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Memory Interoperability for Analytics and Machine Learning

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ScaledML @ Stanford

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Me

- Currently: Software Architect at Two Sigma Investments
- Creator of Python pandas project
- PMC member for Apache Arrow and Apache Parquet
- Author of *Python for Data Analysis*
- Other Python projects: Ibis, Feather, statsmodels

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This talk

- Benefits of interoperable data and metadata
- Challenges to sharing memory between runtime environments
- Apache Arrow: Purpose and C++ architecture
- Opportunities for collaboration
- Example application: pandas 2.0

Changing hardware landscape

- Intel has released first production 3D Xpoint SSD
  - Reported 1000x faster than NAND, less expensive than RAM

- Convergence between RAM vs. shared memory / mmap performance

Changing software landscape

- Next-gen ML / AI frameworks (TensorFlow, Torch, etc.)
- DIY open source architectures for machine learning in production
  - Streaming / batch data processing pipelines
  - Data cleaning and feature engineering
  - Model fitting / scoring / serving

“Zero-copy” memory interfaces

- Enables computational tools to process a dataset **without any additional serialization**, or transfer to a different memory space
- Can do random access on a dataset that does not fit in RAM

- Another interpretation: reading a dataset is a **metadata-only conversion**

Challenges to zero-copy memory sharing

- Cross-language issues
  - Type metadata + logical types
  - Byte/bit-level memory layout

- Language-specific issues
  - In-memory data structures
  - Memory allocation and sharing constructs

What is pandas?

- Popular in-memory data manipulation tool for Python
  - Focused on tabular datasets (“data frames”)
- Sprawling codebase spanning multiple areas
  - IO for many data formats
  - Array manipulations / data preparation
  - OLAP-style analytics
- Internals implemented using NumPy array objects

NumPy

- Tensor memory model ("ndarray") for numeric data
  - Strided, homogeneously-typed, byte-addressable memory
  - APL-inspired semantics
  - Zero-copy construction from compatible memory layouts

- Computational tools support both strided and contiguous memory access

pandas: Technical debt + Architectural issues

- Tensor library like NumPy awkward fit for pandas use cases
  - Multidimensionality + strided memory access complicated algorithms
  - Lack of built-in missing value support
  - Weak on native string, variable length, or nested types

- pandas at core a “in-memory columnar” problem, similar to analytical SQL engines

Thesis: Tensors and Tables

- 2 data structures best suited for zero-copy sharing
  - **Tensors**: N-dimensional, homogeneously-typed arrays
  - **Tables**: Column-oriented, heterogeneously typed

- These data structures can be defined using common memory and metadata primitives

Observations

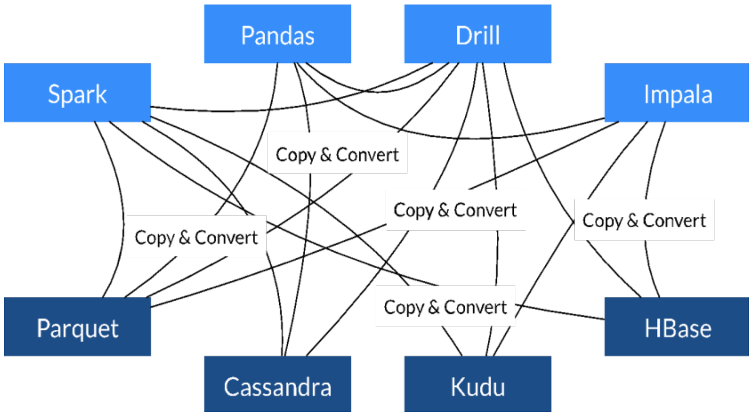
- A Tensor is semantically a multidimensional view of a 1D block of memory
- Writing computational code targeting arbitrary tensors is much more difficult than 1D contiguous arrays
- Tensors of non-fixed size types (e.g. strings) occur less frequently

Apache Arrow

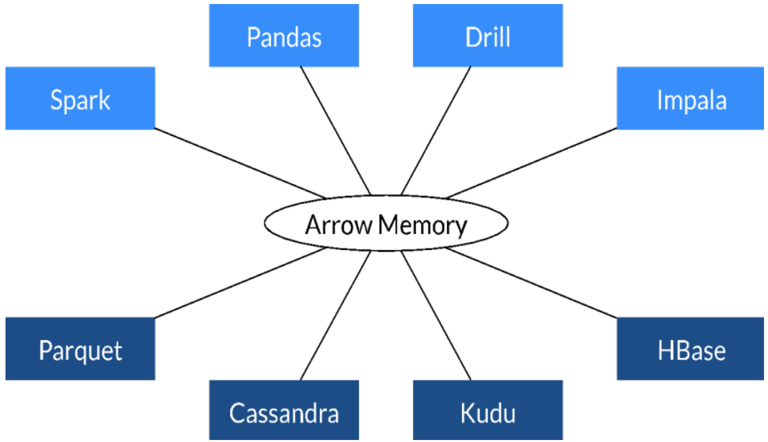
- github.com/apache/arrow
- Collaboration amongst broad set of OSS projects around language-agnostic shared data structures
- Initial focus
  - In-memory columnar tables
  - Canonical metadata
  - Interoperability between JVM and native code (C/C++) ecosystem

High performance data interchange

Today



With Arrow



Source: Apache Arrow

What does Apache Arrow give you?

- **Cache-efficient columnar memory:** optimized for CPU affinity and SIMD / parallel processing, O(1) random value access
- **Zero-copy messaging / IPC:** Language-agnostic metadata, batch/file-based and streaming binary formats
- **Complex schema support**: Flat and nested data types

- **Main implementations in C++ and Java**: with integration tests
  - Bindings / implementations for C, Python, Ruby, Javascript in various stages of development

Arrow in C++

- Reusable memory management and IO subsystem for native code applications
- Layered in multiple components
  - Memory management
  - Type metadata / schemas
  - Array / Table containers
  - IO interfaces
  - Zero-copy IPC / messaging

Arrow C++: Memory management

- `arrow::Buffer`
  - RAII-based memory lifetime with `std::shared_ptr<Buffer>`
  - `arrow::MemoryMappedBuffer:` for memory maps
- `arrow::MemoryPool`
  - Abstract memory allocator for tracking all allocations

Arrow C++: Type metadata

- `arrow::DataType`
  - Base class for fixed size, variable size, and nested datatypes
- `arrow::Field`
  - Type + name + additional metadata
- `arrow::Schema`
  - Collection of fields

Arrow C++: Array / Table containers

- `arrow::Array`
  - 1-dimensional columnar arrays: `Int32Array, ListArray, StructArray,` etc.
  - Support for dictionary-encoded arrays
- `arrow::RecordBatch`
  - Collection of equal-length arrays
- `arrow::Column`
  - Logical table “column” as chunked array
- `arrow::Table`
  - Collection of columns

Arrow C++: IO interfaces

- `arrow::{InputStream, OutputStream}`
- `arrow::RandomAccessFile`
  - Abstract file interface
- `arrow::MemoryMappedFile`
  - Zero-copy reads to `arrow::Buffer`
- Specific implementations for OS files, HDFS, etc.

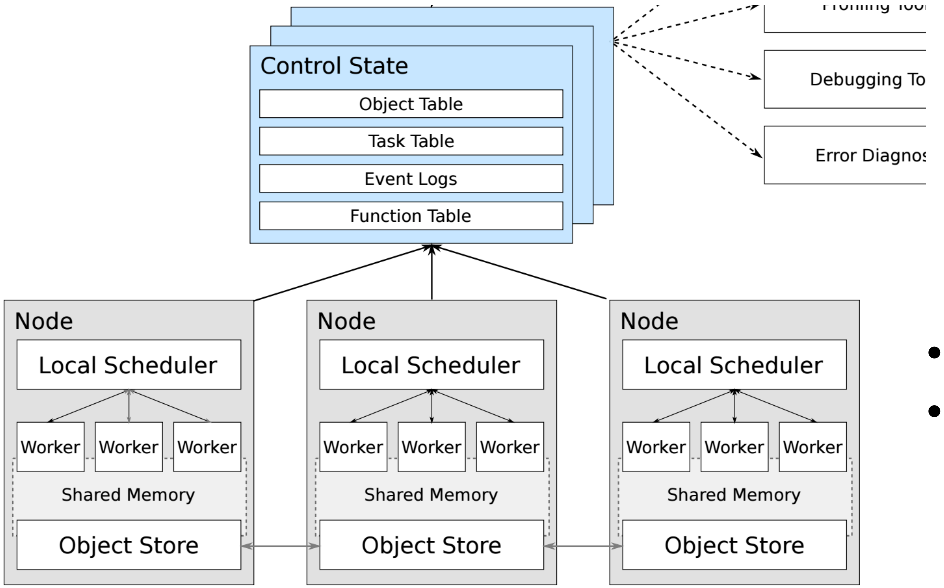
Arrow C++: Messaging / IPC

- Metadata read/write using Google's Flatbuffers library
- Encapsulated Message type
  - Write record batches, read with zero-copy
- `arrow::{FileWriter, FileReader}`
  - Random access / "batch" binary format
- `arrow::{StreamWriter, StreamReader}`
  - Streaming binary format

In development: `arrow::Tensor`

- Targeting interoperability with memory layouts as used in NumPy, TensorFlow, Torch, or other standard tensor-based frameworks
    - data: `arrow::Buffer`
    - shape: dimension sizes
    - strides: memory ordering
- Zero-copy reads using Arrow’s shared memory tools
- Support Tensor math libraries for C++ like **xtensor**

Example use: Ray ML framework from Berkeley RISELab



- **Shared memory-based object store**
- **Zero-copy tensor reads using Arrow libraries**

Source: https://arxiv.org/abs/1703.03924

Example use: pandas 2.0

- In-planning rearchitecture of pandas's internals
  - libpandas — largely Python-agnostic C++11 library
  - Decoupling pandas data structures from NumPy tensors
- Support analytics targeting native Arrow memory
  - Multicore / parallel algorithms
  - Leverage latest SIMD intrinsics
- Lazy-loading DataFrames from primary input formats
  - CSV, JSON, HDF5, Apache Parquet

Other examples

- Spark integration (SPARK-13534)
- Weld integration (ARROW-649)

Thank you

- Building code and community around
  - IO subsystems
  - Metadata
  - Data structures and in-memory formats