

## Holistic Extensibility for Integrated Data Analysis Pipelines in DAPHNE

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## Modern Data-driven Applications











### Deployment Challenges



## Project Consortium

- **14 Partner Institutions** from 7 European Countries
- Different Backgrounds
  - Data Management
  - High-Performance Computing
  - ML Systems
  - ML/NLP/Graph Algorithms
  - Simulation & Optimization
- Different Application Domains
- Academia and Industry







Univerza v Mariboru, Slovenia



universität Basel, Switzerland

## Example Use Cases

- DLR Earth Observation
  - ESA Sentinel-1/2 datasets → 4PB/year
  - Training of local climate zone classifiers on So2Sat LCZ42 (15 experts, 400K instances, 10 labels each, ~55GB HDF5)
  - ML pipeline: preprocessing, ResNet-20, climate models

- IFAT Semiconductor Ion Beam Tuning
- KAI Semiconductor Material Degradation
- AVL Vehicle Development Process (ejector geometries, KPIs)
- ML-assisted simulations, data cleaning, augmentation
- Cleaning during exploratory query processing --

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[Xiao Xiang Zhu et al: So2Sat LCZ42: A Benchmark Dataset for the Classification of Global Local Climate Zones. **GRSM 8(3) 2020**] [So2Sat LC42: https://mediatum.ub.tum.de/1454690]









AVL of



## **Overview of DAPHNE**

### System Architecture



#### System Architecture

DaphneLib (API)         Python API w/ lazy evaluation		Pl w/ lazy evaluation
DaphneDSL (Domain-specific Language)		
	DaphneIR (MLIR Dialect)	
▲	Optimizatio	on Passes
MLIR-Based Compilation Chain	New Runtime Abstractions for Data, Devices, Operations	
	Hierarchical Scheduling	
Device Kernels (CPU, GPU, FPGA, Storage)	Vectorized Execution Engine (Fused Op Pipelines)	Sync/Async I/O Buffer/Memory Management
Local (embedded) and Distributed Environments (standalone, HPC, data lake, cloud, DB)		

### Language Abstractions





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## **Optimizing Compiler**





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### Runtime





#### System Architecture

#### **Distributed and Local Vectorized Execution**

- Coarse grained tasks and cache-conscious data binding
- Fused operator pipelines on tiles/vectors of data
- Device kernels for heterogeneous hardware
- Integration of **computational storage** (e.g., eBPF programs)
- Scheduling for load balancing (e.g., for ops on sparse data)
- Different distributed backends (e.g., gRPC, OpenMPI)

#### Example: linear regression model training (simplified)





## Holistic Extensibility

### Challenges



#### **DAPHNE Overall Objective: Open and <b>extensible** system infrastructure

### **Increasing specialization**

#### #1 Data #2 Data #3 Data **Placement** (Value) Types Representations Local vs distributed FP32, FP64, INT8, graph INT32, INT64, UINT8, CPUs/ BF16, TF32, NUMA (intel) dense sparse Intel<sup>®</sup> Xeon Gold Processor FlexPoint compressed GPUs m23 FP32 m10 e8 FPGAs/ **Sparsity Exploitation** e5 m10 FP16 **INVIDIA ASICs** e8 m7 from Algorithms to HW BF16 BITTITI A100]

### Hardware Challenges

- DM+ML+HPC share compilation • and runtime techniques / converging cluster hardware
- End of Dennard scaling
- End of Moore's law
- Amdahl's law

## Holistic Extensibility



• Every relevant aspect of a system for IDA pipelines should be extensible by the user without a deep understanding of the system



### Research challenges

- How to balance expressiveness vs. increased system complexity?
- How to achieve superb performance underneath abstractions?

## Low Barrier of Entry



- Typically, all three aspects need to interact to fully integrate a novel hardware device
- But: low barrier of entry required for user adoption
  - No unnecessary effort
  - No unnecessary restrictions
  - · Ideally no need to touch target system's code base
- Facilitate exploratory specialization

### Examples

- Add single physical operator for accelerator, but not entire engine
- New data/value type should work with existing physical operators (with acceptable performance), no need for re-implementation
- No requirement for deep integration into optimizer (allow usage via hints for initial experiments)



## Towards Holistic Extensibility in DAPHNE





#### Abstractions for cost models Interesting properties

#### **Balance of expressiveness and complexity**

#### **Efficiency underneath abstractions**



#### **Propagation of hints**

#### **Optimize access to extension catalog**

- Building upon existing works on extensible DBMSs from 1980/90s
- Tailored to needs of today's data processing systems for IDA pipelines

[Michael J. Carey, Laura M. Haas: Extensible Database Management Systems. SIGMOD Rec. 19(4) 1990]



## Adding a New Physical Operator



#### • 1 Implementation

- C++ function, operation-specific interface
- Lots of freedom inside the implementation
- Offering APIs for common tasks (data transfer, memory management, ...)

#### 2 Registration

- Provide basic information to make DAPHNE compiler aware of new kernel
- Optionally more information (interesting properties/traits, cost models, ...)

#### • 3 Utilization

- Automatically through multiple dispatch based on data/value types
- automatically through cost models
- Manually in DaphneDSL

#### **Planned extensions (examples)**

- Kernels for various hardware backends
- Readers/writers for various file formats
- Readers/writers for special storage hardware

oid myMatMul(	C++	
<pre>DenseMatrix<float>&amp; res,</float></pre>		
<pre>const DenseMatrix<float>* lhs, const DenseMatrix<float>* rhs</float></float></pre>		
{ // e.g., cublasSgemm(), etc.	mył	Kernels.s

Operation	daphne::MatMulOp	ovtoncion
Func name	myMatMul	catalog
Shared lib	myKernels.so	
Backend	GPU	
Input types	[DenseMat <float>, DenseMat<float>]</float></float>	
Output types	[DenseMat <float>]</float>	
<pre>// Fully automatic (default) C = A @ B; // Choose exact kernel</pre>		
C = <u>SmyMatMul</u> (A, B); // Choose backend C = A (_GPU B;		

## Adding a New Data/Value Type



#### 1 Implementation

 Interface of DAPHNE matrix or frame (get/set/append values, slice, ...)

#### • 2 Registration

Logical type	Frame
Type name	ArrowFrame
Shared lib	myDataTypes.so
•••	

#### 3 Utilization

- Automatically via cost models (e.g., physical size, access patterns, ...)
- Manually via hints/casts in DaphneDSL

```
// Choose data representation
AF = as.ArrowFrame(F);
```

#### Associated operations as ordinary kernels (print/parse, cast, read/write from/to file)

#### 1 Implementation

• New C++ type (e.g., struct) with interface for interplay with DAPHNE data types

#### 2 Registration

Type name	Quantized8
Size	8 bit

#### 3 Utilization

- Explicitly by the user (application semantics)
   xQ = as.matrix<Quantized8>(X);
- Internal selection by the system (e.g., runtime-accuracy trade-off)

#### **Planned extensions (examples)**

- Data types for data layouts of various libraries
- Data types for various sparse matrix formats
- Value types for quantized, packed, complex, ...

## Extending the Optimizer or Scheduler



### 1 Implementation



- Leverage extensible nature of MLIR-based optimizing compiler
- Implement new MLIR pass

### 2 Registration

- Use MLIR-provided means
- Also: integration of 3<sup>rd</sup>-party dialects from the MLIR ecosystem

### 3 Utilization

Configure DAPHNE optimizer chain to use new pass at the right stage

#### Planned extensions (examples)

- Passes employing new extensions
- Passes deciding placement on accelerators
- Extensions for propagation/estimation of interesting data properties

### 1 Implementation

Also follow specific interface

### 2 Registration

Name	Guided Self-Scheduling (GSS)
Туре	dynamic

### 3 Utilization

- Manual selection as default scheme /bin/daphne --scheduler GSS myScript.daph
- Manual selection for a part of a script

scheduler="GSS", nthreads=32] {
 // complex calculations

#### Planned extensions (examples)

- Various static/dynamic self-scheduling techniques for local multi-threaded and distributed execution



## Summary

## Summary

### Holistic Extensibility for Systems tailored to today's IDA Pipelines

- To address increasing specialization
- Low barrier of entry for adoption by researchers and users

### Current Status

- Running DAPHNE prototype
- Ongoing work in various components
- Extensibility features: WIP

### • Why should you care?

- Simple integration of prototypes (e.g., for novel hardware)
- Easy experimentation for researchers
- Open for collaborations

### **• DAPHNE**

# Integrated Data Analysis (IDA) Pipelines **DM + ML + HPC**

#### DAPHNE overall objective: Open and extensible system infrastructure

[Patrick Damme et al.: DAPHNE: An Open and Extensible System Infrastructure for Integrated Data Analysis Pipelines, CIDR 2022]



## Open source (Apache v2 license) https://github.com/daphne-eu/daphne v0.2 released on July 31, 2023

Towards inclusive developer community





## Feel free to get in touch: patrick.damme@tu-berlin.de

https://daphne-eu.eu/

https://github.com/daphne-eu

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https://www.linkedin.com/in/daphne-eu-project-695735230/



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