BY A2;` Selectivity: 10%

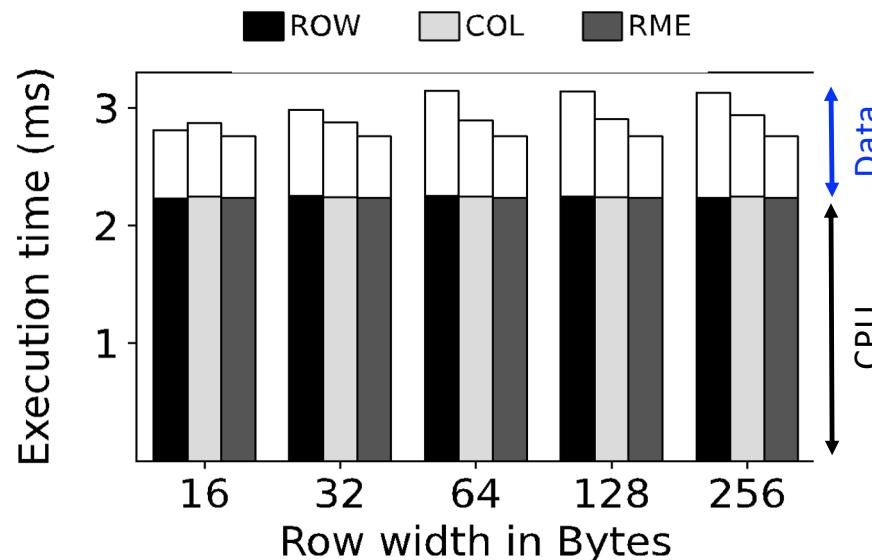


RME outperforms both ROW and COL

Column size: 4 Bytes

Join Over Two Tables

Q4: `SELECT S.A1 , R.A3 FROM S JOIN R ON S.A2 = R.A2;`



RME reduces data movement up to 41%

Column size: 4 Bytes

RME Scales with Data Size

TPC-H Q1

```
SELECT l_returnflag, l_linestatus,
       SUM(l_quantity), SUM(l_extendedprice),
       SUM(l_extendedprice*(1-l_discount)),
       SUM(l_extendedprice*(1-l_discount)*(1+l_tax)),
       AVG(l_quantity), AVG(l_extendedprice),
       AVG(l_discount),
       COUNT(*)
  FROM lineitem
 WHERE
   l_shipdate <= '1998-12-01' - '[DELTA]' day (3)
 GROUP BY l_returnflag, l_linestatus
 ORDER BY l_returnflag, l_linestatus;
```

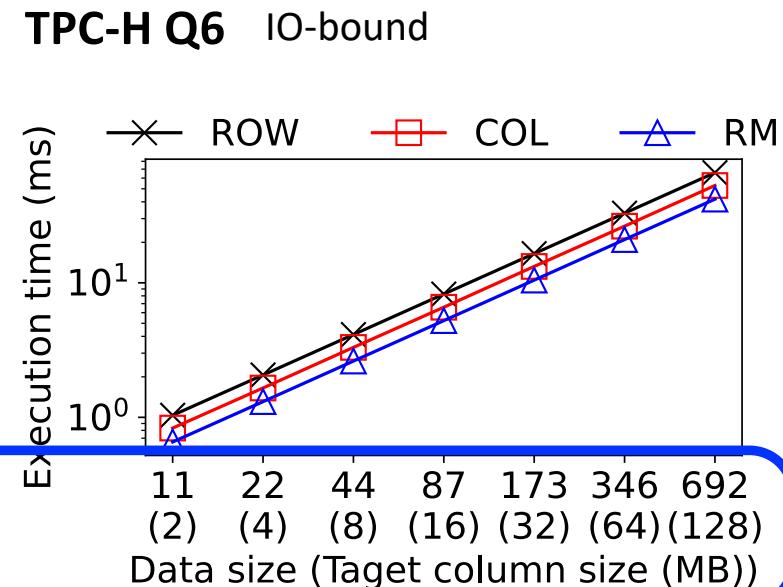
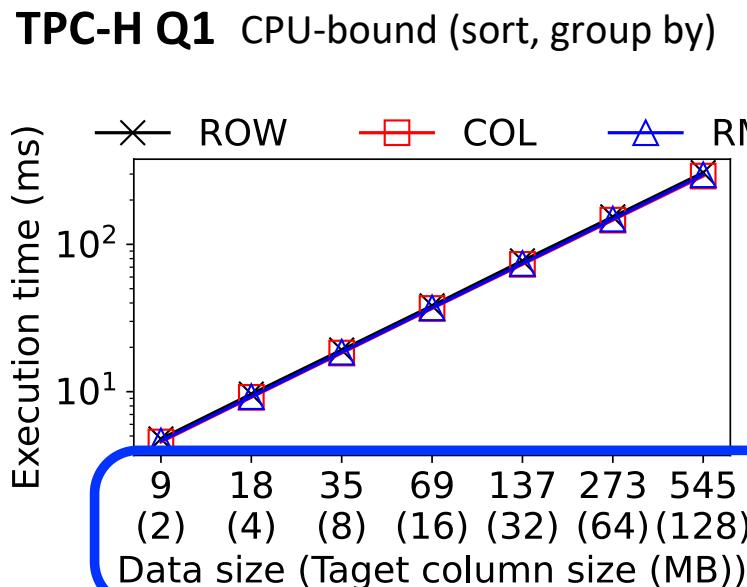
Selectivity: 95%, projectivity: 24%

TPC-H Q6

```
SELECT
       SUM(l_extendedprice*l_discount)
  FROM lineitem
 WHERE
   l_shipdate >= '[DATE]' and
   l_shipdate < '[DATE]' + 1 year and
   l_discount > [DISCOUNT] - 0.01 and
   l_discount < [DISCOUNT] + 0.01 and
   l_quantity < [QUANTITY];
```

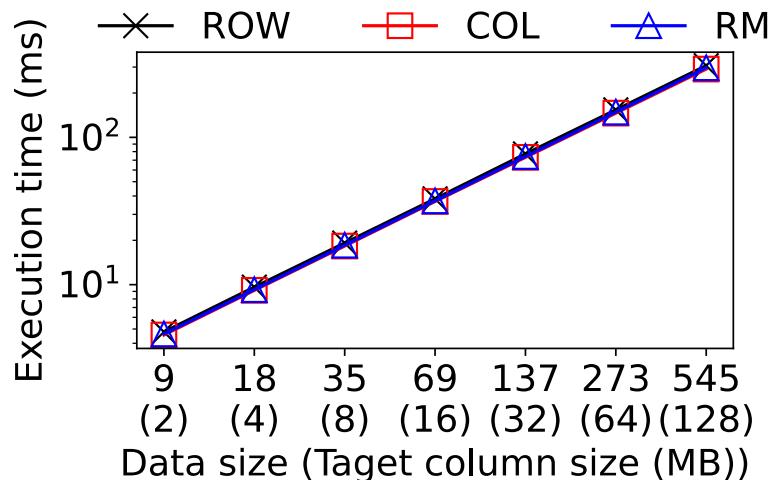
Selectivity: 15%, projectivity: 18%

RME Scales with Data Size



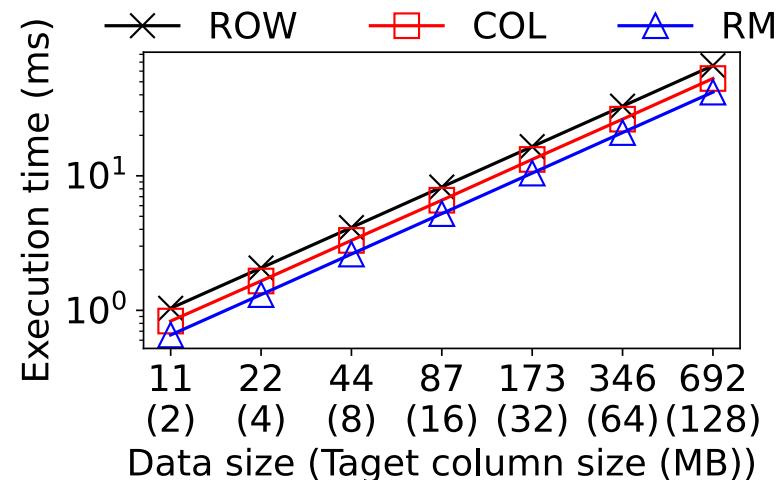
RME Scales with Data Size

TPC-H Q1 CPU-bound (sort, group by)



**CPU overhead dominates
data movement cost**

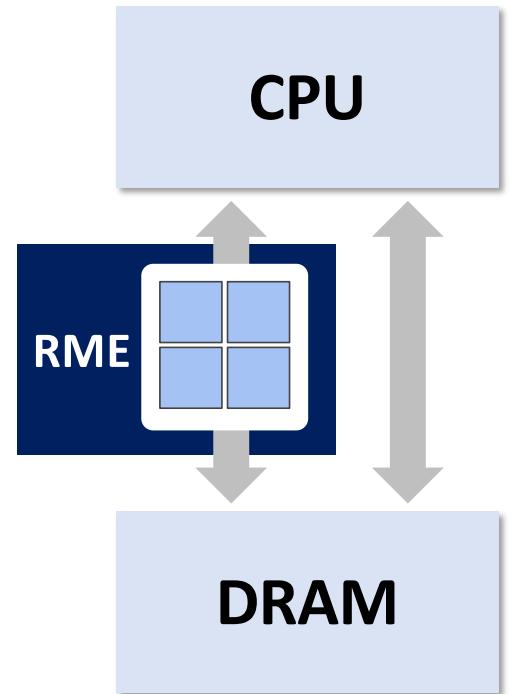
TPC-H Q6 IO-bound



RME benefits regardless of data size

Summary

- **Relational Memory**
 - a novel SW/HW co-design paradigm
 - every query always has access to the optimal data layout
- ***ephemeral variables***
 - a simple and lightweight abstraction to use RM
- Relational Memory enables opportunities for innovation across the data system architecture.



Relational Fabric, ICDE '23

Future Work



Data Transformation for ML workloads

Matrix and tensor slicing



Integrating with Real DBMS

Exploring query optimization



DRAM Controller Augmentation

Utilizing bank interleaving and
parallelism

Thank you

Ju Hyoung Mun (jmun@bu.edu)

