



Sören Metje

## GPU Computing with Python

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- 2 GPU Computing
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# Motivation

## Why Python?

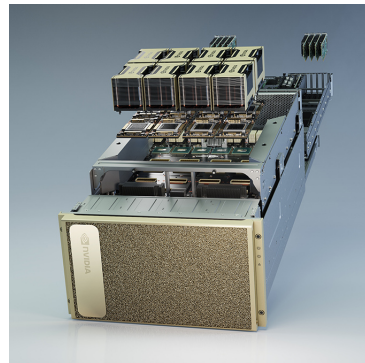
- High-level programming
- Compatible with many platforms and systems
- Many high quality frameworks and libraries
- Widely distributed in many different domains
- Big community



# Motivation

## Why GPU Computing?

- Reduce wall-clock time
- Achieve higher cost-efficiency

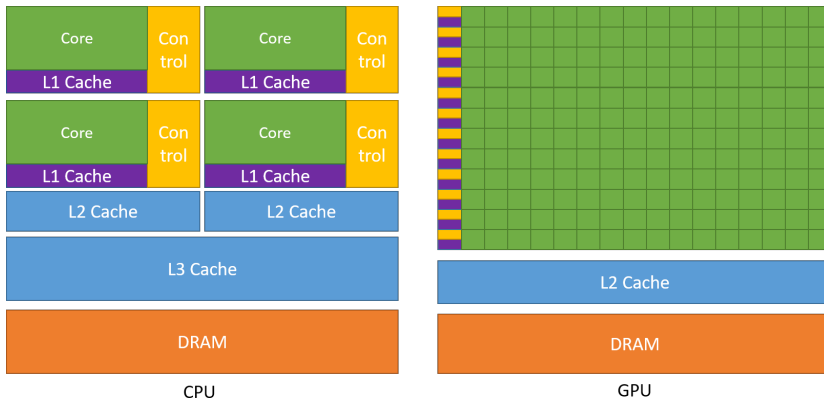


Source: NVIDIA - GPU-Accelerated Google Cloud [NVId]

# Outline

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# GPU Architecture



Source: CUDA Toolkit Documentation [NVIa]

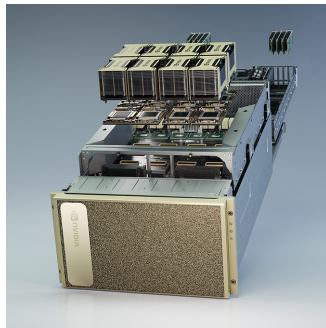
# Use Cases

## When to use GPU Computing?

- Large data set available
- Parallel processing possible
- Use cases: Fluid dynamics, Image processing, Deep learning, ...

## When **not** to use GPU Computing?

- Data set is too small
- Data set is too big (exceeds GPU memory size)
- Large amount of small sequential operations



Source: NVIDIA - GPU-Accelerated Google Cloud [NVId]

# CUDA

## Definition

NVIDIA CUDA (Compute Unified Device Architecture) is a **parallel computing platform** and programming model for general computing on **GPUs**.



- Initial release: June 23, 2007
- Gives access to the GPU's virtual instruction set
- Enables execution of compute kernels
- Accessible through frameworks, libraries, and compiler directives
- Closed source



# CUDA Compute Kernel

## Definition

A compute kernel is a **function** compiled for accelerators (such as GPUs).

C++

```
1  __global__ void VecAdd(float* A, float* B, float* C) {  
2      int i = threadIdx.x;  
3      C[i] = A[i] + B[i];  
4  }  
5  
6  int main() {  
7      // ...  
8      VecAdd<<<1, N>>>(A, B, C); // blocks per grid, threads per block  
9  }
```

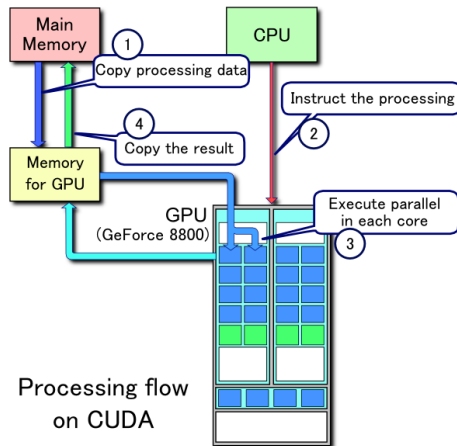
# Compute Kernel Limitations

- Allowed operations: basic math operations, if / else, for / while loops
- Can not explicitly return a value
- Write results to passed array

C++

```
1  __global__ void VecAdd(float* A, float* B, float* C) {  
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6  int main() {  
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8      VecAdd<<<1, N>>>(A, B, C); // blocks per grid, threads per block  
9  }
```

# CUDA Processing Flow



Source: Wikipedia - CUDA [Wika]

# AMD ROCm

## Definition

AMD ROCm (Radeon Open Compute) is a software stack for **GPU programming**.

- "NVIDIA CUDA for AMD GPUs"
- Initial release: November 14, 2016
- Available on [GitHub](#) (open-source)
- Supported by:
  - ▶ PyTorch
  - ▶ TensorFlow
  - ▶ CuPy
- Not as widely supported as NVIDIA CUDA
- Gaining traction in the TOP500



# TOP 500 List

Rank	System	Cores	Rmax (PFlop/s)	Rpeak (PFlop/s)	Power (kW)
1	<b>Frontier</b> - HPE Cray EX235a, AMD Optimized 3rd Generation EPYC 64C 2GHz, AMD Instinct MI250X, Slingshot-11, HPE DOE/SC/Oak Ridge National Laboratory United States	8,730,112	1,102.00	1,685.65	21,100
2	<b>Supercomputer Fugaku</b> - Supercomputer Fugaku, A64FX 48C 2.2GHz, Tofu interconnect D, Fujitsu RIKEN Center for Computational Science Japan	7,630,848	442.01	537.21	29,899
3	<b>LUMI</b> - HPE Cray EX235a, AMD Optimized 3rd Generation EPYC 64C 2GHz, AMD Instinct MI250X, Slingshot-11, HPE EuroHPC/CSC Finland	1,110,144	151.90	214.35	2,942
4	<b>Summit</b> - IBM Power System AC922, IBM POWER9 22C 3.07GHz, NVIDIA Volta GV100, Dual-rail Mellanox EDR Infiniband, IBM DOE/SC/Oak Ridge National Laboratory United States	2,414,592	148.60	200.79	10,096

Source: TOP 500 List - June 2022 [[TOP](#)]

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# Python Frameworks for GPU Computing

## Computing Frameworks

- Numba
- CuPy
- Scikit-cuda
- RAPIDS
- Triton (presented by Dimitris Oikonomou on 2022-05-19)
- ...

## Deep Learning Frameworks

- PyTorch
- TensorFlow
- Keras
- ...

# Python Frameworks for GPU Computing

## Computing Frameworks

- Numba
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- ...

## Deep Learning Frameworks

- PyTorch
- TensorFlow
- Keras
- ...



# Numba

## Definition

Numba is a **just-in-time compiler** for numerical functions in Python.

- Translates Python functions to optimized machine code at runtime
- Compiles code for CPU and GPU
- Supports
  - ▶ NVIDIA GPUs: CUDA
  - ▶ ~~AMD GPUs: ROCm (deprecated)~~
- Available on [GitHub](#) (open-source)



# Numba - Development



Mar 4, 2012 – Jun 13, 2022

Contributions: Commits ▼

Contributions to main, excluding merge commits and bot accounts



Source: GitHub - Numba [\[Gita\]](#)

# Numba - Programming Approaches

## 2 Approaches for GPU Programming

- Universal functions
- CUDA Kernels



# Numba - Universal Functions

## Definition

A universal function (or ufunc for short) is a **function** that operates on arrays in an element-by-element fashion.

Python

```
1  from numba import vectorize
2
3  @vectorize(['float32(float32, float32)'])
4  def add_ufunc(x, y):
5      return x + y
6
7  n = 100000
8  a = np.arange(n).astype(np.float32)
9  b = 2 * a
10 out = add_ufunc(a, b)
```

# Numba - Universal Functions on GPU

Python

```
1  from numba import vectorize
2
3  @vectorize(['float32(float32, float32)'], target='cuda')
4  def add_ufunc(x, y):
5      return x + y
```

- 1 Compile CUDA kernel
- 2 Allocate GPU memory
- 3 Copy data to the GPU
- 4 Executed CUDA kernel
- 5 Copy result back to the CPU
- 6 Return the result

# Numba - CUDA Kernels

Python

```
1  from numba import cuda
2  import numpy as np
3
4  @cuda.jit
5  def add_kernel(x, y, out):
6      start, stride = cuda.grid(1), cuda.gridsize(1)  # 1 = one dim. thread grid
7      for i in range(start, x.shape[0], stride):
8          out[i] = x[i] + y[i]
9
10 x = np.arange(100000).astype(np.float32)
11 y = np.arange(100000).astype(np.float32)
12 out = np.empty_like(x)
13 add_kernel[30, 128](x, y, out)  # blocks per grid, threads per block
14 print(out)  # [0.0 2.0 4.0 ... 1.99998e+05]
```

# CuPy

## Definition

CuPy is a NumPy/SciPy-compatible **array library** for GPU-accelerated computing.

- "NumPy for GPU computing"
- Provides various math operations
- Supports
  - ▶ NVIDIA GPUs: CUDA
  - ▶ AMD GPUs: ROCm (experimental)
- Available on [GitHub](#) (open-source)



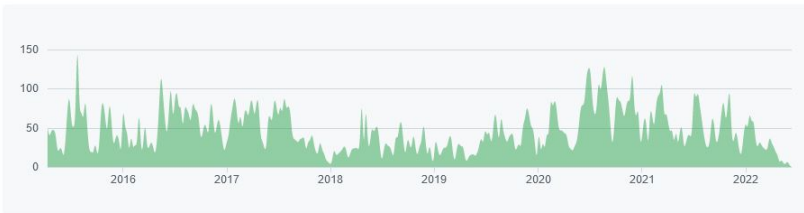
# CuPy - Development



Apr 12, 2015 – Jun 13, 2022

Contributions: Commits ▾

Contributions to master, excluding merge commits and bot accounts



Source: GitHub - CuPy [[Gitb](#)]



# CuPy - Math Functions

Python

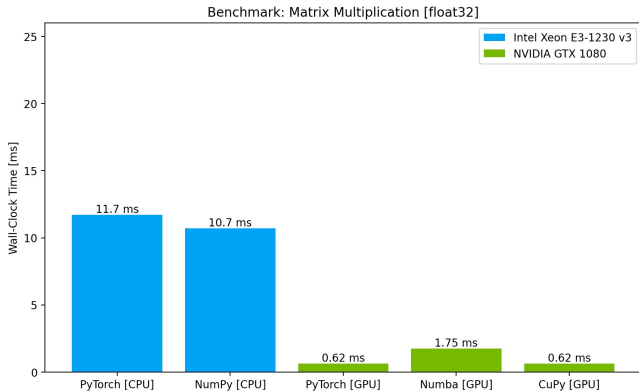
```
1  import cupy as cp
2
3  x = cp.arange(1000000)
4  y = x * 2
5
6  out1 = cp.add(x, y) # array([      0,      3,      6, ..., 2999997])
7  out2 = cp.sum(x)   # array(704982704)
8  out3 = cp.linalg.norm(x) # array(18257281.65280911)
9  # ...
10 # All common NumPy functions are supported by CuPy
```

# CuPy - CUDA Kernels

Python

```
1 import cupy as cp
2
3 add = cp.RawKernel(r'''
4 extern "C" __global__ void add(const int* p, const int* q, int* z) {
5     int tid = blockDim.x * blockIdx.x + threadIdx.x;
6     z[tid] = p[tid] + q[tid];
7 }
8 ''', 'add')
9 x = cp.arange(100000, dtype=int)
10 y = cp.arange(100000, dtype=int)
11 out = cp.zeros(100000, dtype=int)
12 add((250, 1), (1024, 1), (x, y, out)) # blocks per grid, threads per block
13 print(out) # array([ 0 2 4 ... 199994 199996 199998])
```

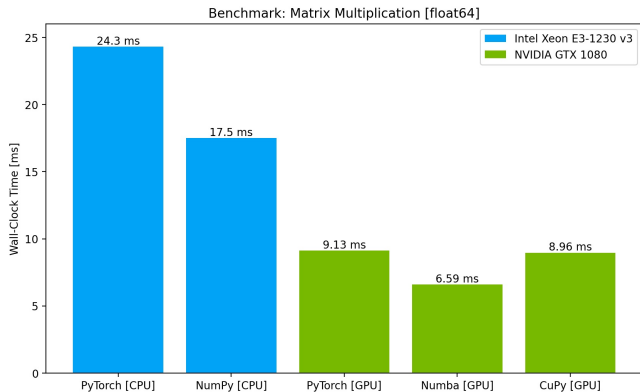
# Benchmark - Matrix Multiplication



Wall-clock time in milliseconds for computing result of fast matrix multiplication. Mean of 100 loops and 4 runs.  
Multiplied a 1024x2048 matrix and a 2048x512 matrix of float32.  
Measured time does not count in time to copy matrices to GPU and result matrix back from GPU.

Code for benchmarking is available on [GWDG GitLab](#)

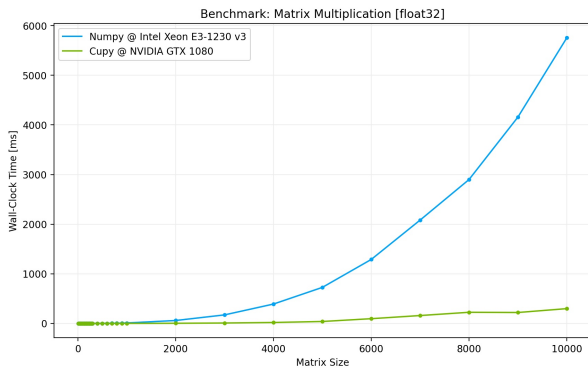
# Benchmark - Matrix Multiplication Float64



Wall-clock time in milliseconds for computing result of fast matrix multiplication. Mean of 100 loops and 4 runs.  
Multiplied a 1024x2048 matrix and a 2048x512 matrix of float64.  
Measured time does not count in time to copy matrices to GPU and result matrix back from GPU.

Code for benchmarking is available on [GWDG GitLab](#)

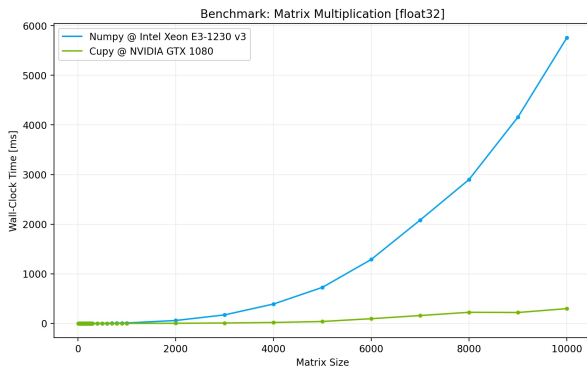
# Benchmark - Matrix Multiplication



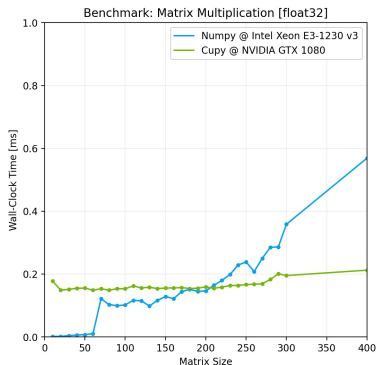
Wall-clock time in milliseconds for computing result of fast matrix multiplication. Mean of 10 loops and 3 runs. Multiplied 2 square matrices of float32 with given size. Not measured time to copy matrices to and from GPU.

Code for benchmarking is available on [GWDG GitLab](#)

# Benchmark - Matrix Multiplication



Wall-clock time in milliseconds for computing result of fast matrix multiplication. Mean of 10 loops and 3 runs. Multiplied 2 square matrices of float32 with given size. Not measured time to copy matrices to and from GPU.



Code for benchmarking is available on [GWDG GitLab](#)

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# New Trends

## What's new?

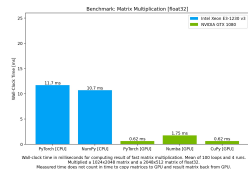
- GPUs get more powerful
- More complex models and computations
- New high-level Python frameworks provide features for various use cases
- ROCm (open-source) is gaining traction



# Summary

## ■ GPUs

- ▶ achieve massive data parallelism
- ▶ reduce **wall-clock time**
- ▶ increase **cost efficiency**



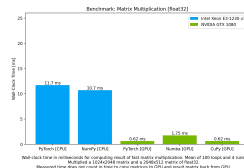
# Summary

## ■ GPUs

- ▶ achieve massive data parallelism
- ▶ reduce **wall-clock time**
- ▶ increase **cost efficiency**

## ■ Numba Advantages

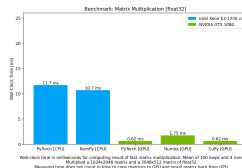
- ▶ Enables implementing **own universal functions & kernels** in Python running on GPU



# Summary

## ■ GPUs

- ▶ achieve massive data parallelism
- ▶ reduce **wall-clock time**
- ▶ increase **cost efficiency**



## ■ Numba Advantages

- ▶ Enables implementing **own universal functions & kernels** in Python running on GPU

## ■ CuPy Advantages

- ▶ Easily move **existing NumPy code** towards GPU computing
- ▶ Directly use NumPy-style **array operations** and execute them on GPU
- ▶ Great starting-point to **learn** about GPU computing

# References I



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**Google.** *Google Colab.* URL: <https://colab.research.google.com/>.

# GPU as a Service

Instance Size	GPUs - Tesla V100	GPU Peer to Peer	GPU Memory (GB)	vCPUs	Memory (GB)	Network Bandwidth	EBS Bandwidth	On-Demand Price/hr*	1-yr Reserved Instance Effective Hourly*	3-yr Reserved Instance Effective Hourly*
p3.2xlarge	1	N/A	16	8	61	Up to 10 Gbps	1.5 Gbps	\$3.06	\$1.99	\$1.05
p3.8xlarge	4	NVLink	64	32	244	10 Gbps	7 Gbps	\$12.24	\$7.96	\$4.19
p3.16xlarge	8	NVLink	128	64	488	25 Gbps	14 Gbps	\$24.48	\$15.91	\$8.39
p3dn.24xlarge	8	NVLink	256	96	768	100 Gbps	19 Gbps	\$31.218	\$18.30	\$9.64

Example Pricing: Amazon EC2 P3 instances. Source: AWS [[Ama](#)]

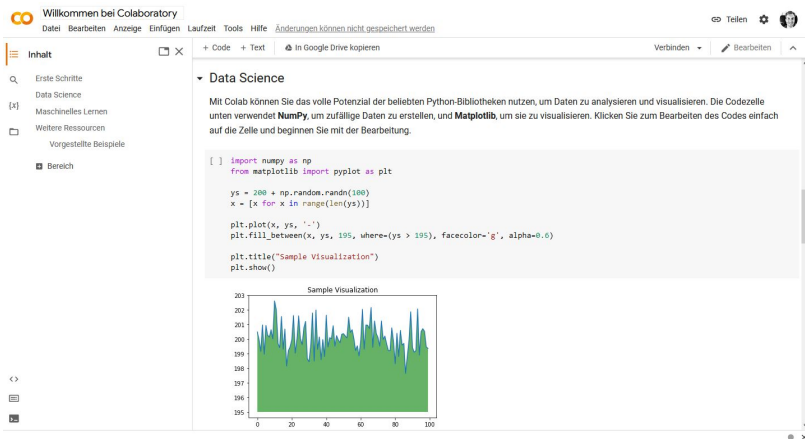
## Advantages

- Scalable resources
- On-demand pricing

## Disadvantages

- Expense for large periods of time
- Data confidentiality not guaranteed depending on vendor

# GPU as a Service



Google Colab Jupyter Notebooks. Source: Google [Goo]



# NVIDIA PTX

## Definition

NVIDIA PTX (Parallel Thread Execution) is a low-level parallel thread execution **virtual machine** and instruction set architecture (ISA)

- Exposes the GPU as a data-parallel computing device
- Interprets compiled code (analog to Java byte code interpreted by JVM)

## Advantage

- Achieves portability of source code among multiple NVIDIA GPUs