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Machine Learning for CUDA+MPI Design Rules

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Automatic Discovery of Implementation Rules for Fast GPU + MPI Operations

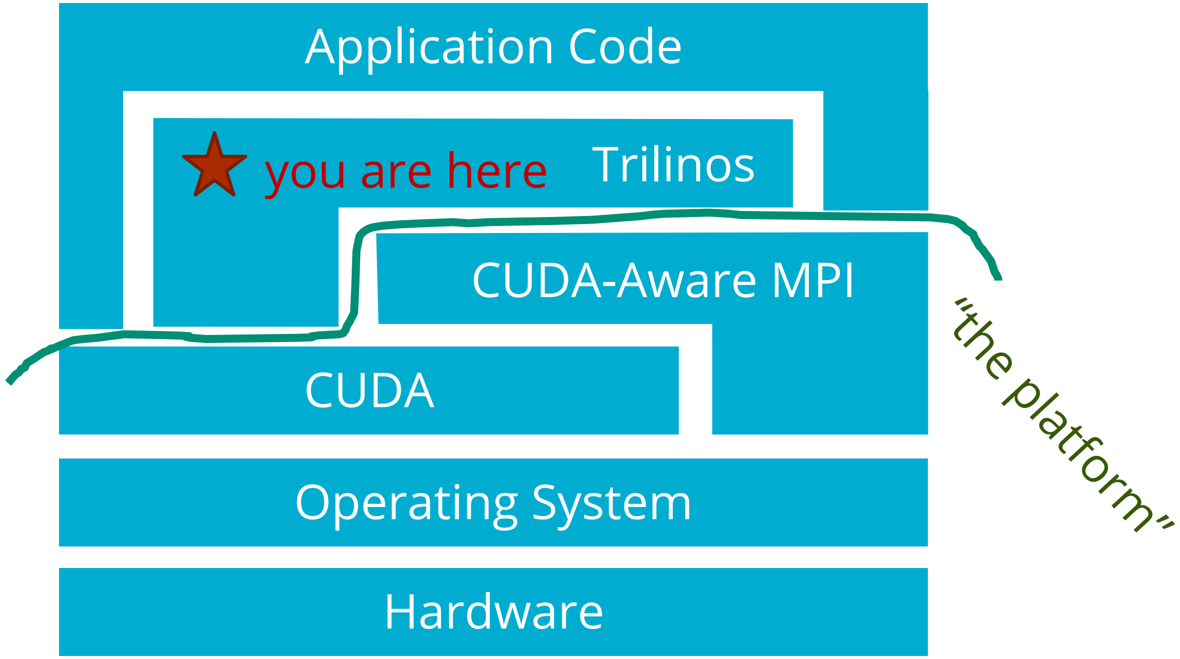
- Fast libraries for heterogeneous architectures
  - Mapping computation onto processors
  - Choosing communication strategy
  - Unpredictable performance interaction
- Prototype automatic tooling for discovering important design decisions
  - Reduced developer effort for performance on new systems
  - Maintain human provenance of library design
  - e.g. Modernize Tpetra MPI+GPU distributed linear algebra operations

Key Challenge	How it's Done
Large Design Space	• Express operation as a directed acyclic graph (DAG) of operations • Monte-Carlo Tree Search (MCTS) to identify and explore regions of interest
Extract performance insight	• Empirical benchmarking • Feature vector for each implementation • Decision tree training for design rules

Initial results pass “sniff test,” working on broader experiments and quantitative evaluation

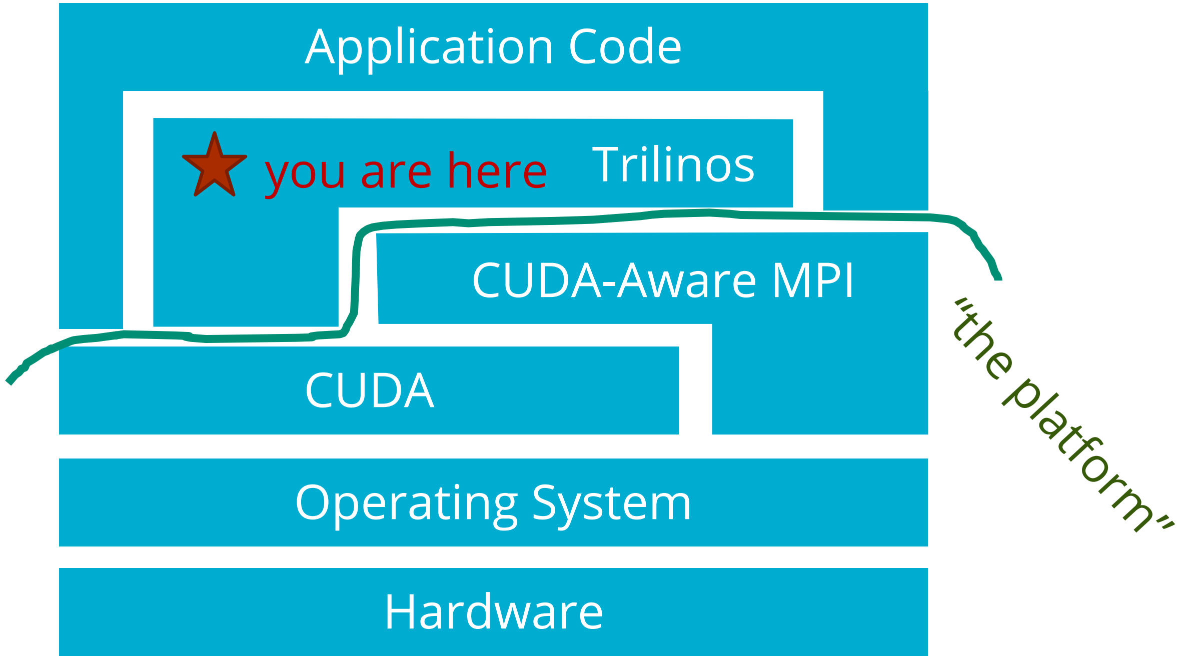
Libraries are built on existing lower-level primitives

- Our libraries (and applications) are combinations of existing library and vendor operations
  - and code to coordinate them
  - and code to implement custom behavior

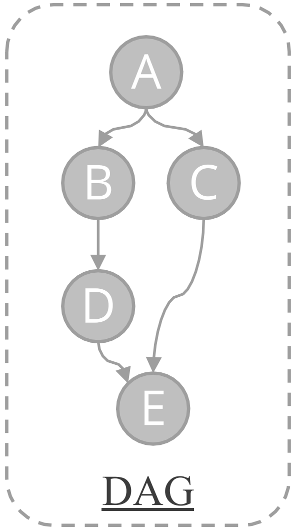


Libraries are built on existing lower-level primitives

- Our libraries (and applications) are combinations of existing library and vendor operations
  - and code to coordinate them
  - and code to implement custom behavior
- Performance changes at many layers for new platforms
  - new hardware,
  - new CUDA version,
  - new OS version,
  - etc.



Prototype Implementation in C++ and Python

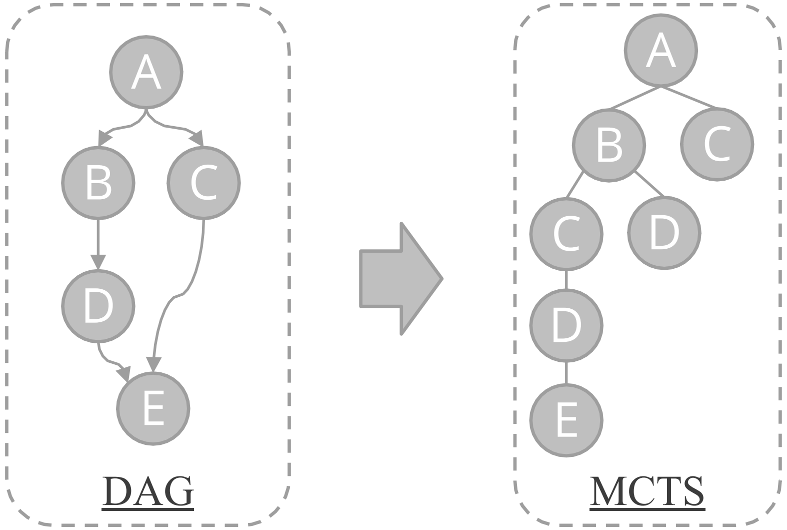


DAG of operations describes design space

C++ / CUDA / MPI

Python / scikit-learn

Prototype Implementation in C++ and Python



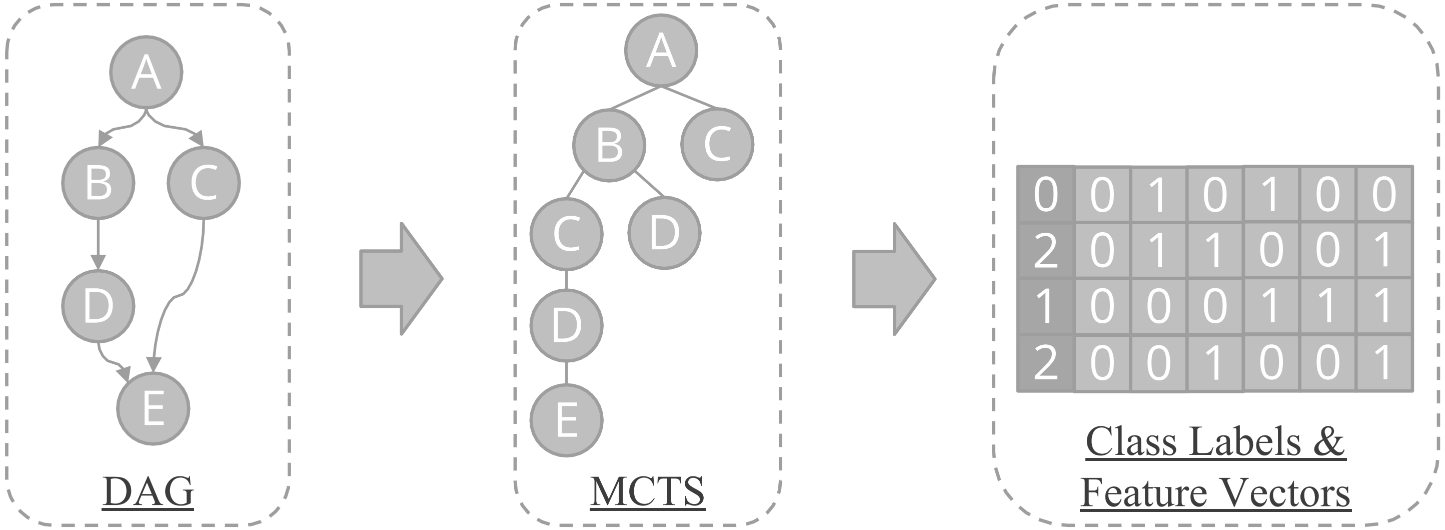
DAG of operations describes design space

MCTS searches order of operations and resource assignment

C++ / CUDA / MPI

Python / scikit-learn

Prototype Implementation in C++ and Python



0	0	1	0	1	0	0
2	0	1	1	0	0	1
1	0	0	0	1	1	1
2	0	0	1	0	0	1

DAG of operations describes design space

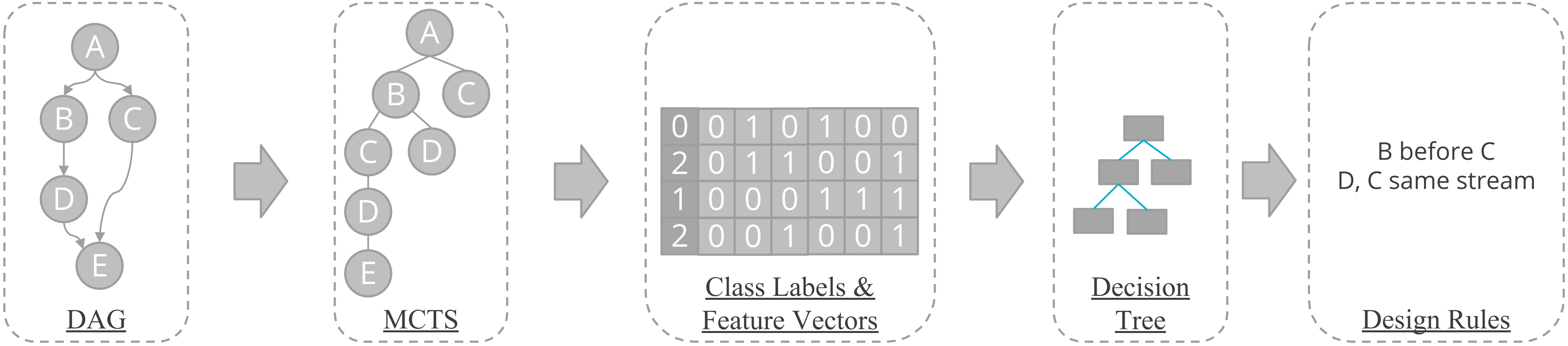
MCTS searches order of operations and resource assignment

Sequence-to-vector transformation for labels

C++ / CUDA / MPI

Python / scikit-learn

Prototype Implementation in C++ and Python



0	0	1	0	1	0	0
2	0	1	1	0	0	1
1	0	0	0	1	1	1
2	0	0	1	0	0	1

B before C
D, C same stream

DAG of operations describes design space

MCTS searches order of operations and resource assignment

Sequence-to-vector transformation for labels

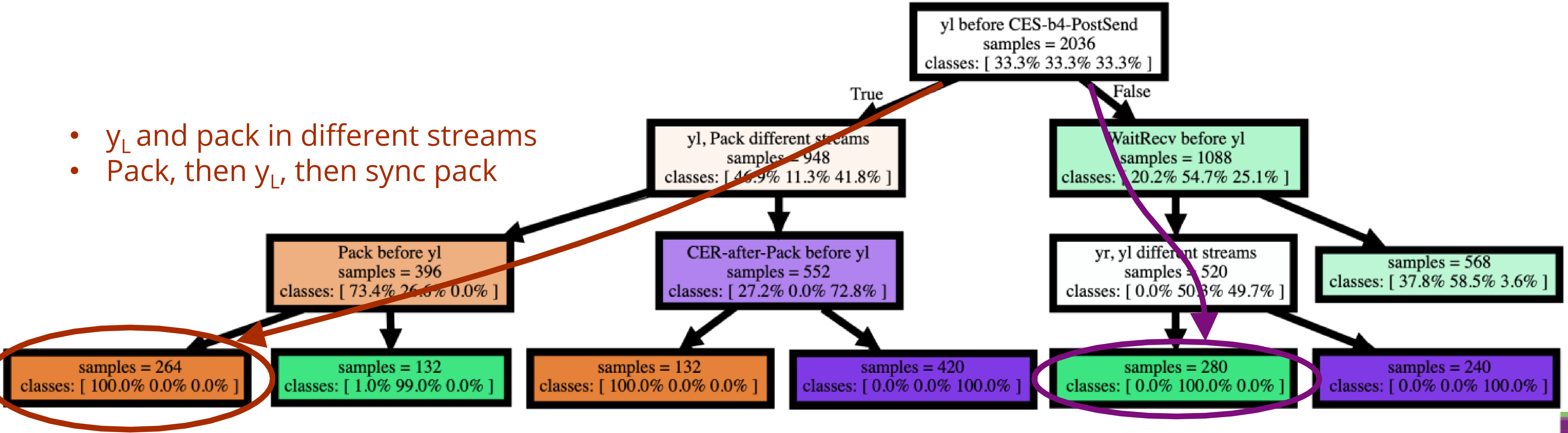
Decision tree training to identify discriminating design space features

C++ / CUDA / MPI

Python / scikit-learn

Decision Tree Training to Determine which Rules Discriminate between Classes

- y_L and pack in different streams
- Pack, then y_L, then sync pack



yl before CES-b4-PostSend
samples = 2036
classes: [33.3% 33.3% 33.3%]

True

False

yl, Pack different streams
samples = 948
classes: [46.9% 11.3% 41.8%]

WaitRecv before yl
samples = 1088
classes: [20.2% 54.7% 25.1%]

Pack before yl
samples = 396
classes: [73.4% 26.6% 0.0%]

CER-after-Pack before yl
samples = 552
classes: [27.2% 0.0% 72.8%]

yr, yl different streams
samples = 520
classes: [0.0% 50.3% 49.7%]

samples = 568
classes: [37.8% 58.5% 3.6%]

samples = 264
classes: [100.0% 0.0% 0.0%]

samples = 132
classes: [1.0% 99.0% 0.0%]

samples = 132
classes: [100.0% 0.0% 0.0%]

samples = 420
classes: [0.0% 0.0% 100.0%]

samples = 280
classes: [0.0% 100.0% 0.0%]

samples = 240
classes: [0.0% 0.0% 100.0%]

- sync pack before y_L
- WaitRecv before y_L
- $y_{L,}$ y_R in same stream

Each path through the tree is a set of design rules that define a performance class

Vision for this work

- Current
  - C++ MCTS implementation for MPI/CUDA codes with multiple streams
  - Prototype feature-vector and decision tree training using SciKit in Python
  - Available at github.com/sandialabs/tenzing
- Upcoming
  - Applying initial results to Tpetra distributed linear algebra package in Trilinos
- Future Explorations
  - Identify unexpected performance effects on target platforms (“performance bugs”)
  - What to do as communication / computation are more tightly integrated
- Summary
  - Represent CUDA+MPI operation as DAG
  - Automatically generate human-interpretable rules for library design
  - Maintain human provenance of implementation (no “black boxes”)