## **Unlocking GPU potential with JIT**

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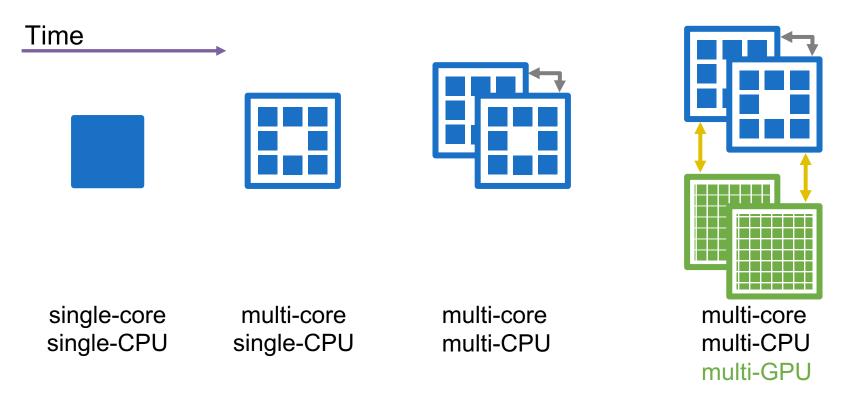






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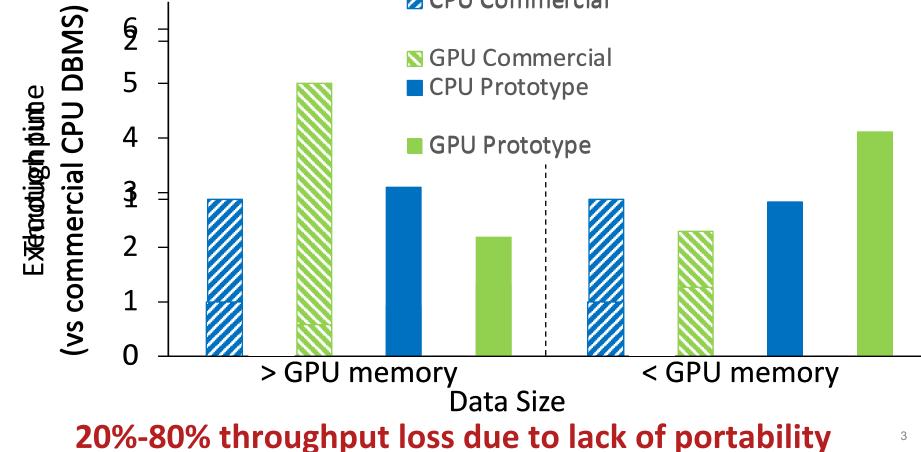
#### One hardware does not fit all



#### Rethink query engines for accelerator-level parallelism



# One hardware fits all: The end of an efficient story





# **Designing query engines for heterogeneous HW**



#### **Decomposition of design space to find sweet spot**





### **OLAP in heterogeneous servers: design space**

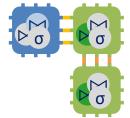
[CIDR2019]



- ➡ Performance depends on µ-arch
- Tune operators to memory hierarchy specifics

intra-device 🗳

- Portability impacted by specialization
- Inject target-specific info using codegen



#### inter-device

- Limited device inter-operability
- Encapsulate heterogeneity and balance load

#### **Selective obliviousness**

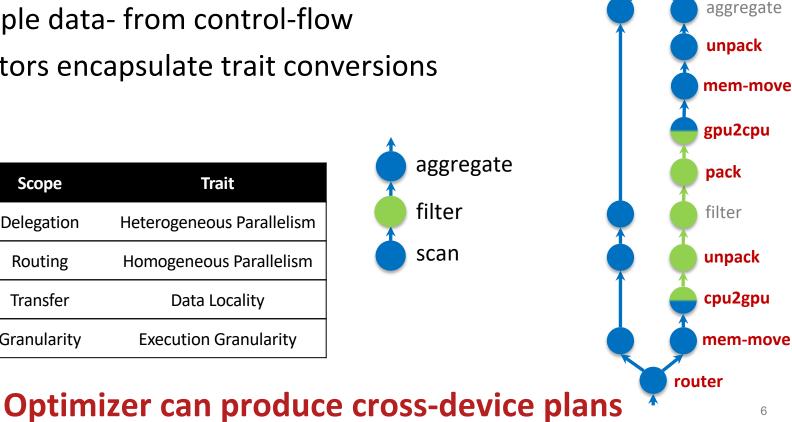


## **Inter-device: HetExchange**



- Decouple data- from control-flow
- Operators encapsulate trait conversions

Scope	Trait
Delegation	Heterogeneous Parallelism
Control Routing	Homogeneous Parallelism
Data Transfer Granularity	Data Locality
	Execution Granularity
	Delegation Routing Transfer



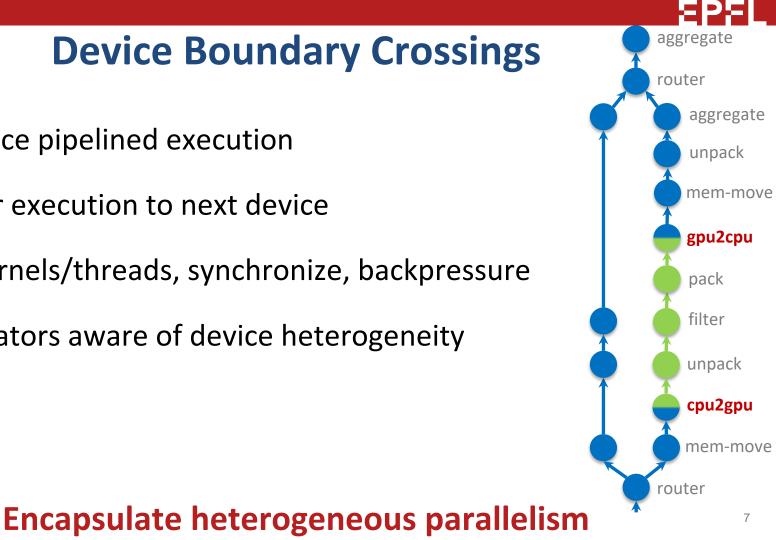
aggregate

router



## **Device Boundary Crossings**

- Cross-device pipelined execution
- Hand-over execution to next device
- Launch kernels/threads, synchronize, backpressure
- Only operators aware of device heterogeneity

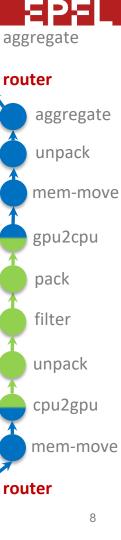




### **Concurrent Execution**

- Horizontal & Vertical parallelism
- Instantiate pipelines multiple times
- Routing policies: load-balance, partition, locality

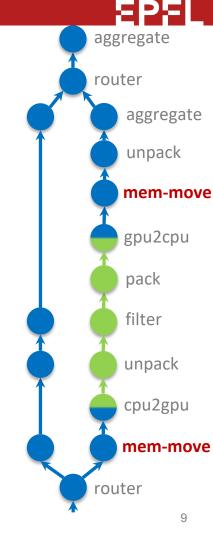
#### Encapsulate homogeneous parallelism





## **Data Transfers**

- Handle memory transfers/prefetching
- Hide memory topology
- Overlap transfers with execution



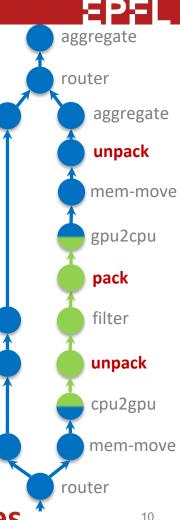
#### Hide memory heterogeneity



## **Execution Granularity**

- Processing: in-registers => tuple-at-a-time
- Memory transfers: packets => block-at-a-time
- Transition between execution granularities
- Create homogeneous (reg. policy) packets

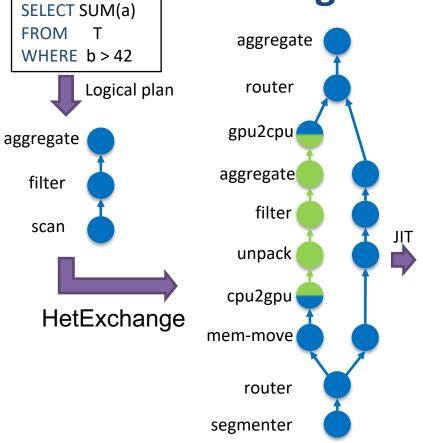








#### **Heterogeneity-aware plans**



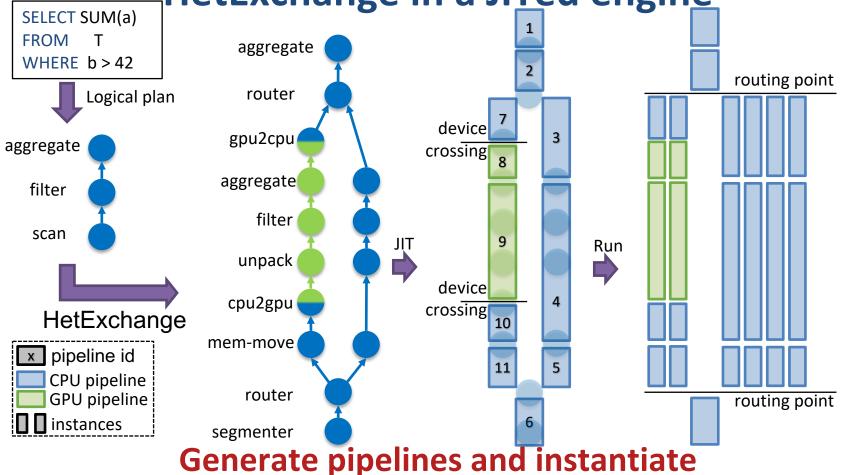
### Efficiency & Operator portability





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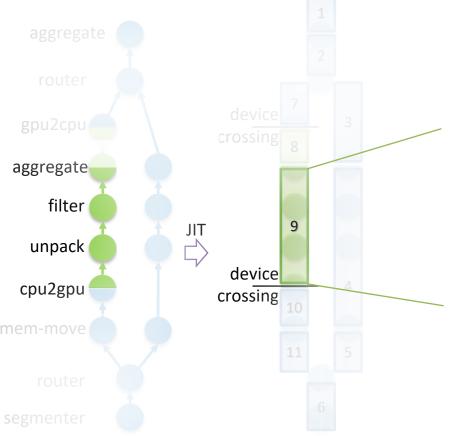
#### HetExchange in a JITed engine







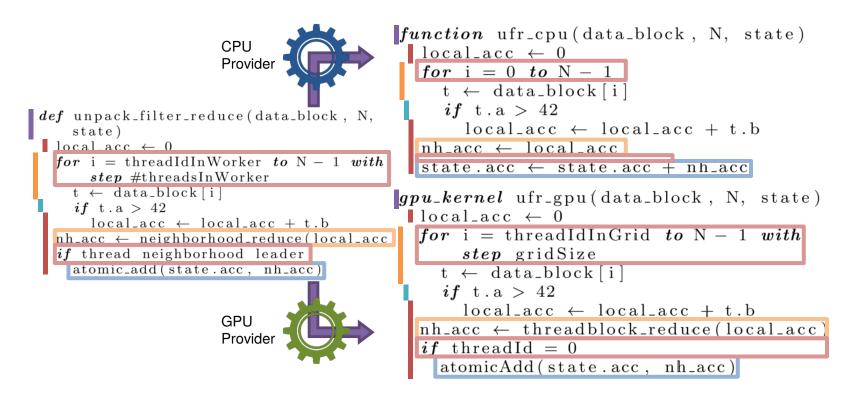
#### **HetExchange in a JITed engine**







#### **Device providers**



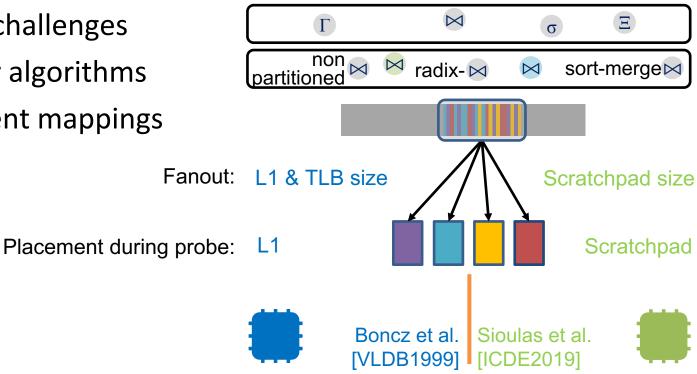
#### Inject target-specific info using the JIT infrastructure





### **Device-optimized operators**

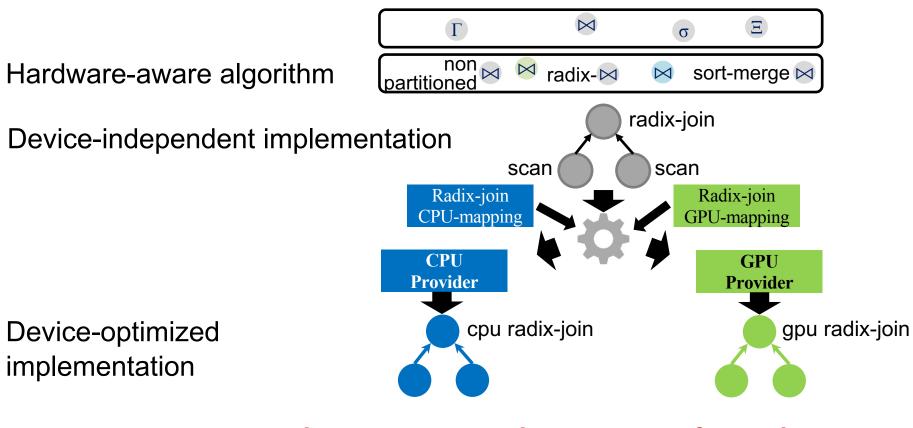
- Same challenges
- Similar algorithms
- Different mappings



#### **Reuse algorithms, specialize mappings to hardware**



### Hardware-dependent JIT code



Lower generic description to device-specific code





### **Experimental Setup**

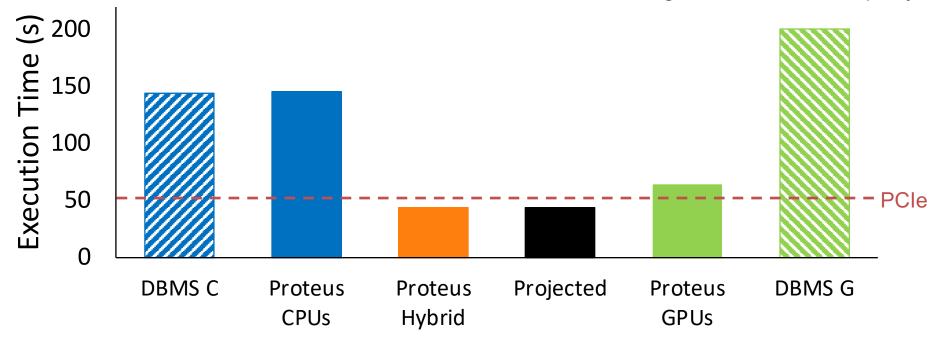
- 2x Intel Xeon E5-2650L v3 12-core @ 1.80GHz, 256GB RAM
- 2x NVIDIA GeForce GTX1080, 8GB, PCIe3 x16 per GPU
- DBMS C/G: state-of-the-art commercial DBMS
  - DBMS C: CPU-based, vector-at-a-time, SIMD, based on MonetDB/X100
  - DBMS G: GPU-based, JIT engine





#### **Performance on CPU-resident data**

#### SSB SF1000, 600GB CSV working set: 92-138GB / query



Hybrid throughput = 88.5% (CPU-only + GPU-only), on average



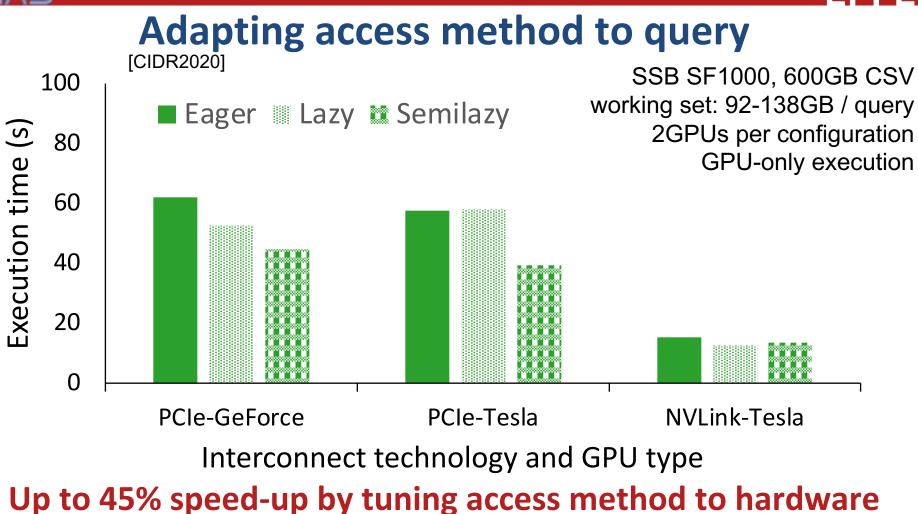


### A glimpse into the future

- Effect of interconnects and GPU compute power
- Access to high-throughput network









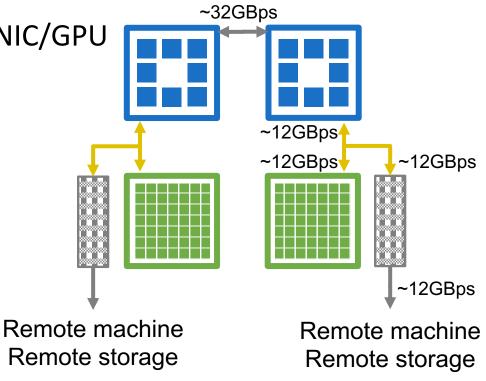


### Towards placing the CPU on the side

• Shared & limited PCIe buses to NIC/GPU

• Similar intra/inter-server BW

• Direct NIC-GPU access (RDMA)



#### Avoid CPU bottleneck => Device-centric OLAP engines <sup>21</sup>





### JIT unleashes ALP

- Run on all available devices
- Relational operators oblivious to heterogeneity
- Fast: Inject target-specific information through codegen
- Result: 5x-10x versus CPU-/GPU-specialized systems

