The Platform Inside and Out
Release 0.15

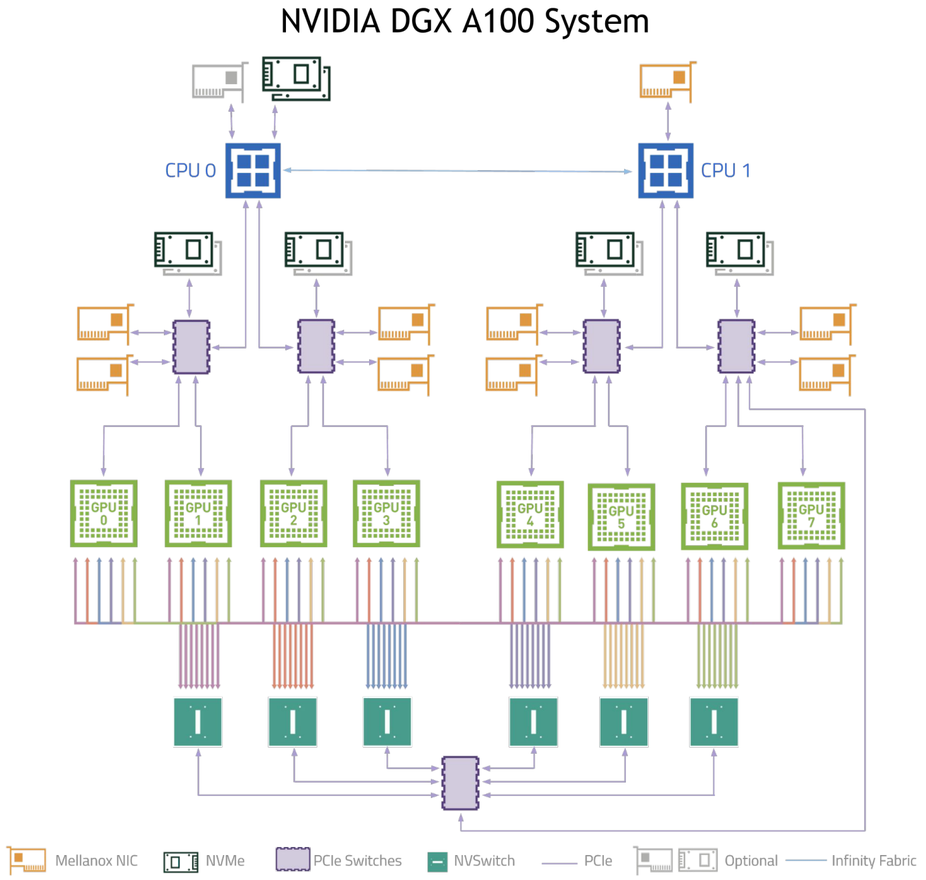
Joshua Patterson – Senior Director, RAPIDS Engineering

Why GPUs?

Numerous hardware advantages

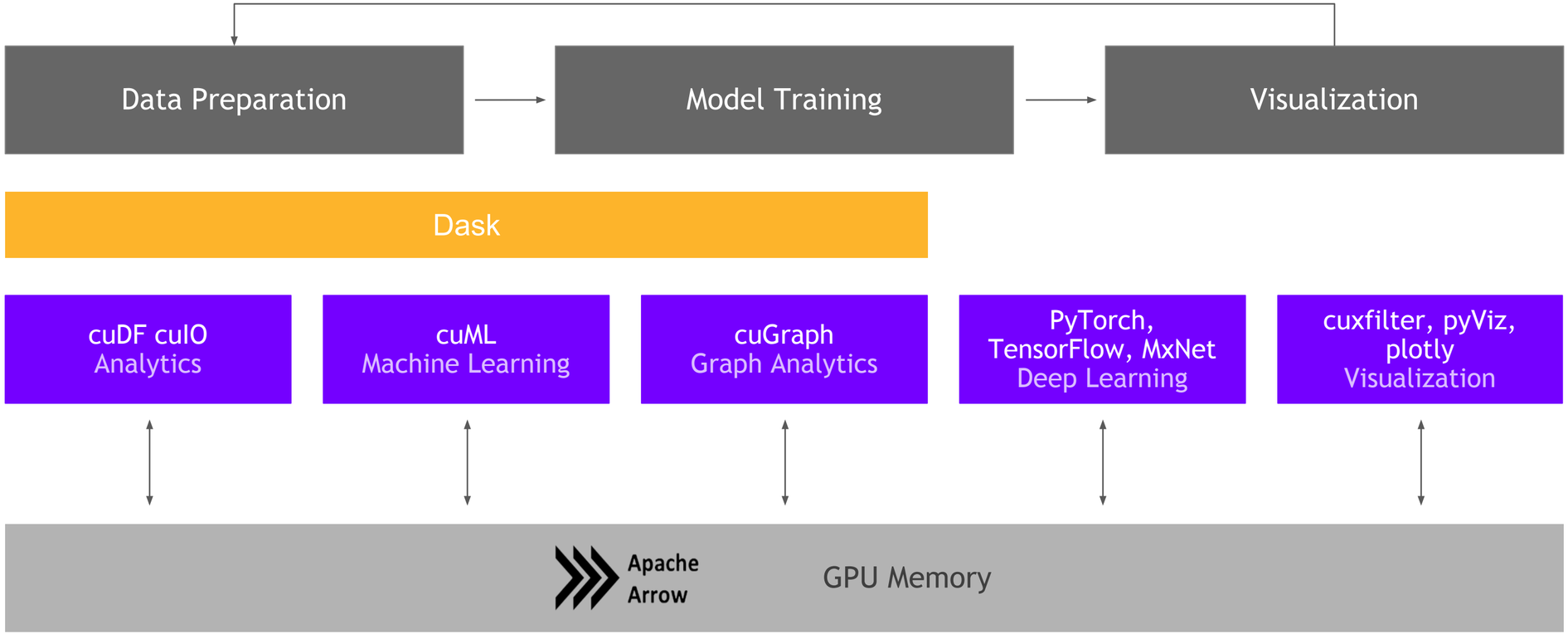
- Thousands of cores with up to ~20 TeraFlops of general purpose compute performance
- Up to 1.5 TB/s of memory bandwidth
- Hardware interconnects for up to 600 GB/s bidirectional GPU <--> GPU bandwidth
- Can scale up to 16x GPUs in a single node

Almost never run out of compute relative to memory bandwidth!



RAPIDS

End-to-End GPU Accelerated Data Science



Data Processing Evolution

Faster Data Access, Less Data Movement

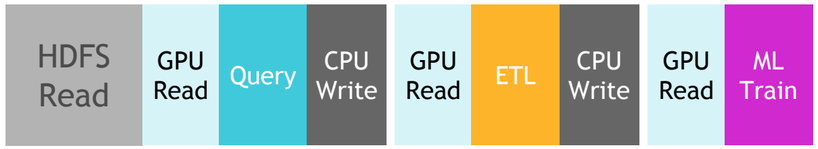
Hadoop Processing, Reading from Disk

25-100x Improvement
Less Code
Language Flexible
Primarily In-Memory

Spark In-Memory Processing

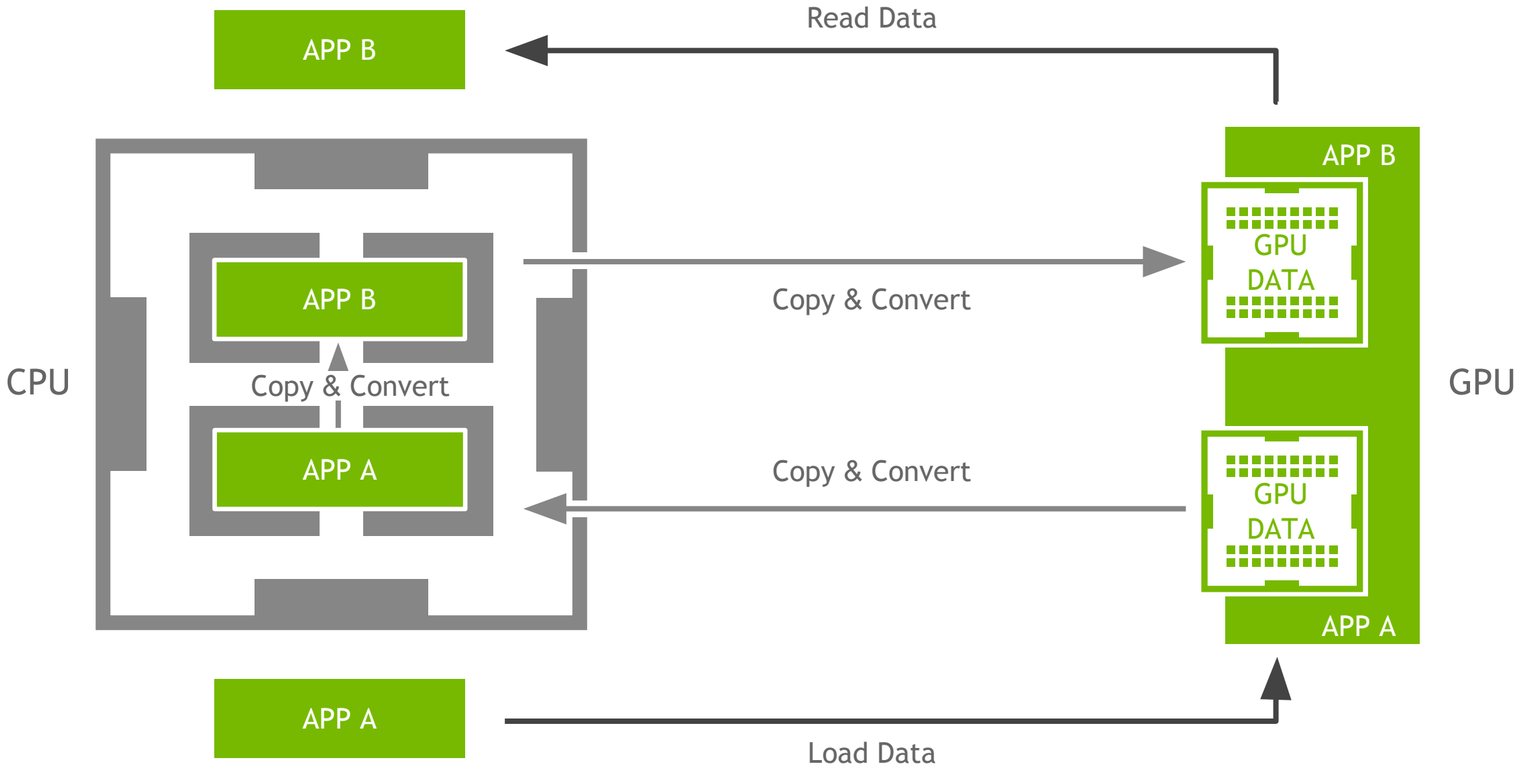
5-10x Improvement
More Code
Language Rigid
Substantially on GPU

Traditional GPU Processing



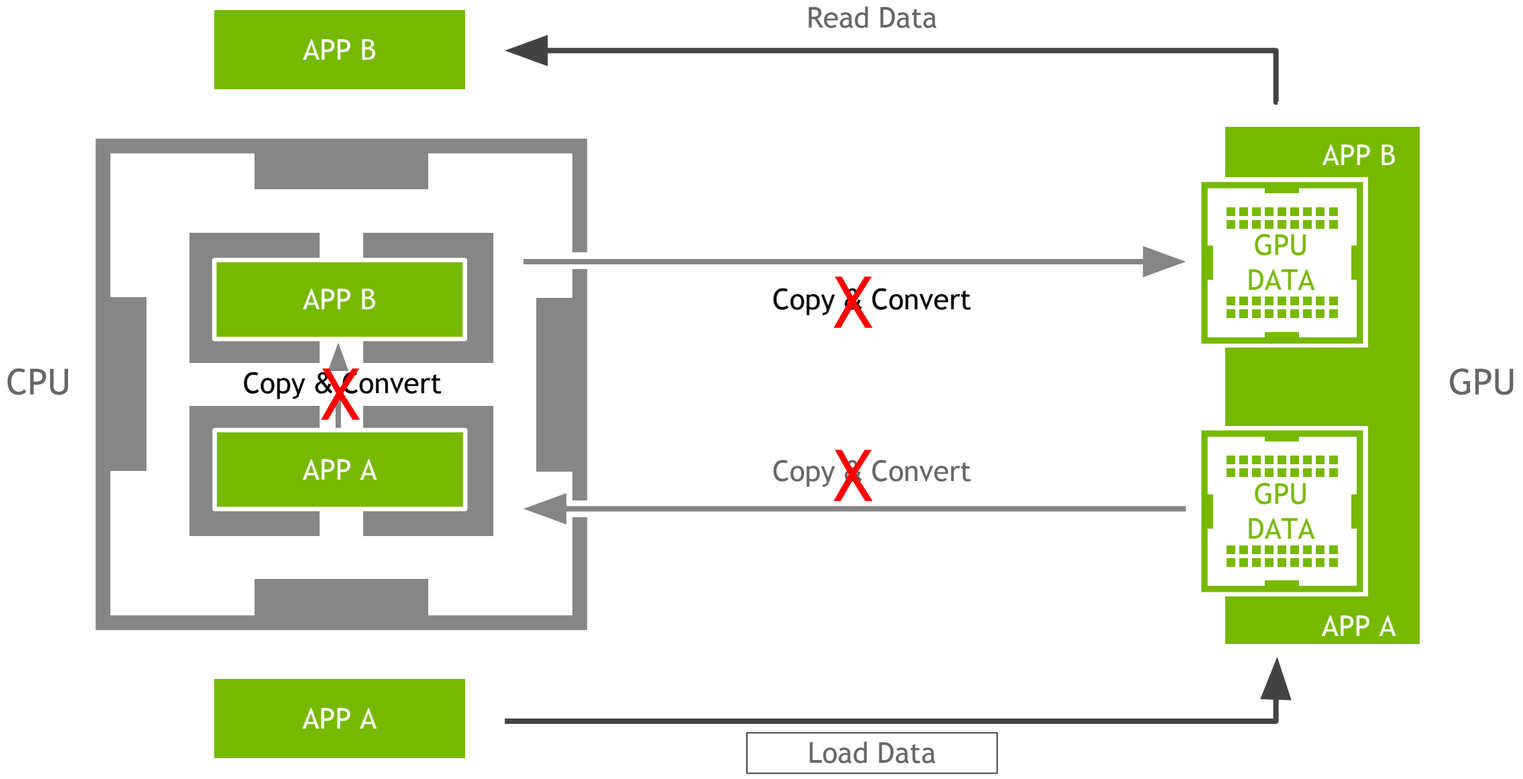
Data Movement and Transformation

The Bane of Productivity and Performance

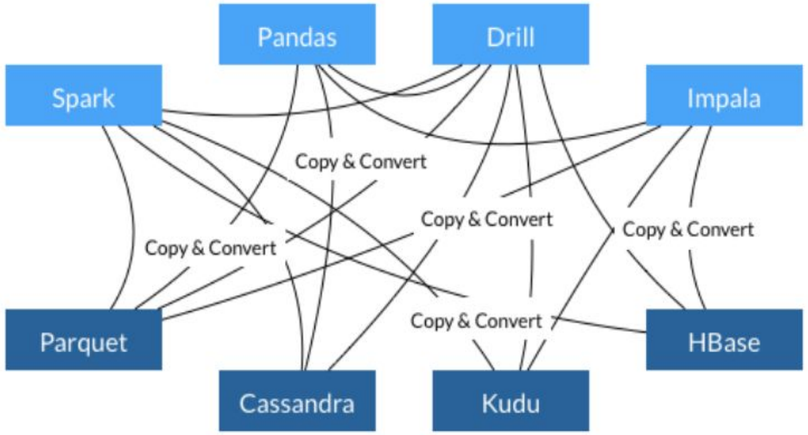


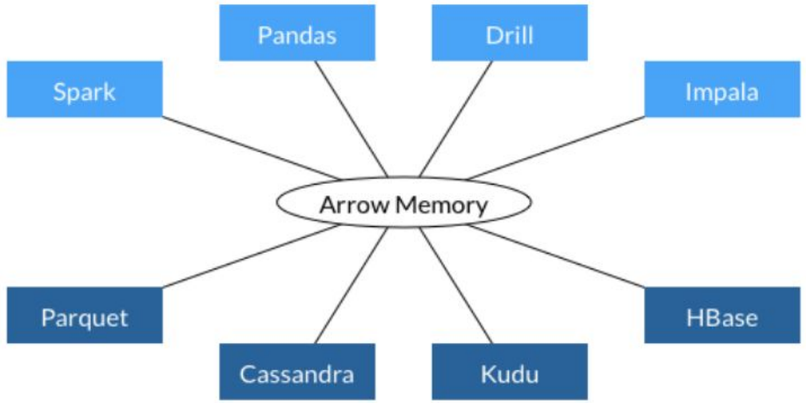
Data Movement and Transformation

What if We Could Keep Data on the GPU?



Learning from Apache Arrow





- Each system has its own internal memory format
- 70-80% computation wasted on serialization and deserialization
- Similar functionality implemented in multiple projects

- All systems utilize the same memory format
- No overhead for cross-system communication
- Projects can share functionality (eg, Parquet-to-Arrow reader)

Source: From Apache Arrow Home Page - https://arrow.apache.org/

Data Processing Evolution

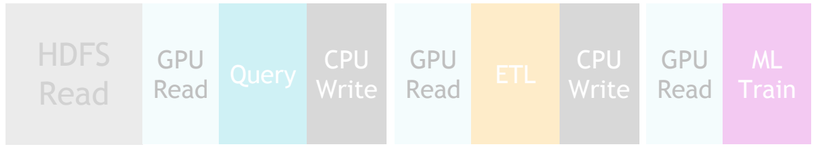
Faster Data Access, Less Data Movement

Hadoop Processing, Reading from Disk

Spark In-Memory Processing

25-100x Improvement
Less Code
Language Flexible
Primarily In-Memory

Traditional GPU Processing



5-10x Improvement
More Code
Language Rigid
Substantially on GPU

RAPIDS

50-100x Improvement
Same Code
Language Flexible
Primarily on GPU

Lightning-fast performance on real-world use cases

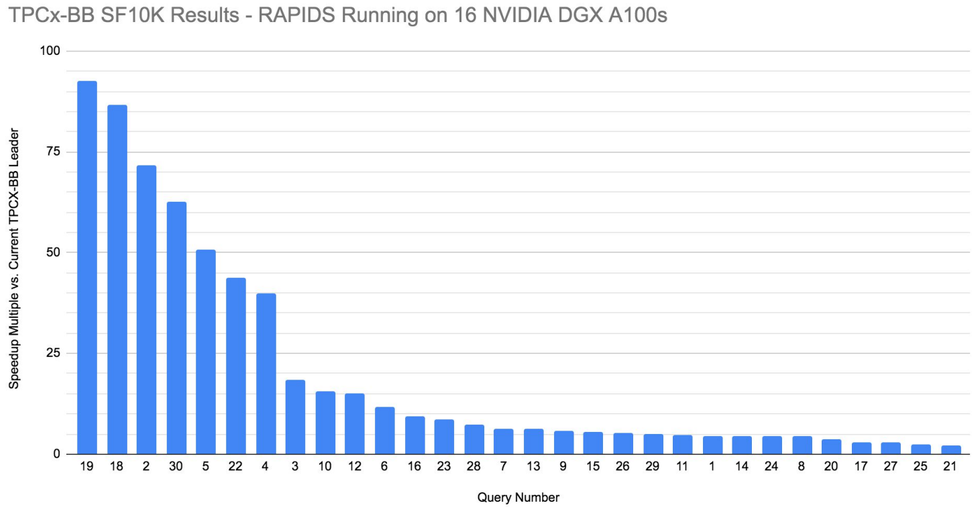
Up to 350x faster queries; Hours to Seconds!

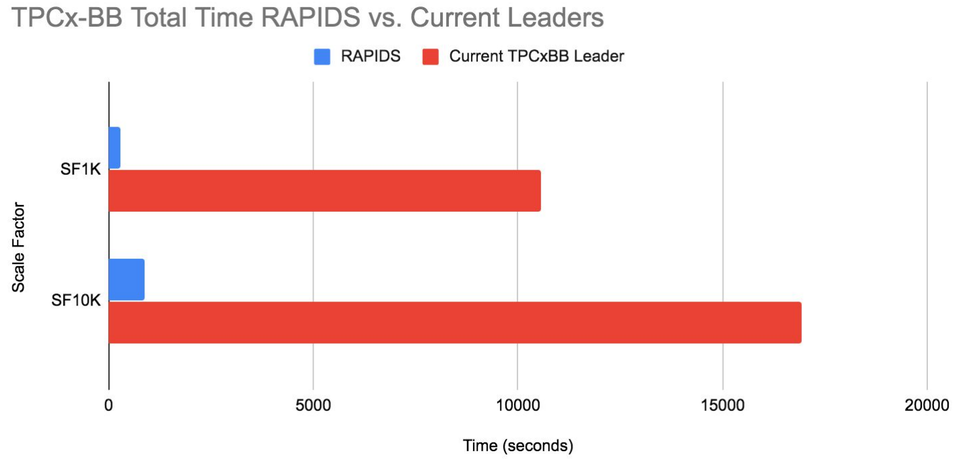
TPCx-BB is a data science benchmark consisting of 30 end-to-end queries representing real-world ETL and Machine Learning workflows, involving both structured and unstructured data. It can be run at multiple “Scale Factors”.

- SF1 - 1GB
- SF1K - 1 TB
- SF10K - 10 TB

RAPIDS results at SF1K (2 DGX A100s) and SF10K (16 DGX A100s) show GPUs provide dramatic cost and time-savings for small scale *and* large-scale data analytics problems

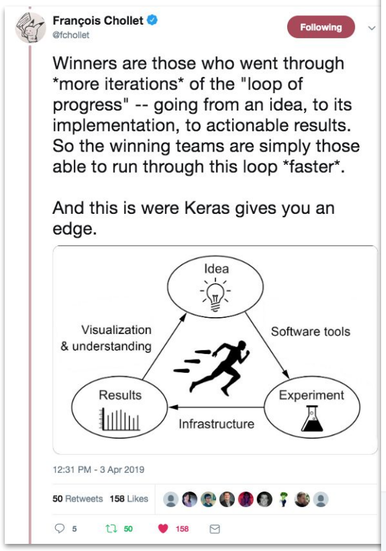
- SF1K 37.1x average speed-up
- SF10K 19.5x average speed-up (7x Normalized for Cost)

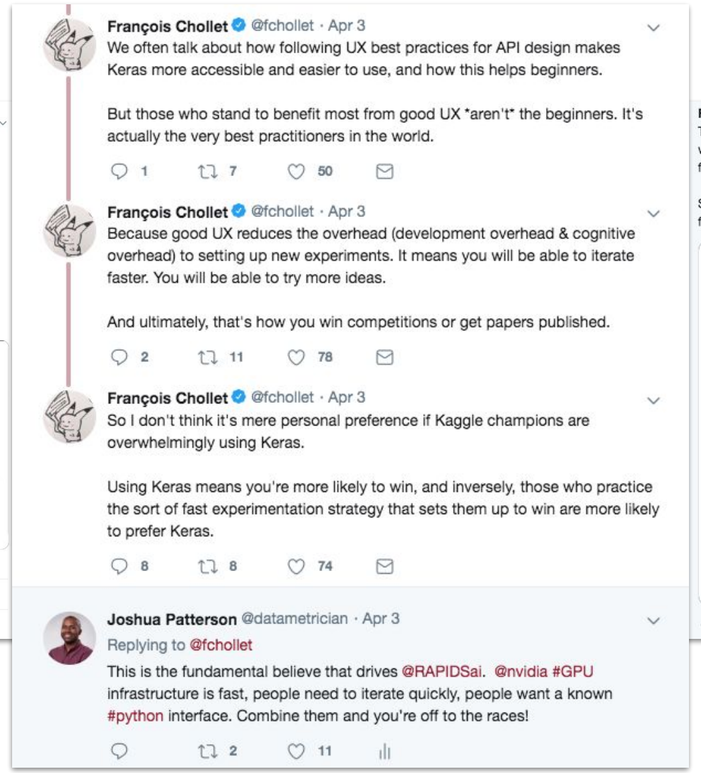


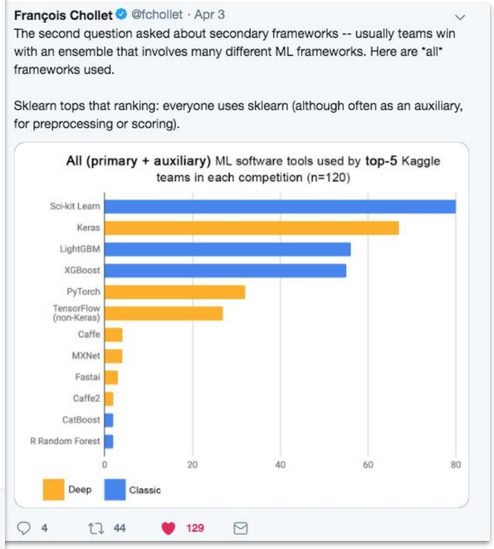


Speed, UX, and Iteration

The Way to Win at Data Science







kaggle

RAPIDS 0.15 Release Summary

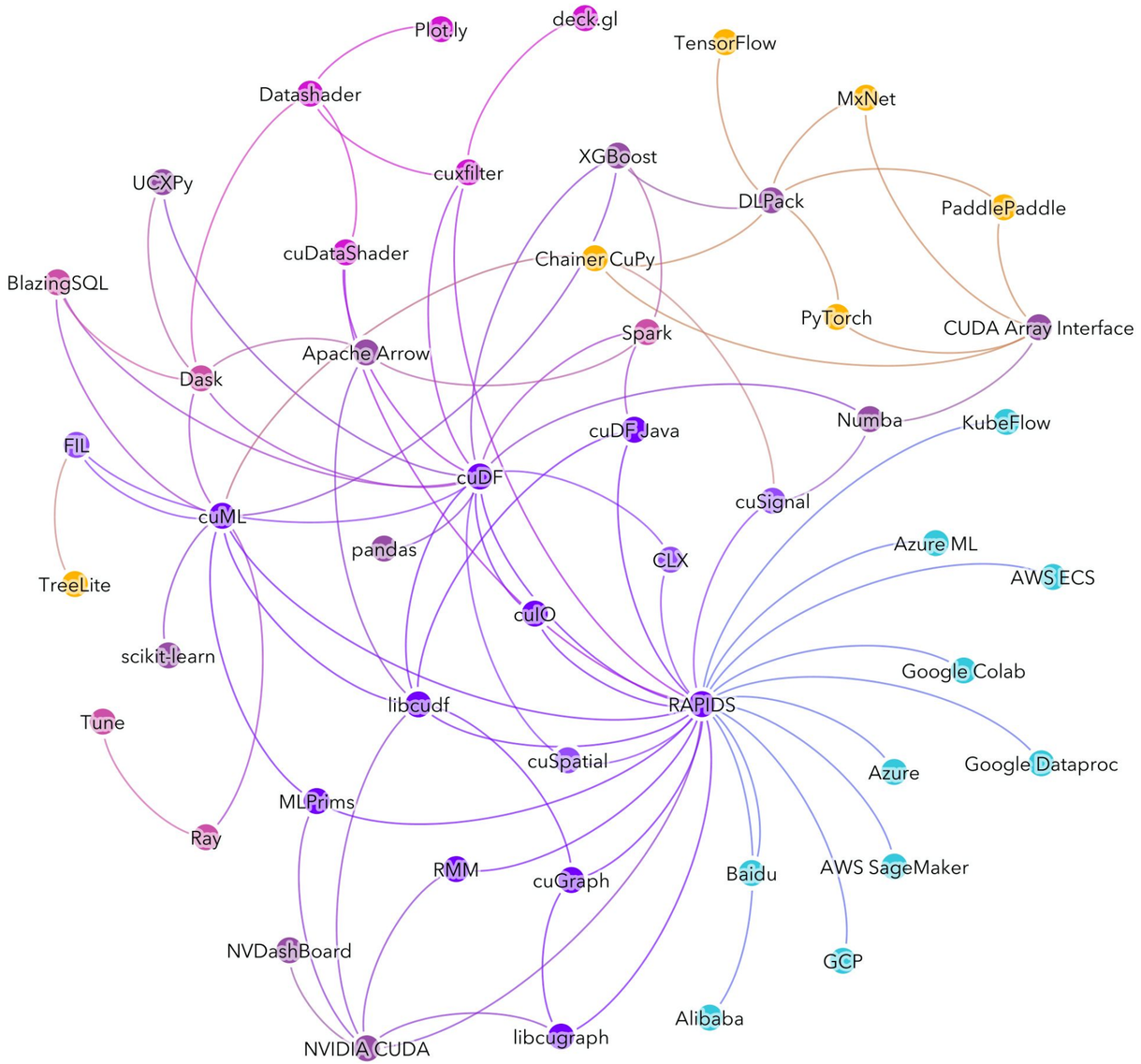
What's New in Release 0.15?

- **CUDA 11 and Ampere** support added across all libraries.
- **cuDF** adds unsigned integer and timedelta (duration) dtypes support as well as experimental support for a List dtype, Kafka as a supported data source, Groupby.rolling() support, and additional NLP preprocessing functions.
- **cuML** machine learning library adds scikit-learn compatible NLP preprocessors, initial AutoARIMA support, MNMG kNN classification and regression wrappers, accelerated multi-class forest inference, SVM sample weights and probability prediction, and an experimental Incremental PCA model for out-of-core fitting.
- **cuGraph** initial version of the Leiden algorithm, added Edge Betweenness Centrality, improved Louvain and the ECG analytics, and added the HITS algorithm.
- **UCX-Py** adds reusable endpoints, Cython optimizations, code clean up, and bug fixes.
- **BlazingSQL** now supports out-of-core query execution, which enables queries to operate on datasets dramatically larger than available GPU memory.
- **cuSignal** adds multi-point kalman filter, improved embedded GPU support, and performance optimizations.
- **cuSpatial** adds point-to-nearest polyline queries and accelerated point-in-polygon via quadtree.
- **cuxfilter** will have a delayed release, but now has large graph support. See Notice RGN4 in our docs for details.
- **RMM** deprecates the CNMeM, adds per-thread default stream support, adds `binning_memory_resource.

RAPIDS Everywhere

The Next Phase of RAPIDS

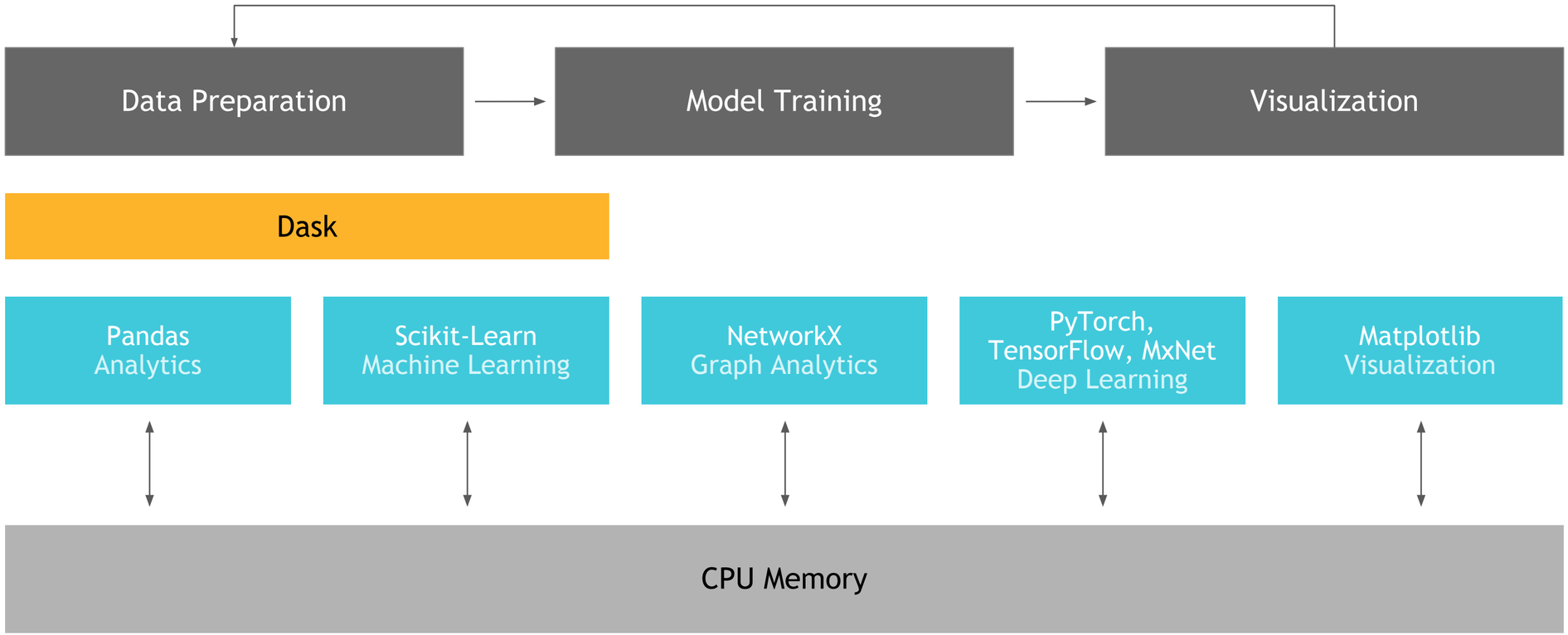
Exactly as it sounds—our goal is to make RAPIDS as usable and performant as possible wherever data science is done. We will continue to work with more open source projects to further democratize acceleration and efficiency in data science.



RAPIDS Core

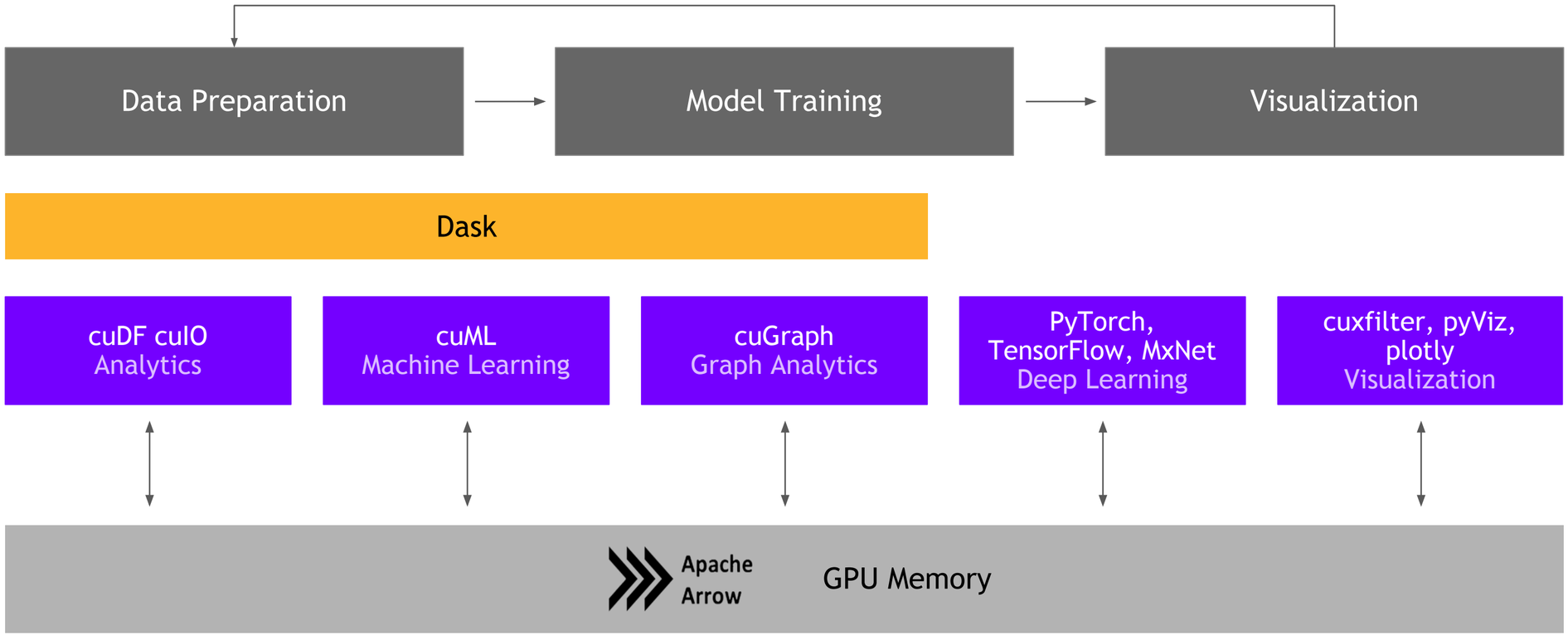
Open Source Data Science Ecosystem

Familiar Python APIs



RAPIDS

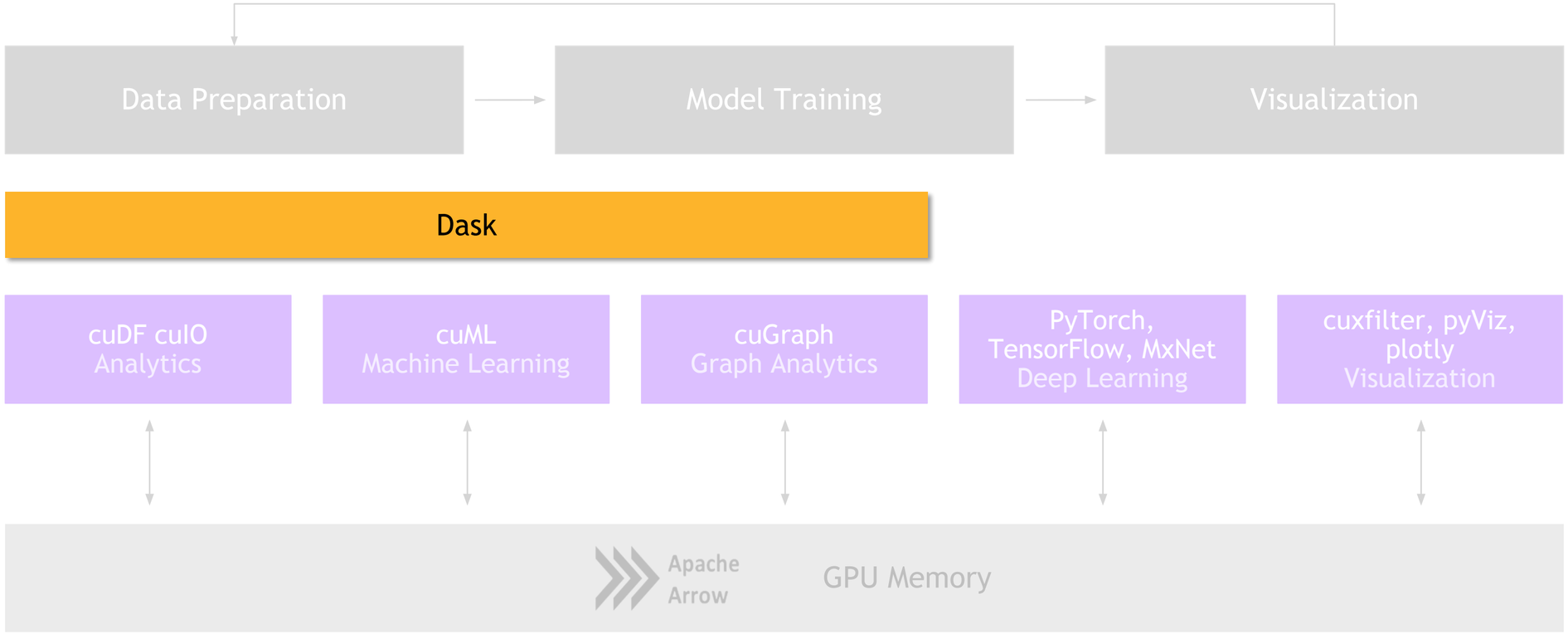
End-to-End Accelerated GPU Data Science



Dask

RAPIDS

Scaling RAPIDS with Dask



Why Dask?

DEPLOYABLE

- **HPC:** SLURM, PBS, LSF, SGE
- **Cloud:** Kubernetes
- **Hadoop/Spark:** Yarn

PYDATA NATIVE

- **Easy Migration:** Built on top of NumPy, Pandas Scikit-Learn, etc
- **Easy Training:** With the same APIs
- **Trusted:** With the same developer community

EASY SCALABILITY

- Easy to install and use on a laptop
- Scales out to thousand node clusters

POPULAR

- Most Common parallelism framework today in the PyData and SciPy community

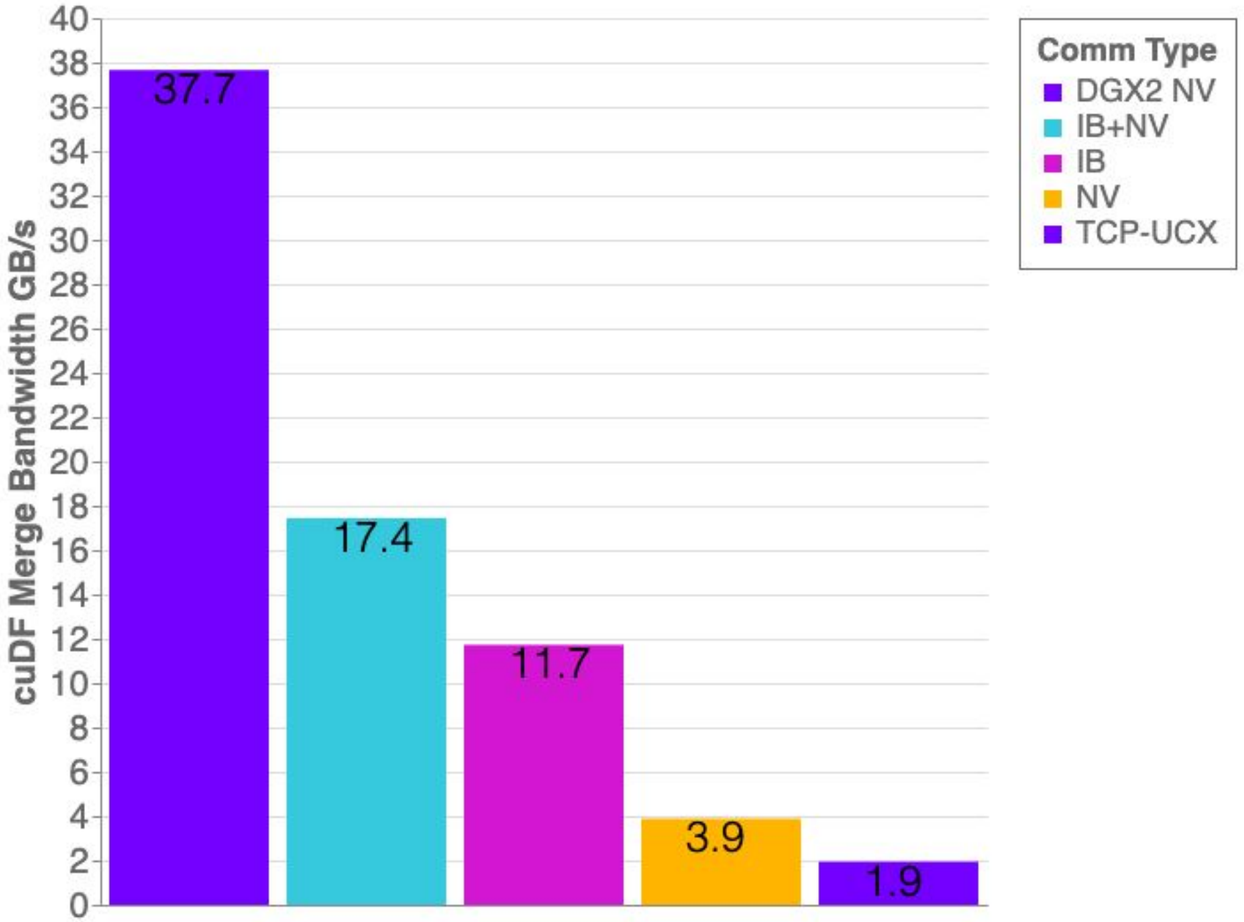
Why OpenUCX?

Bringing Hardware Accelerated Communications to Dask

- TCP sockets are slow!
- UCX provides uniform access to transports (TCP, InfiniBand, shared memory, NVLink)
- Alpha Python bindings for UCX (ucx-py)
- Will provide best communication performance, to Dask based on available hardware on nodes/cluster

```
conda install -c conda-forge -c rapidsai \
  cudatoolkit=<CUDA version> ucx-proc=*=gpu ucx ucx-py
```

Benchmarks: Distributed cuDF Random Merge



cuDF v0.14, UCX-PY 0.14

- Running on NVIDIA DGX-2:
  - GPU: NVIDIA Tesla V100 32GB
  - CPU: Intel(R) Xeon(R) CPU 8168 @ 2.70GHz

- Benchmark Setup:
  - DataFrames: Left/Right 1x int64 column key column, 1x int64 value columns
  - Merge: Inner
  - 30% of matching data balanced across each partition

Scale Up with RAPIDS

Scale Up / Accelerate

RAPIDS AND OTHERS

Accelerated on single GPU

NumPy -> CuPy/PyTorch/..
Pandas -> cuDF
Scikit-Learn -> cuML
Numba -> Numba

RAPIDS

PYDATA

NumPy, Pandas, Scikit-Learn,
Numba and many more

Single CPU core
In-memory data

Numba NumPy pandas PyData scikit learn

Scale Out with RAPIDS + Dask with OpenUCX

Scale Up / Accelerate

RAPIDS AND OTHERS

Accelerated on single GPU

NumPy -> CuPy/PyTorch/..
Pandas -> cuDF
Scikit-Learn -> cuML
Numba -> Numba

RAPIDS

RAPIDS + DASK WITH OPENUCX

Multi-GPU
On single Node (DGX)
Or across a cluster

RAPIDS

DASK

PYDATA

NumPy, Pandas, Scikit-Learn, Numba and many more

Single CPU core
In-memory data

Numba NumPy pandas PyData scikit learn

DASK

Multi-core and distributed PyData

NumPy -> Dask Array
Pandas -> Dask DataFrame
Scikit-Learn -> Dask-ML
… -> Dask Futures

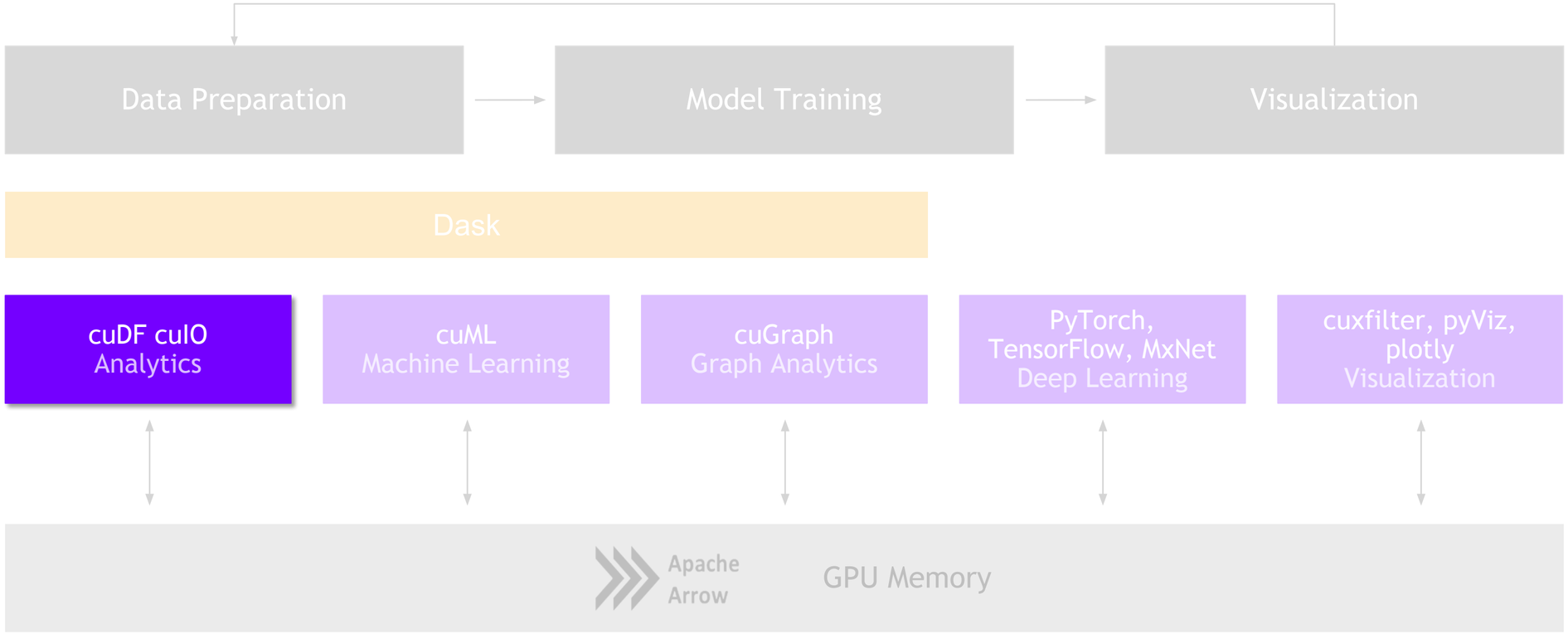
DASK

Scale Out / Parallelize

cuDF

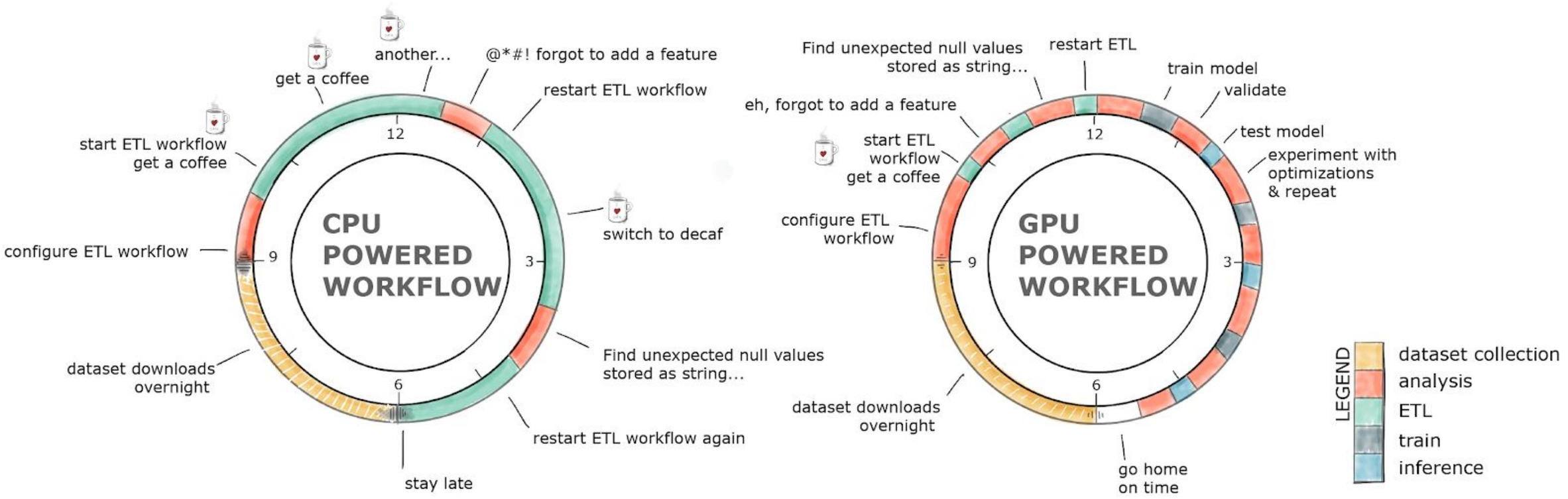
RAPIDS

GPU Accelerated Data Wrangling and Feature Engineering

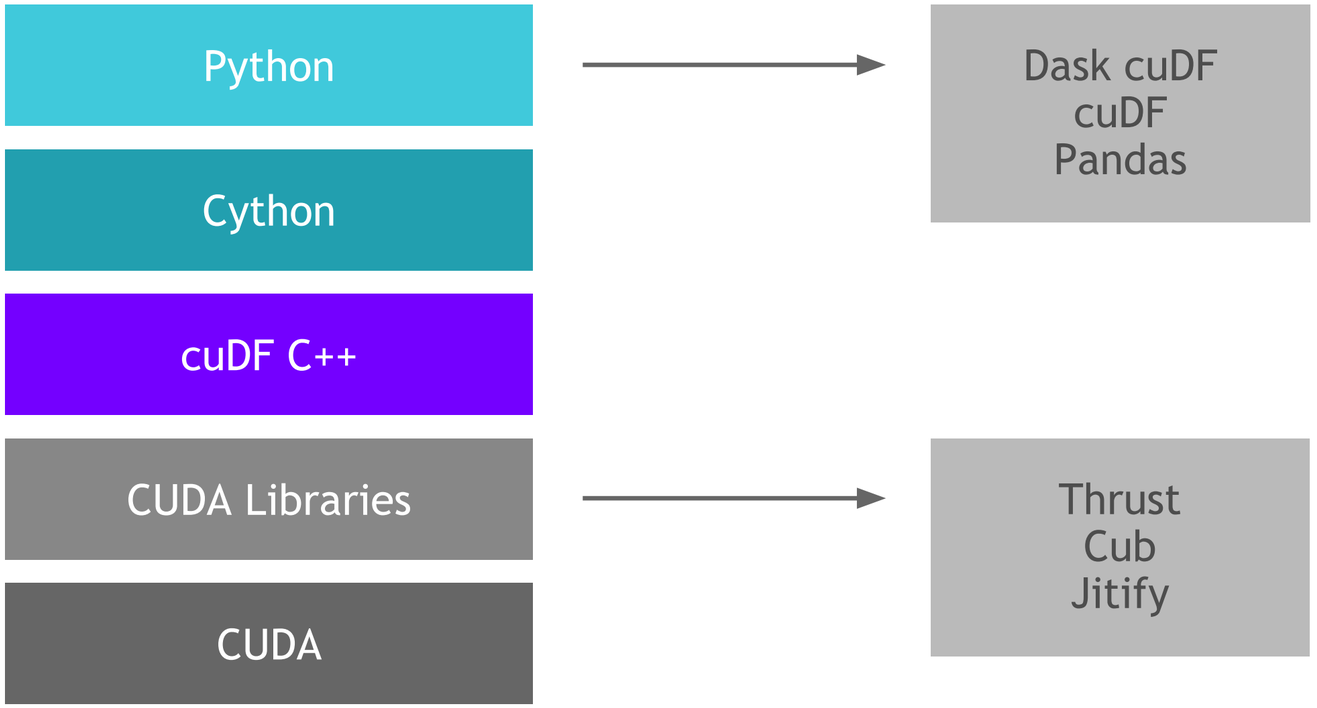


GPU-Accelerated ETL

The Average Data Scientist Spends 90+% of Their Time in ETL as Opposed to Training Models



ETL Technology Stack



ETL - the Backbone of Data Science

libcuDF is…

CUDA C++ LIBRARY

- Table (dataframe) and column types and algorithms
- CUDA kernels for sorting, join, groupby, reductions, partitioning, elementwise operations, etc.
- Optimized GPU implementations for strings, timestamps, numeric types (more coming)
- Primitives for scalable distributed ETL

```
std::unique_ptr<table>
gather(table_view const& input,
       column_view const& gather_map, …)
{
    // return a new table containing
    // rows from input indexed by
    // gather_map
}
```

ETL - the Backbone of Data Science

cuDF is…

PYTHON LIBRARY

- A Python library for manipulating GPU DataFrames following the Pandas API
- Python interface to CUDA C++ library with additional functionality
- Creating GPU DataFrames from Numpy arrays, Pandas DataFrames, and PyArrow Tables
- JIT compilation of User-Defined Functions (UDFs) using Numba

In [2]:
```
#Read in the data. Notice how it decompresses as it reads the data into memory.
gdf = cudf.read_csv('/rapids/Data/black-friday.zip')
```

In [3]:
```
#Taking a look at the data. We use "to_pandas()" to get the pretty printing.
gdf.head().to_pandas()
```

Out[3]:

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Product_Ca
0	1000001	P00069042	F	0-17	10	A	2	0	3
1	1000001	P00248942	F	0-17	10	A	2	0	1
2	1000001	P00087842	F	0-17	10	A	2	0	12
3	1000001	P00085442	F	0-17	10	A	2	0	12
4	1000002	P00285442	M	55+	16	C	4+	0	8

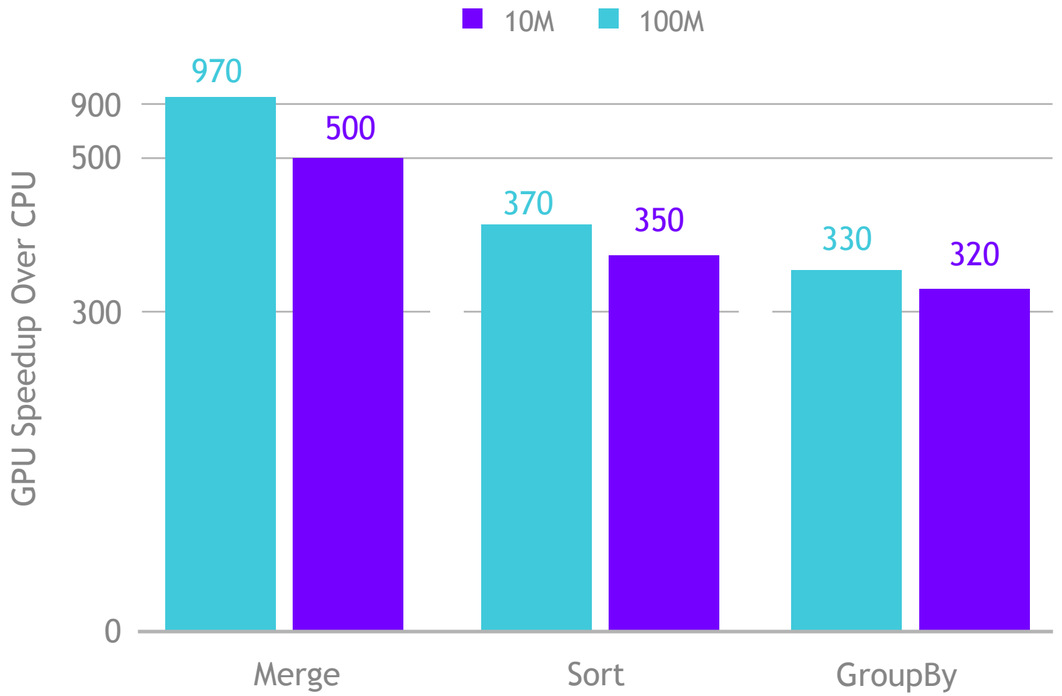
In [6]:
```
#grabbing the first character of the years in city string to get rid of plus sign, and converting
 to int
gdf['city_years'] = gdf.Stay_In_Current_City_Years.str.get(0).stoi()
```

In [7]:
```
#Here we can see how we can control what the value of our dummies with the replace method and turn
strings to ints
gdf['City_Category'] = gdf.City_Category.str.replace('A', '1')
gdf['City_Category'] = gdf.City_Category.str.replace('B', '2')
gdf['City_Category'] = gdf.City_Category.str.replace('C', '3')
gdf['City_Category'] = gdf['City_Category'].str.stoi()
```

Benchmarks: Single-GPU Speedup vs. Pandas

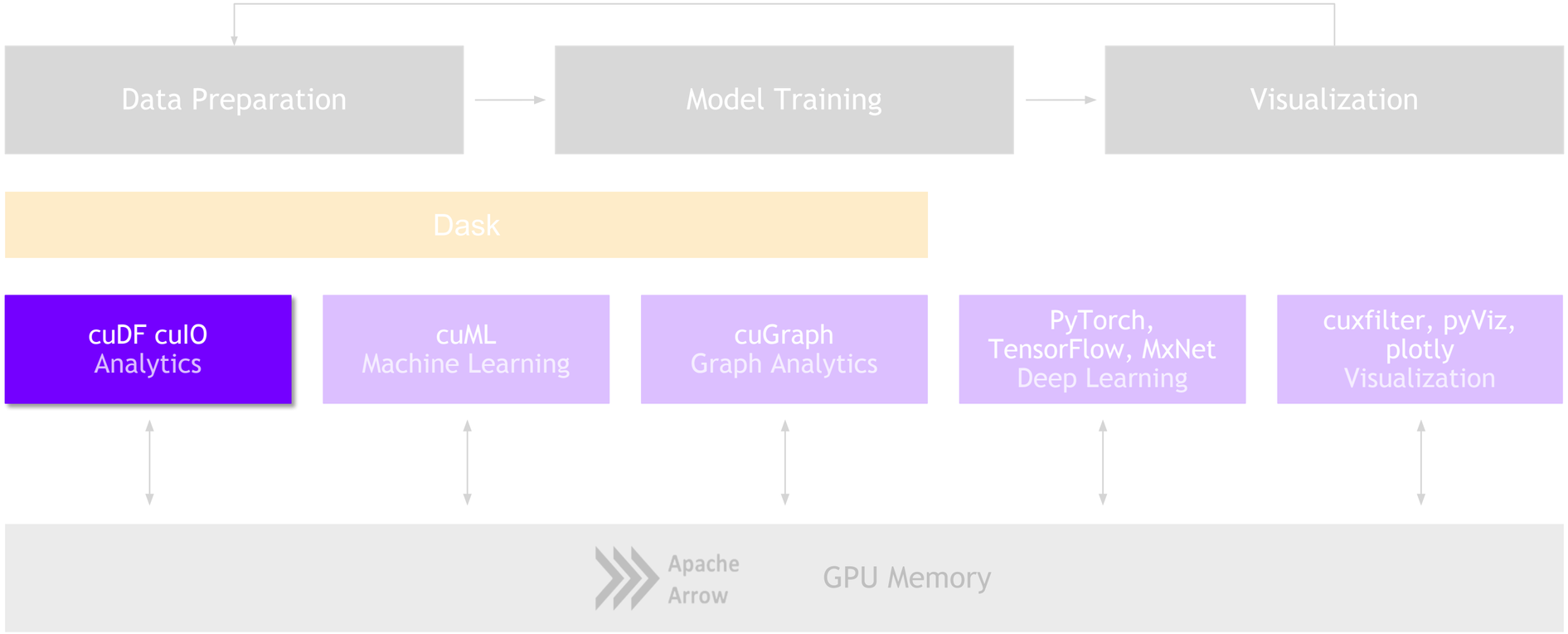
cuDF v0.13, Pandas 0.25.3

- Running on NVIDIA DGX-1:
  - GPU: NVIDIA Tesla V100 32GB
  - CPU: Intel(R) Xeon(R) CPU E5-2698 v4 @ 2.20GHz
- Benchmark Setup:
  - RMM Pool Allocator Enabled
  - DataFrames: 2x int32 columns key columns, 3x int32 value columns
  - Merge: inner; GroupBy: count, sum, min, max calculated for each value column



ETL - the Backbone of Data Science

cuDF is Not the End of the Story



ETL - the Backbone of Data Science

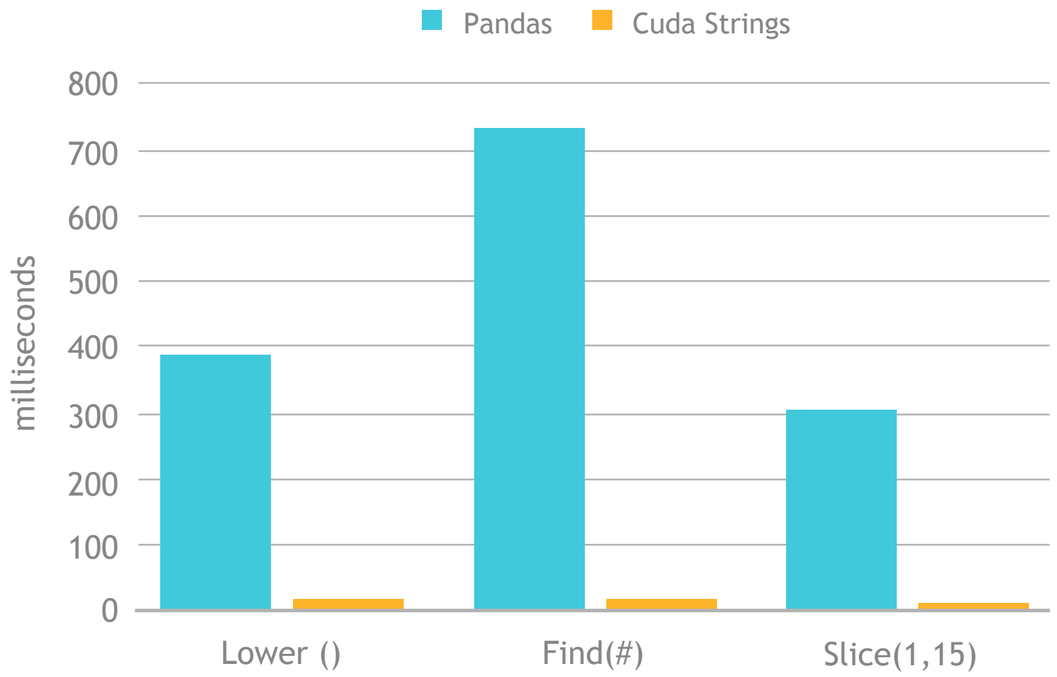
String Support

CURRENT V0.15 STRING SUPPORT

- Regular Expressions
- Element-wise operations
  - Split, Find, Extract, Cat, Typecasting, etc…
- String GroupBys, Joins, Sorting, etc.
- Categorical columns fully on GPU
- Native String type in libcudf C++
- NLP Preprocessors
  - Tokenizers, Normalizers, Edit Distance, Porter Stemmer, etc.

FUTURE V0.16+ STRING SUPPORT

- Further performance optimization
- JIT-compiled String UDFs



Extraction is the Cornerstone

cuIO for Faster Data Loading

- Follow Pandas APIs and provide >10x speedup
- CSV Reader, CSV Writer
- Parquet Reader, Parquet Writer
- ORC Reader, ORC Writer
- JSON Reader
- Avro Reader
- GPU Direct Storage integration in progress for bypassing PCIe bottlenecks!
- Key is GPU-accelerating both parsing and decompression

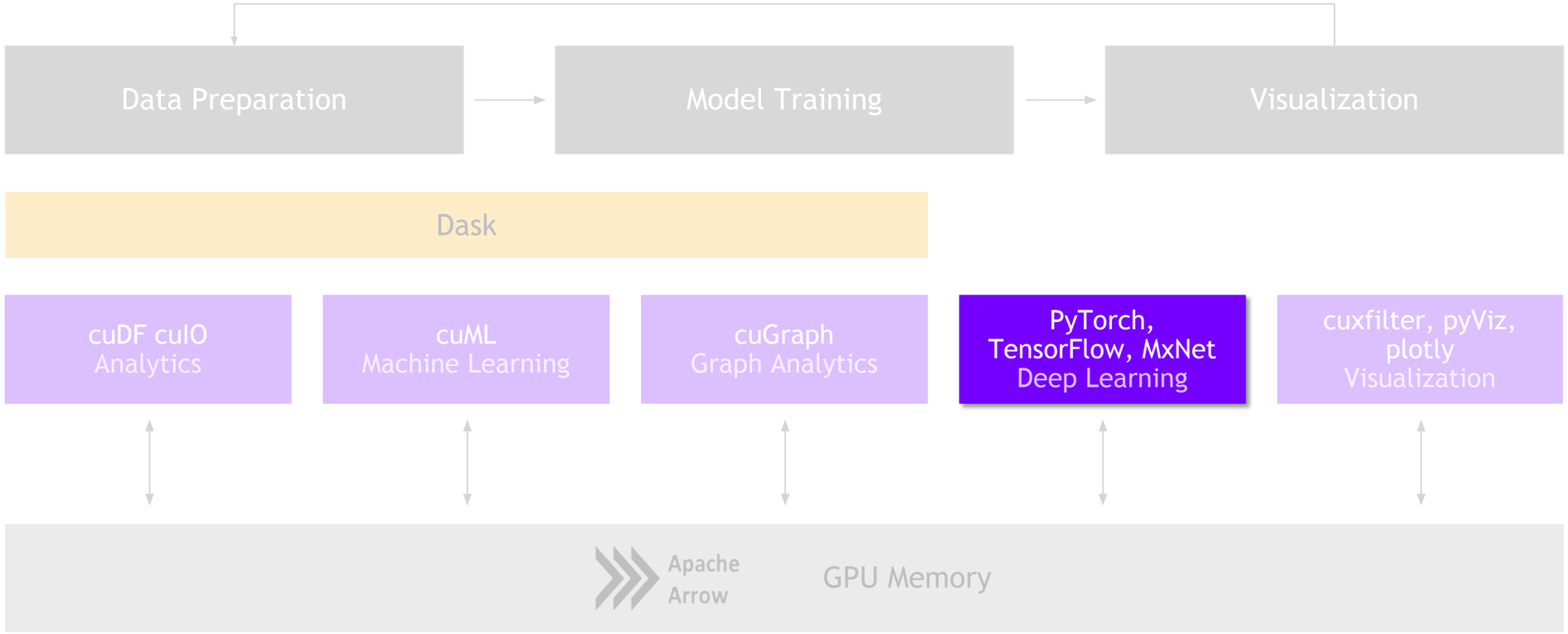
```
1]: import pandas, cudf

2]: %time len(pandas.read_csv('data/nyc/yellow_tripdata_2015-01.csv'))

CPU times: user 25.9 s, sys: 3.26 s, total: 29.2 s
Wall time: 29.2 s
2]: 12748986

3]: %time len(cudf.read_csv('data/nyc/yellow_tripdata_2015-01.csv'))

CPU times: user 1.59 s, sys: 372 ms, total: 1.96 s
Wall time: 2.12 s
3]: 12748986

4]: !du -hs data/nyc/yellow_tripdata_2015-01.csv

1.9G    data/nyc/yellow_tripdata_2015-01.csv
```

Source: Apache Crail blog: SQL Performance: Part 1 - Input File Formats

ETL is Not Just DataFrames!

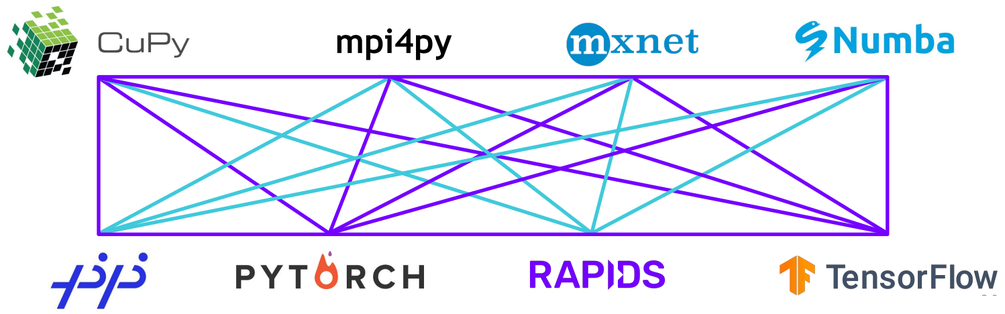
RAPIDS

Building Bridges into the Array Ecosystem



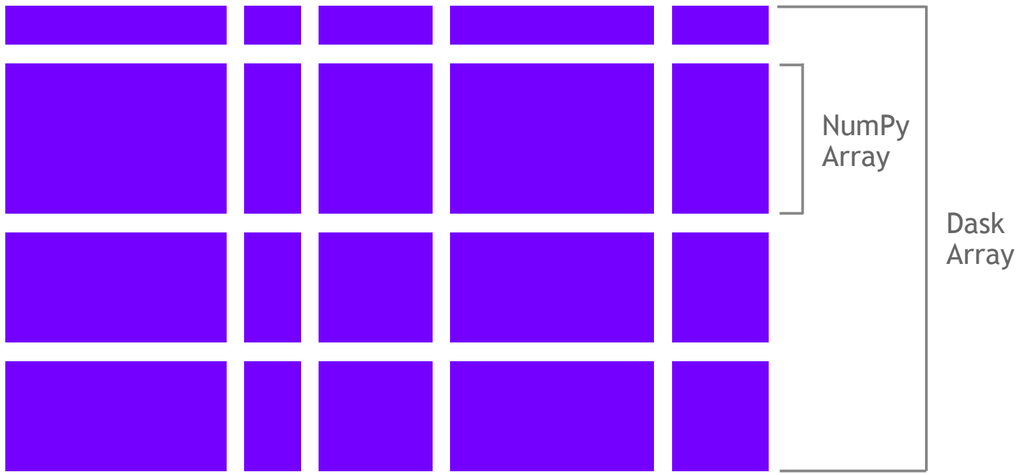
Interoperability for the Win

- Real-world workflows often need to share data between libraries
- RAPIDS supports device memory sharing between many popular data science and deep learning libraries
- Keeps data on the GPU--avoids costly copying back and forth to host memory
- Any library that supports DLPack or `__cuda_array_interface__` will allow for sharing of memory buffers between RAPIDS and supported libraries



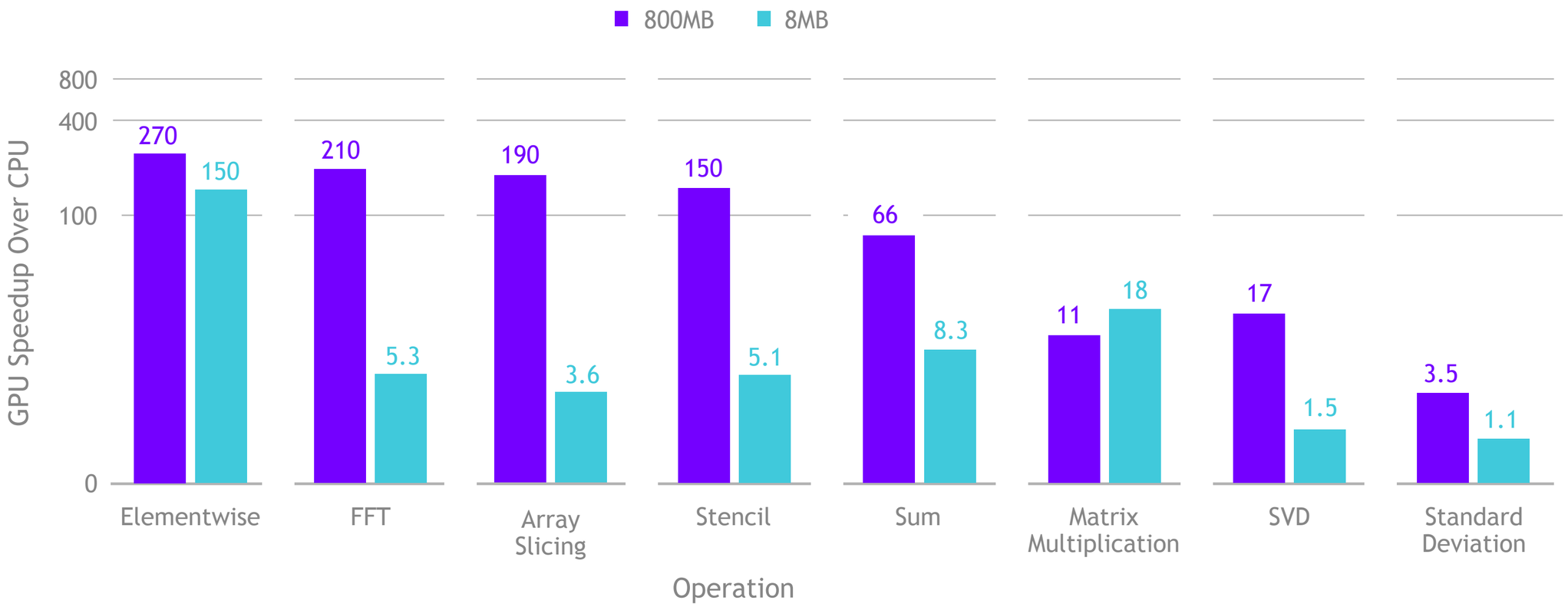
ETL – Arrays and DataFrames

Dask and CUDA Python Arrays



- Scales NumPy to distributed clusters
- Used in climate science, imaging, HPC analysis up to 100TB size
- Now seamlessly accelerated with GPUs

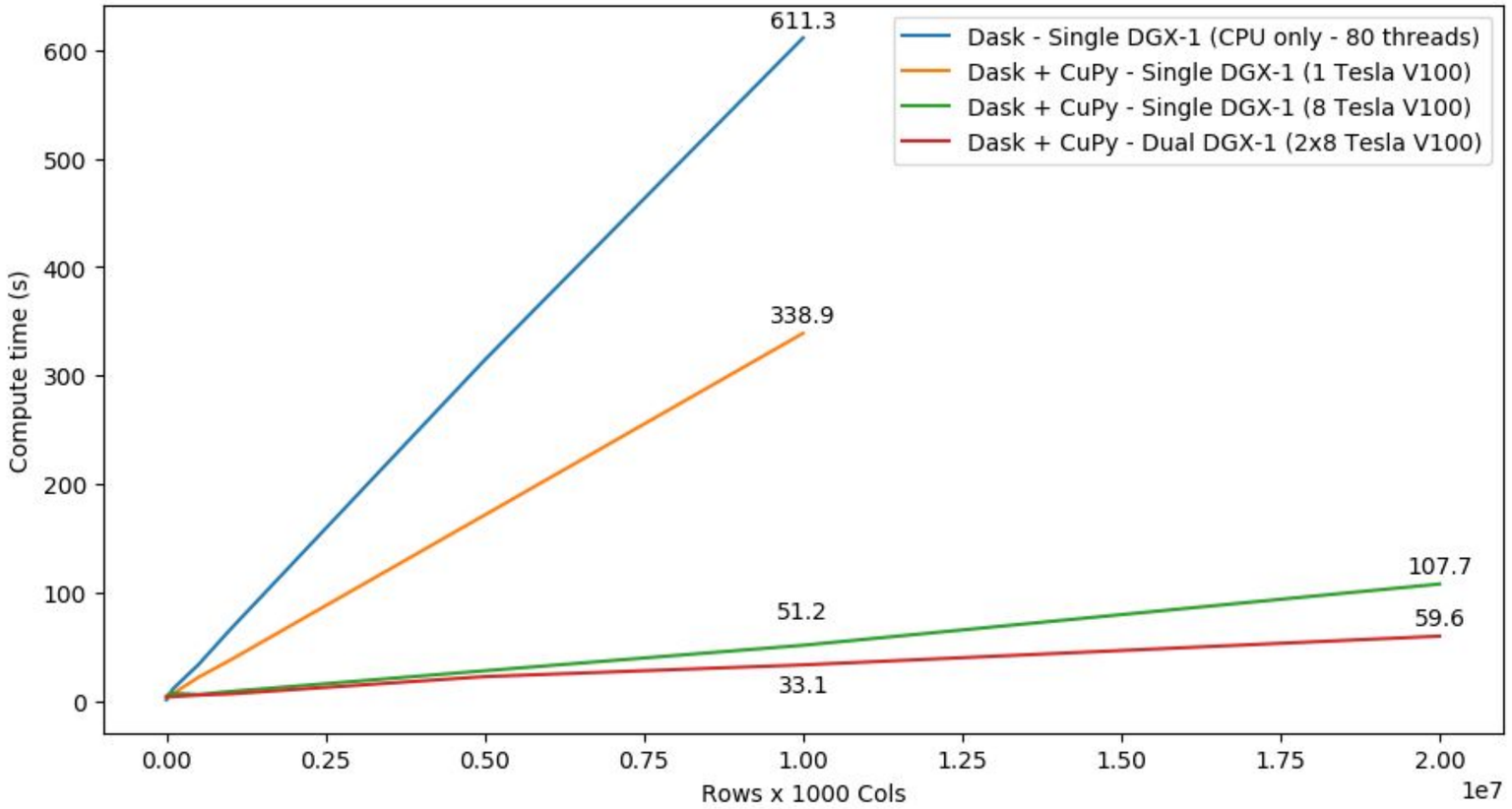
Benchmark: Single-GPU CuPy vs NumPy



More details: https://blog.dask.org/2019/06/27/single-gpu-cupy-benchmarks

SVD Benchmark

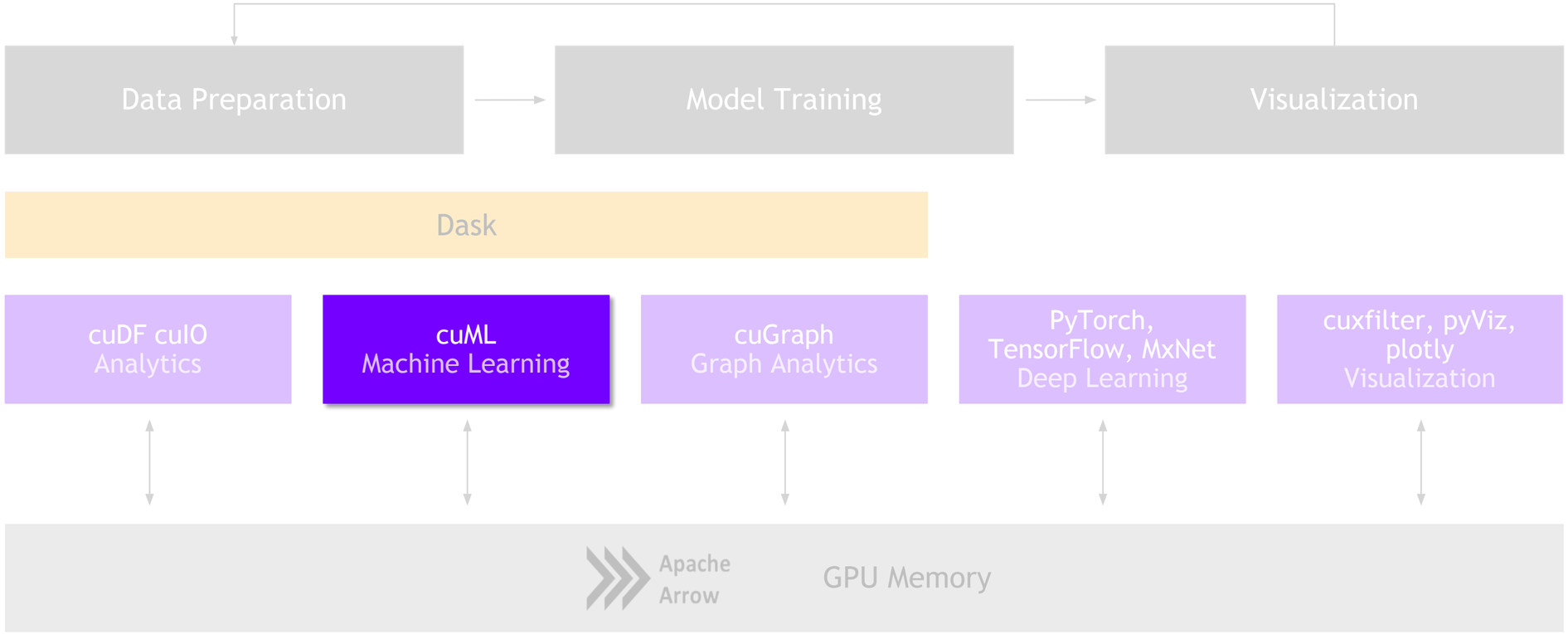
Dask and CuPy Doing Complex Workflows



cuML

Machine Learning

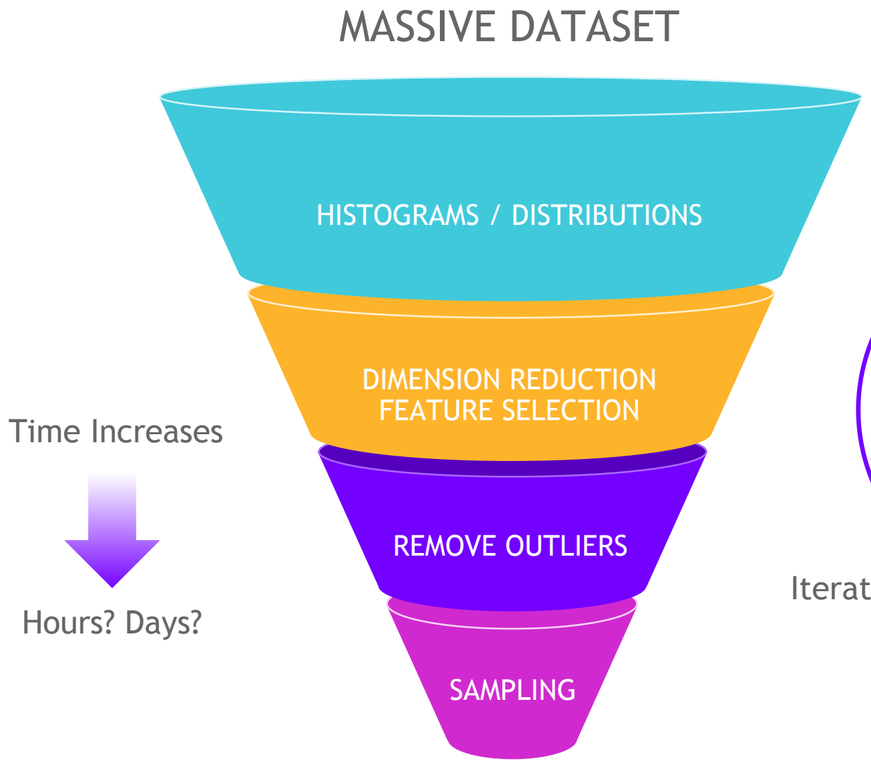
More Models More Problems

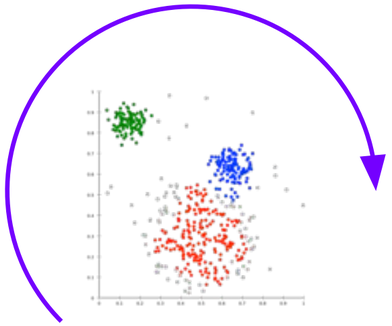


Problem

Data Sizes Continue to Grow

Better to start with as much data as possible and explore / preprocess to scale to performance needs.

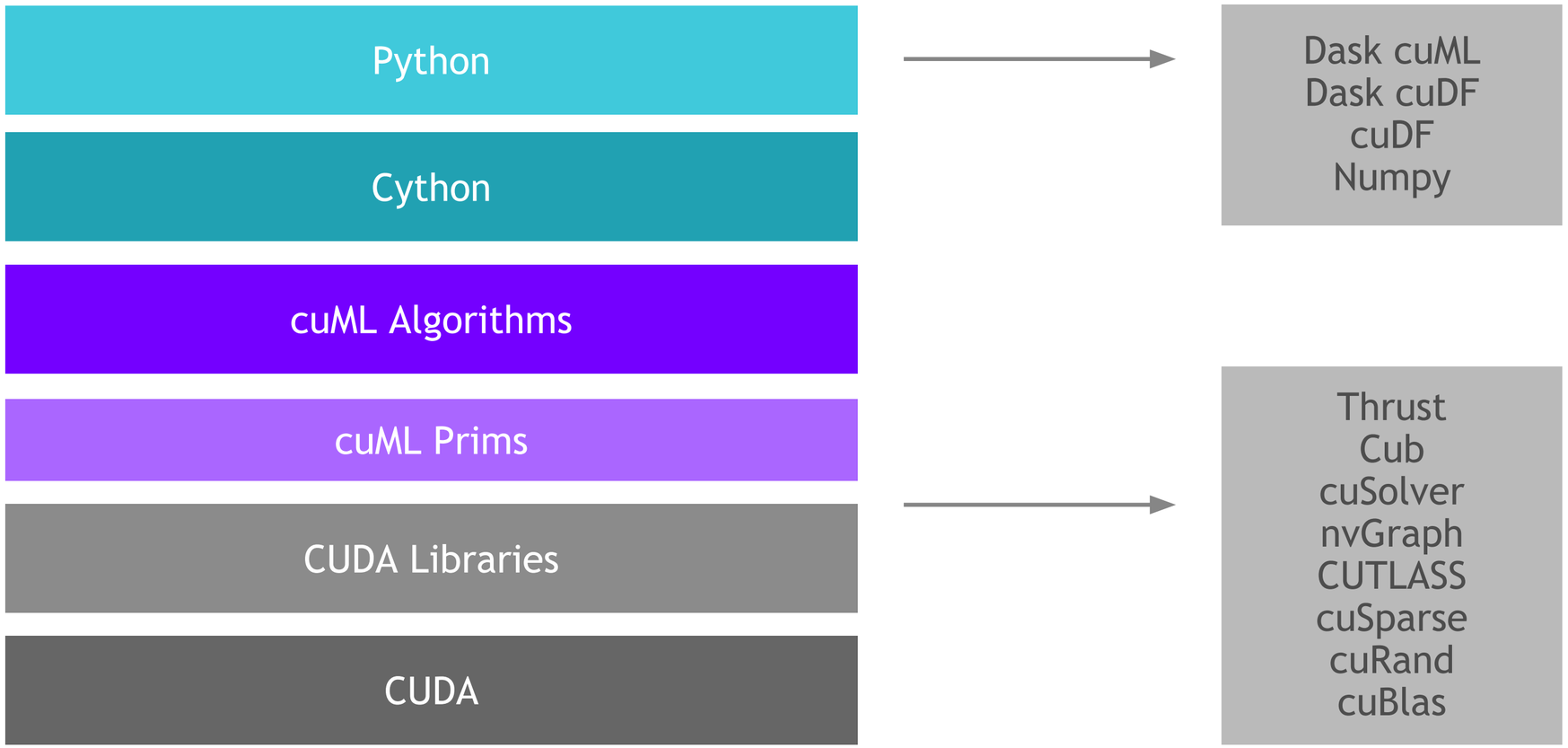




Iterate. Cross Validate & Grid Search.
Iterate Some More.

Meet Reasonable Speed vs Accuracy Trade-off

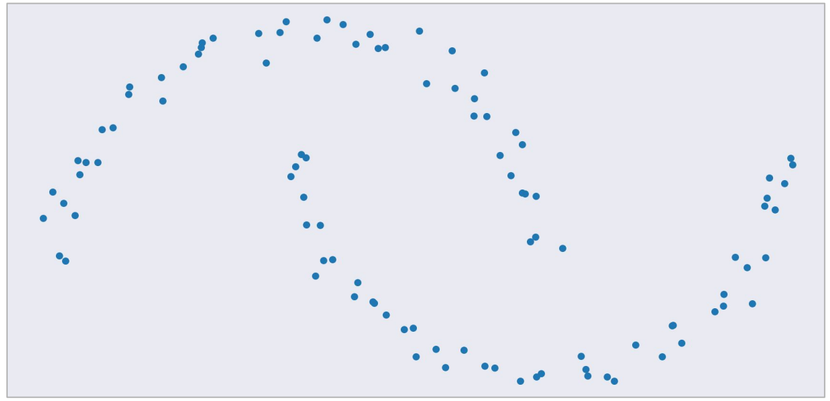
ML Technology Stack



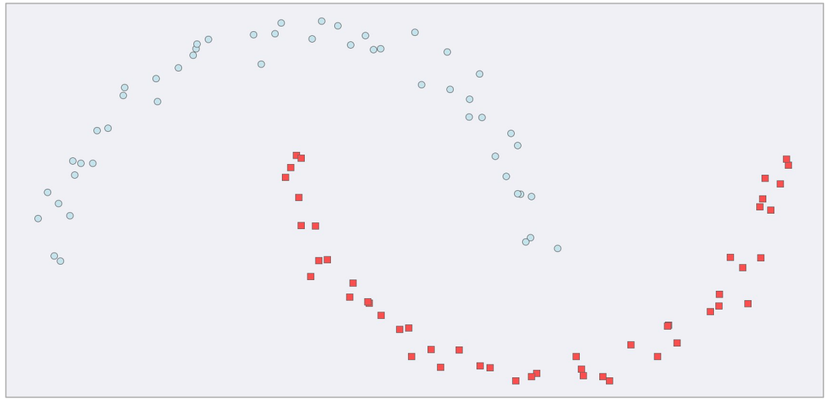
RAPIDS Matches Common Python APIs

CPU-based Clustering

```
from sklearn.datasets import make_moons
import pandas


X, y = make_moons(n_samples=int(1e2),
                  noise=0.05, random_state=0)

X = pandas.DataFrame({'fea%d'%i: X[:, i]
                  for i in range(X.shape[1])})
```



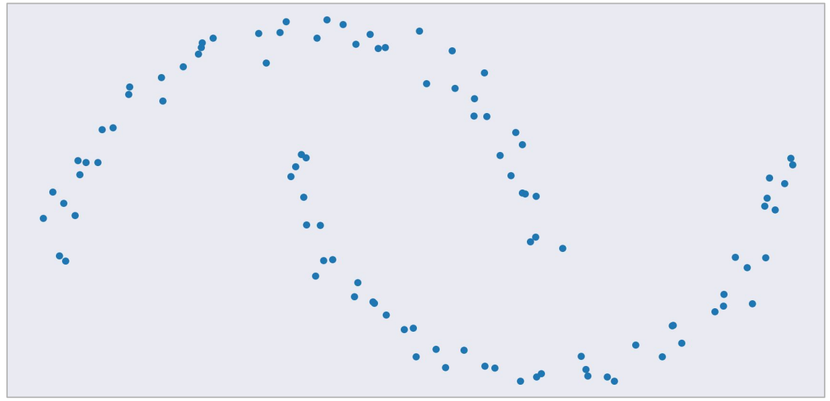
```
from sklearn.cluster import DBSCAN
dbscan = DBSCAN(eps = 0.3, min_samples = 5)

dbscan.fit(X)

y_hat = dbscan.predict(X)
```



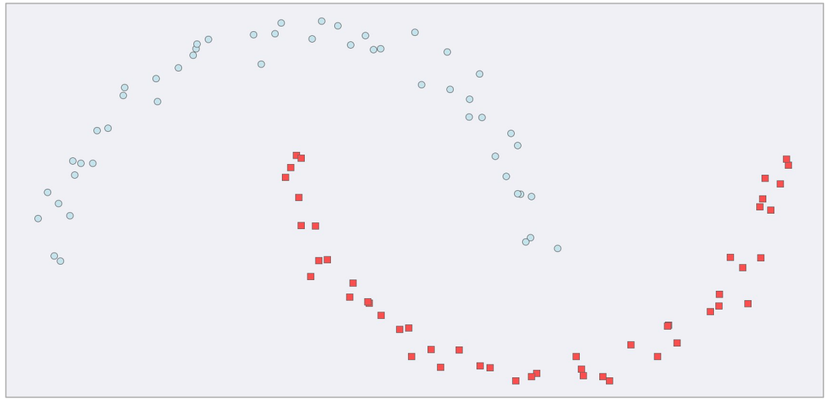
RAPIDS Matches Common Python APIs

GPU-accelerated Clustering

```
from sklearn.datasets import make_moons
import cudf


X, y = make_moons(n_samples=int(1e2),
                  noise=0.05, random_state=0)

X = cudf.DataFrame({'fea%d'%i: X[:, i]
                  for i in range(X.shape[1])})
```

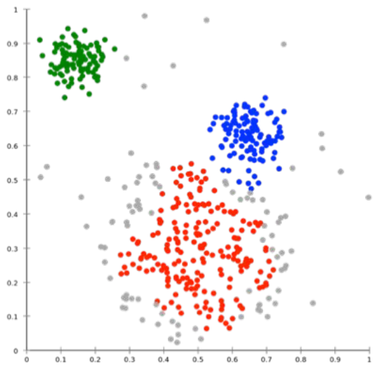


```
from cuml import DBSCAN
dbscan = DBSCAN(eps = 0.3, min_samples = 5)

dbscan.fit(X)

y_hat = dbscan.predict(X)
```



Algorithms

GPU-accelerated Scikit-Learn



Cross Validation

Hyper-parameter Tuning

More to come!

Classification / Regression

Decision Trees / Random Forests
Linear/Lasso/Ridge/ElasticNet Regression
Logistic Regression
K-Nearest Neighbors
Support Vector Machine Classification and Regression
Naive Bayes

Inference

Random Forest / GBDT Inference (FIL)

Preprocessing

Text vectorization (TF-IDF / Count)
Target Encoding
Cross-validation / splitting

Clustering Decomposition & Dimensionality Reduction

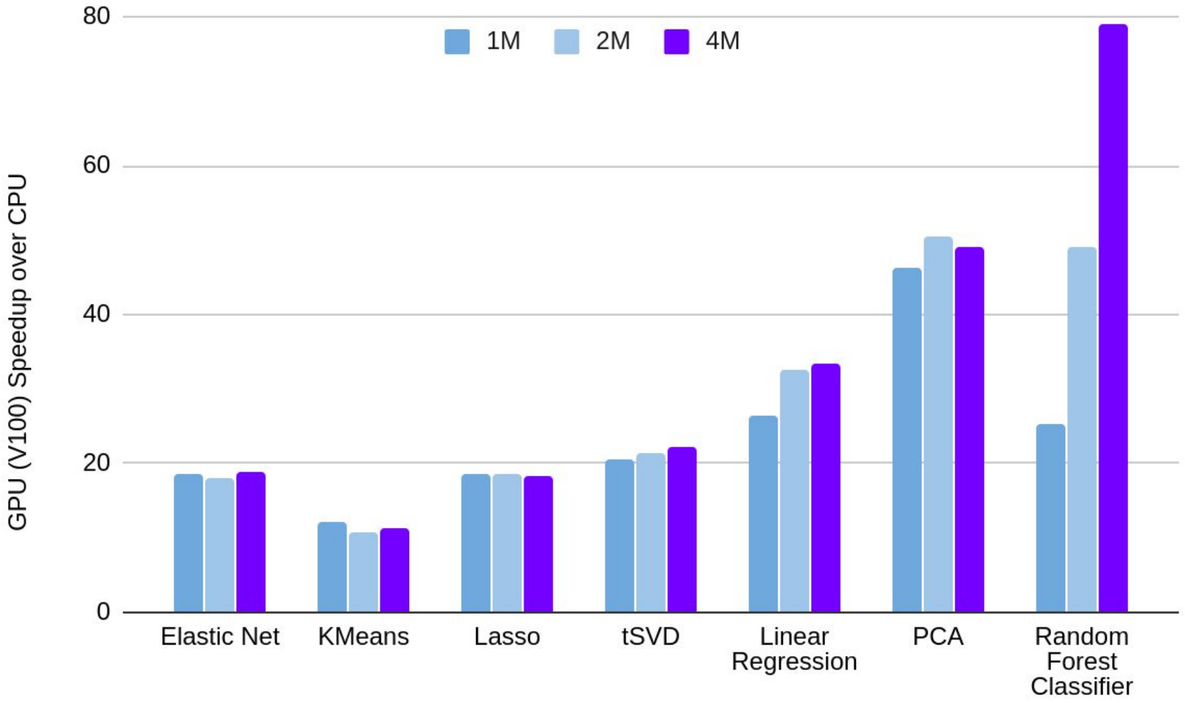
K-Means
DBSCAN
Spectral Clustering
Principal Components
Singular Value Decomposition
UMAP
Spectral Embedding
T-SNE

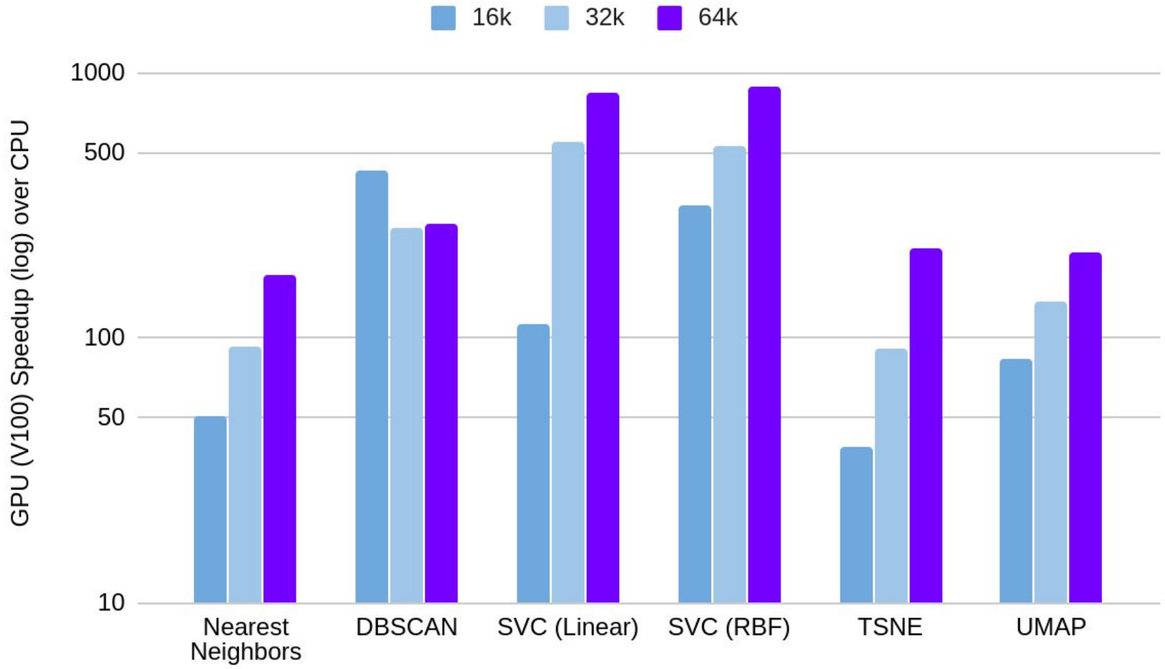
Time Series

Holt-Winters
Seasonal ARIMA / Auto ARIMA

Key:
*Preexisting | **NEW or enhanced for 0.15***

Benchmarks: Single-GPU cuML vs Scikit-learn (WIP)





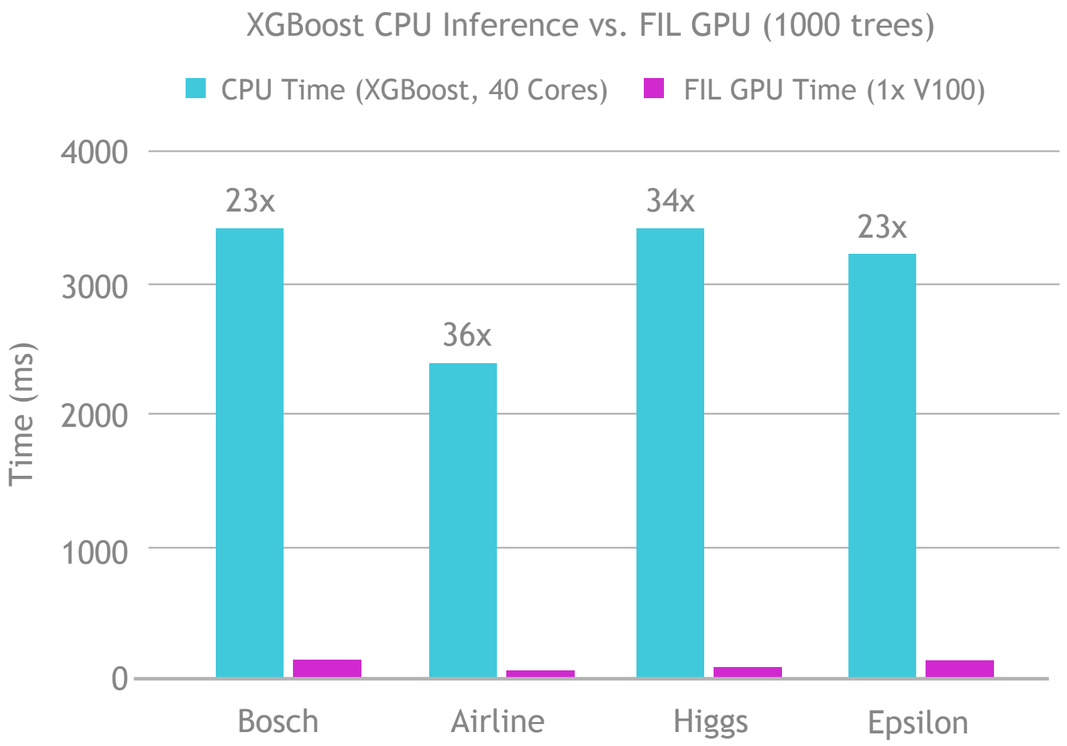
1x V100 vs. 2x 20 Core CPUs (DGX-1, RAPIDS 0.15)

Forest Inference

Taking Models From Training to Production

cuML's Forest Inference Library accelerates prediction (inference) for random forests and boosted decision trees:

- Works with existing saved models (XGBoost, LightGBM, scikit-learn RF cuML RF soon)
- Lightweight Python API
- Single V100 GPU can infer up to 34x faster than XGBoost dual-CPU node
- Over 100 million forest inferences

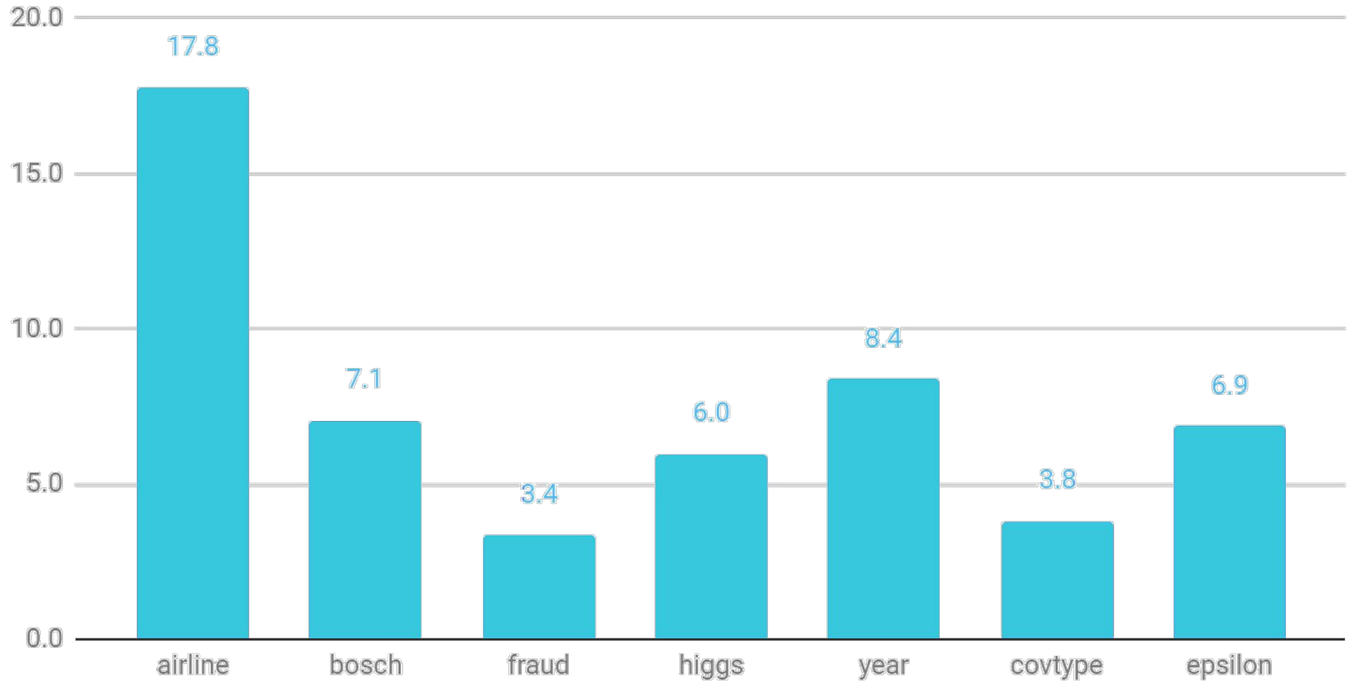


XGBoost + RAPIDS: Better Together

- RAPIDS comes paired with XGBoost 1.1 (as of 0.14)
- XGBoost now builds on the GoAI interface standards to provide zero-copy data import from cuDF, cuPY, Numba, PyTorch and more
- Official Dask API makes it easy to scale to multiple nodes or multiple GPUs
- gpu_hist tree builder delivers huge perf gains

  Memory usage when importing GPU data decreased by 2/3 or more
- New objectives support Learning to Rank on GPU

All RAPIDS changes are integrated upstream and provided to all XGBoost users – via pypi or RAPIDS conda



XGBoost speedup on GPUs comparing a single NVIDIA V100 GPU to a dual 20-core Intel Xeon E5-2698 server

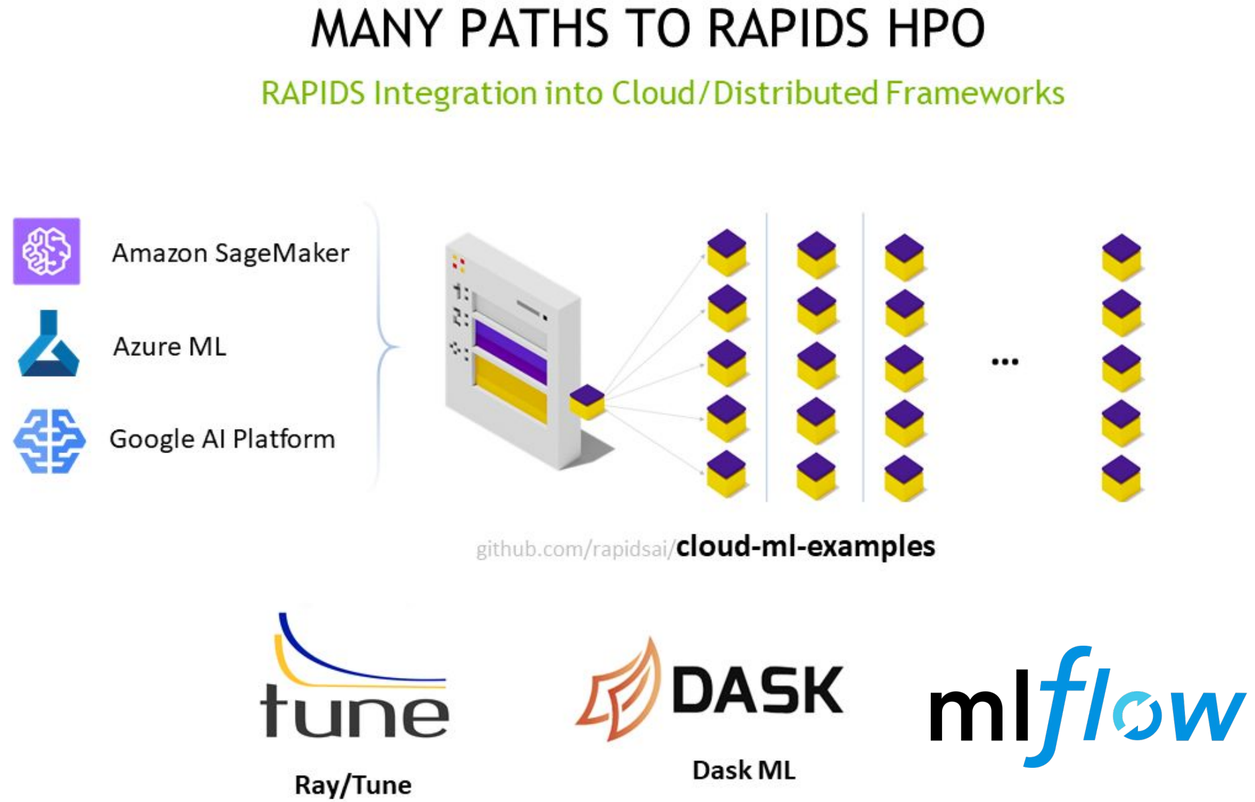
RAPIDS Integrated into Cloud ML Frameworks

Accelerated machine learning models in RAPIDS give you the flexibility to use hyperparameter optimization (HPO) experiments to explore all variants to find the most accurate possible model for your problem.

With GPU acceleration, RAPIDS models can train 40x faster than CPU equivalents, enabling more experimentation in less time.

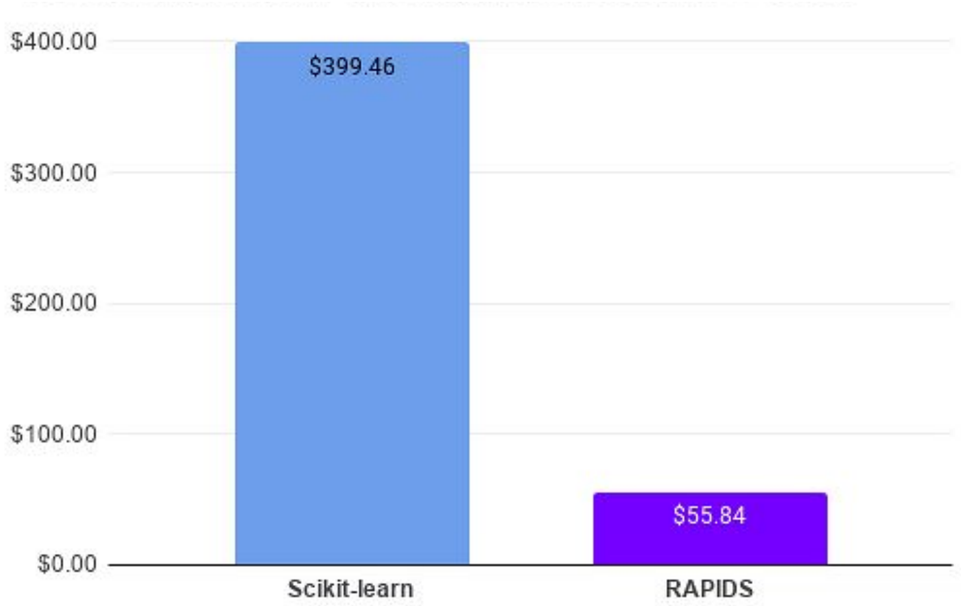
The RAPIDS team works closely with major cloud providers and OSS solution providers to provide code samples to get started with HPO in minutes

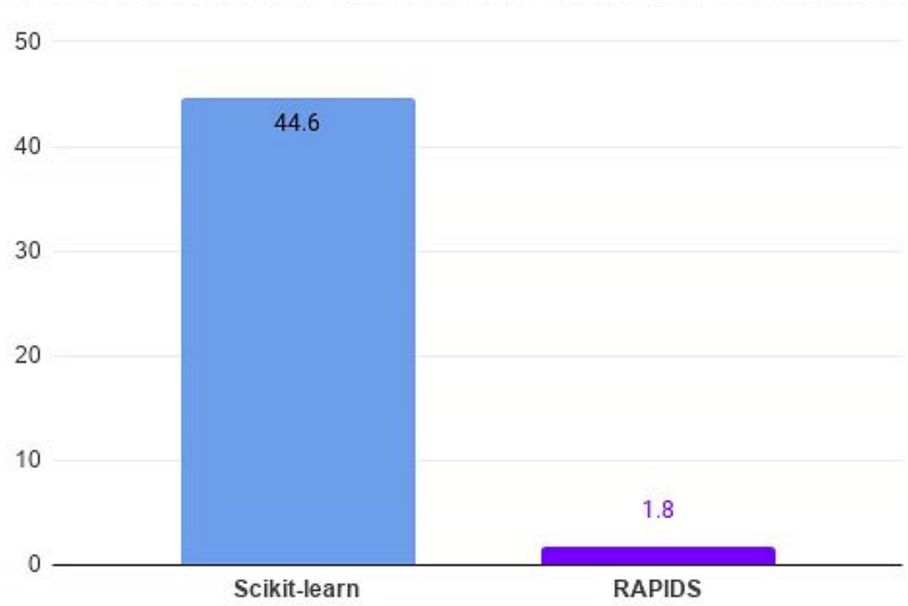
https://rapids.ai/hpo



HPO Use Case: 100-Job Random Forest Airline Model

Huge speedups translate into >7x TCO reduction





Based on sample Random Forest training code from cloud-ml-examples repository, running on Azure ML. 10 concurrent workers with 100 total runs, 100M rows, 5-fold cross-validation per run.

GPU nodes: 10x Standard_NC6s_v3, 1 V100 16G, vCPU 6 memory 112G, Xeon E5-2690 v4 (Broadwell) - $3.366/hour
CPU nodes: 10x Standard_DS5_v2, vCPU 16 memory 56G, Xeon E5-2673 v3 (Haswell) or v4 (Broadwell) - $1.017/hour"

Road to 1.0 - cuML

June 2020 - RAPIDS 0.15

cuML	Single-GPU	Multi-Node-Multi-GPU
Gradient Boosted Decision Trees (GBDT)		
Linear Regression		
Logistic Regression		
Random Forest		
K-Means		
K-NN		
DBSCAN		
UMAP		
Holt-Winters		
ARIMA		
T-SNE		
Principal Components		
Singular Value Decomposition		
SVM		

Road to 1.0 - cuML

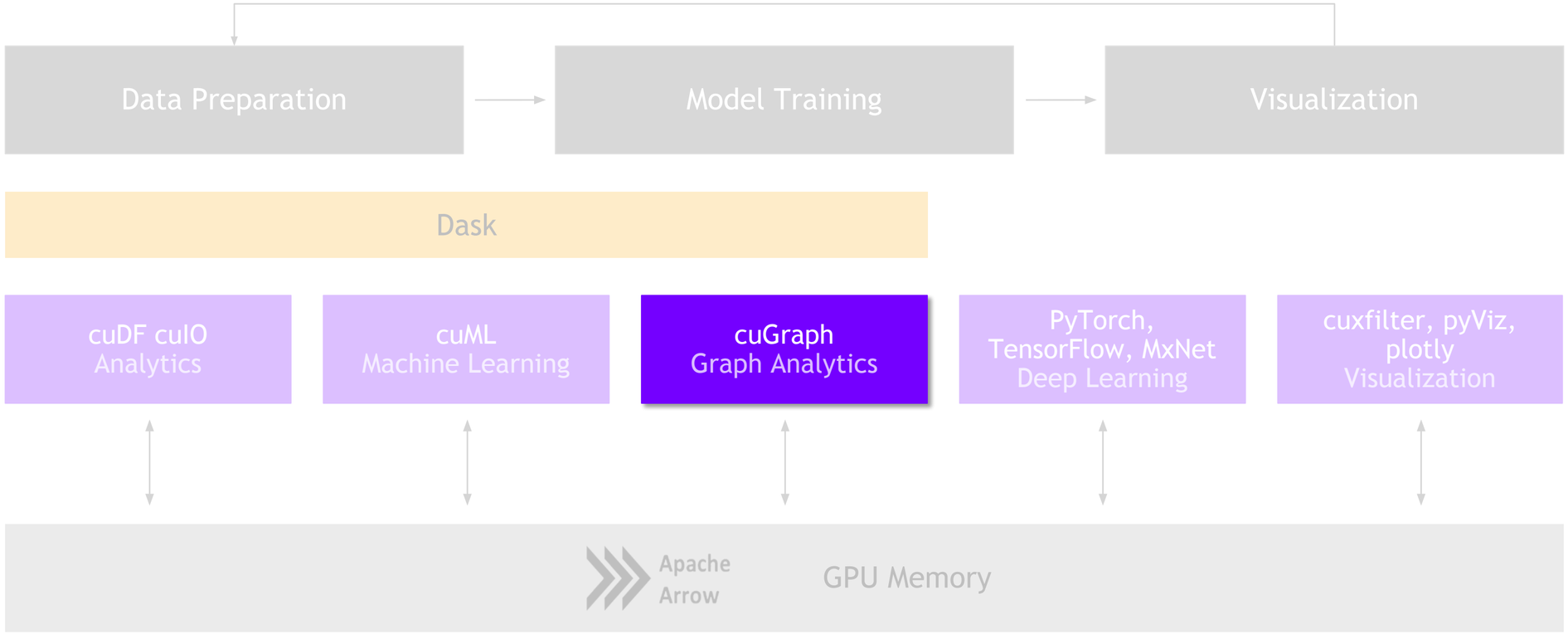
2020 EOY Plan

cuML	Single-GPU	Multi-Node-Multi-GPU
Gradient Boosted Decision Trees (GBDT)		
Linear Regression		
Logistic Regression		
Random Forest		
K-Means		
K-NN		
DBSCAN		
UMAP		
Holt-Winters		
ARIMA		
T-SNE		
Principal Components		
Singular Value Decomposition		
SVM		

cuGraph

Graph Analytics

More Connections, More Insights



Goals and Benefits of cuGraph

Focus on Features and User Experience

BREAKTHROUGH PERFORMANCE

- Up to 500 million edges on a single 32GB GPU
- Multi-GPU support for scaling into the billions of edges

SEAMLESS INTEGRATION WITH cuDF AND cuML

- Property Graph support via DataFrames

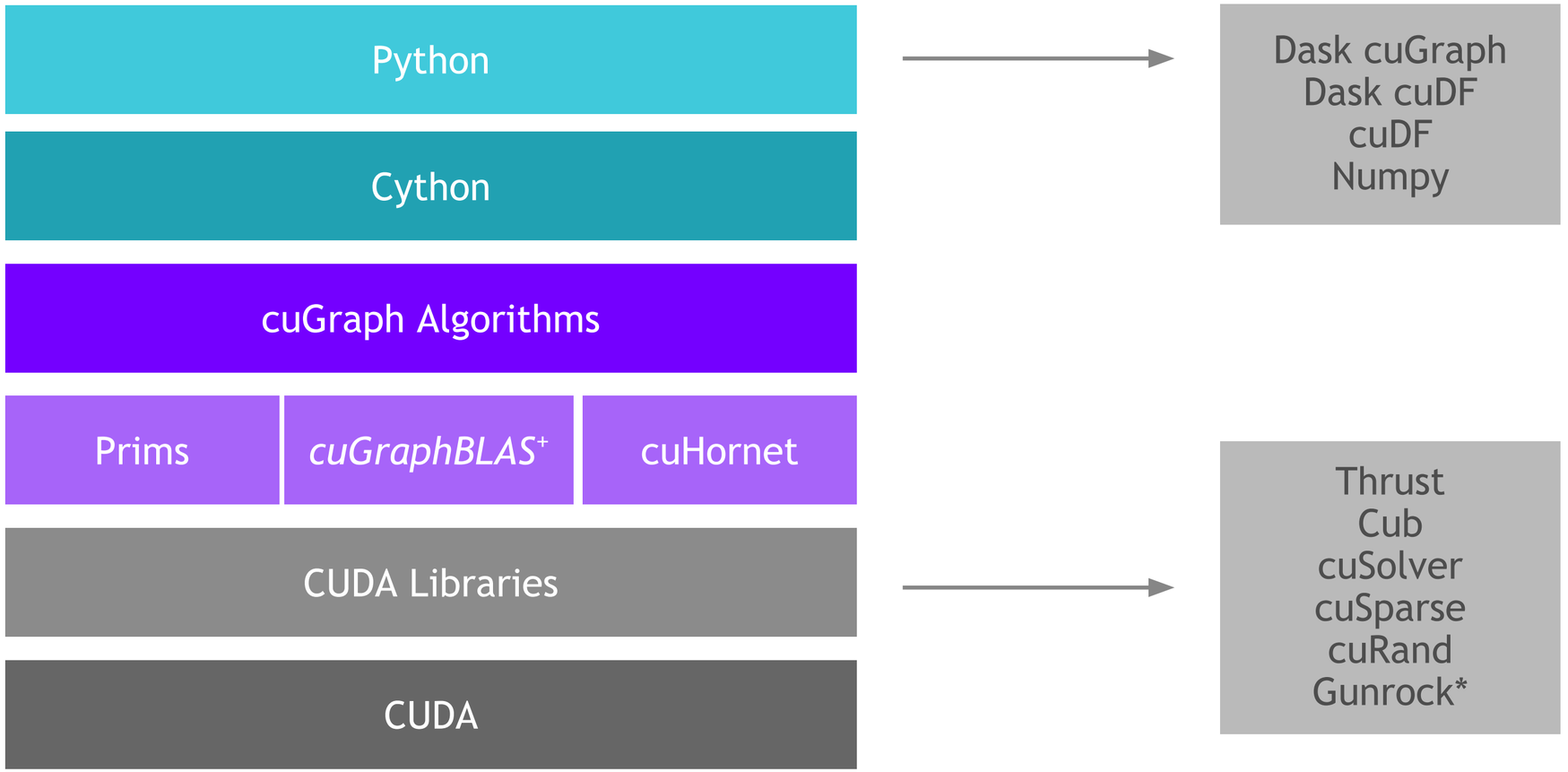
MULTIPLE APIs

- **Python:** Familiar NetworkX-like API
- **C/C++:** lower-level granular control for application developers

GROWING FUNCTIONALITY

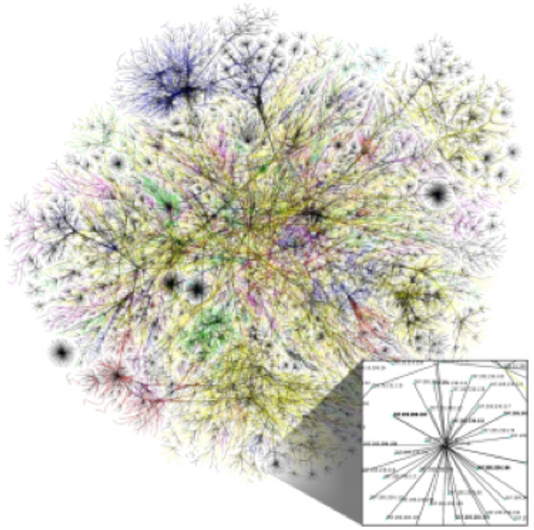
- Extensive collection of algorithm, primitive, and utility functions

Graph Technology Stack



+cuGraphBLAS is still in development and will be ready late 2020

** Gunrock is from UC Davis*

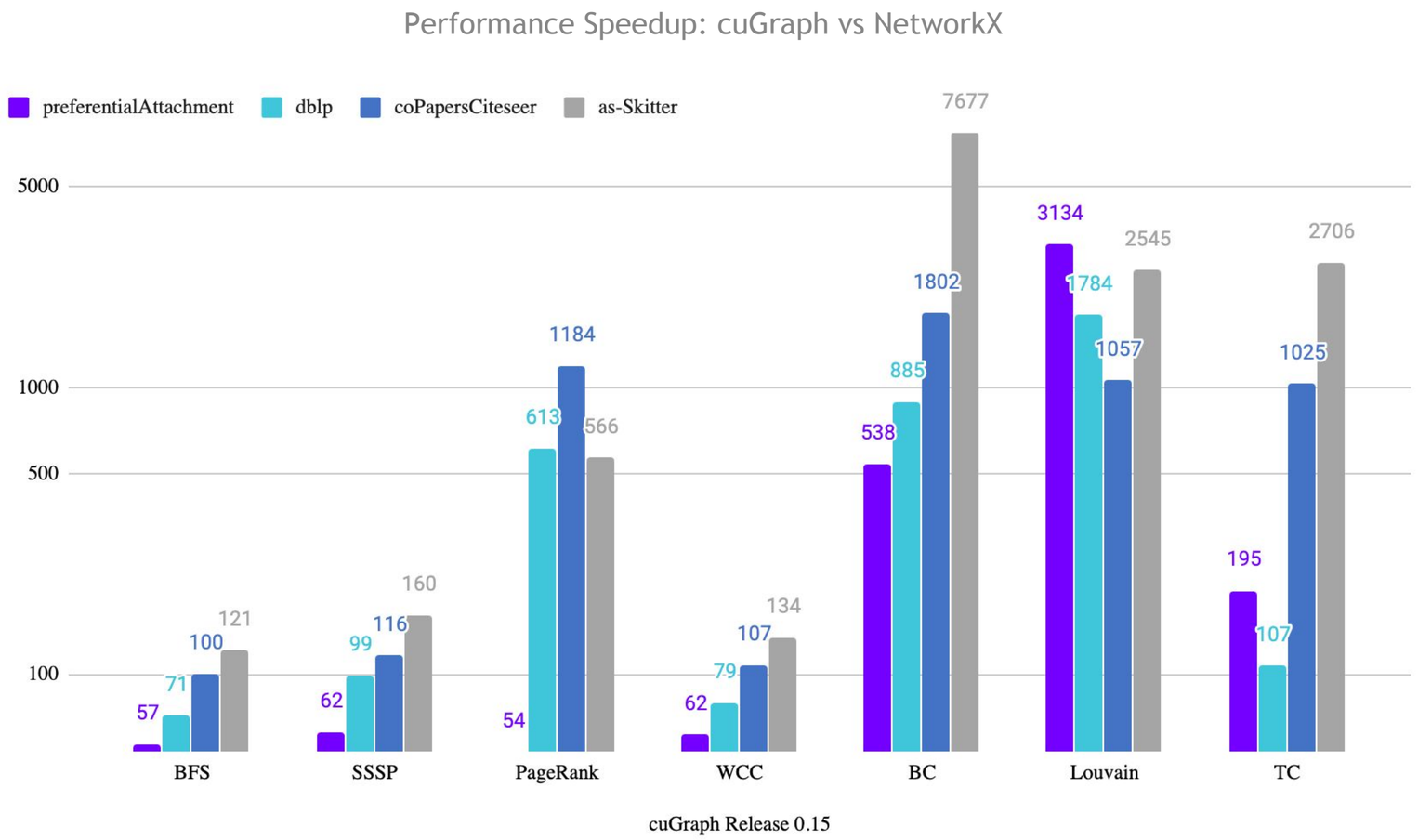


Algorithms

GPU-accelerated NetworkX

	Community	Spectral Clustering - Balanced Cu and Modularity Maxim Louvain and ***Leiden*** Ensemble Clustering for Graphs KCore and KCore Number Triangle Counting K-Truss
	Components	Weakly Connected Components Strongly Connected Components
	Link Analysis	Page Rank (Multi-GPU) Personal Page Rank ***HITS***
Graph Classes Subgraph Extraction	Structure	
	Link Prediction	Jaccard Weighted Jaccard Overlap Coefficient
Renumbering Auto-Renumbering Force Atlas 2	Utilities	
	Traversal	Single Source Shortest Path (SSSP) Breadth First Search (BFS)
	Centrality	Katz ***Betweenness Centrality (Vertex and Edge)***

Benchmarks: Single-GPU cuGraph vs NetworkX



Dataset	Nodes	Edges
preferentialAttachment	100,000	999,970
Dblp-2010	326,186	1,615,400
coPapersCiteseer	434,102	32,073,440
As-Skitter	1,696,415	22,190,596

Multi-GPU PageRank Performance

PageRank Portion of the HiBench Benchmark Suite

HiBench Scale	Vertices	Edges	CSV File (GB)	# of GPUs	# of CPU Threads	Pagerank for 3 Iterations (secs)
Huge	5,000,000	198,000,000	3	1		1.1
BigData	50,000,000	1,980,000,000	34	3		5.1
BigData x2	100,000,000	4,000,000,000	69	6		9.0
BigData x4	200,000,000	8,000,000,000	146	12		18.2
BigData x8	400,000,000	16,000,000,000	300	16		31.8
BigData x8	400,000,000	16,000,000,000	300		800*	5760*

**BigData x8, 100x 8-vCPU nodes, Apache Spark GraphX ⇒ 96 mins!*

Road to 1.0

December 2019 - RAPIDS 0.15

cuGRAPH	Single-GPU
Page Rank	
Personal Page Rank	
Katz	
Betweenness Centrality	
Spectral Clustering	
Louvain	
Ensemble Clustering for Graphs	
K-Truss & K-Core	
Connected Components (Weak & Strong)	
Triangle Counting	
Single Source Shortest Path (SSSP)	
Breadth-First Search (BFS)	
Jaccard & Overlap Coefficient	
Force Atlas 2	
Leiden	

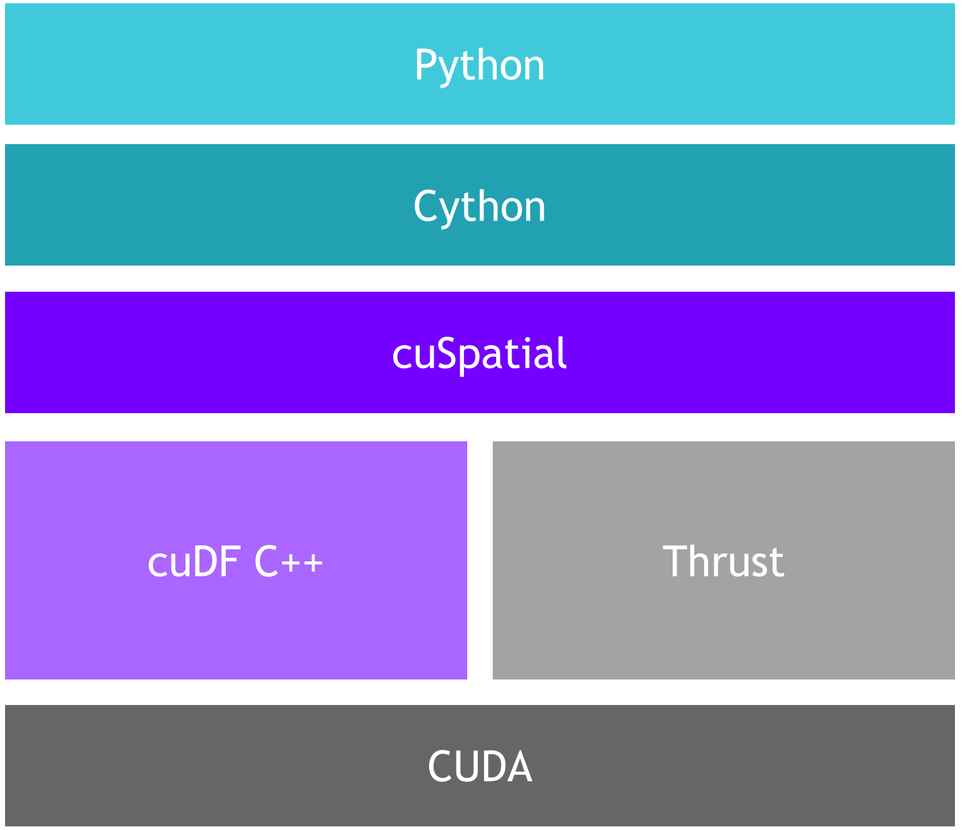
Road to 1.0

2020 EOY Plan

cuGRAPH	Single-GPU	Multi-Node-Multi-GPU
Page Rank		
Personal Page Rank		
Katz		
Betweenness Centrality		
Spectral Clustering		
Louvain		
Ensemble Clustering for Graphs		
K-Truss & K-Core		
Connected Components (Weak & Strong)		
Triangle Counting		
Single Source Shortest Path (SSSP)		
Breadth-First Search (BFS)		
Jaccard & Overlap Coefficient		
Force Atlas 2		
Hungarian Algorithm		
Leiden		

cuSpatial

cuSpatial Technology Stack



cuSpatial

BREAKTHROUGH PERFORMANCE & EASE OF USE

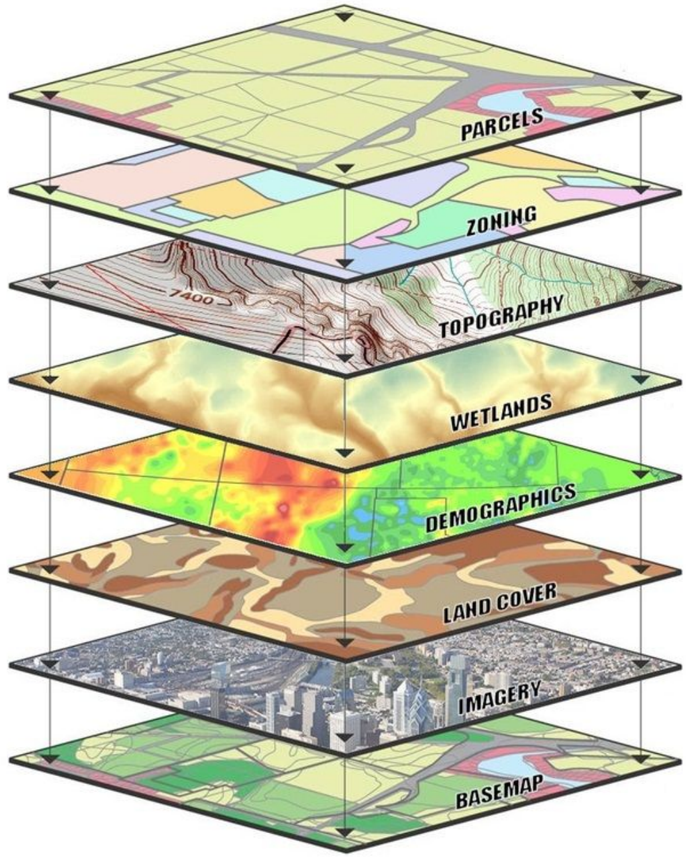
- Up to 1000x faster than CPU spatial libraries
- Python and C++ APIs for maximum usability and integration

GROWING FUNCTIONALITY

- Extensive collection of algorithm, primitive, and utility functions for spatial analytics

SEAMLESS INTEGRATION INTO RAPIDS

- cuDF for data loading, cuGraph for routing optimization, and cuML for clustering are just a few examples



cuSpatial
0.15 and Beyond

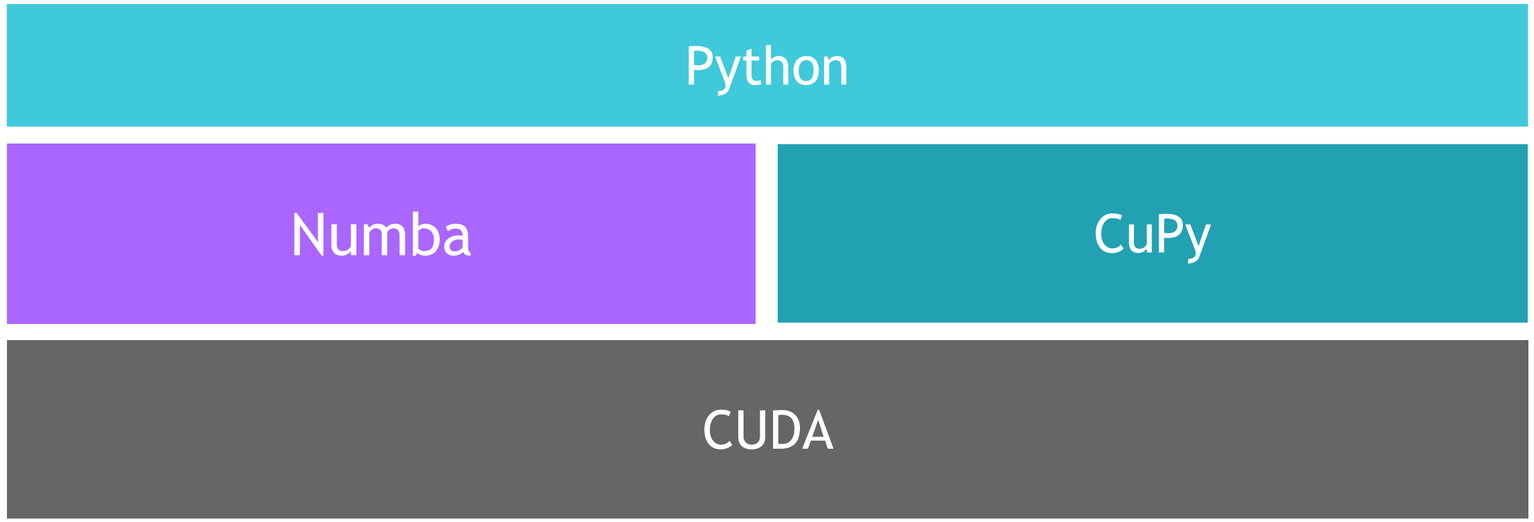
Layer	0.15 Functionality	Functionality Roadmap (0.16)
High-level Analytics	C++ Library w. Python bindings enabling distance, speed, trajectory similarity, trajectory clustering	Symmetric segment path distance
Graph Layer	cuGraph	cuGraph
Query Layer	Spatial Window, Nearest polyline	Nearest Neighbor, Spatiotemporal range search and joins
Index Layer	Quadtree	
Geo-operations	Point in polygon (PIP), Haversine distance, Hausdorff distance, lat-lon to xy transformation	ST_distance and ST_contains
Geo-Representation	Shape primitives, points, polylines, polygons	Fiona/Geopandas I/O support and object representations

cuSpatial
Performance at a Glance

cuSpatial Operation	Input Data	cuSpatial Runtime	Reference Runtime	Speedup
Point-in-Polygon Test	1.3+ million vehicle point locations and 27 Region of Interests	1.11 ms (C++) 1.50 ms (Python) [Nvidia Titan V]	334 ms (C++, optimized serial) 130468.2 ms (python Shapely API, serial) [Intel i7-7800X]	301X (C++) 86,978X (Python)
Haversine Distance Computation	13+ million Monthly NYC taxi trip pickup and drop-off locations	7.61 ms (Python) [Nvidia T4]	416.9 ms (Numba) [Nvidia T4]	54.7X (Python)
Hausdorff Distance Computation (for clustering)	52,800 trajectories with 1.3+ million points	13.5s [Quadro V100]	19227.5s (Python SciPy API, serial) [Intel i7-6700K]	1,400X (Python)

cuSignal

cuSignal Technology Stack



Unlike other RAPIDS libraries, cuSignal is purely developed in Python with custom CUDA Kernels written with Numba and CuPy (notice no Cython layer).

cuSignal – Selected Algorithms

GPU-accelerated SciPy Signal

Convolution	Convolve/Correlate FFT Convolve Convolve/Correlate 2D
Filtering and Filter Design	Resampling – Polyphase, Upfirdn, Resample Hilbert/Hilbert 2D Wiener Firwin
Waveform Generation	Chirp Square Gaussian Pulse
Wavelets	
Window Functions	Kaiser Blackman Hamming Hanning
Peak Finding	
Spectral Analysis	Periodogram Welch Spectrogram

More to come!

Speed of Light Performance – V100

timeit (7 runs) rather than *time*. Benchmarked with ~1e8 sample signals on a DGX Station

Method	Scipy Signal (ms)	cuSignal (ms)	Speedup (xN)
fftconvolve	27300	85.1	320.8
correlate	4020	47.4	84.8
resample	14700	45.9	320.2
resample_poly	2360	8.29	284.6
welch	4870	45.5	107.0
spectrogram	2520	23.3	108.1
convolve2d	8410	9.92	847.7

Learn more about cuSignal functionality and performance by browsing the notebooks

Efficient Memory Handling

Seamless Data Handoff from cuSignal to PyTorch >=1.4

Leveraging the *__cuda_array_interface__* for Speed of Light End-to-End Performance

```
from numba import cuda
import cupy as cp
import torch
from cusignal import resample_poly

# Create CuPy Array on GPU
gpu_arr = cp.random.randn(100_000_000, dtype=cp.float32)

# Polyphase Resample
resamp_arr = resample_poly(gpu_arr, up=2, down=3, window=('kaiser', 0.5))

# Zero Copy to PyTorch
torch_arr = torch.as_tensor(resamp_arr, device='cuda')

# Confirm Pointers
print('Resample Array: ', resamp_arr.__cuda_array_interface__['data'])
print('Torch Array: ', torch_arr.__cuda_array_interface__['data'])
```

```
Resample Array:  (140516096213080, False)
Torch Array:  (140516096213080, False)
```

Enabling Online Signal Processing with Zero-Copy Memory

CPU <-> GPU Direct Memory Access with Numba's Mapped Array

```
import numpy as np
import cupy as cp
from numba import cuda
import cusignal
```

```
# Create CPU/GPU Shared Memory, similar to numpy.zeros()
N = 2**18
shared_arr = cusignal.get_shared_mem(N, dtype=np.complex64)
print('CPU Pointer: ', shared_arr.__array_interface__['data'])
print('GPU Pointer: ', shared_arr.__cuda_array_interface__['data'])
```

```
CPU Pointer:  (139895179837440, False)
GPU Pointer:  (139895179837440, False)
```

```
# Load Shared Array with Numpy Array
shared_arr = np.random.randn(N) + 1j*np.random.randn(N)
```

```
%%timeit
# Perform CPU FFT
cpu_fft = np.fft.fft(shared_arr)
```

```
8 ms ± 60.2 µs per loop (mean ± std. dev. of 7 runs, 100 loops each)
```

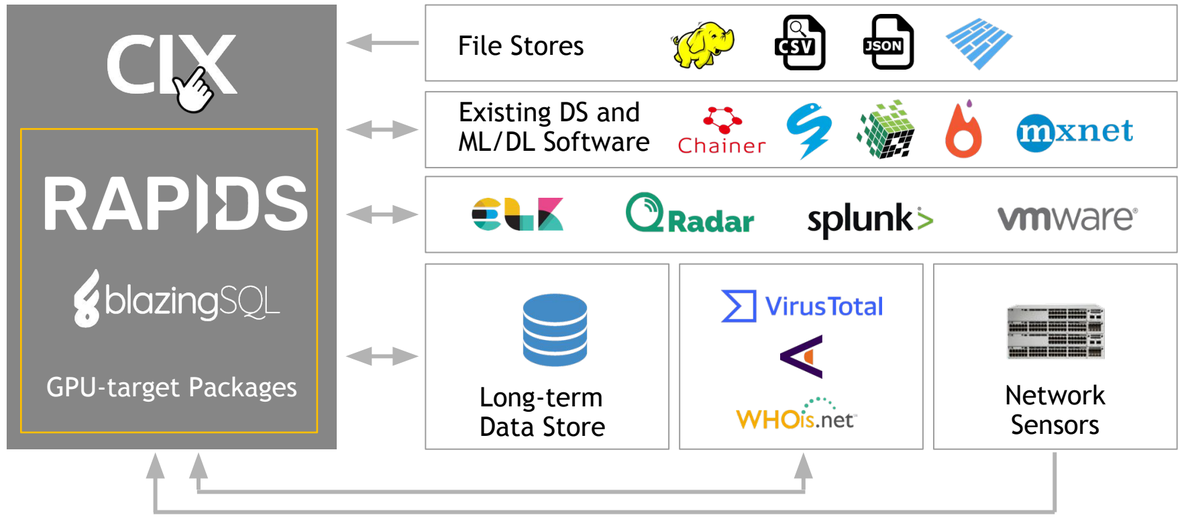
```
%%timeit
# Perform GPU FFT
gpu_fft = cp.fft.fft(cp.asarray(shared_arr))
cp.cuda.Device(0).synchronize()
```

```
866 µs ± 38 µs per loop (mean ± std. dev. of 7 runs, 1000 loops each)
```

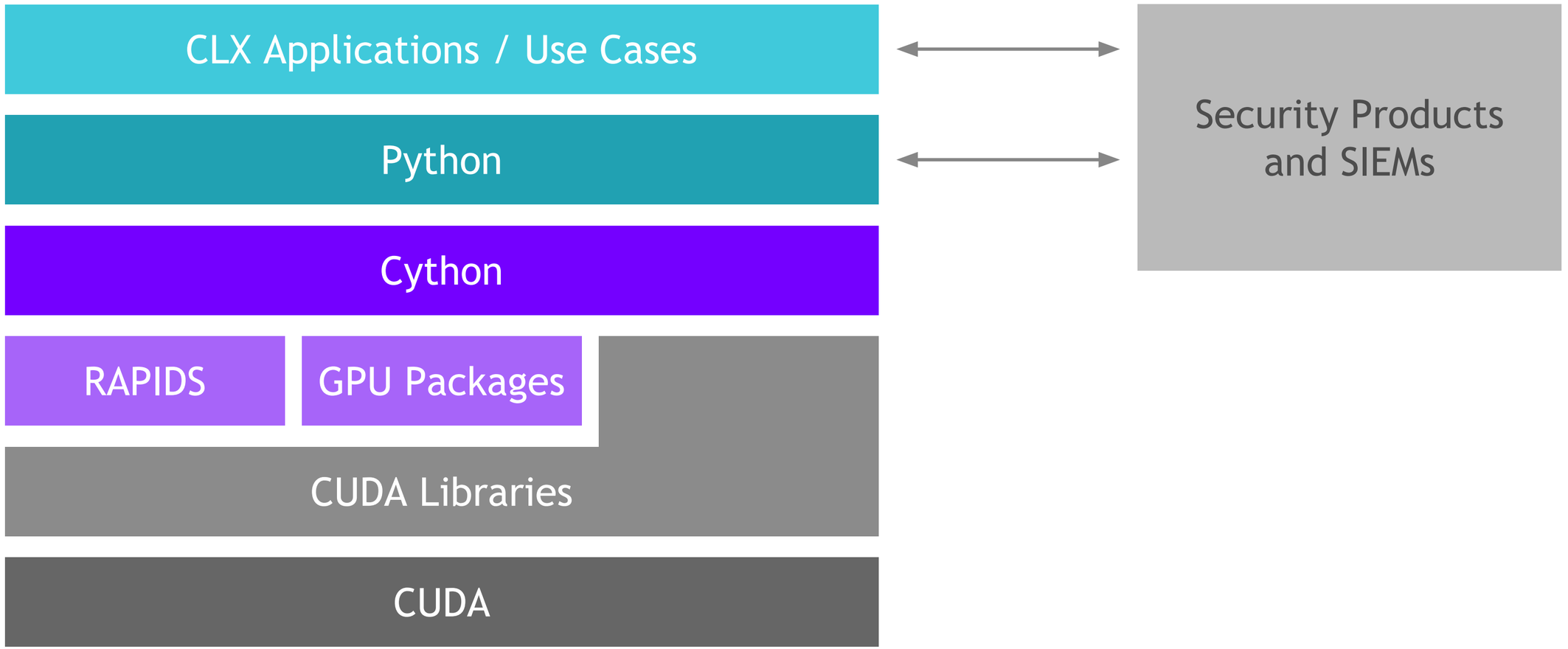
Cyber Log Accelerators

CLX
Cyber Log Accelerators

- Built using RAPIDS and GPU-accelerated platforms
- Targeted towards Senior SOC (Security Operations Center) Analysts, InfoSec Data Scientists, Threat Hunters, and Forensic Investigators
- **Notebooks** geared towards info sec and cybersecurity data scientists and data engineer
- **SIEM integrations** that enable easy data import/export and data access
- Workflow and I/O **components** that enable users to instantiate new use cases while
- Cyber-specific **primitives** that provide accelerated functions across cyber data types



CLX Technology Stack



CLX Contains Various Use Cases and Connectors

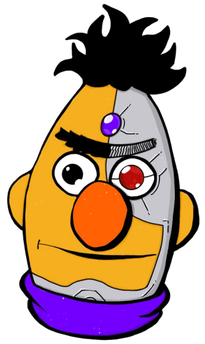
Example Notebooks Demonstrate RAPIDS for Cybersecurity Applications

CLX	Type	Proof-of-Concept	Stable
DGA Detection	Use Case		
Network Mapping	Use Case		
Asset Classification	Use Case		
Phishing Detection	Use Case		
Security Alert Analysis	Use Case		
Splunk Integration	Integration		
CLX Query	Integration		
cyBERT	Log Parsing		
GPU Wordpiece Tokenizer	Pre-Processing		
Accelerated IPv4	Primitive		
Accelerated DNS	Primitive		

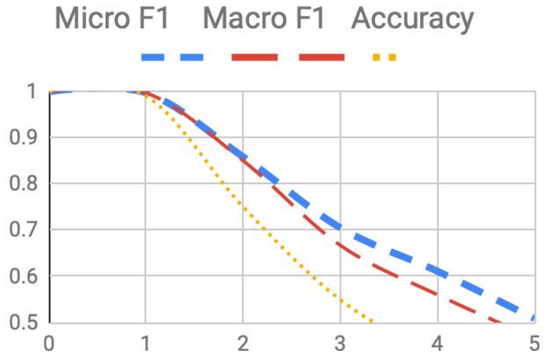
cyBERT

AI Log Parsing for Known, Unknown, and Degraded Cyber Logs

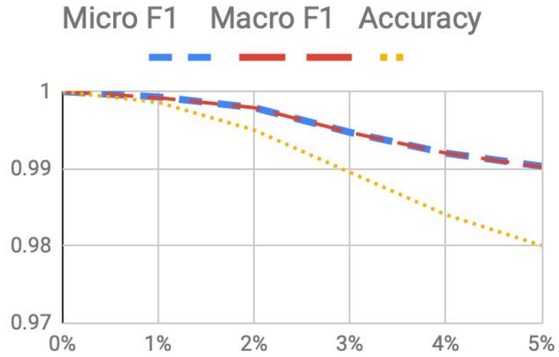
- Provide a flexible method that does not use heuristics/regex to parse cybersecurity logs
- Built using RAPIDS and PyTorch, tested with a variety of language models (including BERT)
- Parsing with **micro-F1 and macro-F1 > 0.999** across heterogeneous log types with a **validation loss of < 0.0048**
- Second version **~160x (min) faster** than first version due to creation of the first all-GPU wordpiece tokenizer that supports non-truncation of logs/sentences



Log Parsing with Inserted Values



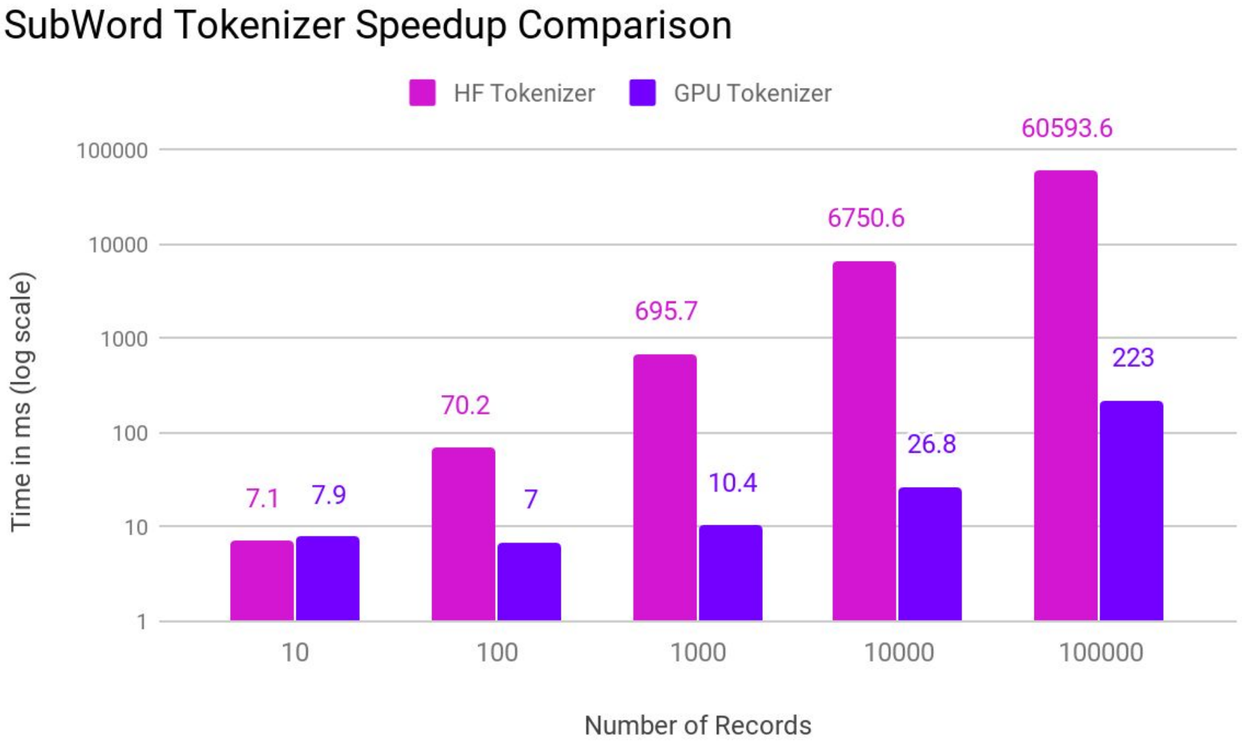
Log Parsing with Missing Values



GPU SubWord Tokenizer

Fully On-GPU Pre-Processing for BERT Training/Inference

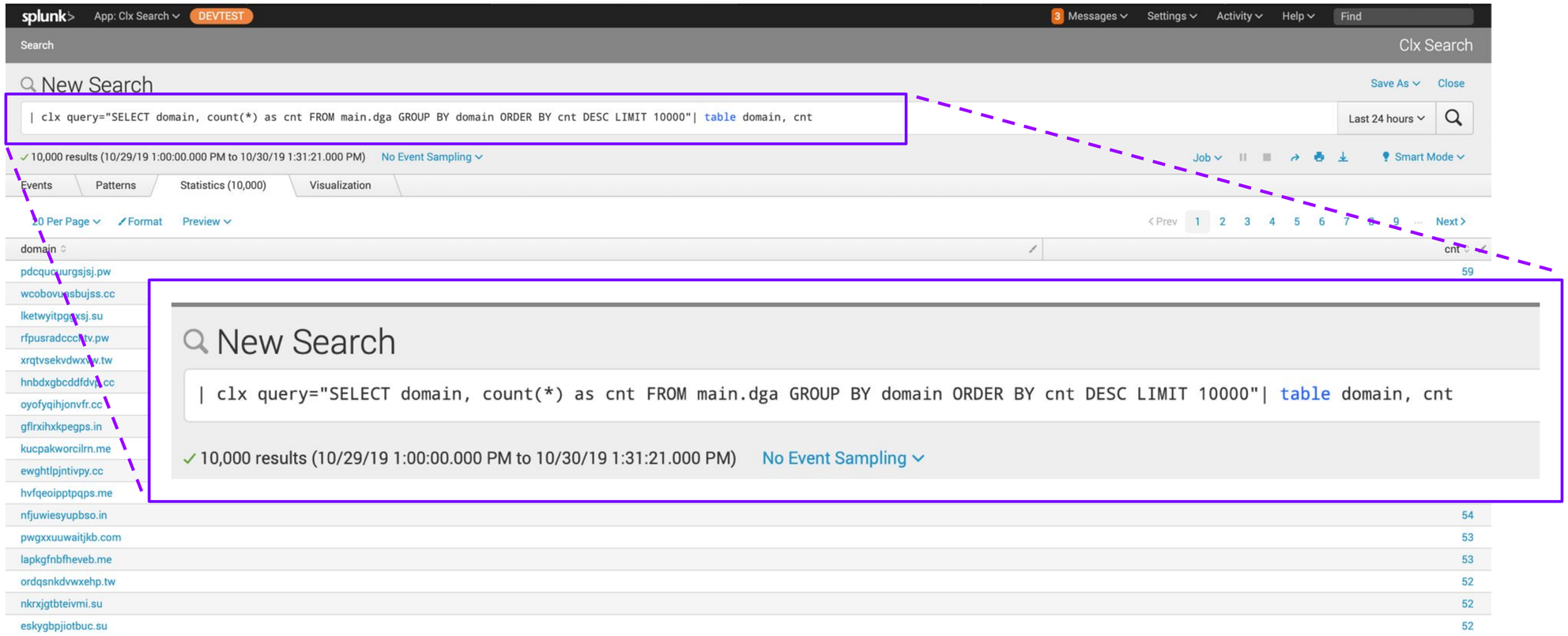
- Only wordpiece tokenizer that supports non-truncation of logs/sentences
- Returns encoded tensor, attention mask, and metadata to reform broken logs
- Supports stride/overlap
- Ready for immediate pipelining into PyTorch for inference
- Up to 270x faster than production-ready Hugging Face wordpiece tokenizer (Python version)



CPU numbers ran on 2x Intel Xeon E5 v4 @ 2.2 GHz. GPU numbers ran on 1x NVIDIA Tesla V100

CLX Query

Query Long-Term Data Store Directly from Splunk



RAPIDS

blazingSQL

CLX

Visualization

cuXfilter

GPU Accelerated Cross-Filtering

STREAMLINED FOR NOTEBOOKS

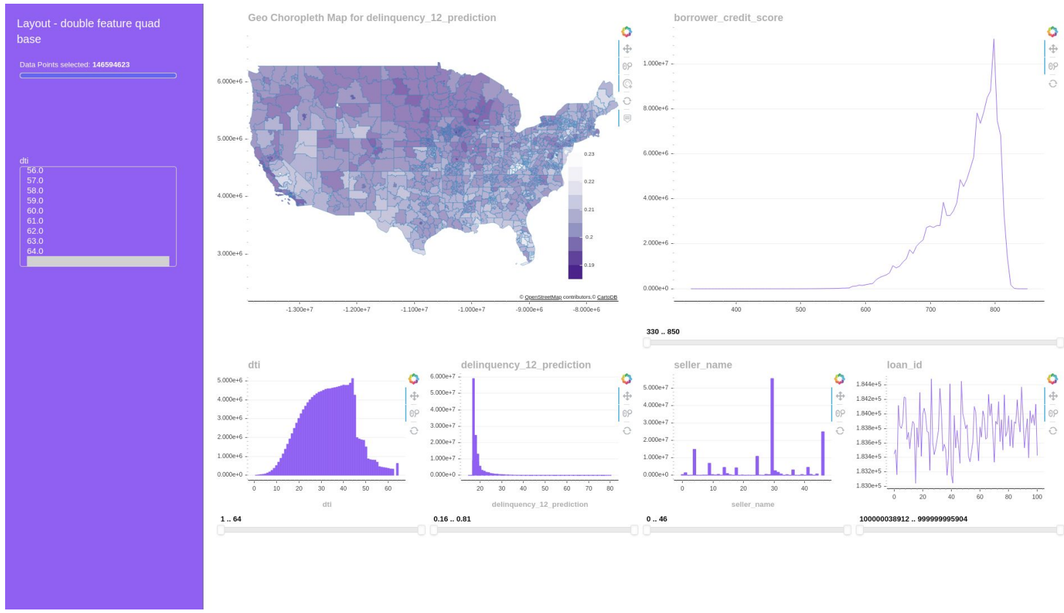
Cuxfilter allows you to visually explore your cuDF dataframes through fully cross-filtered dashboards in less than 10 lines of notebook code.

MINIMAL COMPLEXITY & FAST RESULTS

Select from vetted chart libraries, pre-designed layouts, and multiple themes to find the best fit for a use case, at speeds typically 20x faster per chart than Pandas.

SEAMLESS INTEGRATION WITH RAPIDS

Cuxfilter is designed to be easy to install and use with RAPIDS. Learn more about our approach here.



https://docs.rapids.ai/api/cuxfilter/stable

pyViz Integrations

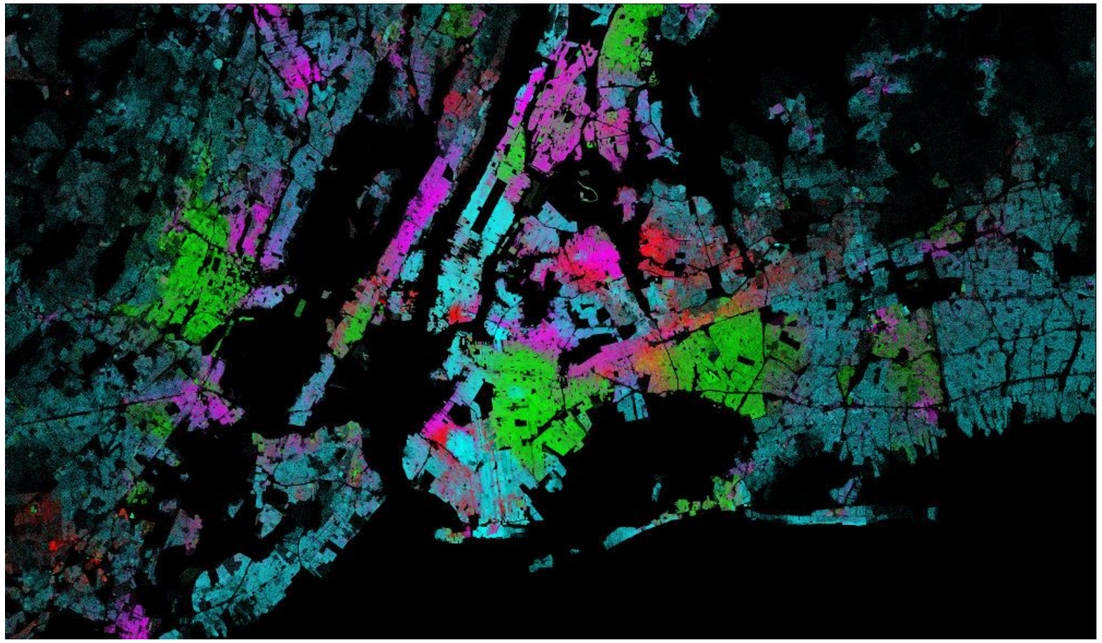
GPU Accelerated Python Visualizations

ACCELERATED PYTHON VIZ

The RAPIDS focus on python makes it straightforward to integrate GPU acceleration for most python visualization libraries. We are currently collaborating with bokeh, plotly, and datashader, among others.

HIGHLIGHT: DATASHADER INTEGRATION

Datashader's ability to visualize billions of points makes it well suited for GPU acceleration. It now includes cuDF integration as well as other enhanced capabilities that offer between a 10-120x speed up. More details here.



https://datashader.org/

Plotly Dash

GPU Accelerated Visualization Apps with Python

PLOTLY & RAPIDS PARTNERSHIP

Plotly Dash now has RAPIDS acceleration, enabling the ease-of-use development and deployment of Dash apps, with the speed of RAPIDS. Find out more on RAPIDS.ai and Plotly's announcement.

300 MILLION DATAPOINT CENSUS EXAMPLE

Interact with data points of every individual in the United States, in real time, with the 2010 Census visualization. Get the code on GitHub and read about details here.

https://github.com/rapidsai/plotly-dash-rapids-census-demo

Community

Ecosystem Partners

CONTRIBUTORS

ADOPTERS

Booz | Allen | Hamilton

OPEN SOURCE

Building on Top of RAPIDS

A Bigger, Better, Stronger Ecosystem for All

NVTabular

ETL library for recommender systems
building off of RAPIDS and Dask

GPU accelerated SQL engine
built on top of RAPIDS

Streamz

Distributed stream processing
using RAPIDS and Dask

NVTabular

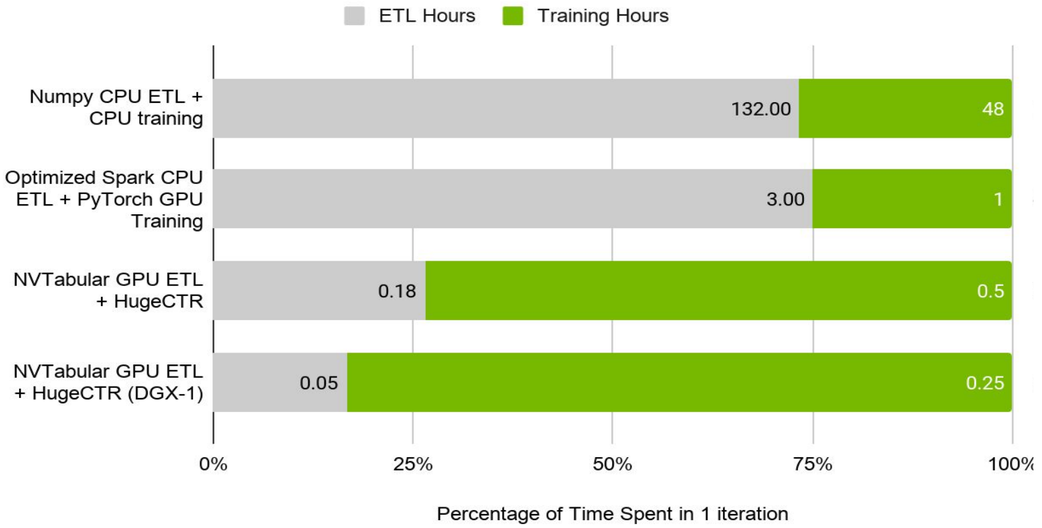
ETL library for recommender systems building off of RAPIDS and Dask

A HIGH LEVEL API BUILDING UPON DASK-CUDF

NVTabular's high level API allows users to think about what they want to do with the data, not how they have to do it or how to scale it, for operations common within recommendation workflows.

ACCELERATED GPU DATALOADERS

Using cuIO primatives and cuDF, NVTabular accelerates dataloading for PyTorch & Tensorflow, removing I/O issues common in deep learning based recommender system models.



BlazingSQL

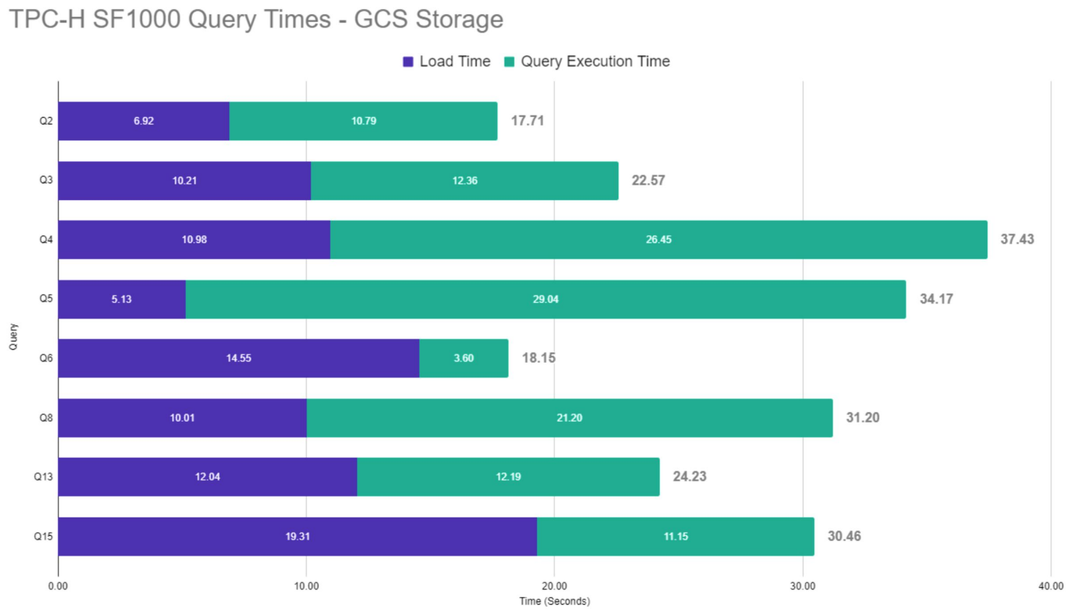
GPU-accelerated SQL engine built with RAPIDS

BLAZING FAST SQL ON RAPIDS

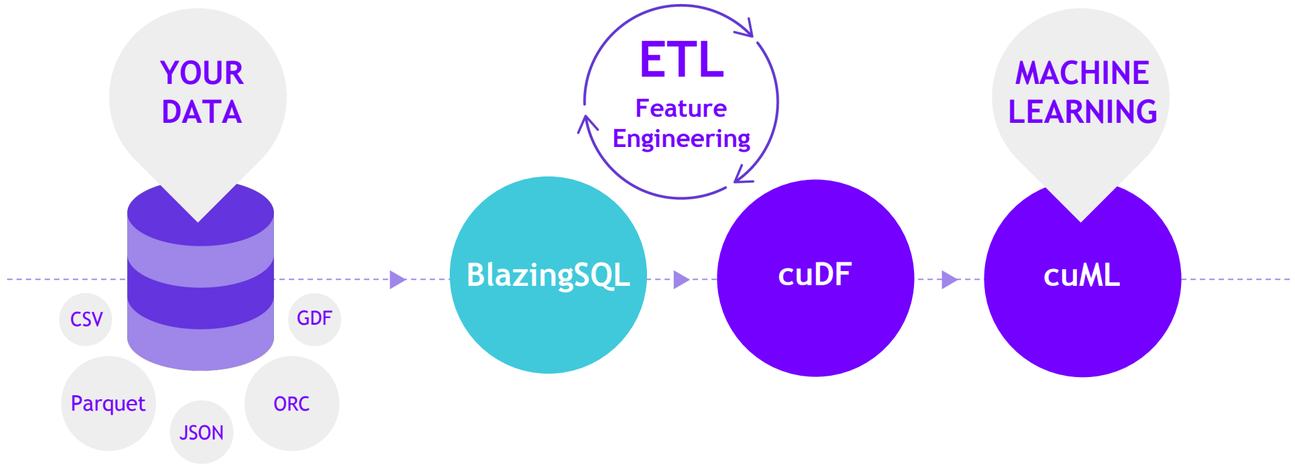
- Incredibly fast distributed SQL engine on GPUs--natively compatible with RAPIDS!
- Allows data scientists to easily connect large-scale data lakes to GPU-accelerated analytics
- Directly query raw file formats such as CSV and Apache Parquet inside Data Lakes like HDFS and AWS S3, and directly pipe the results into GPU memory.

NOW WITH OUT-OF-CORE EXECUTION

- Users no longer limited by available GPU memory
- 10TB workloads on a single Tesla V100 (32GB)!



BlazingSQL




```
from blazingsql import BlazingContext
import cudf

bc = BlazingContext()

bc.s('bsql', bucket_name='bsql', access_key_id='<access_key>', secret_key='<secret_key')

bc.create_table('orders', s3://bsql/orders/')

gdf = bc.sql('select * from orders').get()
```

cuStreamz

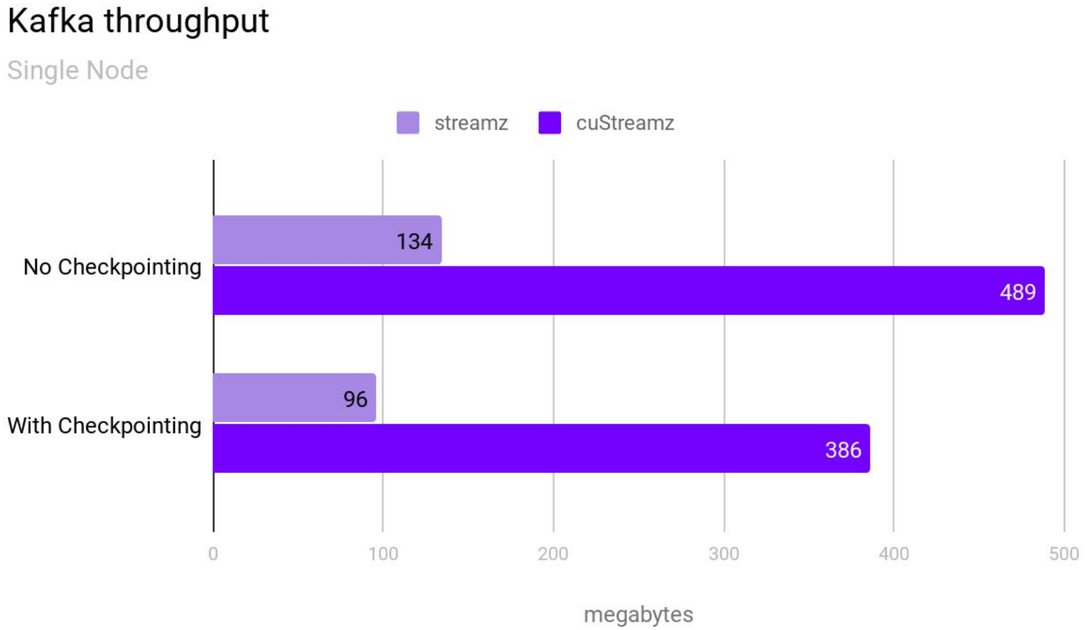
Stream processing powered by RAPIDS

ACCELERATED KAFKA CONSUMER

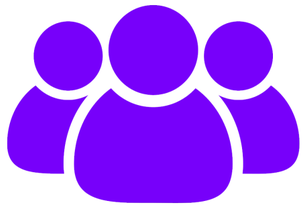
Ingesting Kafka messages to cudf is increased by roughly 3.5 - 4X over standard cpu ingestion. Streaming TCO is lowered by using cheaper VM instance types.

CHECKPOINTING

Streaming job version of “where was I?” Streams can gracefully handle errors by continuing to process a stream at the exact point they were before the error occurred.

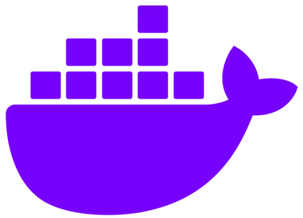


Join the Conversation



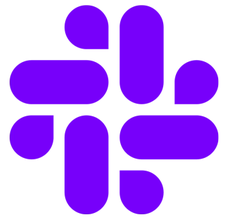
GOOGLE GROUPS

https://groups.google.com/forum/#!forum/rapidsai



DOCKER HUB

https://hub.docker.com/r/rapidsai/rapidsai



SLACK CHANNEL

https://rapids-goai.slack.com/join

STACK OVERFLOW

https://stackoverflow.com/tags/rapids

Contribute Back

Issues, Feature Requests, PRs, Blogs, Tutorials, Videos, QA...Bring Your Best!

cuml

cuML - RAPIDS Machine Learning Library

machine-learning | gpu | machine-learning-algorithms | cuda | nvidia

C++ | Apache-2.0 | 111 | 608 | 186 (26 issues need help) | 31 | Updated 9 minutes ago

cudf

cuDF - GPU DataFrame Library

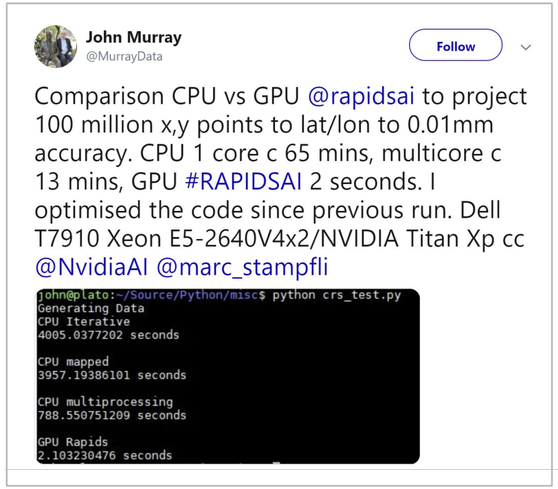
anaconda | gpu | arrow | machine-learning-algorithms | h2o | cuda | pandas

Cuda | Apache-2.0 | 250 | 1,699 | 325 (6 issues need help) | 41 | Updated 31 minutes ago

notebooks-contrib

RAPIDS Community Notebooks

Jupyter Notebook | Apache-2.0 | 56 | 70 | 10 (1 issue needs help) | 8 | Updated 40 minutes ago



RAPIDS Notices

Communicate and document changes to RAPIDS for contributors, core developers, users, and the community

Notice	Title	Topic	RAPIDS Version	Updated
RDN 1 COMPLETED	'dask-xgboost' is deprecated in v0.15 & removed v0.16	Library Deprecation	v0.15	26 August 2020
RGN 1 IN PROGRESS	Stable/Release Branch Renaming to 'main' in v0.15	Git Repo Change	v0.15	26 August 2020
RGN 2 COMPLETED	v0.15 No CUDA 11 Release for 'clx'	Release Change	v0.15	26 August 2020
RGN 4 IN PROGRESS	v0.15 Release Delay for 'cuxfilter'	Release Change	v0.15	26 August 2020
RSN 2 COMPLETED	EOL Python 3.6 & CUDA 10.0 in v0.14	Platform Support Change	v0.14 & v0.15	13 July 2020
RSN 3 COMPLETED	Support for Python 3.8 in v0.15	Platform Support Change	v0.15	17 July 2020
RSN 4 COMPLETED	Support for CUDA 11.0 in v0.15	Platform Support Change	v0.15	26 August 2020

https://docs.rapids.ai/notices

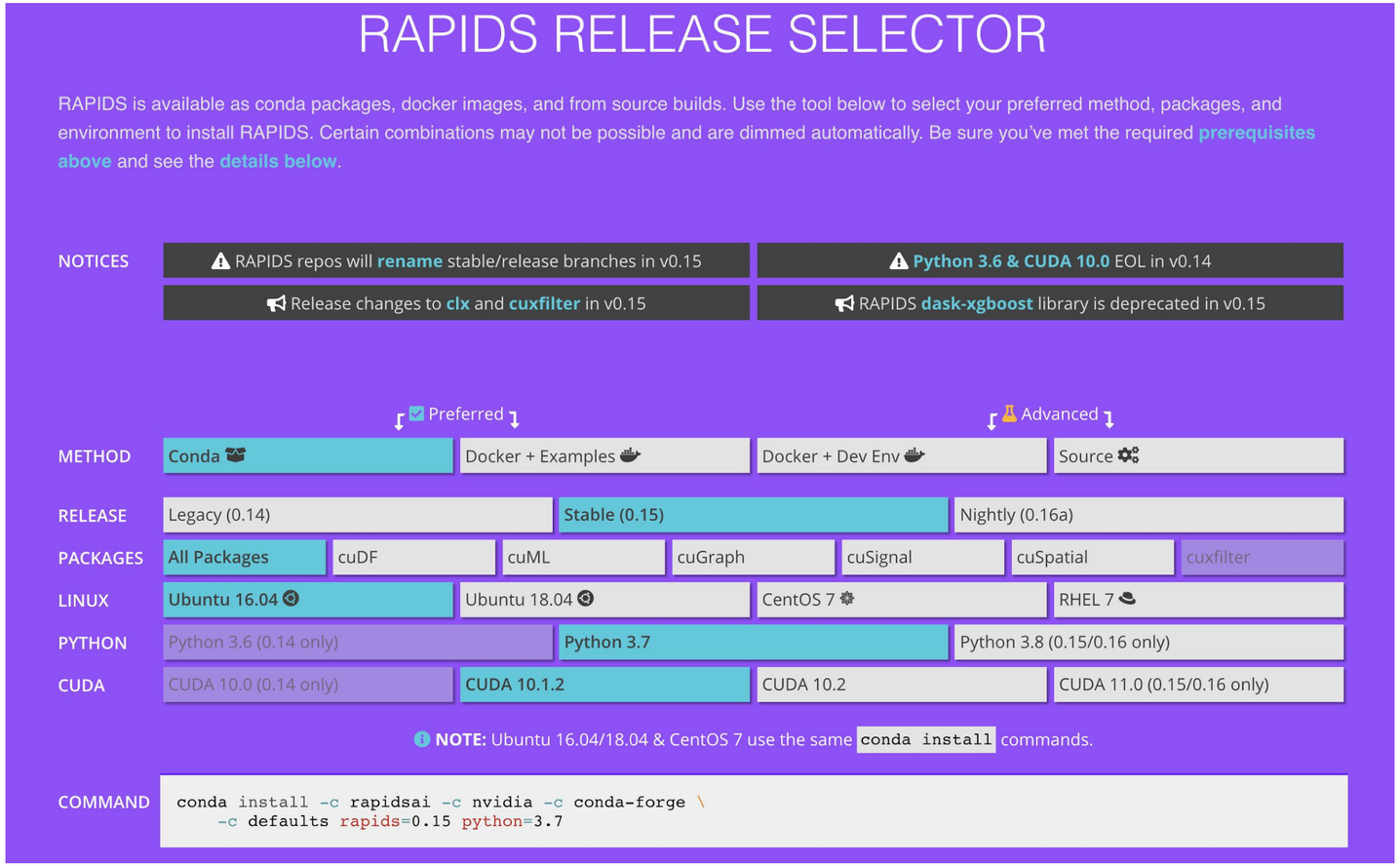
Getting Started

5 Steps to Getting Started with RAPIDS

1. Install RAPIDS on using Docker, Conda, or Colab.
2. Explore our walk through videos, blog content, our github, the tutorial notebooks, and our example workflows.
3. Build your own data science workflows.
4. Join our community conversations on Slack, Google, and Twitter.
5. Contribute back. Don't forget to ask and answer questions on Stack Overflow.

Easy Installation

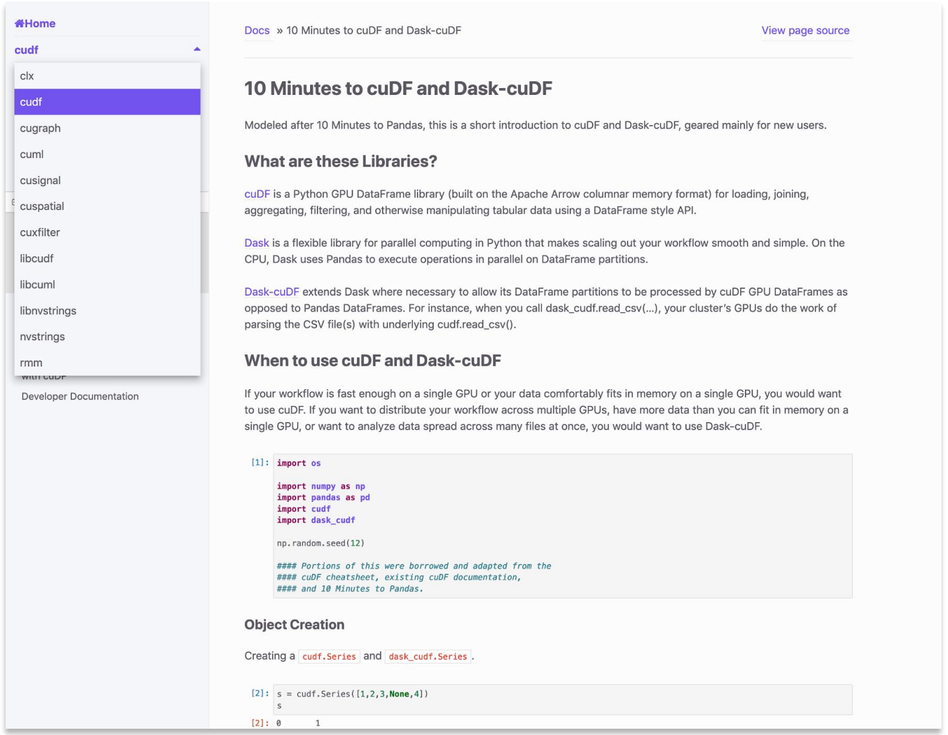
Interactive Installation Guide

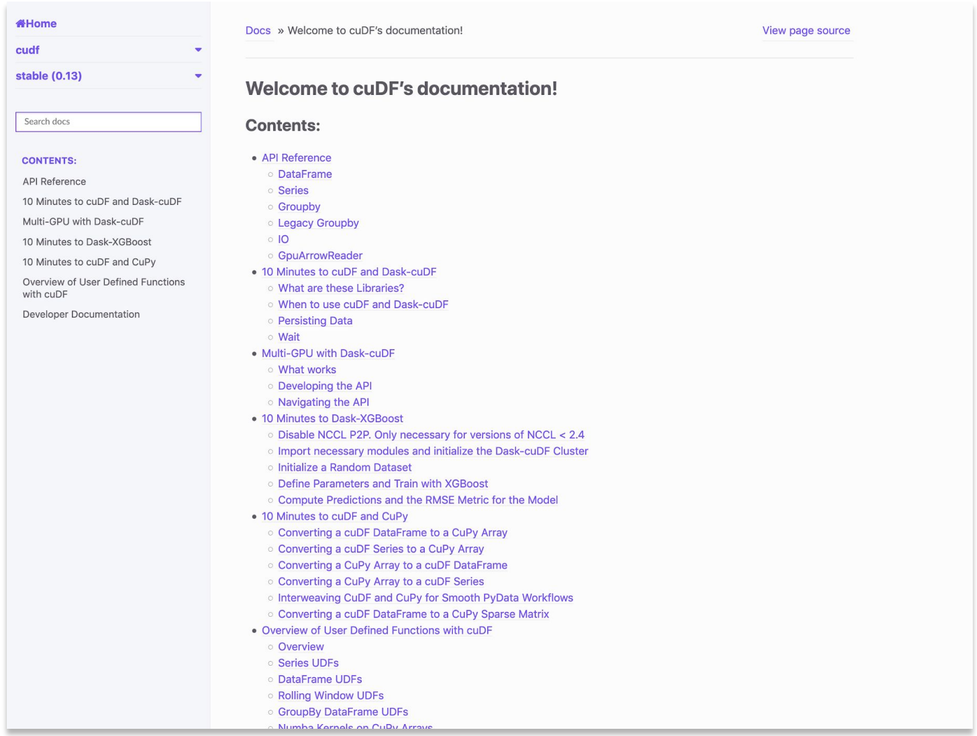


https://rapids.ai/start.html

RAPIDS Docs

Up to Date and Easy to Use

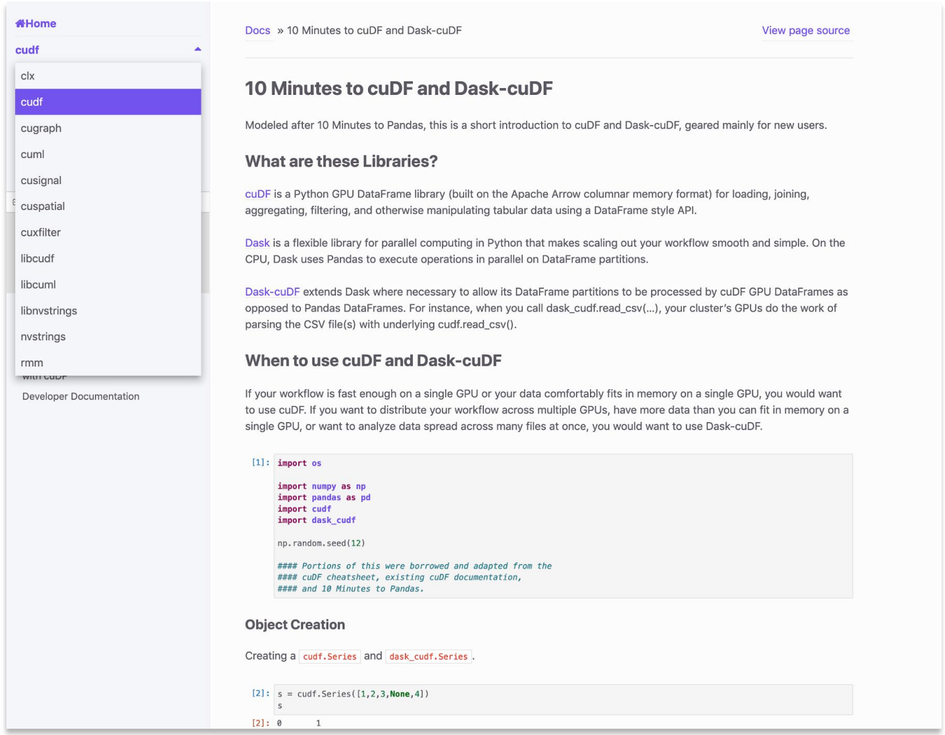




https://docs.rapids.ai

RAPIDS Docs

Easier than Ever to Get Started with cuDF



https://docs.rapids.ai

Explore: RAPIDS Code and Blogs

Check out our Code and How We Use It

README.md

RAPIDS cuDF - GPU DataFrames

build running

NOTE: For the latest stable README.md ensure you are on the `master` branch.

Built based on the Apache Arrow columnar memory format, cuDF is a GPU DataFrame library for loading, joining, aggregating, filtering, and otherwise manipulating data.

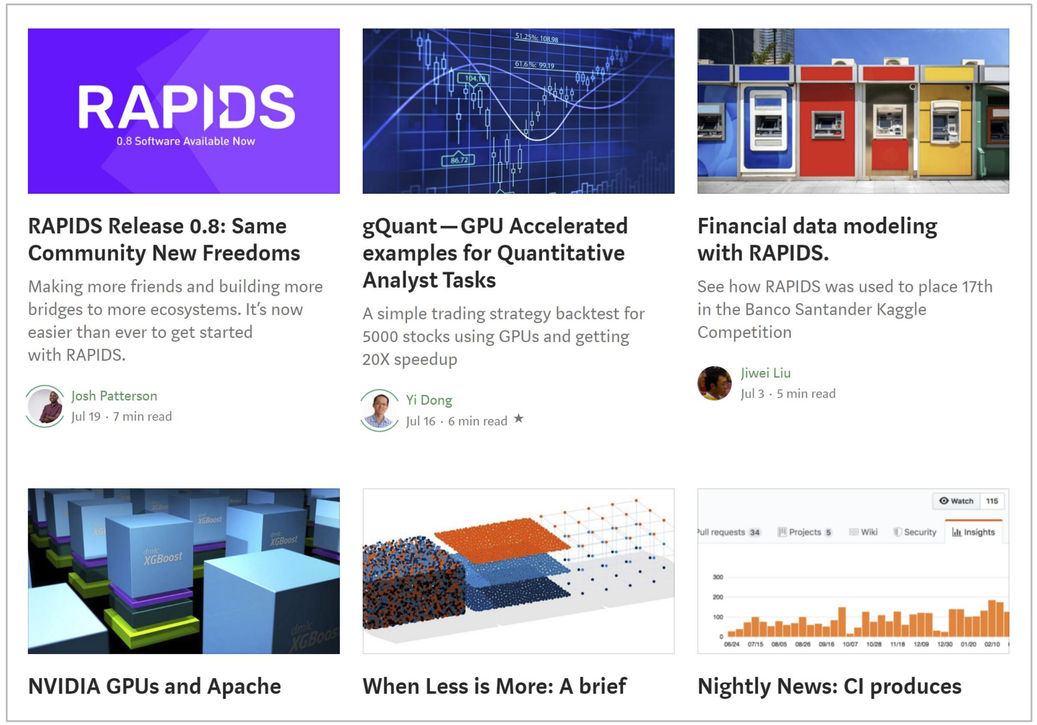
cuDF provides a pandas-like API that will be familiar to data engineers & data scientists, so they can use it to easily accelerate their workflows without going into the details of CUDA programming.

For example, the following snippet downloads a CSV, then uses the GPU to parse it into rows and columns and run calculations:

```
import cudf, io, requests
from io import StringIO

url="https://github.com/plotly/datasets/raw/master/tips.csv"
content = requests.get(url).content.decode('utf-8')

tips_df = cudf.read_csv(StringIO(content))
tips_df['tip_percentage'] = tips_df['tip']/tips_df['total_bill']*100

# display average tip by dining party size
print(tips_df.groupby('size').tip_percentage.mean())
```

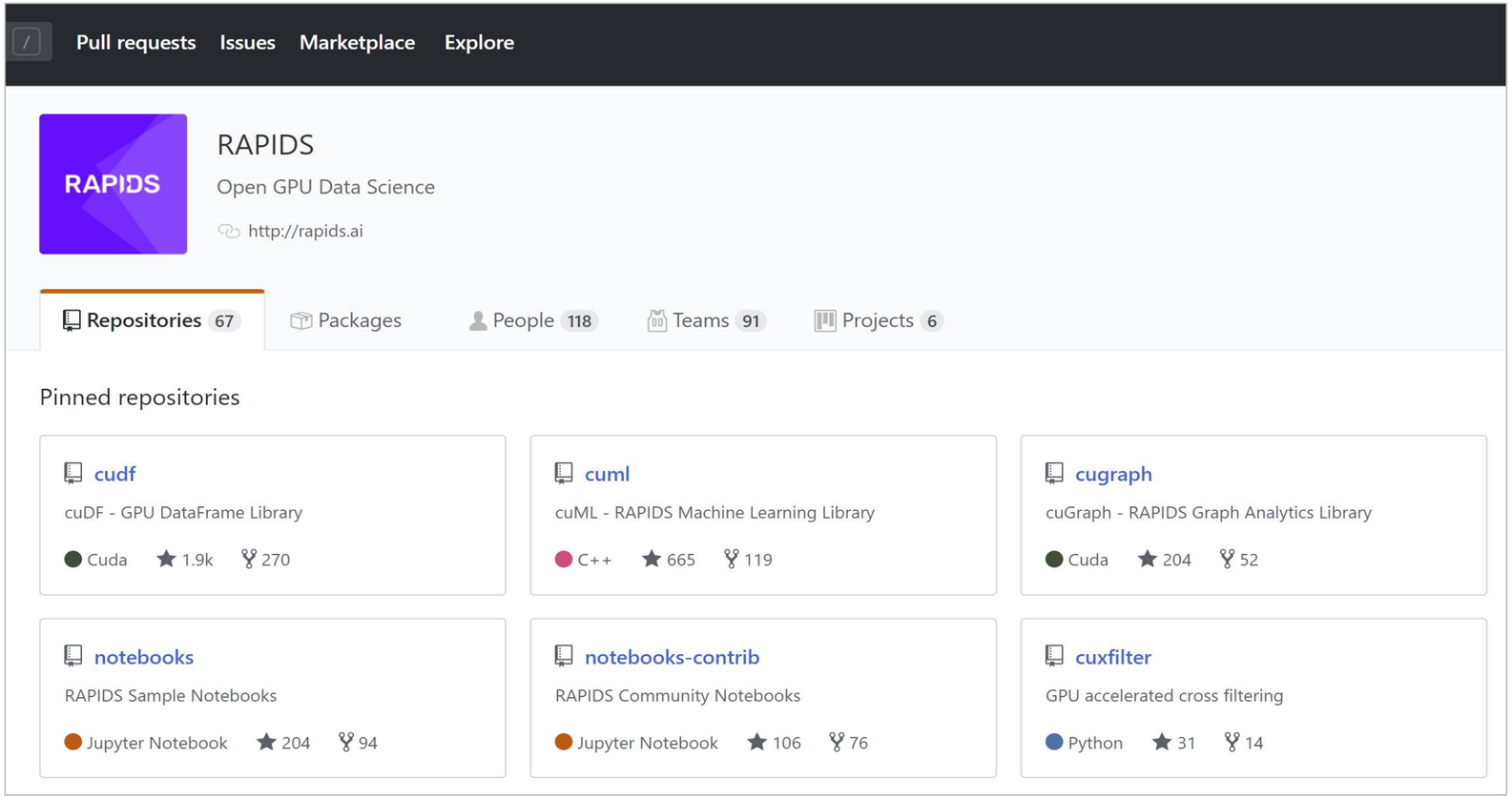
Output:

https://github.com/rapidsai



https://medium.com/rapids-ai

Explore: RAPIDS Github



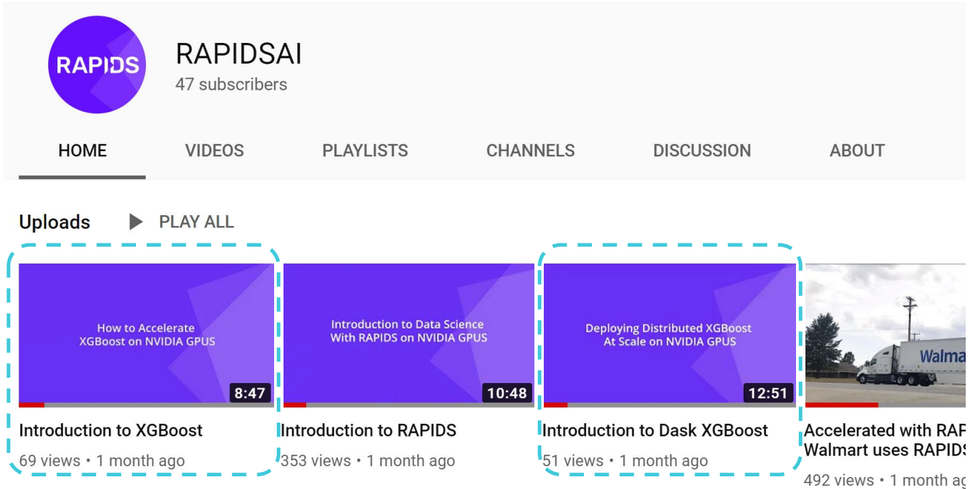
https://github.com/rapidsai

Explore: Notebooks Contrib

intro_tutorials	05_Introduction_to_Dask_cuDF	This notebook shows how to work with cuDF DataFrames distributed across multiple GPUs using Dask.
intro_tutorials	06_Introduction_to_Supervised_Learning	This notebook shows how to do GPU accelerated Supervised Learning in RAPIDS.
intro_tutorials	07_Introduction_to_XGBoost	This notebook shows how to work with GPU accelerated XGBoost in RAPIDS.
intro_tutorials	08_Introduction_to_Dask_XGBoost	This notebook shows how to work with Dask XGBoost in RAPIDS.
intro_tutorials	09_Introduction_to_Dimensionality_Reduction	This notebook shows how to do GPU accelerated Dimensionality Reduction in RAPIDS.
intro_tutorials	10_Introduction_to_Clustering	This notebook shows how to do GPU accelerated Clustering in RAPIDS.

Intermediate Notebooks:

Folder	Notebook Title	Description
examples	DBSCAN_Demo_FULL	This notebook shows how to use DBSCAN algorithm and its GPU accelerated implementation present in RAPIDS.
examples	Dask_with_cuDF_and_XGBoost	In this notebook we show how to quickly setup Dask and train an XGBoost model using cuDF.



Notebooks Contrib Repo has tutorials and examples, and various E2E demos.
RAPIDS Youtube channel has explanations, code walkthroughs and use cases.

RAPIDS

How Do I Get the Software?

GITHUB

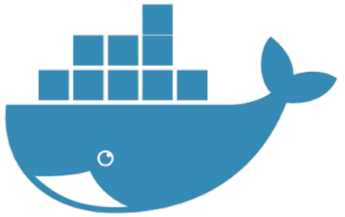
https://github.com/rapidsai

ANACONDA

https://anaconda.org/rapidsai/

NGC

https://ngc.nvidia.com/registry/nvidia-rapidsai-rapidsai



DOCKER

https://hub.docker.com/r/rapidsai/rapidsai/

Deploy RAPIDS Everywhere

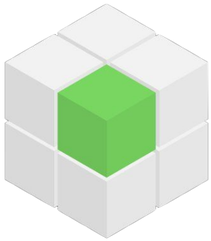
Focused on Robust Functionality, Deployment, and User Experience

Amazon SageMaker

Integration with major cloud providers | Both containers and cloud specific machine instances
Support for Enterprise and HPC Orchestration Layers

Join the Movement

Everyone Can Help!



APACHE ARROW

https://arrow.apache.org/

@ApacheArrow

RAPIDS

https://rapids.ai

@RAPIDSAI

DASK

https://dask.org

@Dask_dev

GPU OPEN ANALYTICS INITIATIVE

http://gpuopenanalytics.com/

@GPUOAI

Integrations, feedback, documentation support, pull requests, new issues, or code donations welcomed!

THANK YOU

Joshua Patterson
joshuap@nvidia.com
@datametrician

RAPIDS