NVIDIA | DEEP LEARNING INSTITUTE

ACCELERATING DATA ENGINEERING PIPELINES

Part 1: Data Storage

For each section, start the GPU task before going through lecture

To see lecture notes, make full screen and click the “notes” button

WELCOME!

Main Goal:

How do we organize and process an unexplored dataset to produce actionable insight?

THE GOALS OF THIS COURSE

- Get used to many different data types / frameworks and how they operate on GPU vs CPU.
- Understand how DAG based frameworks can speed up ETL
- Learn how to visualize data to
  - Assess data quality
  - Allow users to make their own decisions through interactivity

AGENDA

- Part 1: Data Formats
- Part 2: ETL with NVTabular
- Part 3: Data Visualization

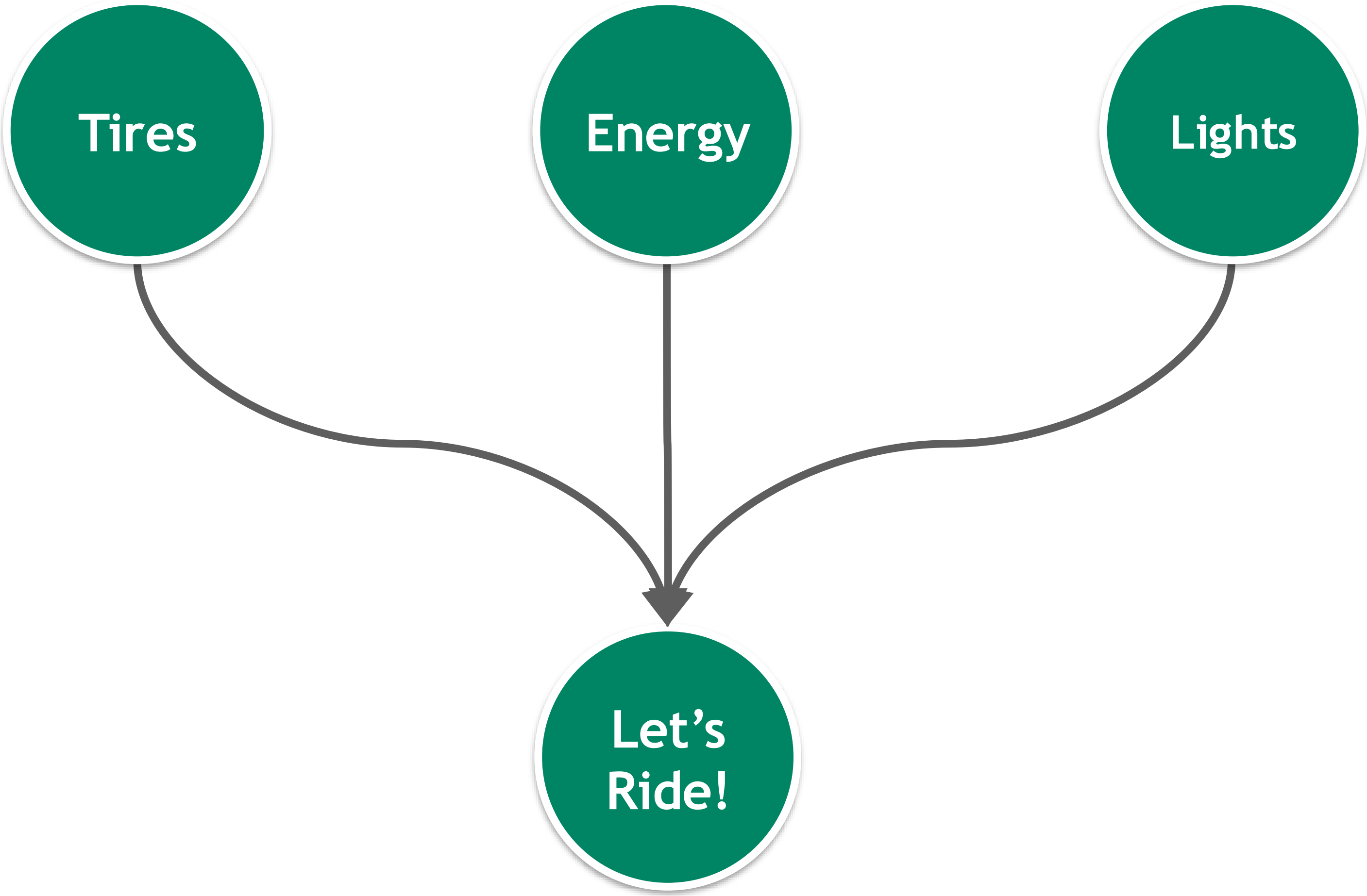
AGENDA – PART 1

- Systems Engineering
- File Formats
- Data Frameworks
- Lab

SYSTEMS ENGINEERING

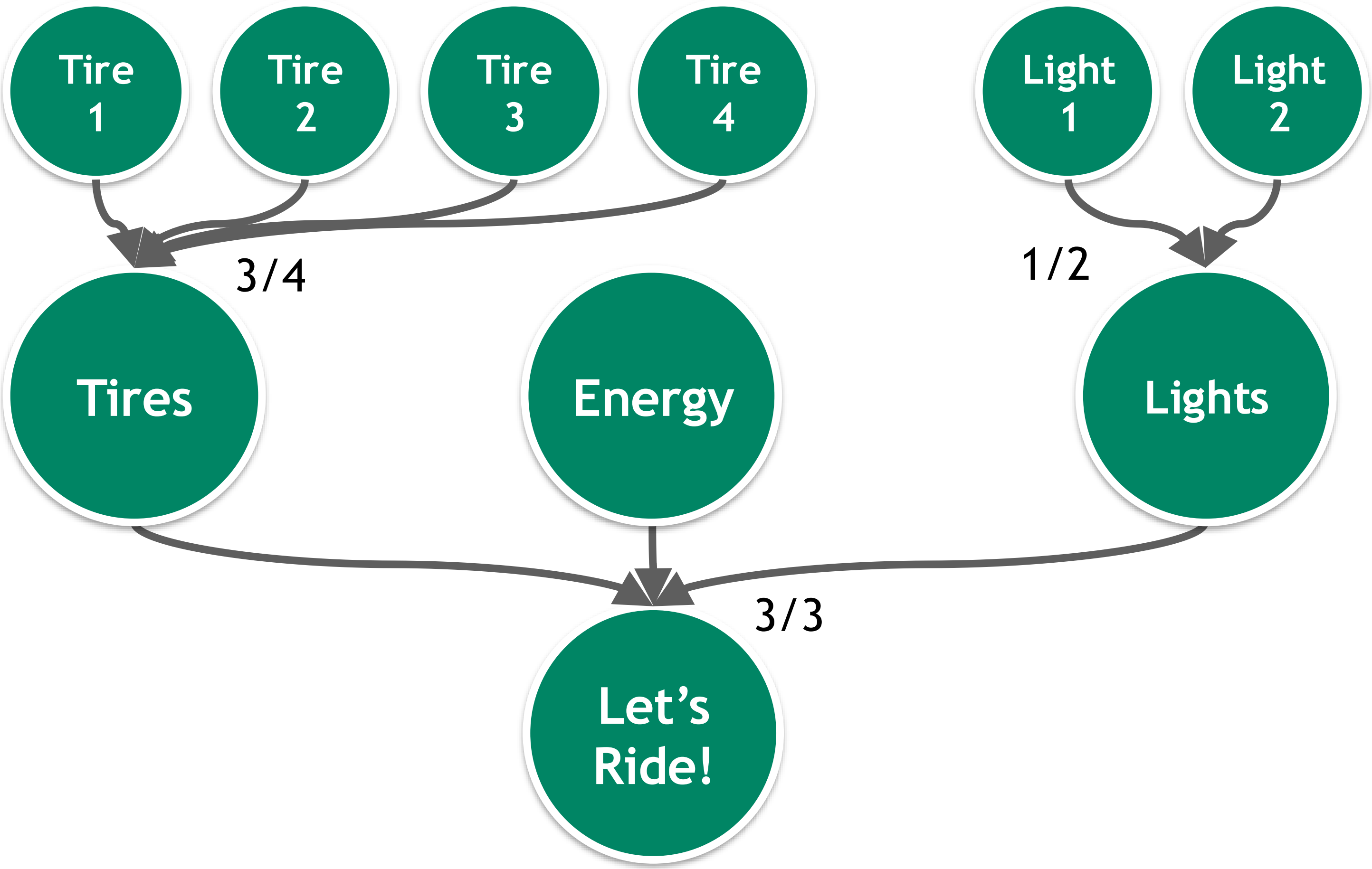
SYSTEM EXAMPLE

Modeling a Car



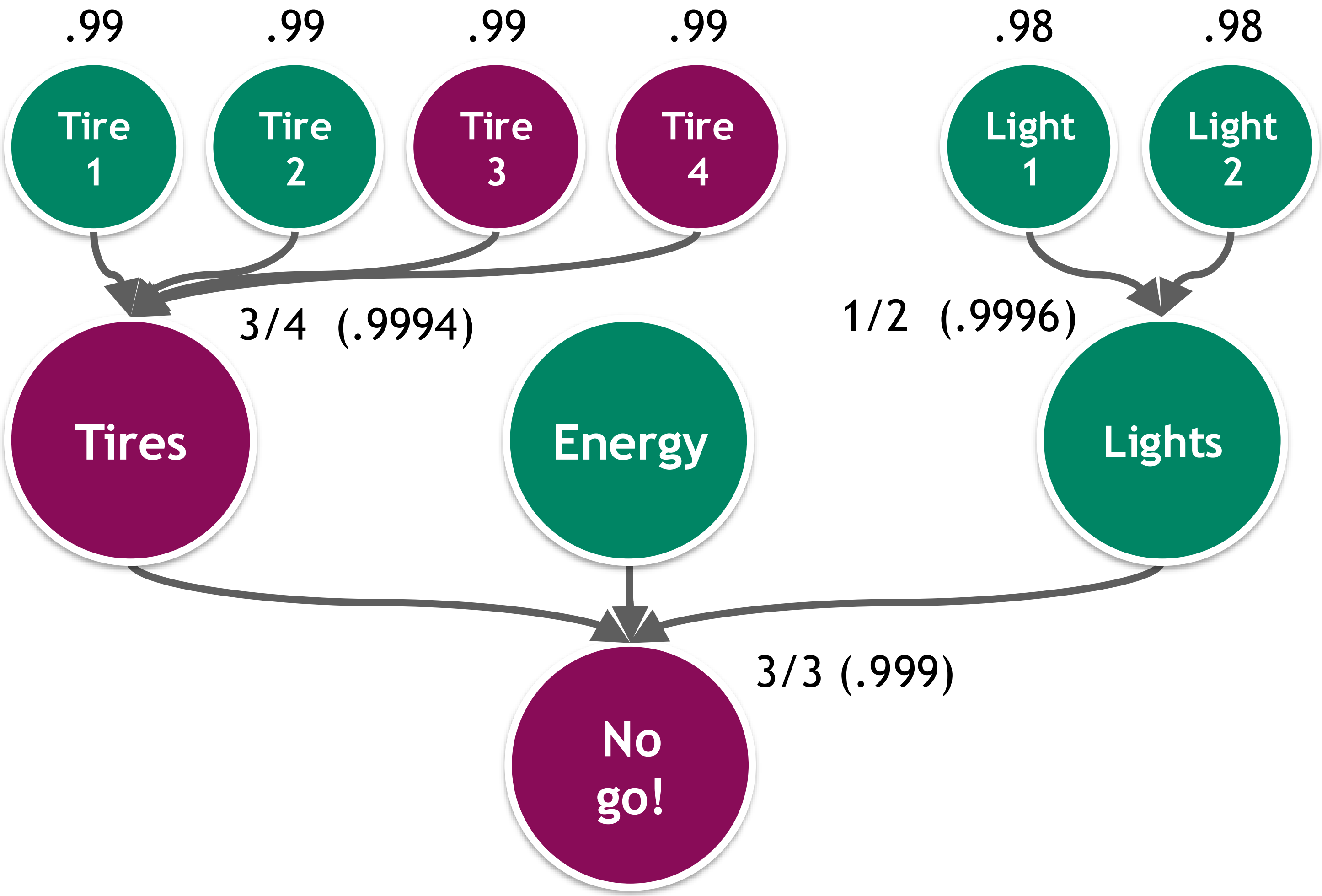
SYSTEM EXAMPLE

Modeling a Car



SYSTEM EXAMPLE

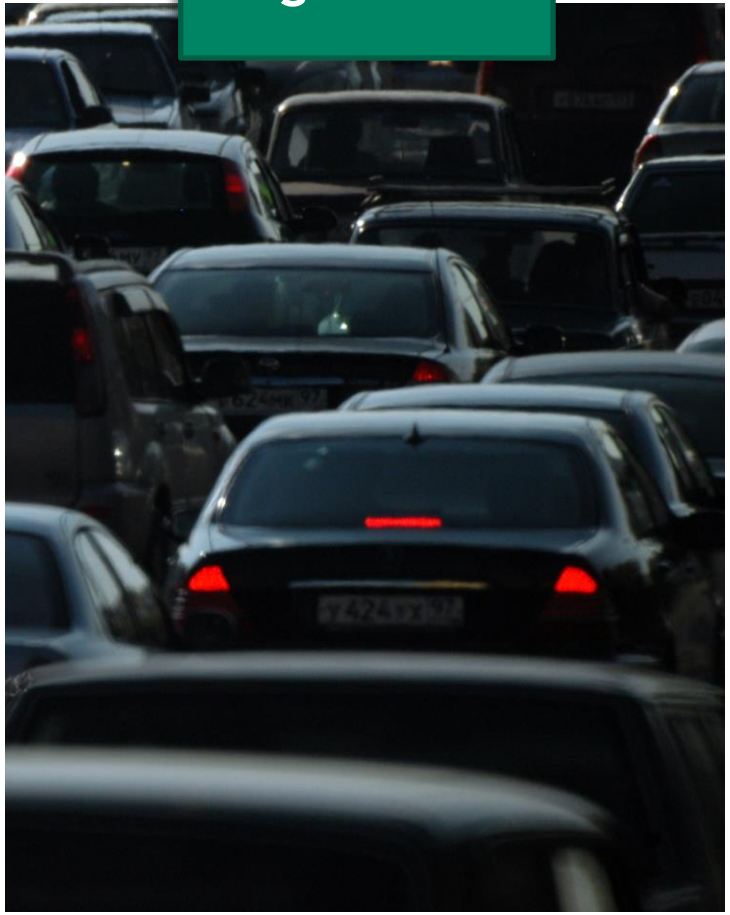
Modeling a Car



SYSTEMS BIG AND SMALL

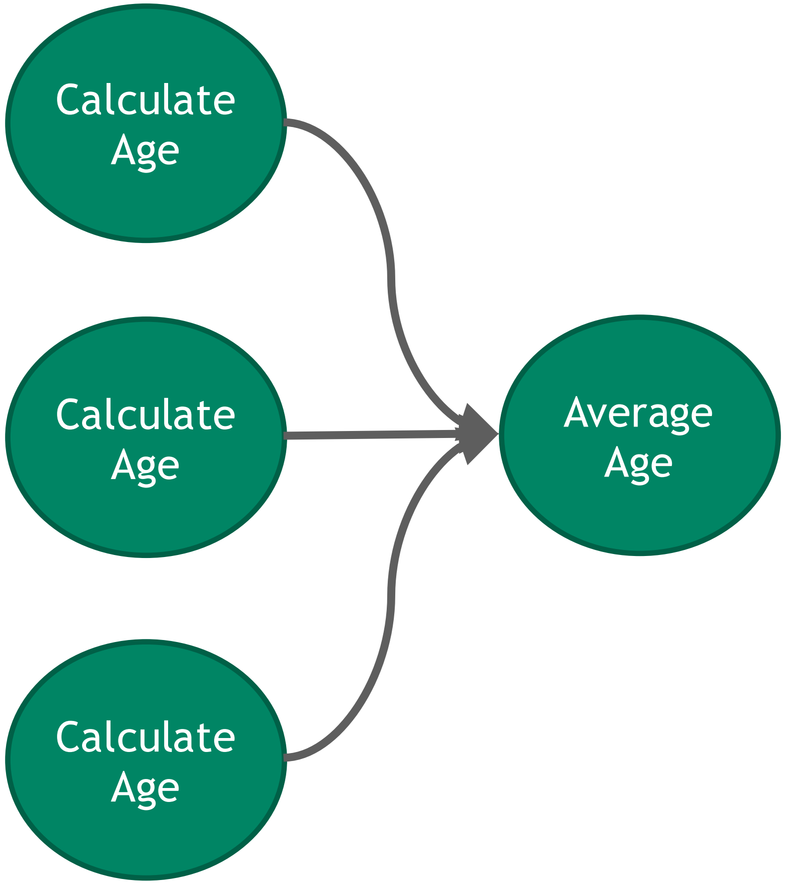
Details

Big Picture

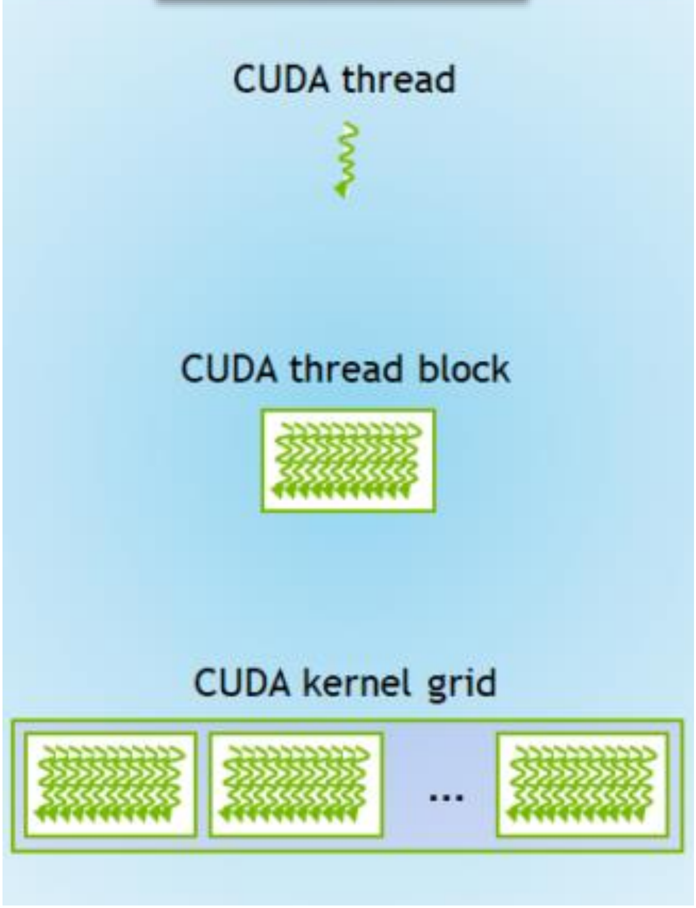


SYSTEM ENGINEERING FOR DATA

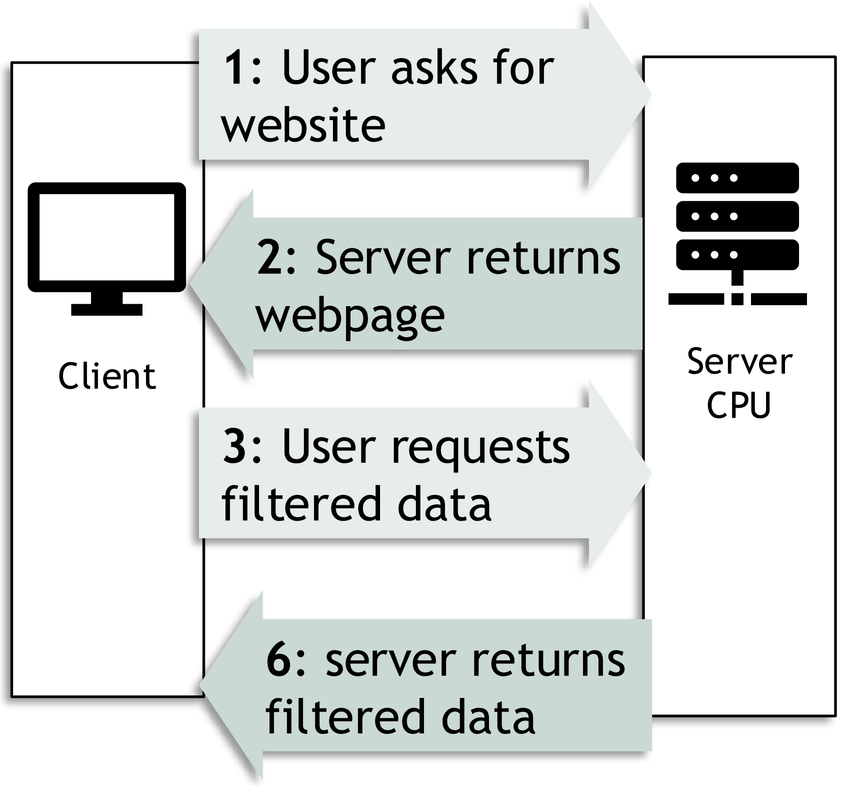
Data Algorithms



Data Hardware



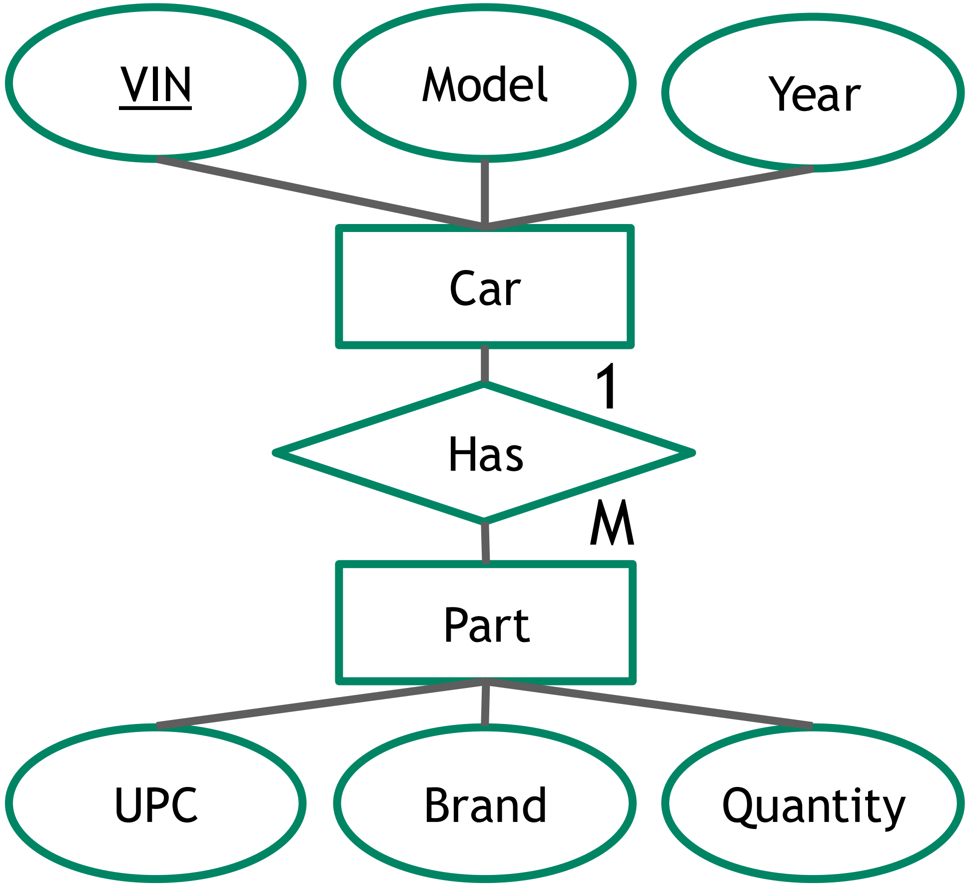
Data Exchange

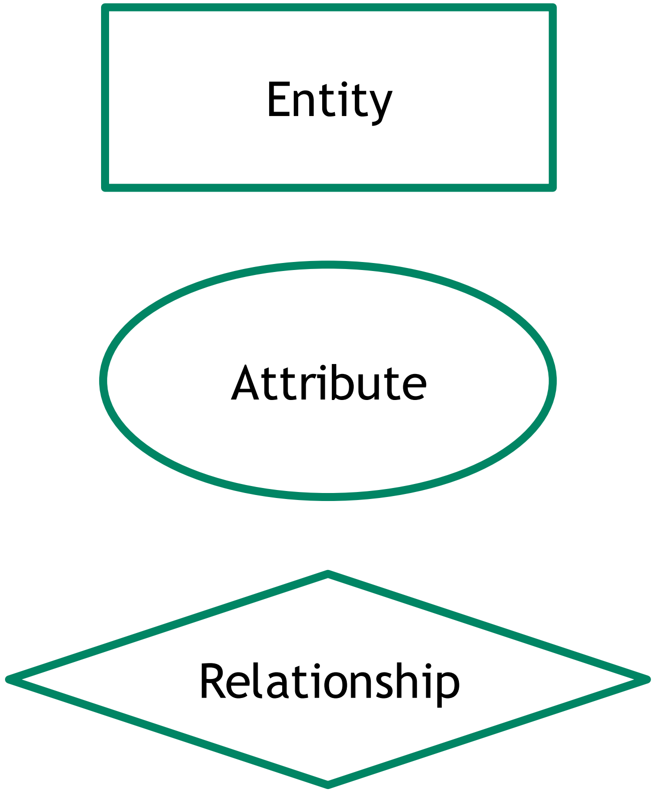


DATA AS A SYSTEM OF ALGORITHMS

DATABASE SYSTEM DESIGN

Enhanced Entity Relationship Diagram





DATABASE SYSTEM DESIGN

From Design to Practice

Cars.csv

```
VIN, Model, Year
1a2b3c, Sedan, 1986
4d5e6g, Convertible, 2011
7h8i9j, Sedan, 1997
```

Parts.csv

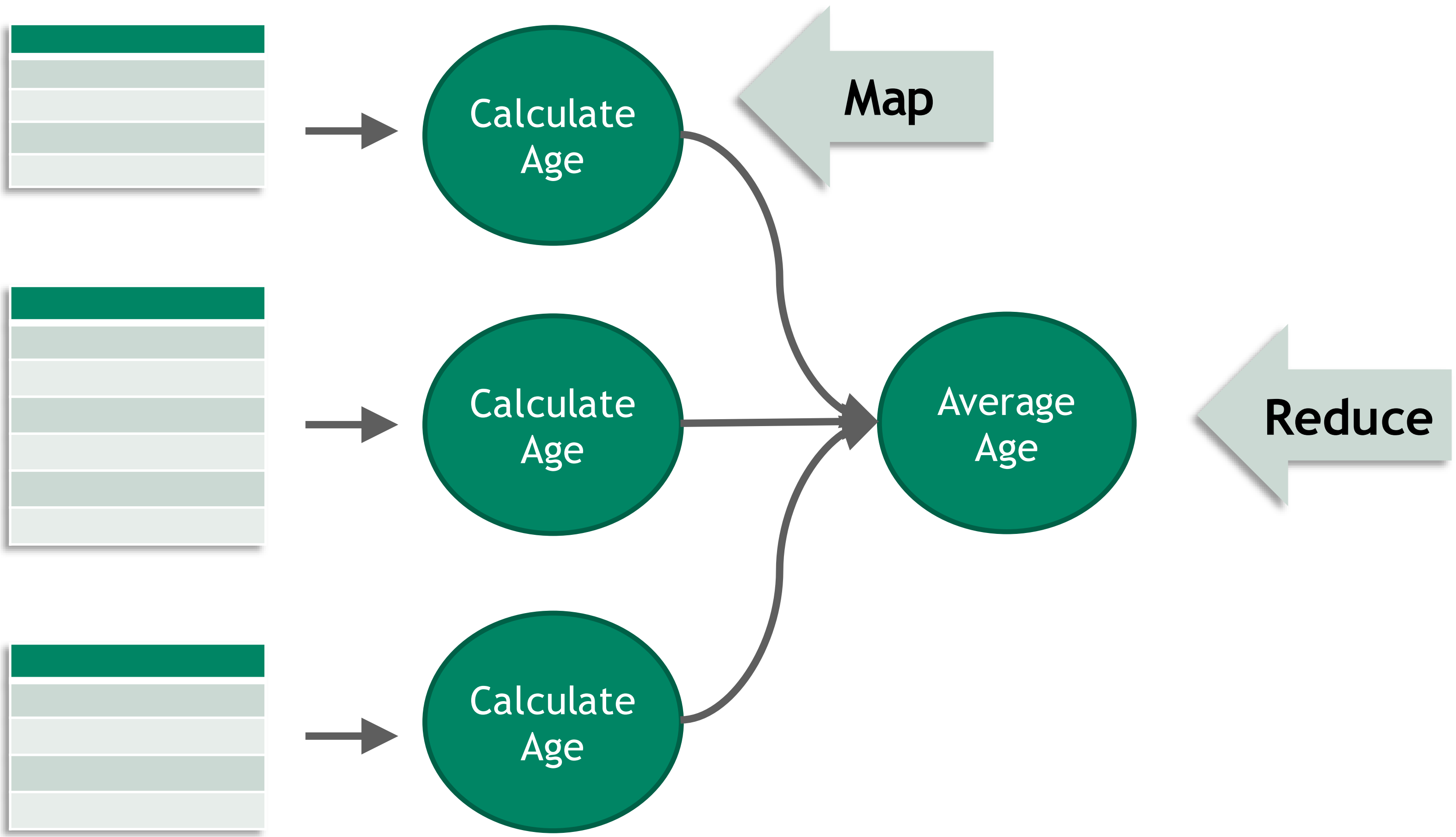
```
VIN, UPC, Brand, Quantity
1a2b3c, 8675309, Generic Lights, 2
1a2b3c, 8675310, Generic Tires, 4
4d5e6g, 8675309, Awesome Lights, 2
4d5e6g, 8675310, Awesome Tires, 4
```

Cars.json

```
{[
  {“VIN”: 1a3b3c,
   “Model”: “Sedan”,
   “Year”: 1986,
   “Parts”: [
        {“UPC”: 8675309,
         “Brand”: “Generic Lights”,
         “Quantity”: 2
        }, {
         {“UPC”: 8675310,
         “Brand”: “Generic Lights”,
…
```

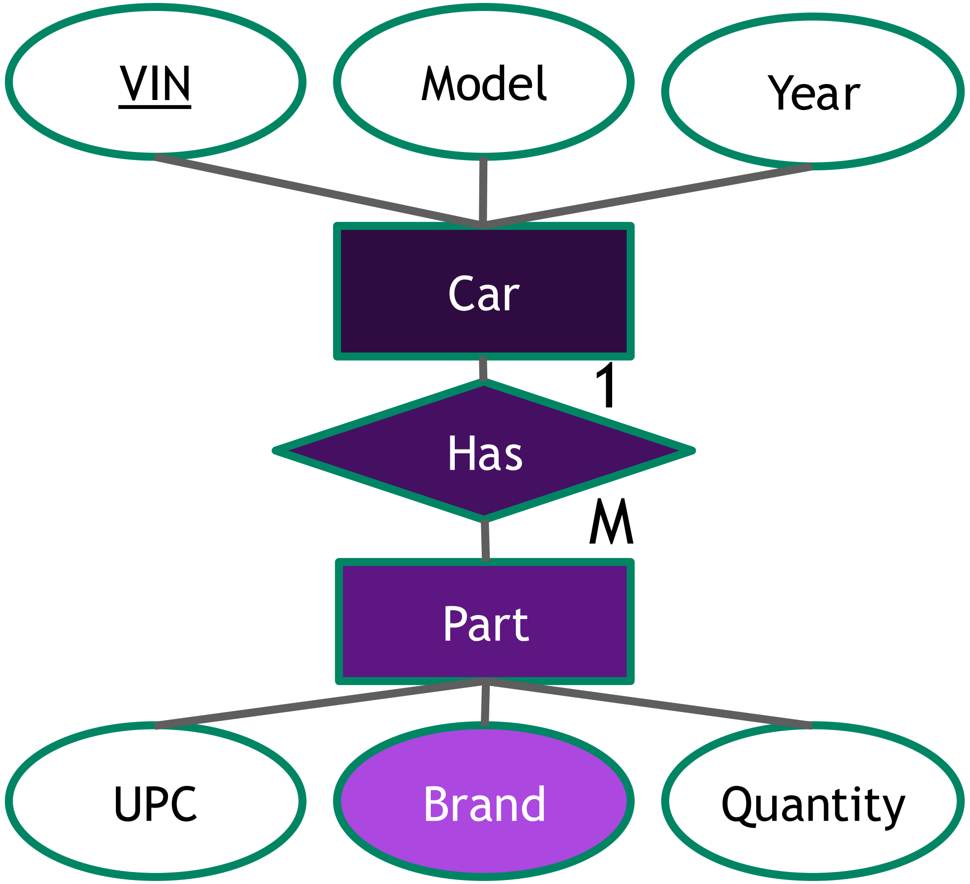
DATABASE SYSTEM DESIGN

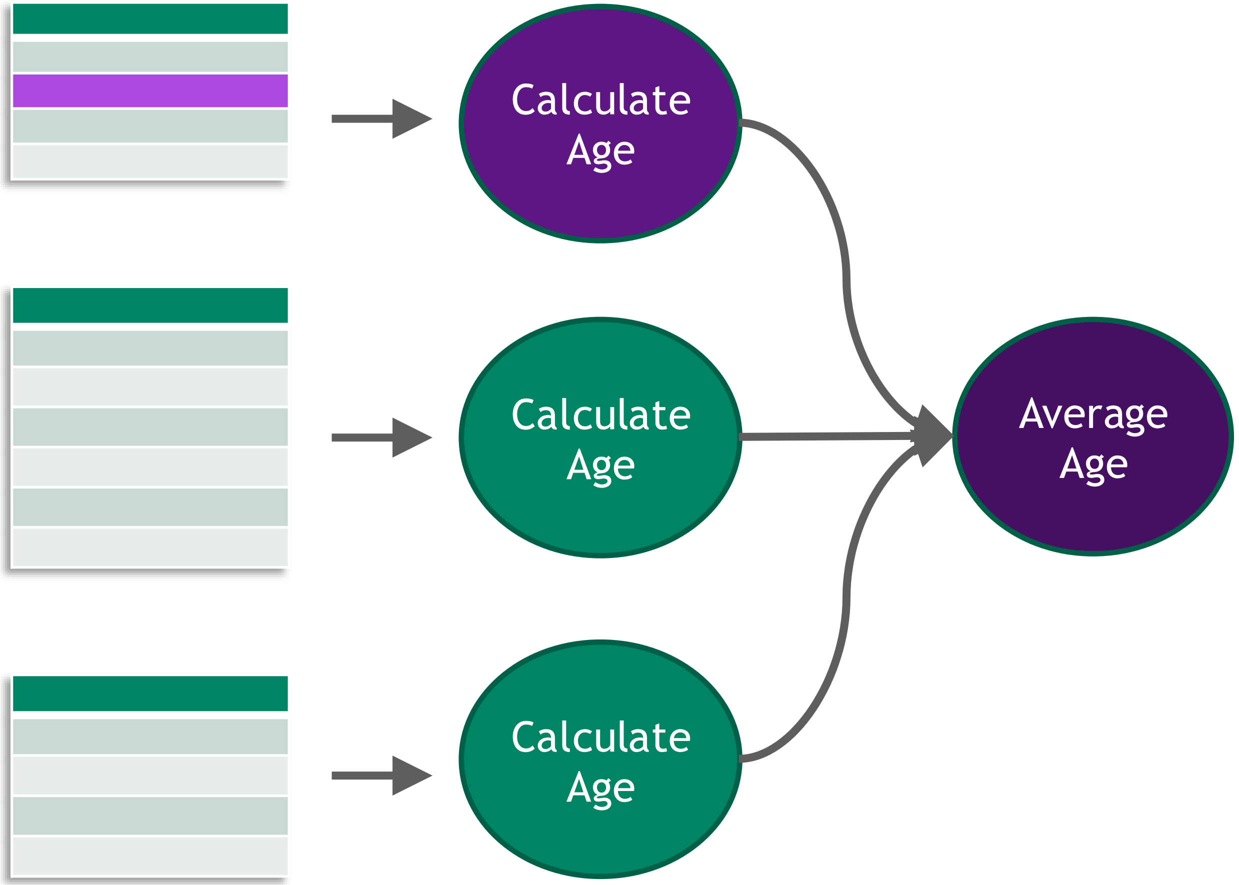
Directed Acyclic Graphs



DATABASE SYSTEM DESIGN

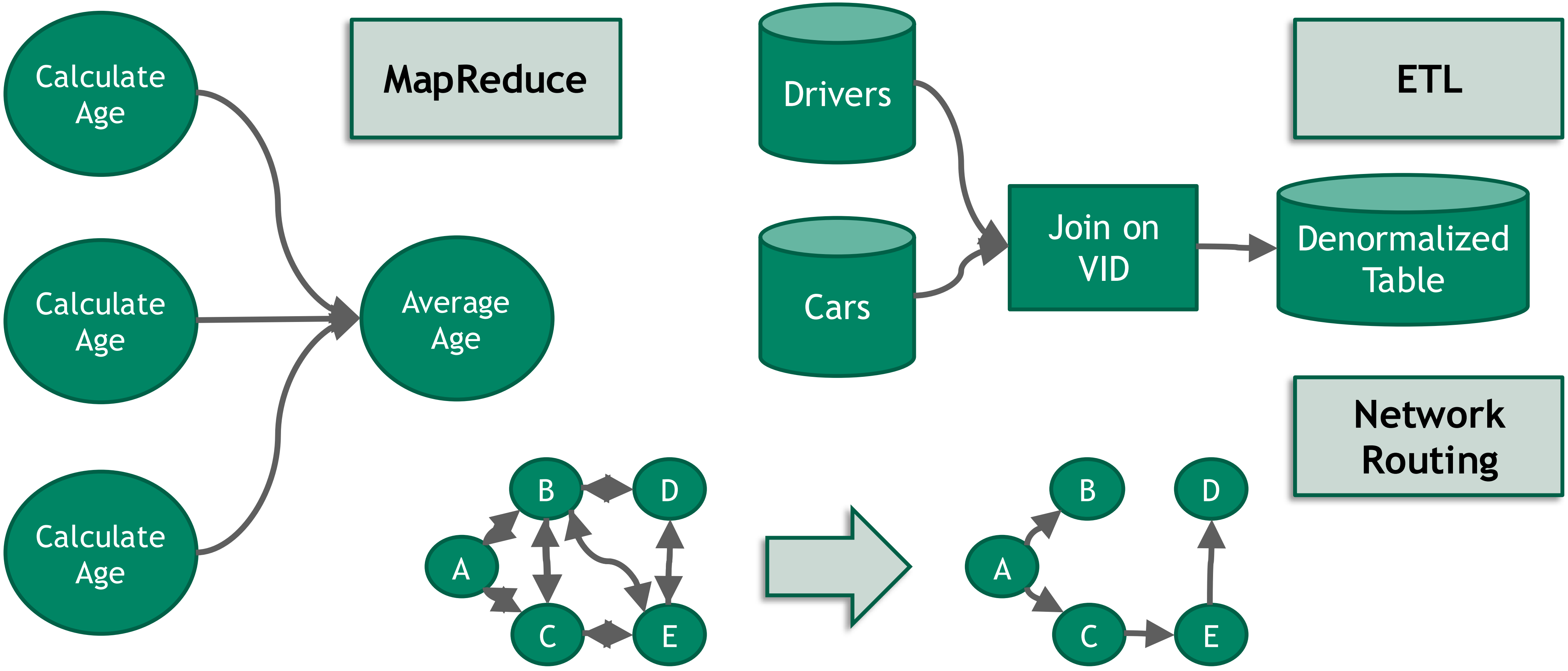
Data Quality





DATABASE SYSTEM DESIGN

Directed Acyclic Graphs



FILE FORMATS

DATA FORMATS

Pick 1 - 2

Flexible

Supports unique schemas

Functional

Usable in many contexts

Scalable

Works well with many data points

These definitions vary based on context:

- Scalable to read or to write?
- Scalable with speed or cost?
- Flexible in the data store or flexible in the application?
- Functional for the server or functional for the client?

PICKING THE BEST FORMAT

CRUD

- Create
  - Add a record
- Read
  - Get record
- Update
  - Change a record
- Delete
  - Remove a record

ROW VS COLUMNAR STORAGE

- Row -

Efficient for

Adding a new record

- Formats
  - CSV (Comma-Separated Values)
  - TSV (Tab-Separated Values)
  - Apache AVRO
- Engines
  - MySQL
  - PostgreSQL

| Columnar |

Efficient for

Data Aggregation

- Formats
  - Apache Parquet
- Engines
  - BigQuery
  - Snowflake
  - Redshift

WRITING

Adding a New Entry

Row Formatted Data

Grace | Hopper | 1906
Blaise | Pascal | 1623
Katherine | Johnson | 1918

Alan | Turing | 1912

Can concatenate to end, or inserted by row number

First	Last	Born
Grace	Hopper	1906
Blaise	Pascal	1623
Katherine	Johnson	1918

+

Alan	Turing	1912

Column Formatted Data

Grace | Blaise | Katherine
Hopper | Pascal | Johnson
1906 | 1623 | 1918

Alan
Turing
1912

Broken up and inserted at the end of each block

ANALYSIS

A.K.A Feature Engineering

Row Formatted Data

Grace | Hopper |
Blaise | Pascal |
Katherine | Johnson |

GH

BP

KJ

First	Last		In.
Grace	Hopper		GH
Blaise	Pascal	>	BP
Katherine	Johnson		KJ
Alan	Turing		AT

Column Formatted Data

Grace | Blaise | Katherine |
Hopper | Pascal | Johnson |

GH | BP | KJ

Broken up and inserted at the end of each block

Can be concatenated to end or inserted by column number

BINARY

Ex: Multimedia File

Pro

- Compact
  - Faster to send and process
- Flexible
  - Many datatypes can easily be converted to binary
    - Great for images

Con

- Hard to visualize without decoding software
  - Difficult to debug data integrity

ASCII

Ex: CSV

Pro

- Simple structure
  - No file metadata
- File is human readable
- Average scalability
  - Easy to join and split multiple CSV files
  - Easy to append a new entry

Con

- Simple structure
  - No file metadata
- Average scalability
  - Data is not compressed as much as other file types

PARQUET

Ex: Hadoop

Pro

- Good compression if many repeated values
- Efficient to read a subset of columns
- Support for complex datatypes like arrays

Con

- Immutable
  - Query results are typically saved in a new file
- Querying for all the attributes of an entity is an expensive operation
- Files are not human readable without a tool

DATA FORMATS COMPARISON

Summary

Properties	CSV	JSON	Parquet	Avro
Columnar			✓	
Compressible	✓	✓	✓	✓
Splittable	✓	✓	✓	✓
Human readable	✓	✓		
Complex data structure		✓		
Schema evolution/validation		✓	✓	✓
Binary			✓	✓

DATA FRAMEWORKS

VERTICAL VS HORIZONTAL SCALING

↑ Vertical ↑

Scales to higher quality hardware

- SQL
- CuPy
- NumPy
- cuDF
- pandas

← Horizontal →

Scales to more partitions / machines

- Dask
- NoSQL
- Spark
- Hadoop

SQL

Structured Query Language

Query

```
SELECT first, last
FROM awesome.people
WHERE born > 1900
```

Table (awesome.people)

first	last	born
Grace	Hopper	1906
Blaise	Pascal	1623
Katherine	Johnson	1918
Alan	Turing	1912

Result

first	last
Grace	Hopper
Katherine	Johnson
Alan	Turing

DATAFRAMES

Pandas (CPU) and cuDF (GPU)

Query

```
df = df[df["born"] > 1900]

df = df["first", "last"]
```

Table
df

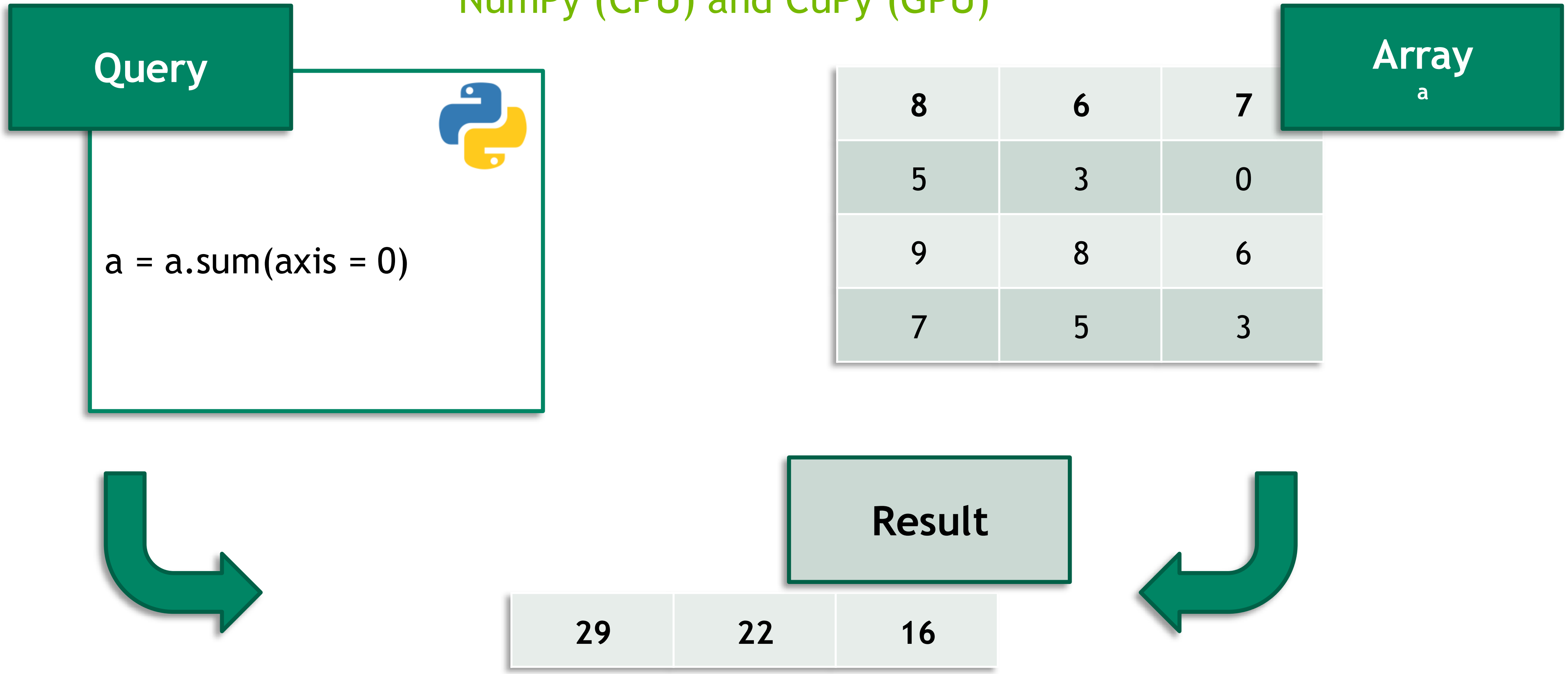
first	last	born
Grace	Hopper	1906
Blaise	Pascal	1623
Katherine	Johnson	1918
Alan	Turing	1912

Result

first	last
Grace	Hopper
Katherine	Johnson
Alan	Turing

MATRICES AND NUMBER ARRAYS

NumPy (CPU) and CuPy (GPU)

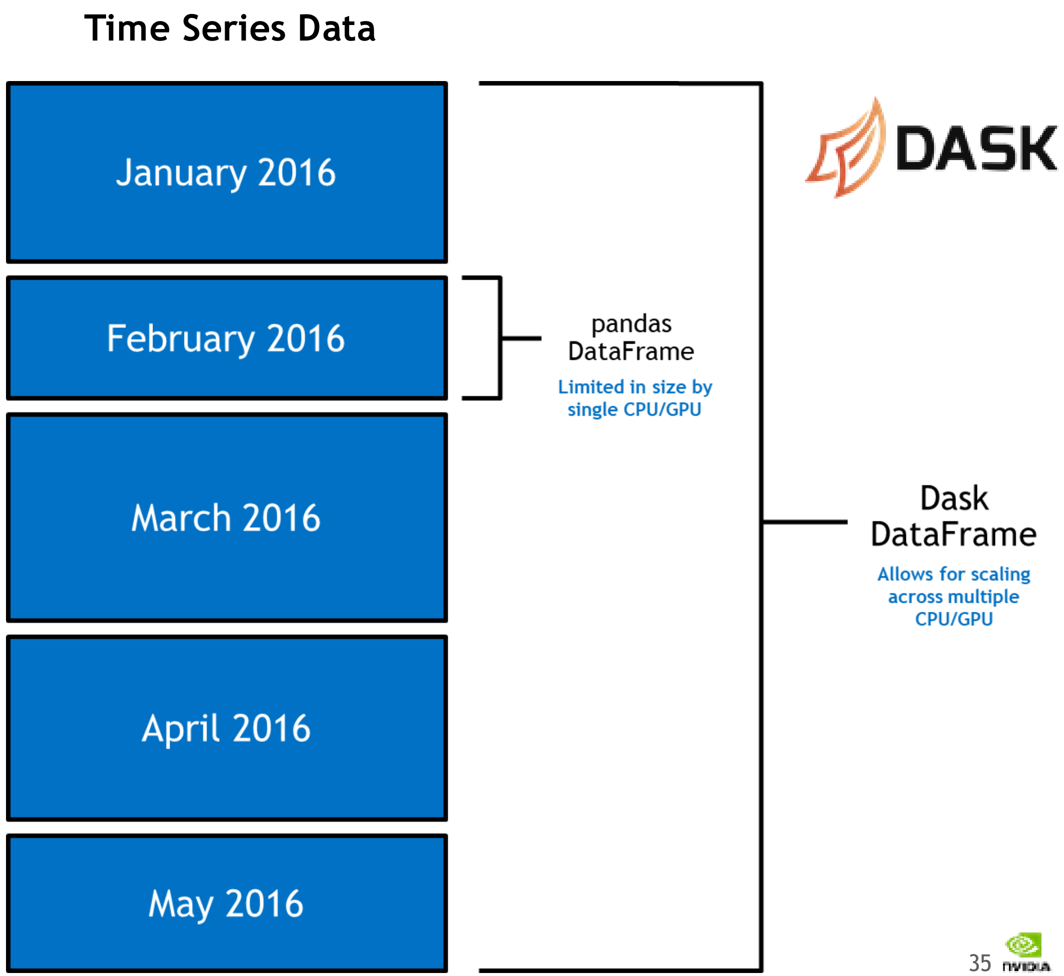


DASK SCALES PYTHON ANALYTICS

SCALE FROM A LAPTOP TO LARGE-SCALE CLUSTERS WITH EASE

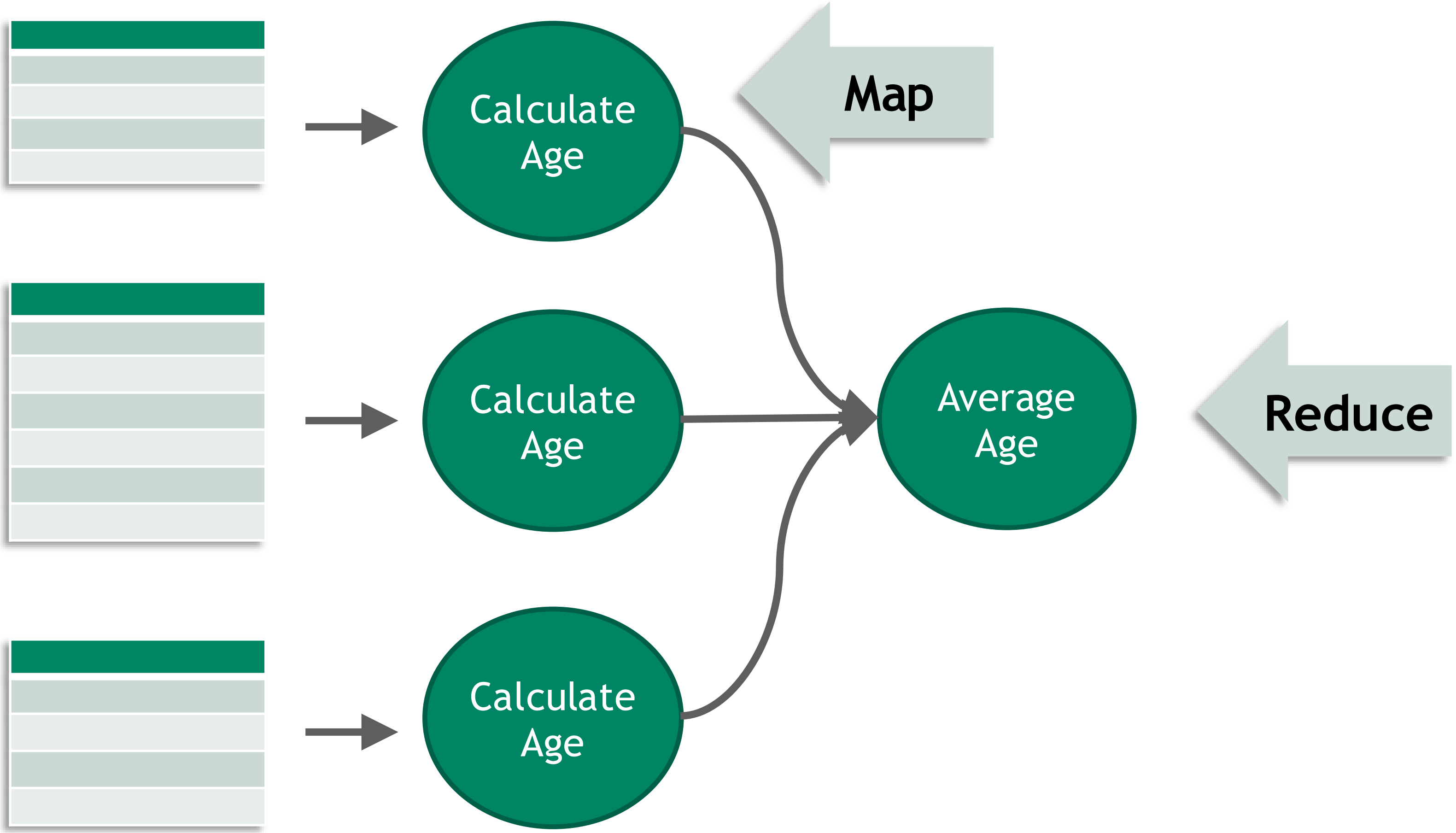
- **Dask** enables data scientists to scale out analytics workloads in native Python. With an optimized scheduler, Dask makes it easy to schedule and execute tasks on distributed computation.

- **Dask** follows the standards set by the PyData ecosystem to provide a familiar, comfortable user experience at scale. When paired with NVTABULAR/RAPIDS, data scientists can leverage the processing power of NVIDIA accelerated compute and distribute across clusters to improve cycle time-reducing time to insights drastically.



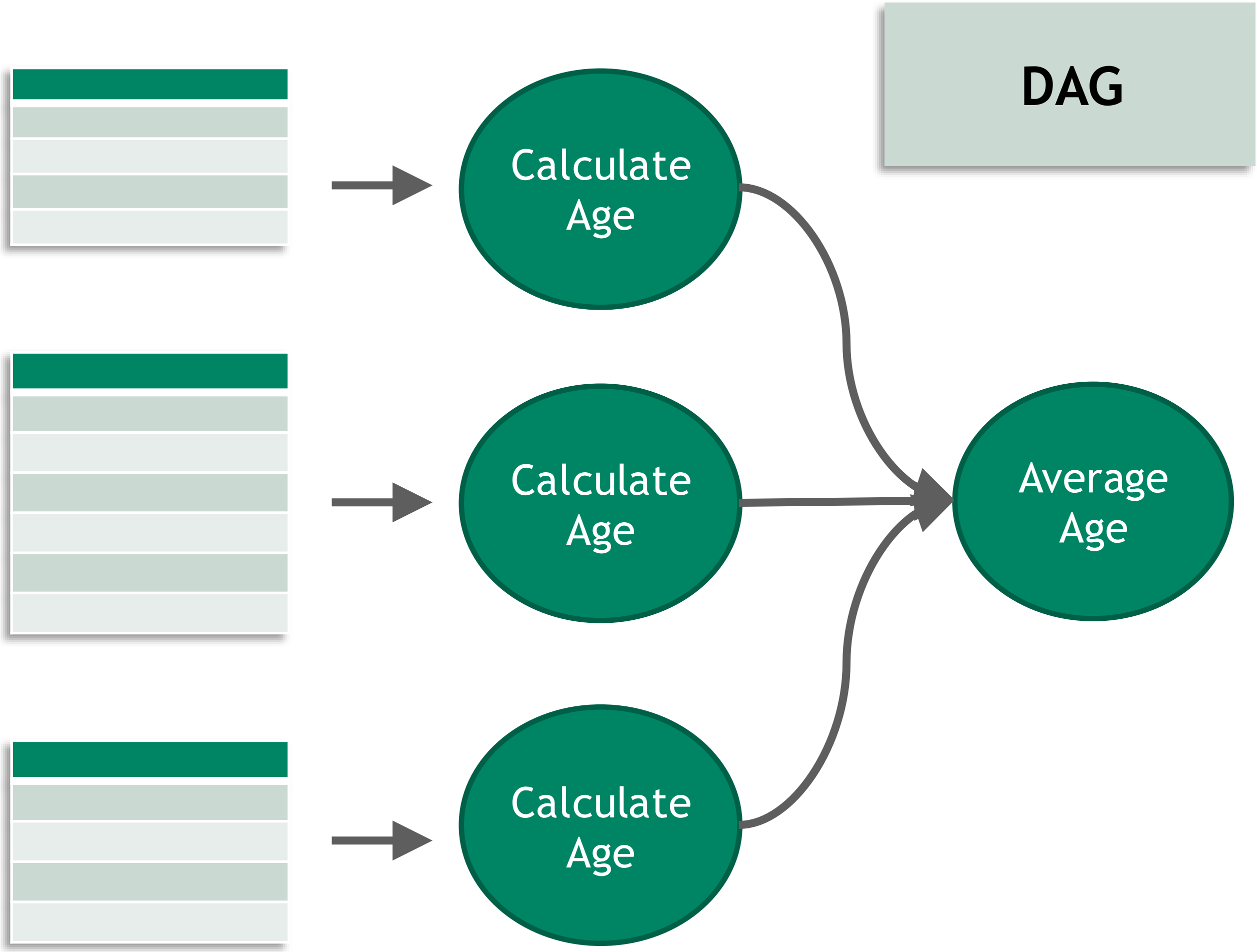
MAPREDUCE

Map to each thread, Reduce all threads to one



LAZY EXECUTION

Building a Factory



RELATIONAL DATABASES

Ex: SQL

Pro

- Well known
- Concise Language
- Relatively fast querying
  - Foreign keys
- Blazing SQL

Con

- Inflexible data structure
  - Some objects do not convert well to table format
- Typically, single server
  - More expensive hardware needed to scale

DATAFRAME

Ex: cuDF, Pandas, R

Pro

Python and R APIs

- cuDF, Pandas

- Compared to SQL, more flexible operations
  - Easier to make user-defined functions and integrate third party libraries

Con

- Single server, not meant for large-scale data manipulation
  - Consider Spark instead
- Compared to SQL, not as scalable

DASK

Ex: Dask DataFrame, Dask-cuDF

Pro

- Large computation can receive a significant speed increase
- Can read large data sources due to partitioning

Con

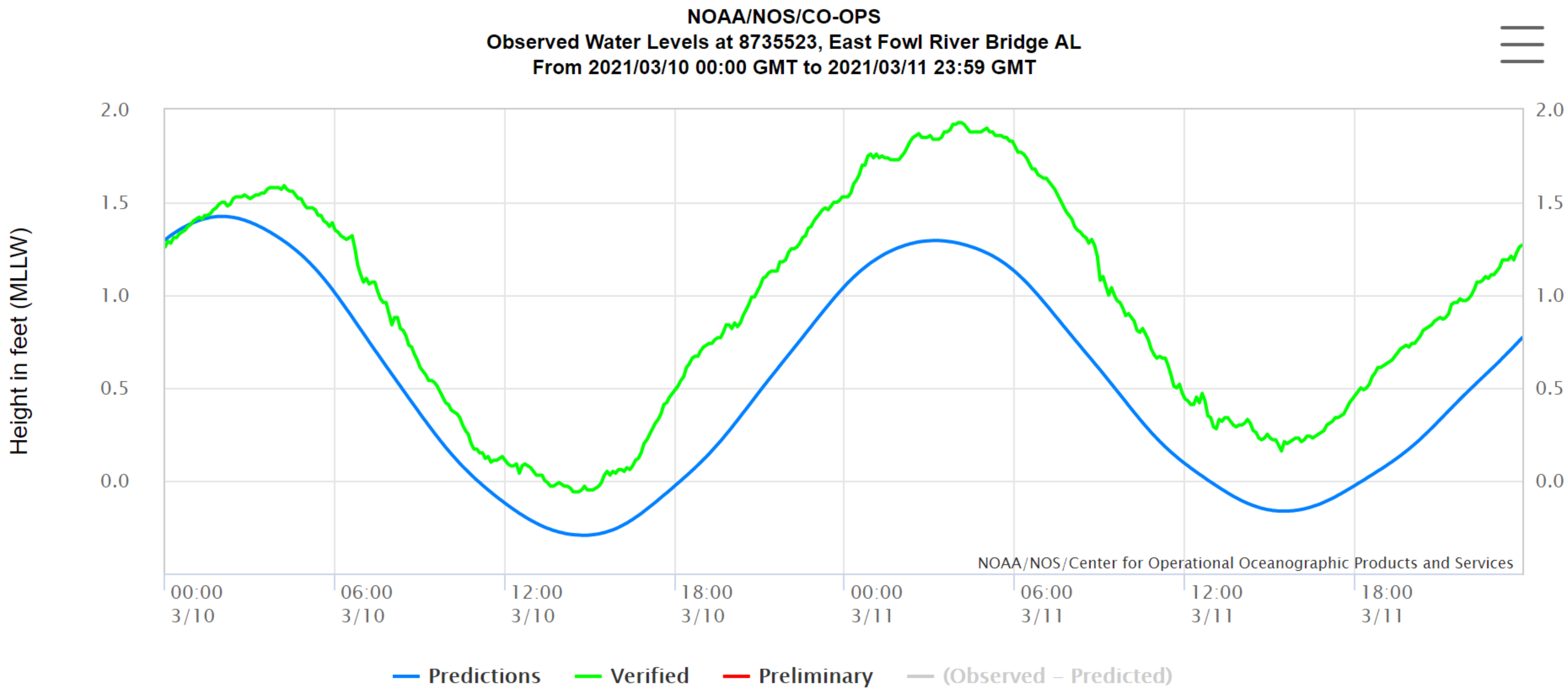
- Large overhead to set up not worth it for small files or limited computation
- Lazy execution can make it tricky to debug

LAB

WEATHER SYSTEMS

Credit: Ralph F. Kresge, Submitted to NOAA

INVESTIGATING WATER LEVEL



LET’S GO!

NVIDIA

DEEP
LEARNING
INSTITUTE