NVIDIA | DEEP LEARNING INSTITUTE

ACCELERATING DATA ENGINEERING PIPELINES

Part 2: Extract, Transform, Load

AGENDA

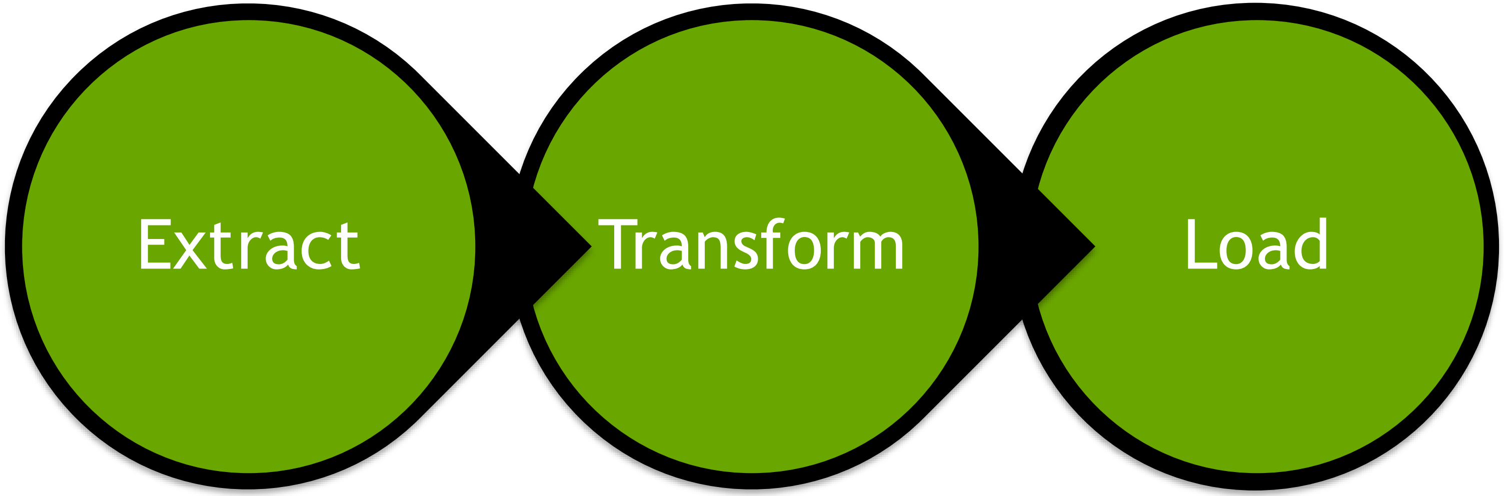
- Part 1: Data Formats
- Part 2: ETL with NVTabular
- Part 3: Data Visualization

AGENDA – PART 2

- ETL Basics
- CUDA
- NVTabular
- Lab

ETL BASICS

DATA MANIPULATION IN 3 “EASY” STEPS



- Pull data from a database
  - SQL, Blob Storage, Image Archive

- Alter the data in some way
  - Cleaning, deduping, feature engineering

- Export transformed data to a new database location

NOT SO EASY TO OPTIMIZE

All parts of the technology stack come into play

Individual Machines

- CPU
- GPU
- RAM
- PCIe

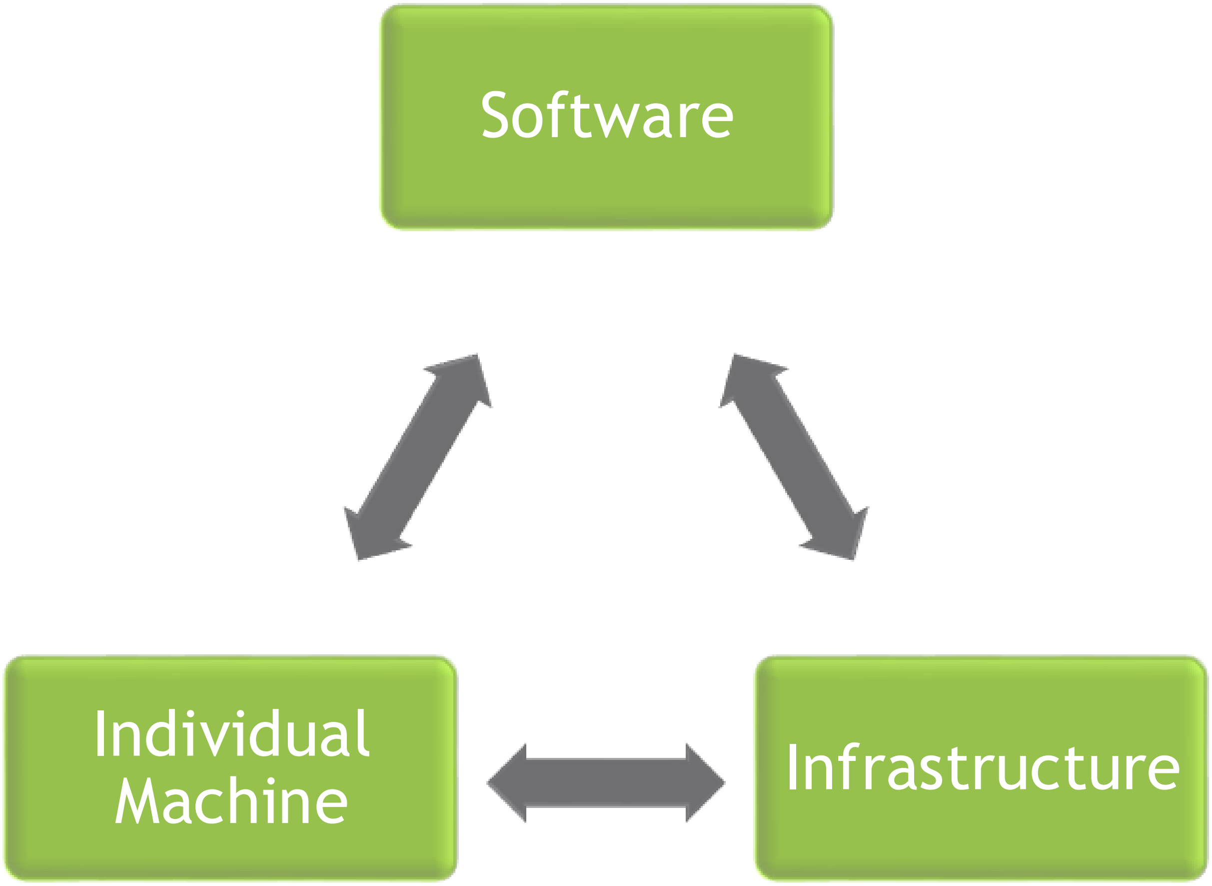
Software

- Python vs C vs SQL
- Algorithm efficiency
- MapReduce
- GPU support

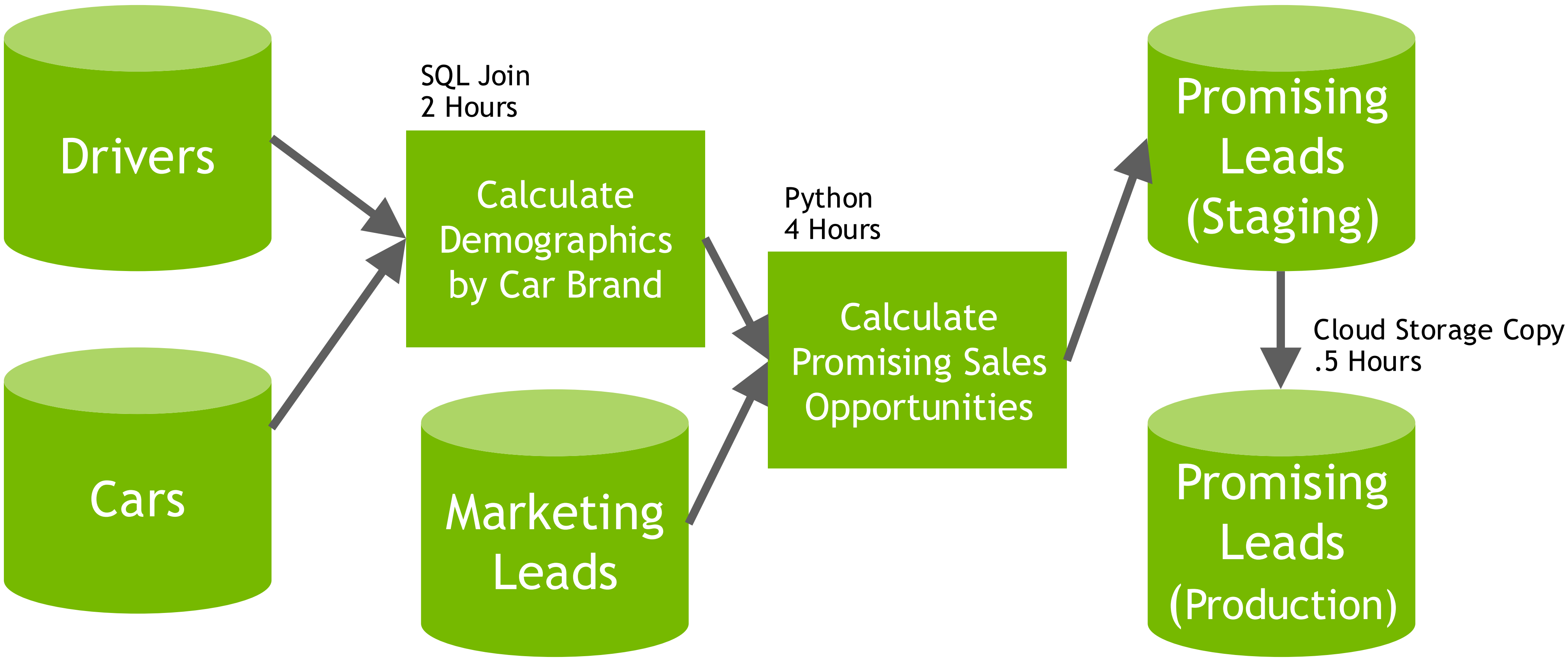
Infrastructure

- Number of servers
- Bandwidth
- Database location
- Client location

THE MOST EFFICIENT PIPELINES CONSIDER ALL AT ONCE



ETL SYSTEMS ENGINEERING



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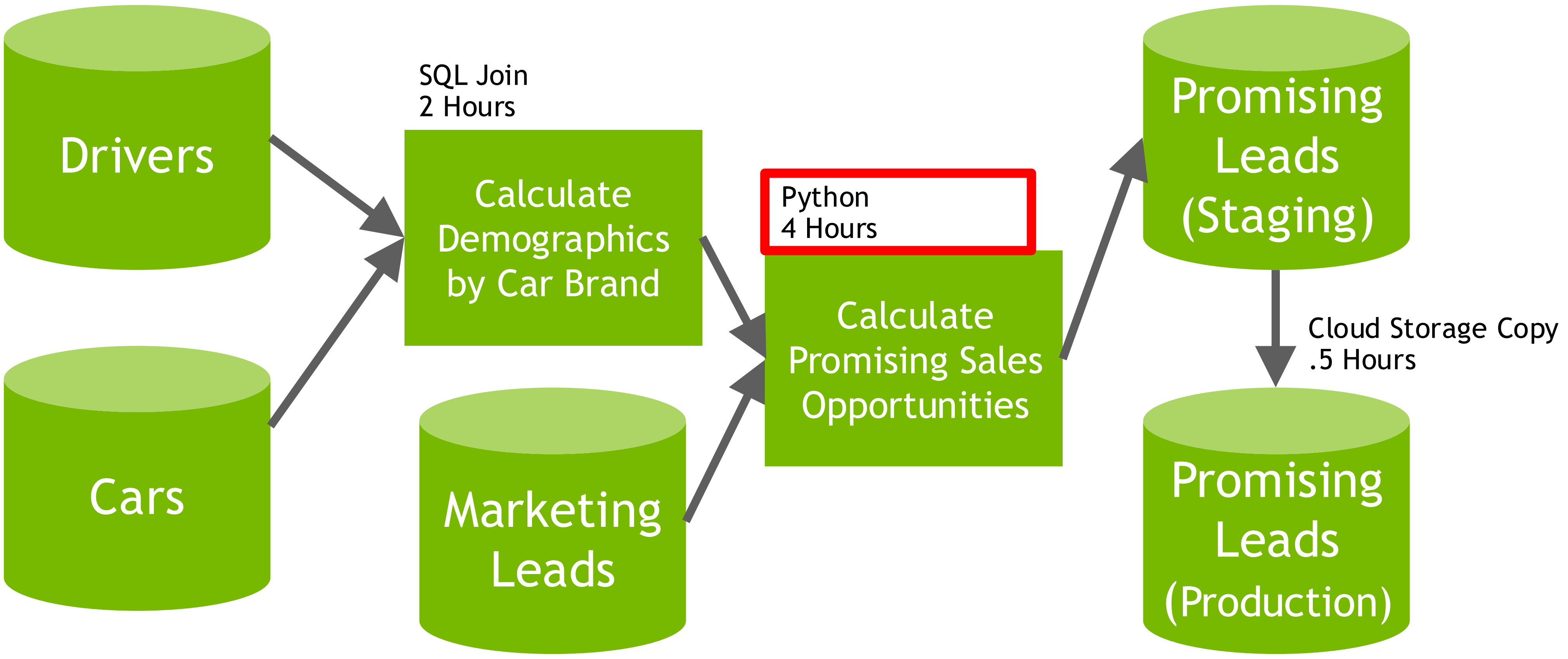
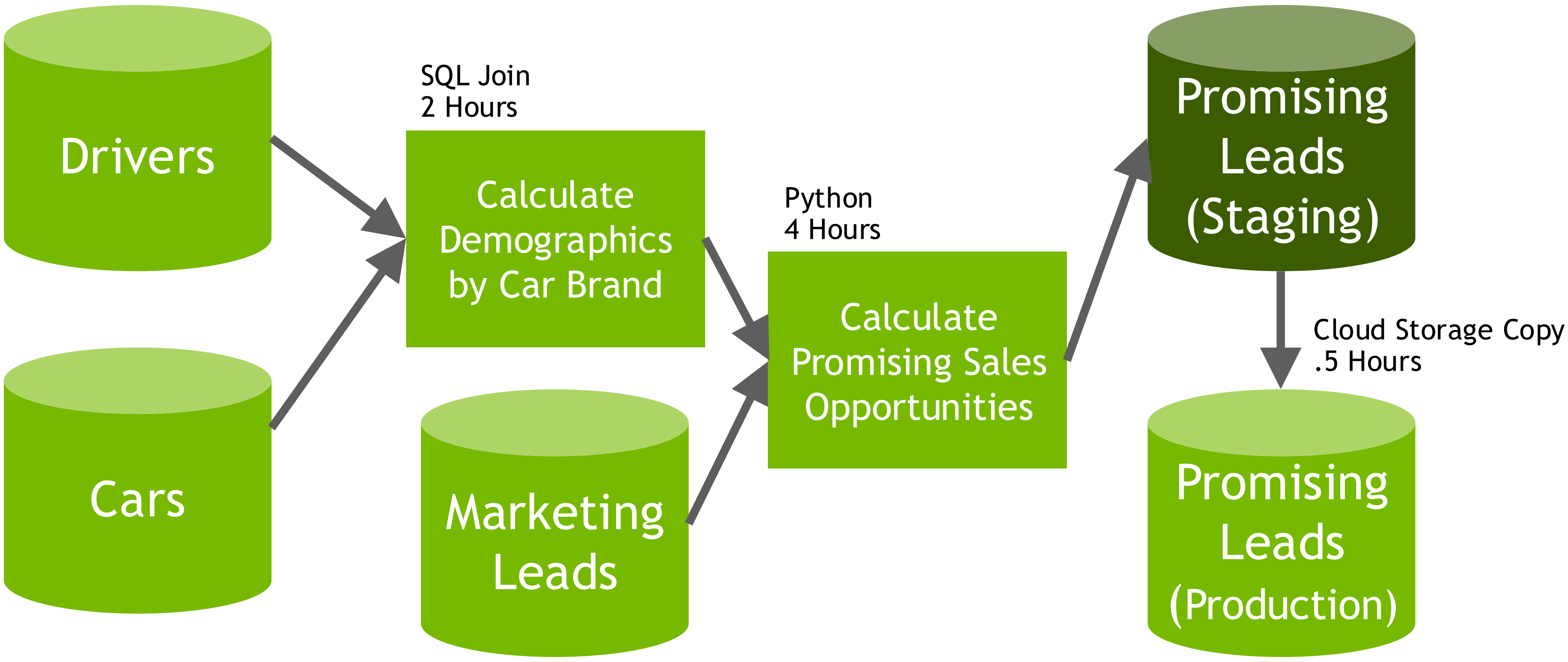


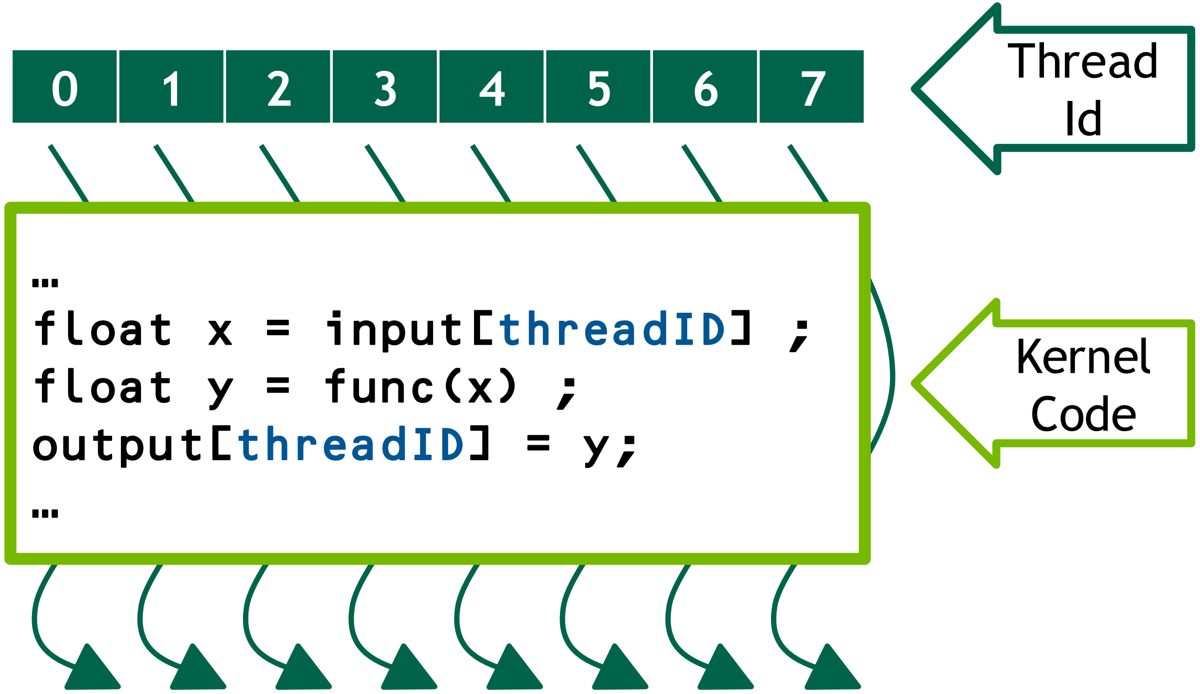
ETL SYSTEMS ENGINEERING



CUDA BASICS

CUDA COMPONENTS

Kernels and Threads



Kernel

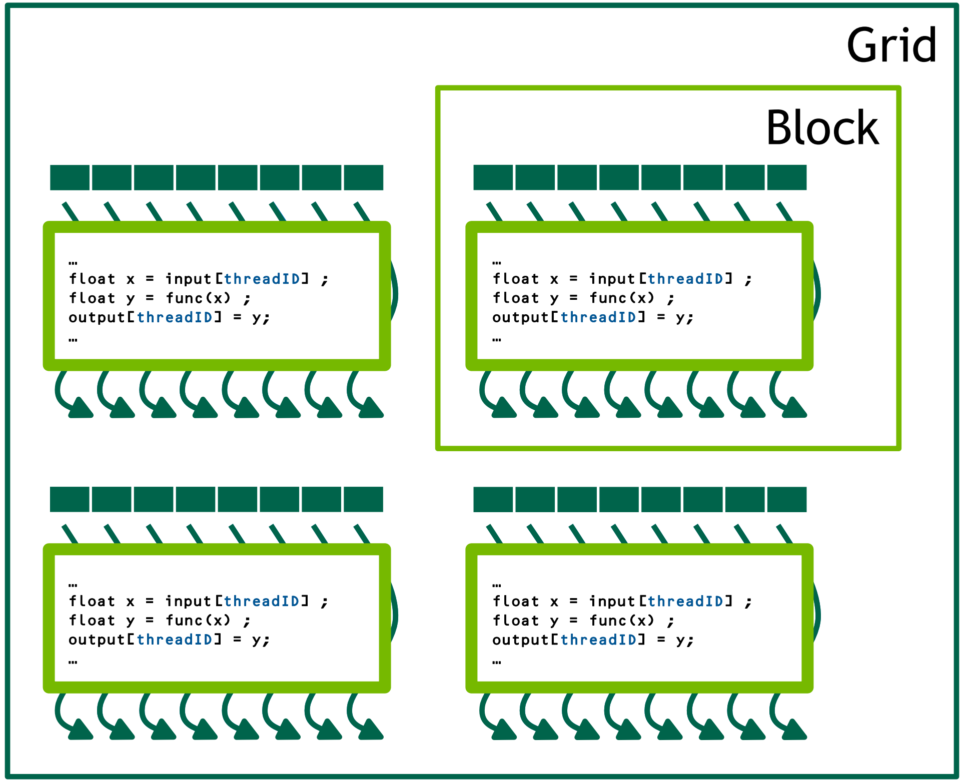
- A function to run in parallel on the GPU

Thread

- Runs an instance of the kernel

CUDA COMPONENTS

Blocks and Grids



Block

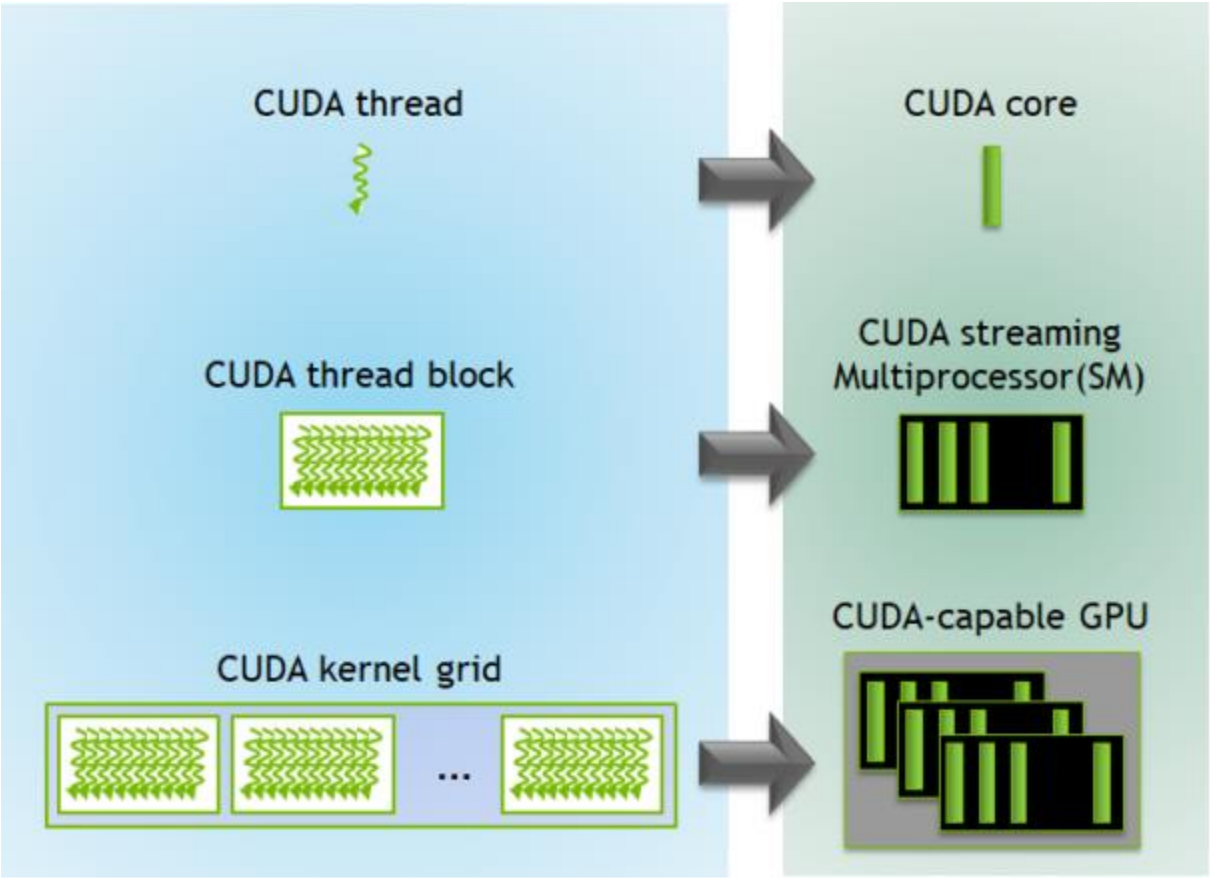
- A group of threads

Grid

- All blocks mapped on the GPU

CUDA COMPONENTS

Hardware to Software



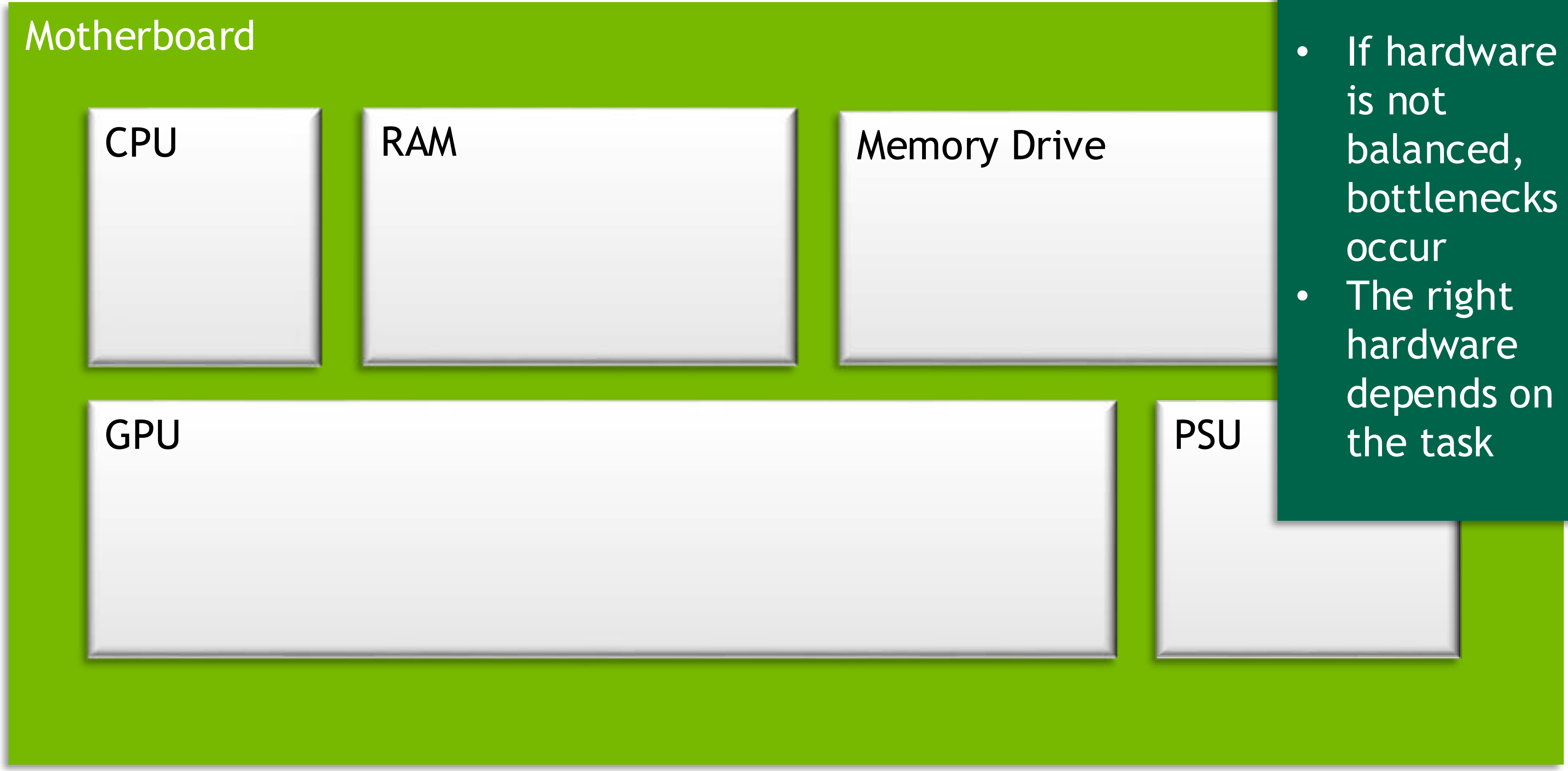
RTX 3080

8704 CUDA Cores

68 Streaming Multiprocessors (SMs)

MORE CORES MORE PERFORMANCE?

A Hardware Integration Example



- If hardware is not balanced, bottlenecks occur
- The right hardware depends on the task

HOW DATA MOVES IN A COMPUTER

A Hardware Integration Example

Motherboard

CPU
1 – 2 Cores per GPU.

RAM
Should be at least a little bigger than GPU RAM. PCIe lane speed can be a factor with massive datasets.

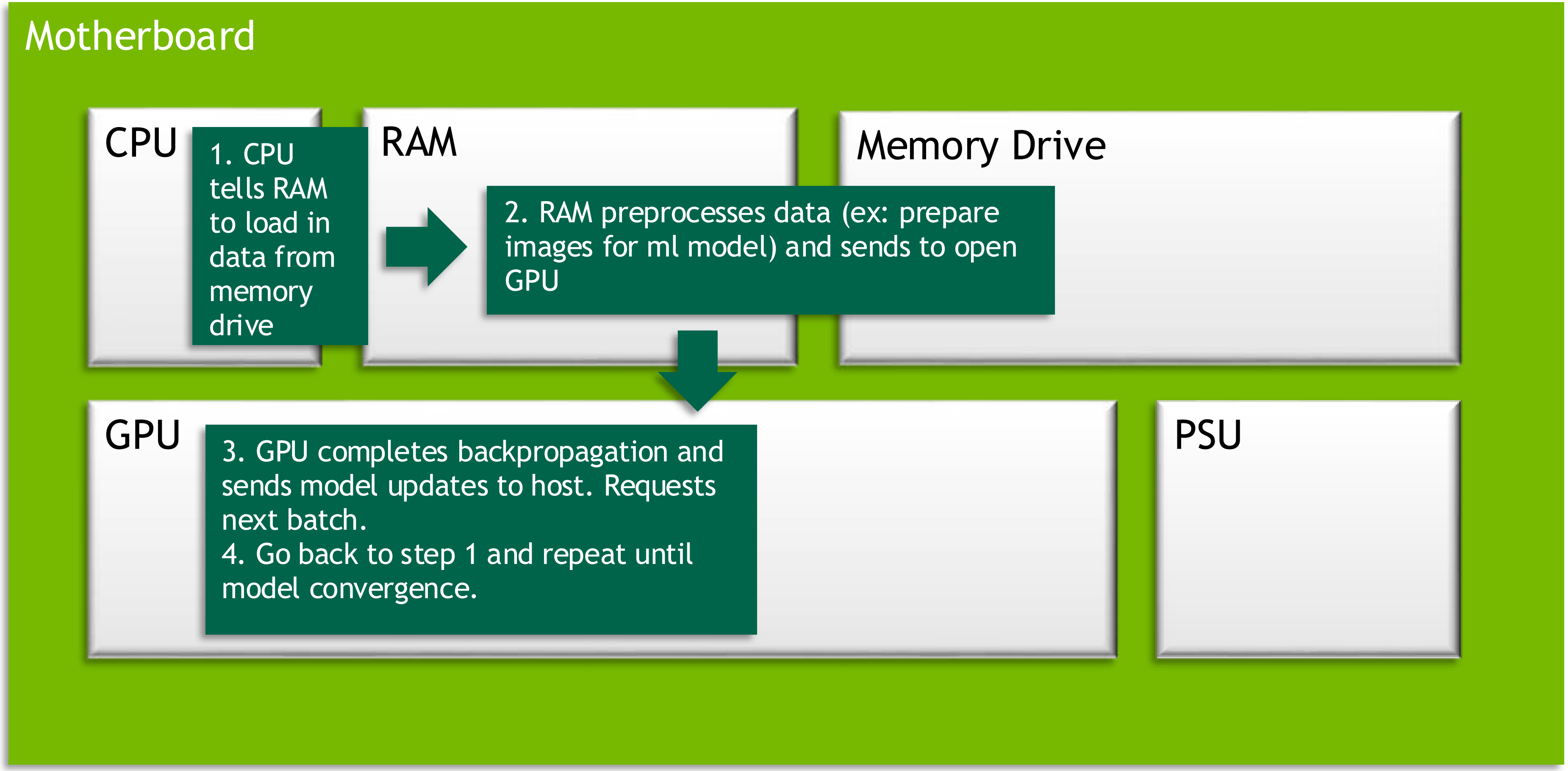
Memory Drive
If the data is too large to be loaded into RAM, then reading speed from the memory drive can be a bottleneck.

GPU
GPUs excel on matrix multiplication computation which is used frequently in ETL and ML model training. RAM speed, GPU speed and Memory Bandwidth can all be a potential bottleneck for computation. Model and data size will impact the efficacy of the GPU.

PSU
There should be enough juice to power all the cool hardware. If it’s not cool, try adding more fans.

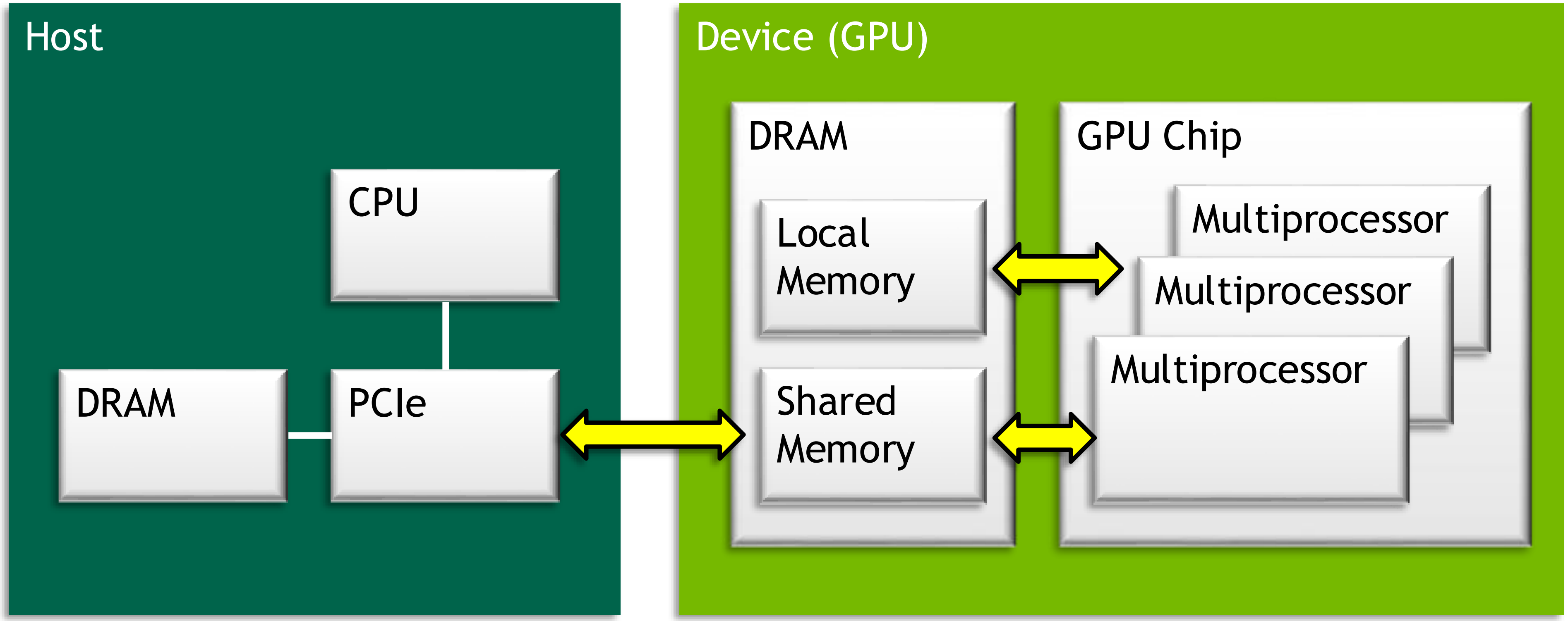
HOW DATA MOVES IN A COMPUTER

A Hardware Integration Example



DEBUGGING: WHY IS MY CPU FASTER THAN MY GPU?

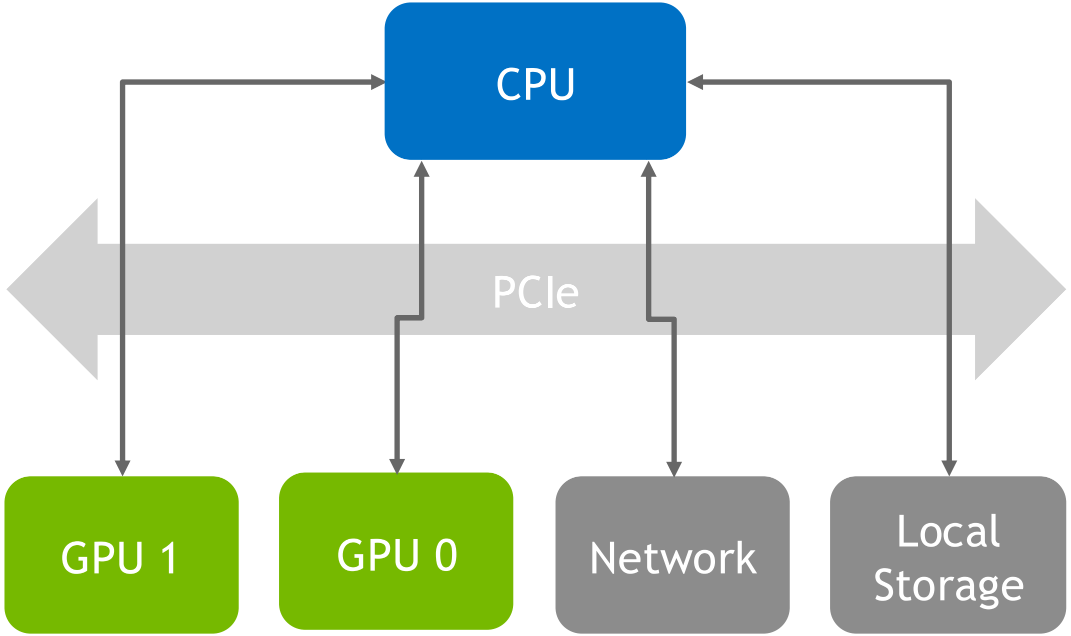
How data moves to the GPU with CUDA



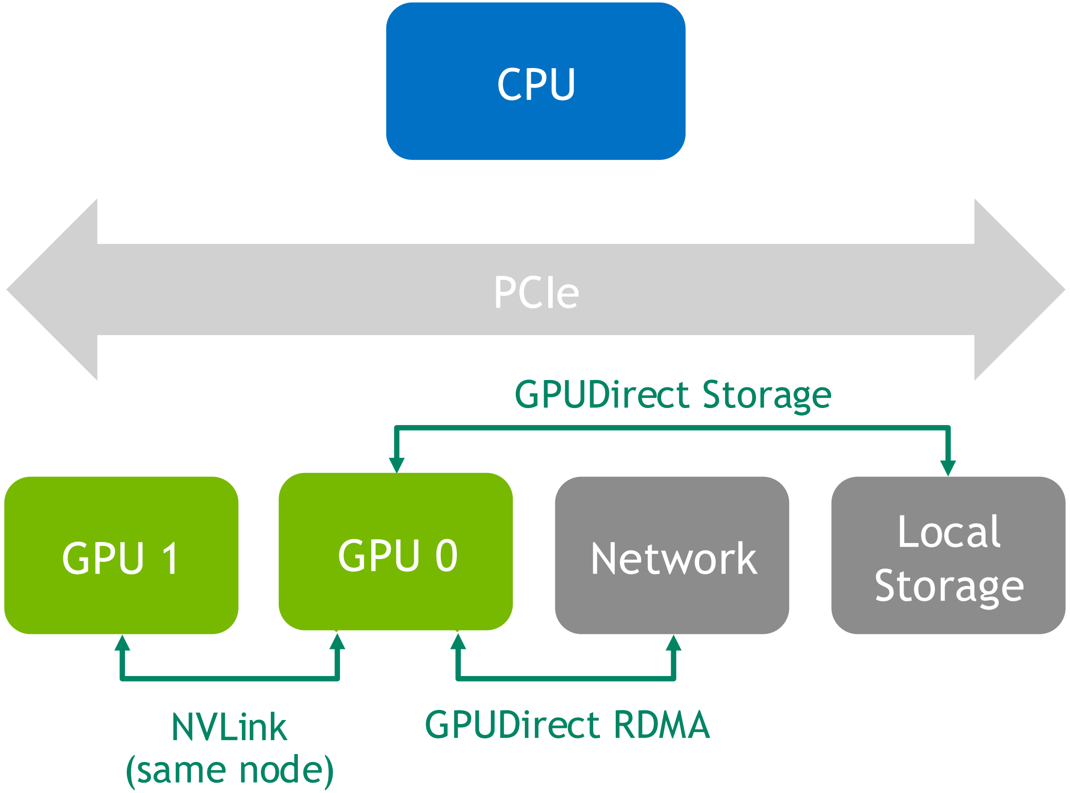
DATA MOVEMENT

CPU vs GPU

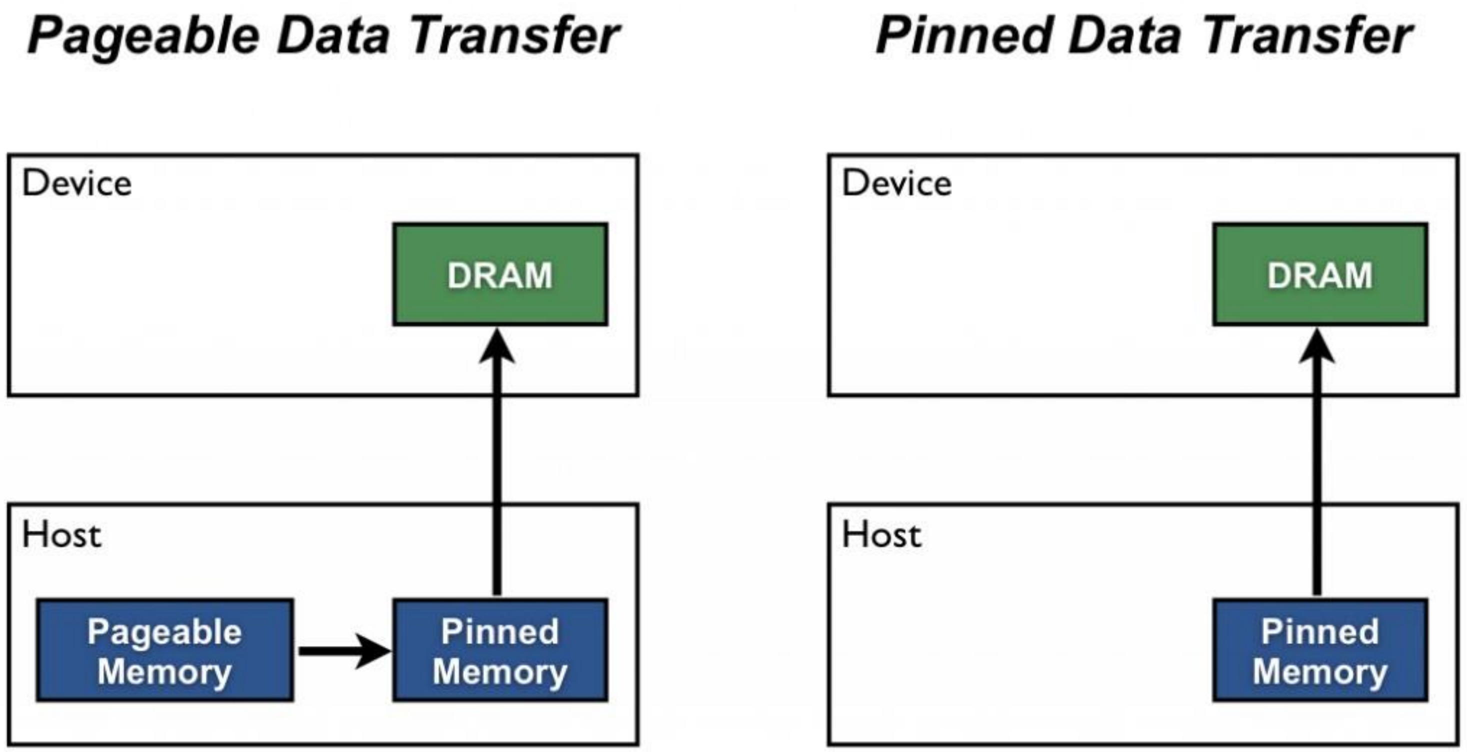
CPU-Centric Data Movement



GPU-Centric Data Movement



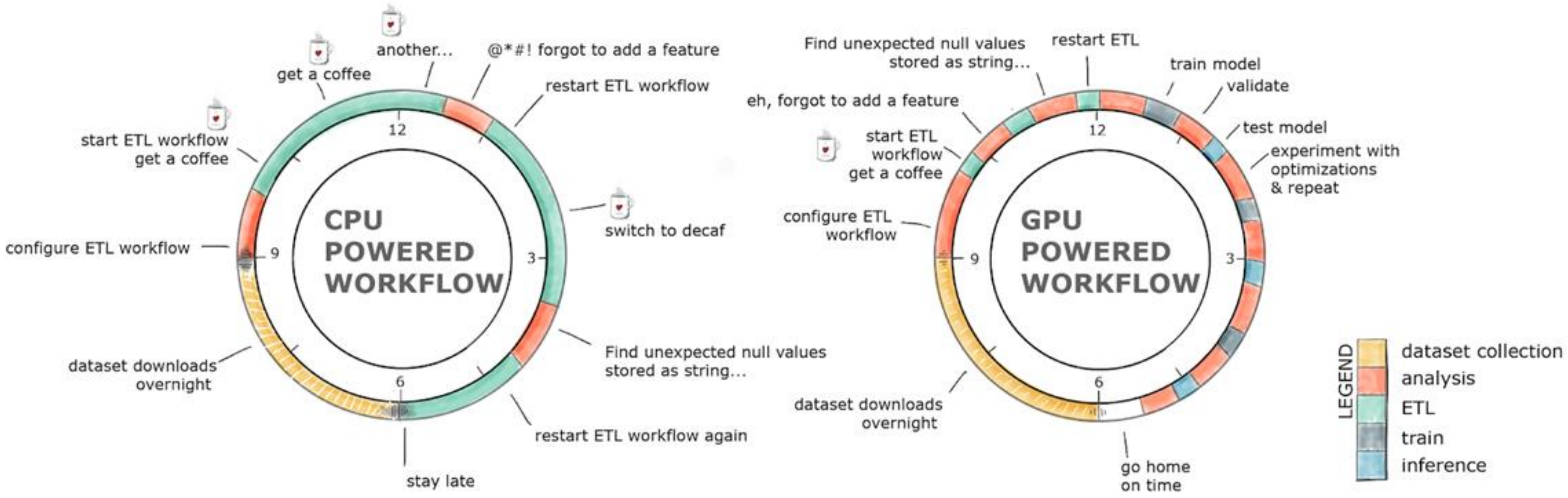
HOW TO OPTIMIZE DATA TRANSFERS



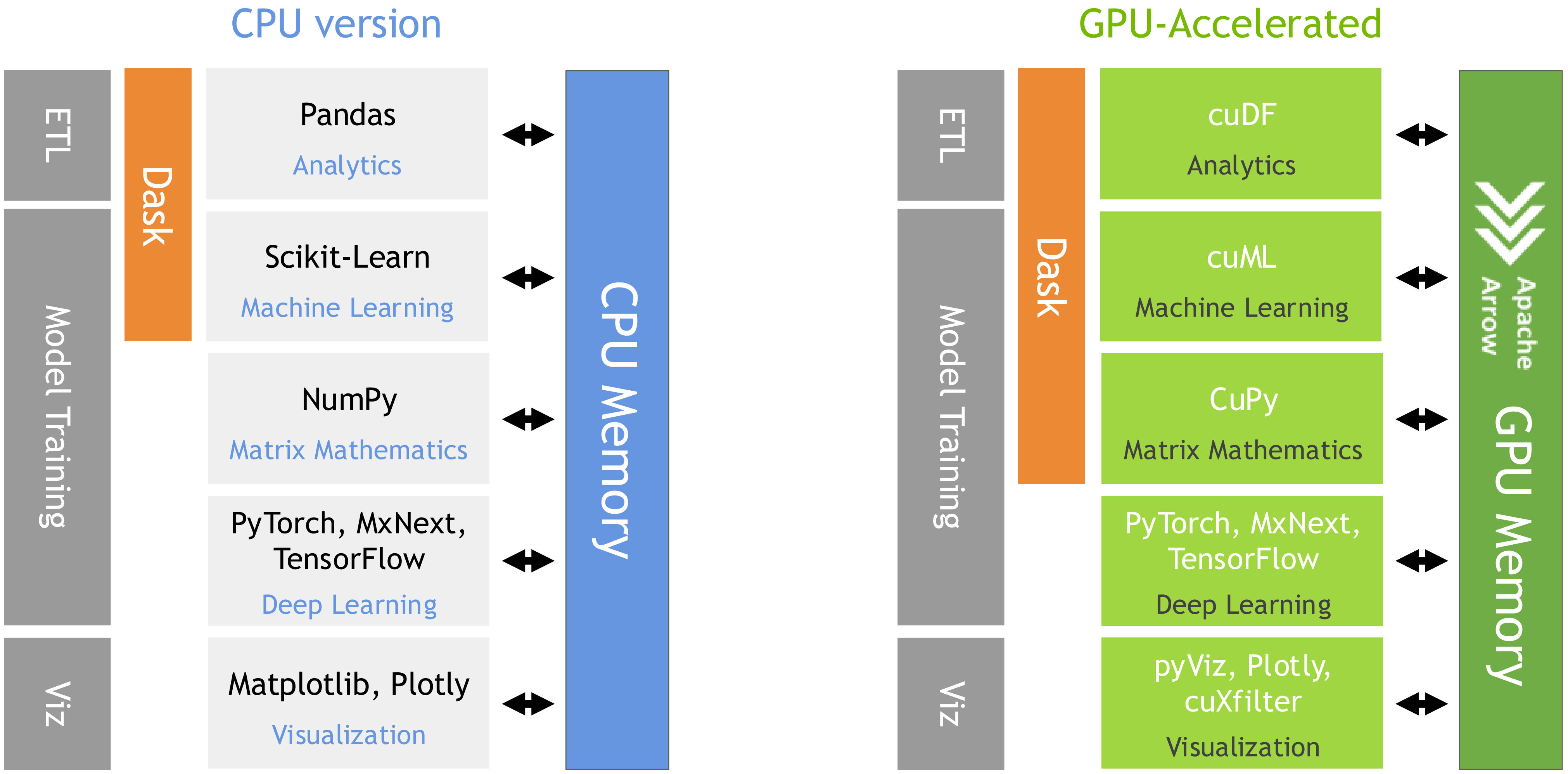
NVTABULAR

GPU-ACCELERATED ETL

The average data scientist spends up to 80% of their time in ETL, as opposed to training models



Built on top of RAPIDS



www.rapids.ai

NVTABULAR KEY FEATURES

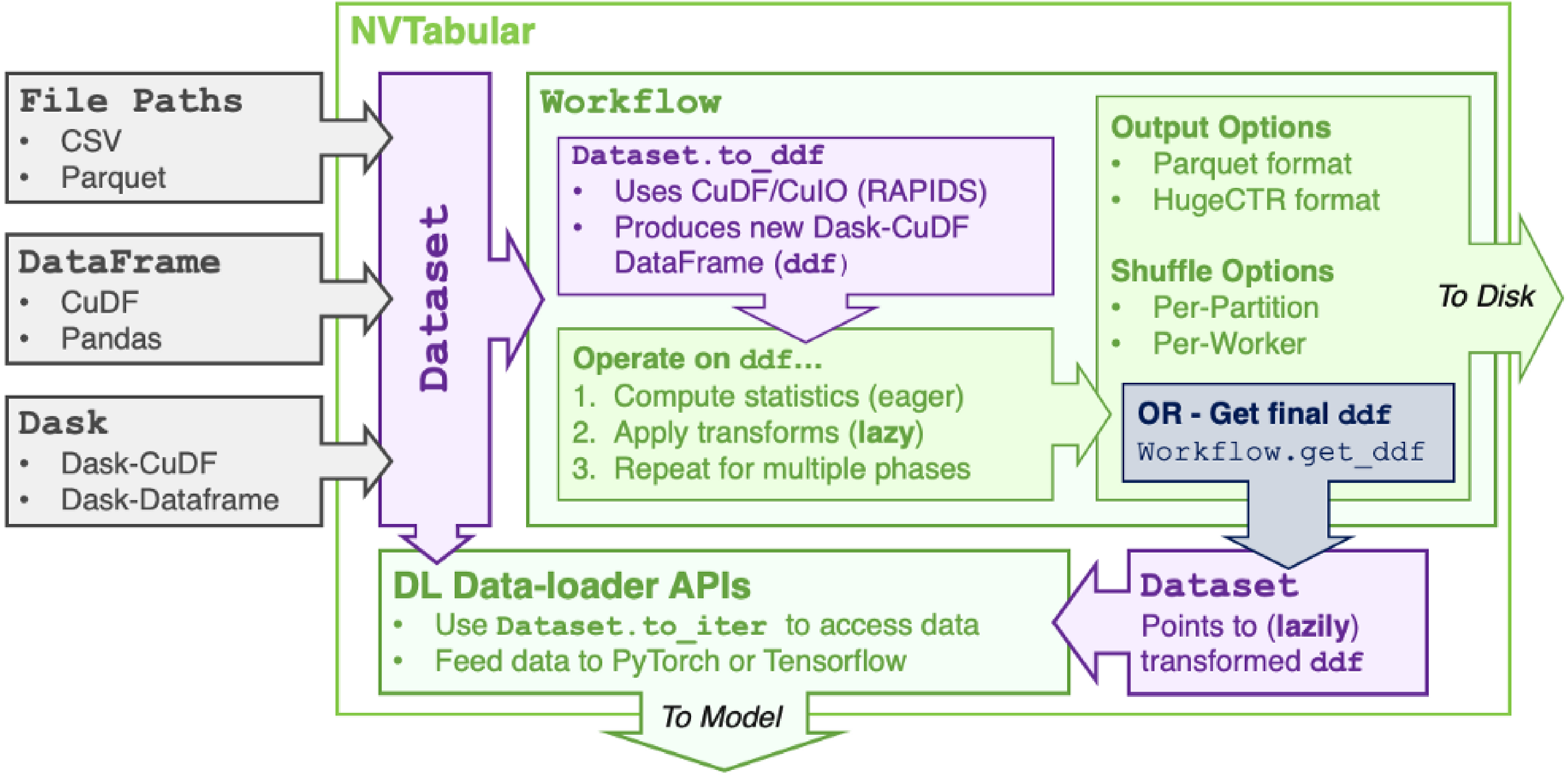
Faster and Easier GPU-based ETL

- GPU-accelerated, eliminating CPU bottlenecks.
- Out-of-core execution. No GPU memory limits and reduced I/O through lazy execution.
- PyTorch, TensorFlow and HugeCTR compatible.
- Filtering outliers or missing values.
- Inputting and filling in missing data.
- Discretization or bucketing of continuous features.
- Creating features by splitting or combining existing features.
- Normalizing numerical features to have zero mean and unit variance.
- Encoding discrete features using one-hot vectors or converting them to continuous integer indices.
- More to come ☺

	NVTabular	pandas
Dataset size limitation	Unlimited	CPU Memory
Code complexity	Simple	Moderate
Lines of code	10 - 20	100 - 1000
Flexibility	Domain specific	General
Data loading Transforms	Yes	No
Inference Transforms	Yes	No

NVTABULAR

Integration with RAPIDS/DASK



NVTabular vs Pandas code

100x fewer lines of code required

```
import glob
import nvtabular as nvt

# Create datasets from input files
train_files = glob.glob("./dataset/train/*.parquet")
valid_files = glob.glob("./dataset/valid/*.parquet")

train_ds = nvt.Dataset(train_files, gpu_memory_frac=0.1)
valid_ds = nvt.Dataset(valid_files, gpu_memory_frac=0.1)
```

Import libraries.

Create training and validation datasets.

```
# Initialise workflow
cat_names = ["C" + str(x) for x in range(1, 27)]   # Specify categorical feature names
cont_names = ["I" + str(x) for x in range(1, 14)]  # Specify continuous feature names
label_name = ["label"] # Specify target feature

proc = nvt.Workflow(cat_names=cat_names, cont_names=cont_names, label_name=label_name)
```

Initialise workflow specifying categorical, and continuous data.

```
# Add feature engineering and pre-processing ops to workflow
proc.add_cont_feature([nvt.ops.ZeroFill(), nvt.ops.LogOp()])
proc.add_cont_preprocess(nvt.ops.Normalize())
proc.add_cat_preprocess(nvt.ops.Categorify(use_frequency=True, freq_threshold=15))
```

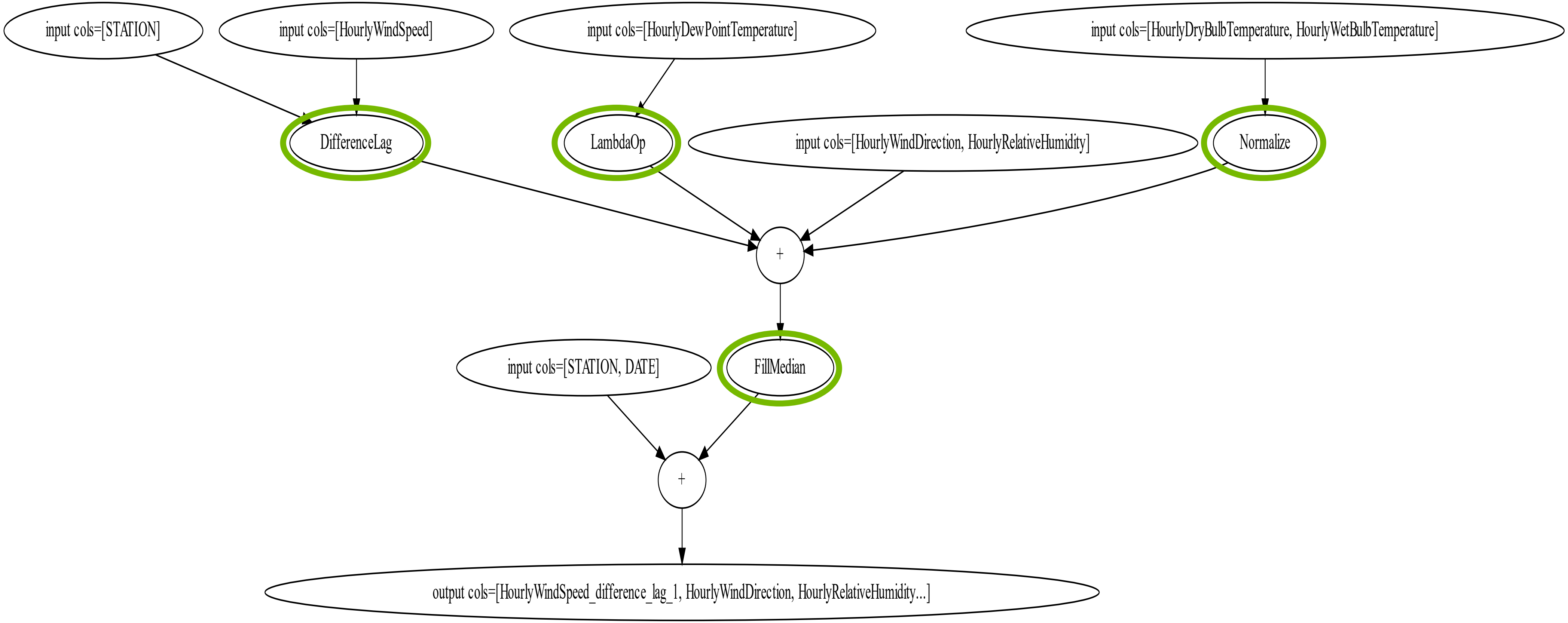
Zero fill any nulls, log transform and normalize continuous variables. Encode categorical data.

```
# Compute statistics, transform data, and export to disk
proc.apply(train_dataset, shuffle=True,  output_path="./processed_data/train", num_out_files=len(train_files))
proc.apply(valid_dataset, shuffle=False, output_path="./processed_data/valid", num_out_files=len(valid_files))
```

Apply the operations, creating new shuffled training and validation datasets.

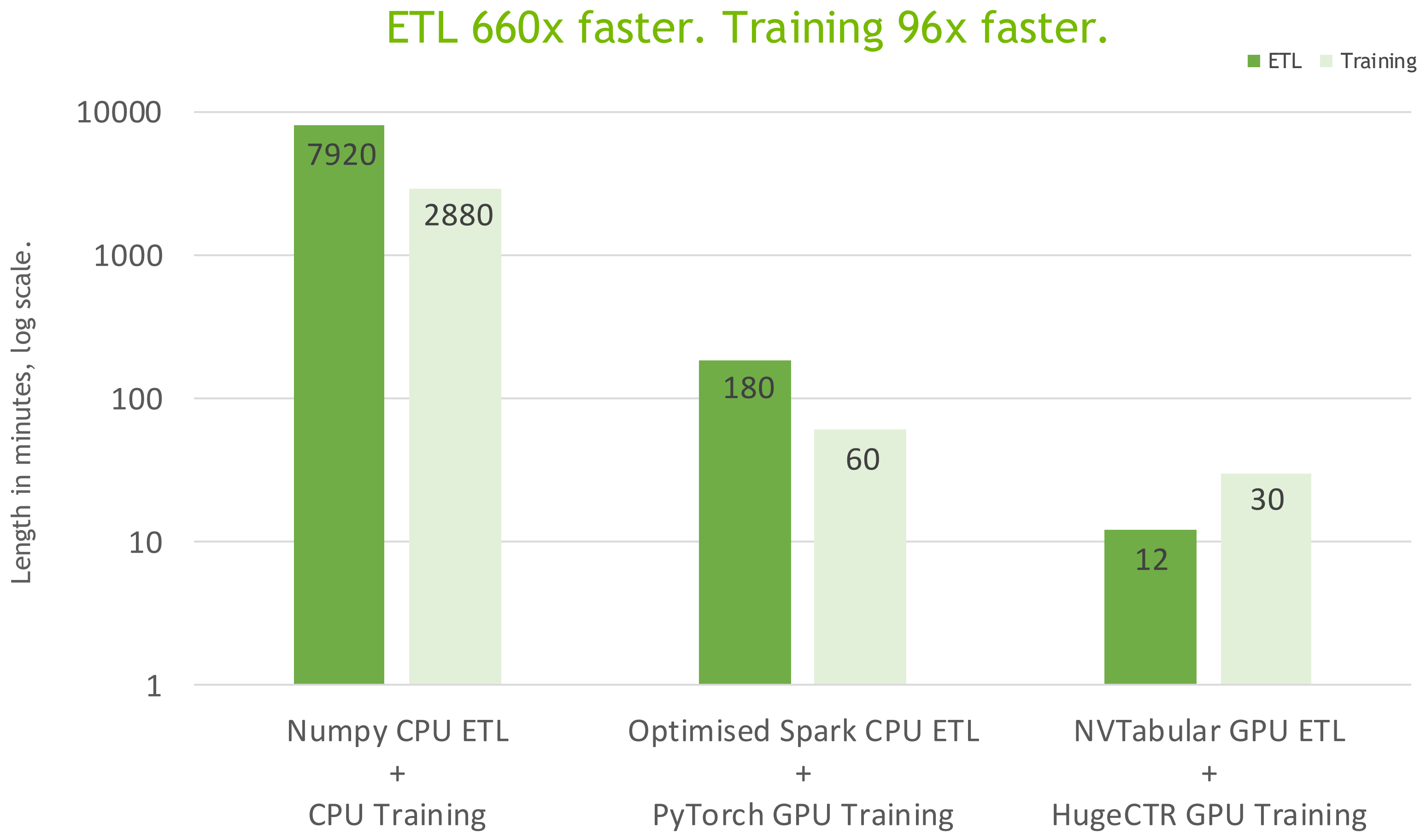
Equivalent Pandas/Numpy code: https://github.com/facebookresearch/dlrm/blob/master/data_utils.py

NVTABULAR DAG



= NVTabular Operations

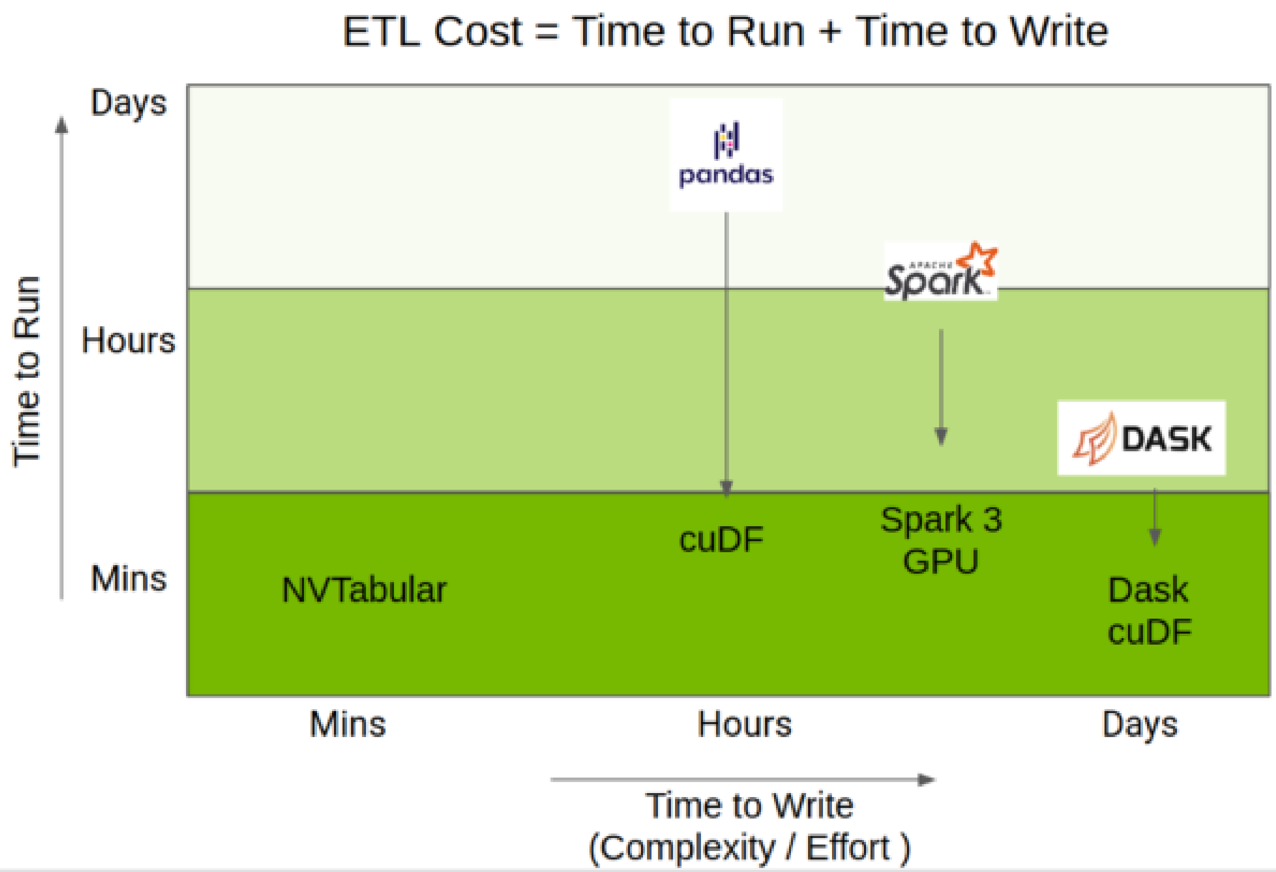
Case Study: 1TB Ads Dataset



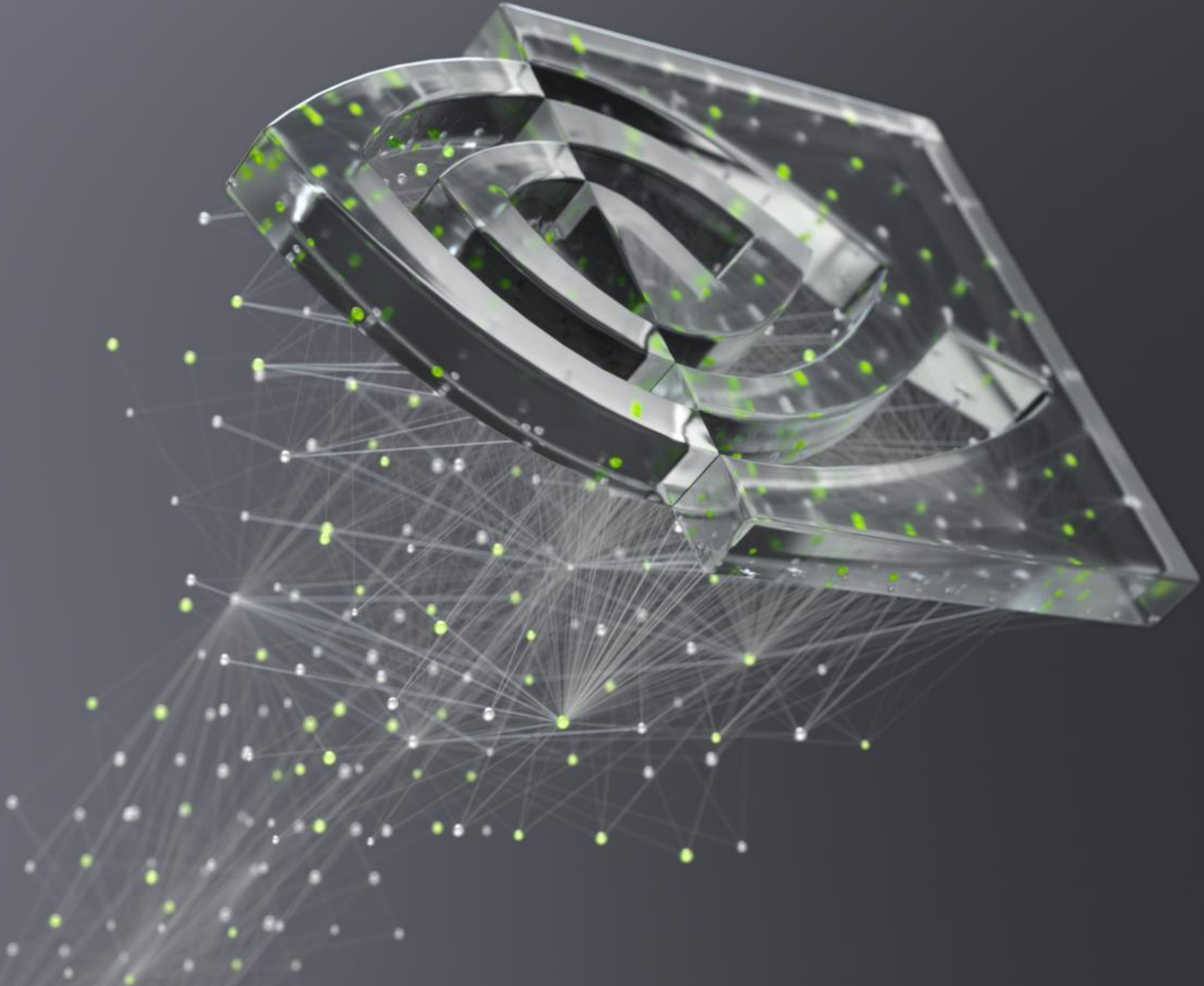
CPU: AWS r5d.24xl, 96 cores, 768 GB RAM
GPU: 1 x NVIDIA V100 32GB

NVTABULAR

Position compared to other popular DataFrame libraries



LET’S GO!



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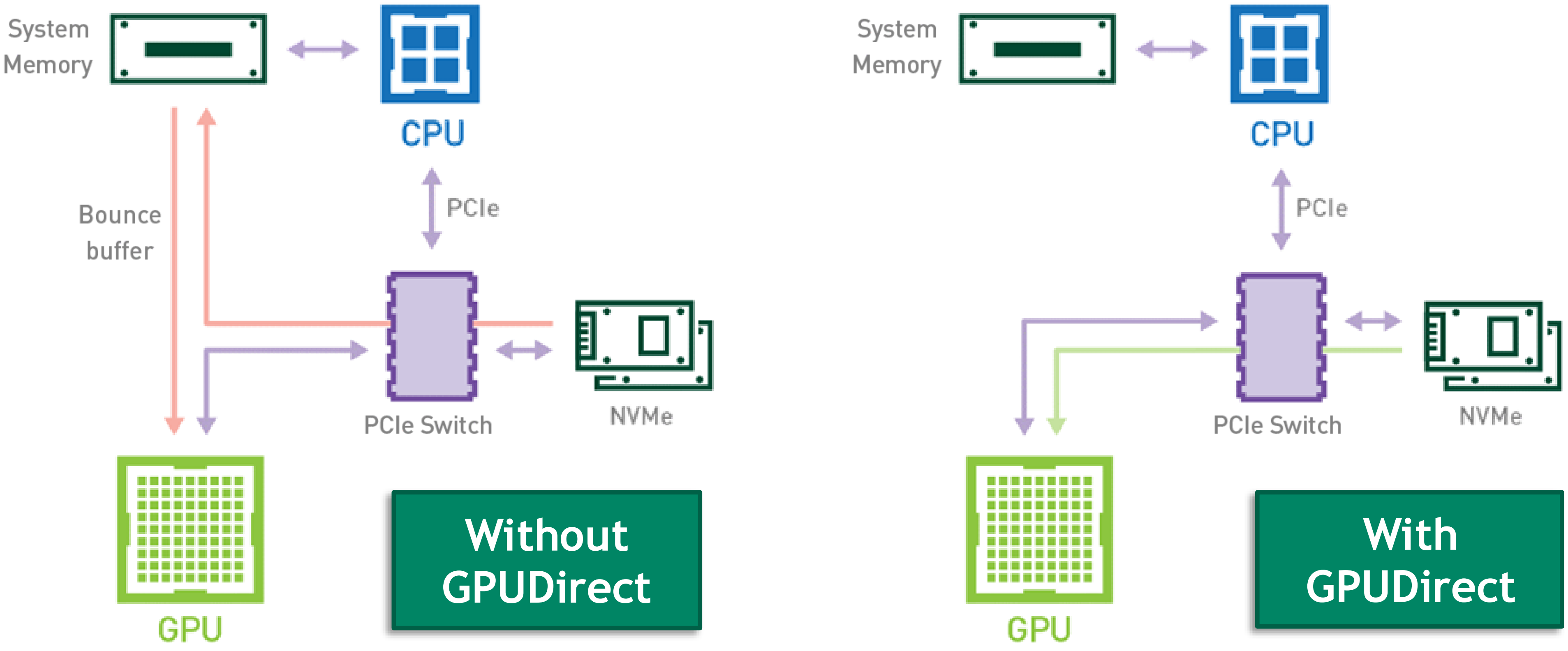
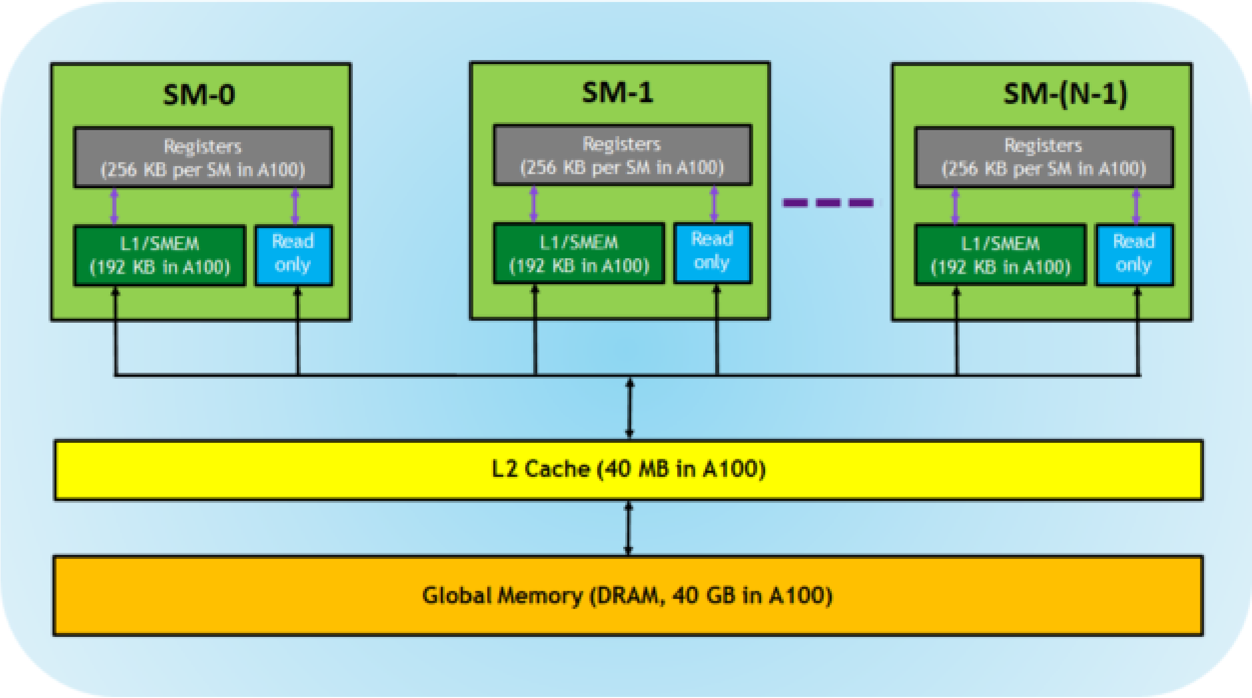
APPENDIX

GPU

Another Hardware Integration Example



MEMORY HIERARCHY IN GPUS



PARTS OF AN ETL PIPELINE

Purpose
- Send instructions to other parts of the system
- Parallelize calculation
- Data transfer
- Data storage

Individual Machine
- CPU - Host
- Devices – GPUs
- PCIe
- Disk Memory

Cloud Servers
- Controller Server
- Workers
- Bandwidth
- Database server

KERNELS AND PAGEABLE MEMORY

Why they do not work together

Kernel requests pageable data from disk memory

Data does not exist.

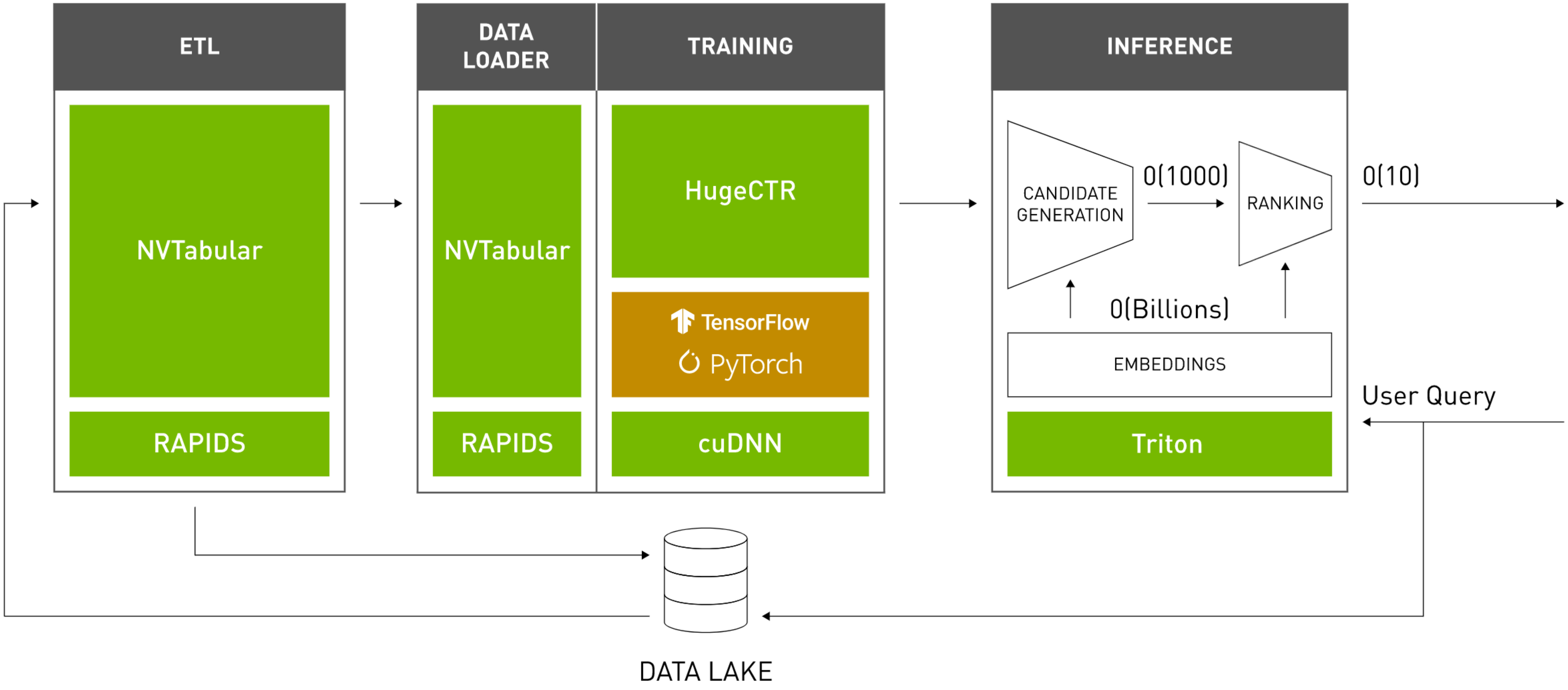
Kernel asks page fault handler to fetch data.

Kernel restarts user-defined code.

Page fault handler not loaded, fault not handled

Infinite loop.

BIG DATA FOR RETAIL



WORKING WITH NVTABULAR

Workflow

Step 1:
Define Column Group

```
cols = ["col_a", "col_b]
```

Step 2:
Transform Columns with Ops

```
cleaned_cols =
      cols >> ops.FillMissing()
```

Step 3:
Define Graph as Workflow

Step 4:
Run Data through Workflow