Intel and Anaconda Extending Numba* to New highs

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Scalable Dataframe Compiler

Numba* extension to compile Numpy* and Pandas* workflows

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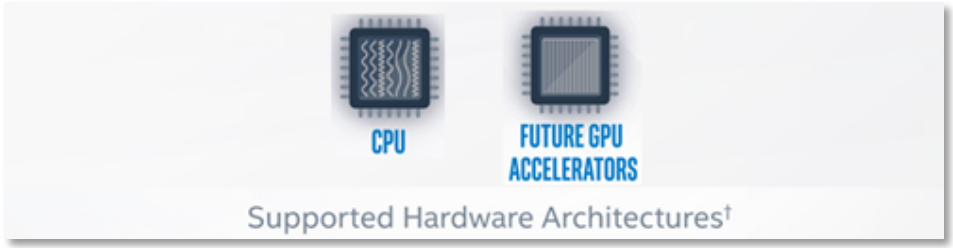


Extending Numba* to support Intel devices beyond CPUs

Intel® Scalable Dataframe Compiler

Extending Numba* to Compile Data Science workflows

Intel SDC in 1 minute

- Extension for Numba* to accelerate AI workflows
  - Goes beyond Numpy* operations to cover typical ETL
    - Lists, dictionaries, tuples
    - Supports more data types (series, dataframes, ASCII/Unicode strings)
- Compiler, not a library
  - Compiles Numpy, Pandas, **and the glue code** around it
  - Just-in-time and ahead-of-time compilation via Numba
- Scales from laptops to multi-core servers
  - Leverages Numba* parallel engine for auto-vectorization and multi-threading
- Open source project
  - Github page https://github.com/IntelPython/sdc
  - Documentation https://intelpython.github.io/sdc-doc/latest/index.html
- Available as conda package and pip wheels
  - `conda install -c intel/label/beta sdc`
  - `pip install -i https://pypi.anaconda.org/intel/label/beta/simple sdc`
  - Python 3.6, 3.7, Windows and Linux
  - 1700+ downloads in less than 2 months

```python
import pandas as pd
from numba import njit

# Dataset for analysis
FNAME = "employees.csv"


# This function gets compiled by Numba*
@njit
def get_analyzed_data():
    df = pd.read_csv(FNAME)
    s_bonus = pd.Series(df['Bonus %'])
    s_first_name = pd.Series(df['First Name'])
    m = s_bonus.mean()
    names = s_first_name.sort_values()
    return m, names


# Printing names and their average bonus percent
mean_bonus, sorted_first_names = get_analyzed_data()
print(sorted_first_names)
print('Average Bonus %:', mean_bonus)
```

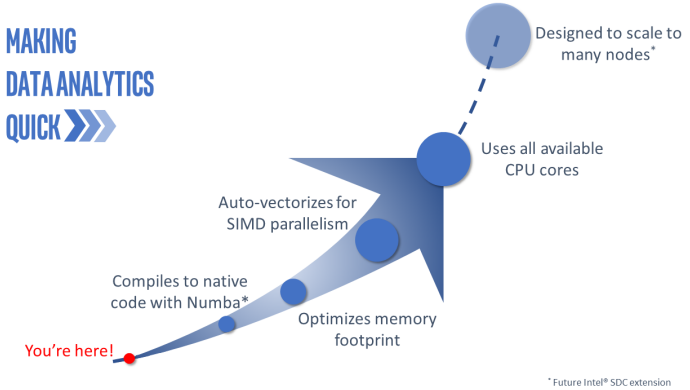
What's in Intel SDC

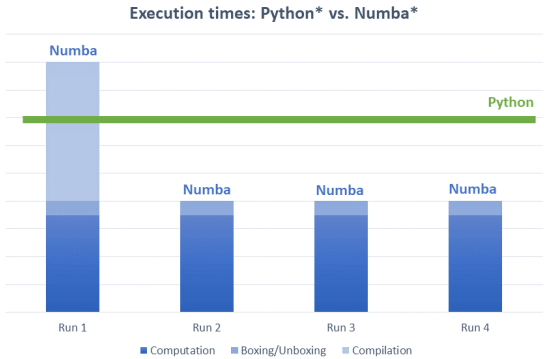
- Supports 170+ most important Pandas* APIs
  - Series, Dataframe, Window, GroupBy, read_csv
  - All major datatypes, including ASCII/Unicode strings
    - Coming soon time series and categoricals

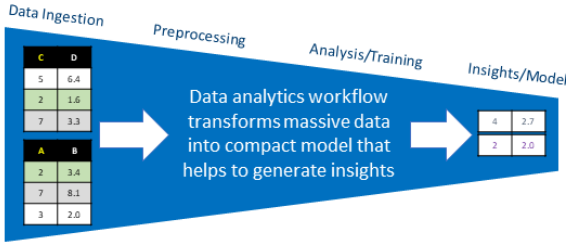
API Reference

- Input/output
  - Flat file
- Series: Columnar Data Structure
  - Constructor
  - Attributes/Operators
  - Type Conversions
  - Indexing and Iteration
  - Binary Operator Functions
  - User-Defined Functions, GroupBy, Window
  - Computations, Descriptive Statistics
  - Re-Indexing, Selection, Label Manipulation
  - Missing Data Handling
  - Re-Shaping, Sorting
  - Combining, Joining, Merging
  - Time Series
  - Accessors
  - Plotting
  - Serialization, Input-Output, Conversion
- Dataframe: Tabular Data Structure
  - Constructor
  - Attributes/Operators
  - Type Conversions
  - Indexing and Iteration
  - Binary Operator Functions
  - User-Defined Functions, GroupBy & Window
  - Computations, Descriptive Statistics
  - Re-Indexing, Selection, Label Manipulation
  - Missing Data Handling
  - Re-Shaping, Sorting, Transposing
  - Combining, Joining, Merging
  - Time Series
  - Plotting
  - Sparse Accessor
  - Serialization, Input-Output, Conversion
- Window
  - Standard moving window functions
  - Standard expanding window functions
  - Exponentially-weighted moving window functions
- GroupBy
  - Indexing, iteration
  - Function application
  - Computations / descriptive stats

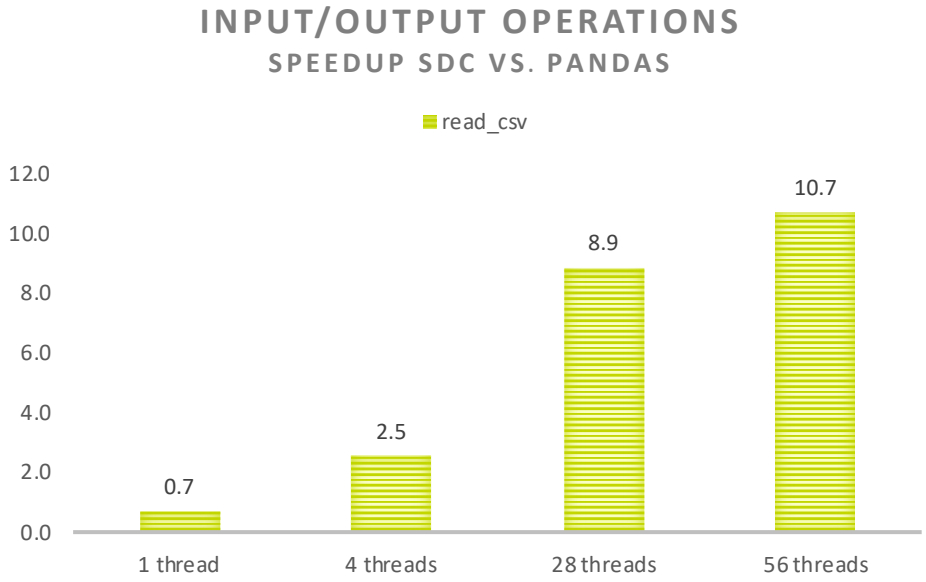
Numba/SDC performance aspects





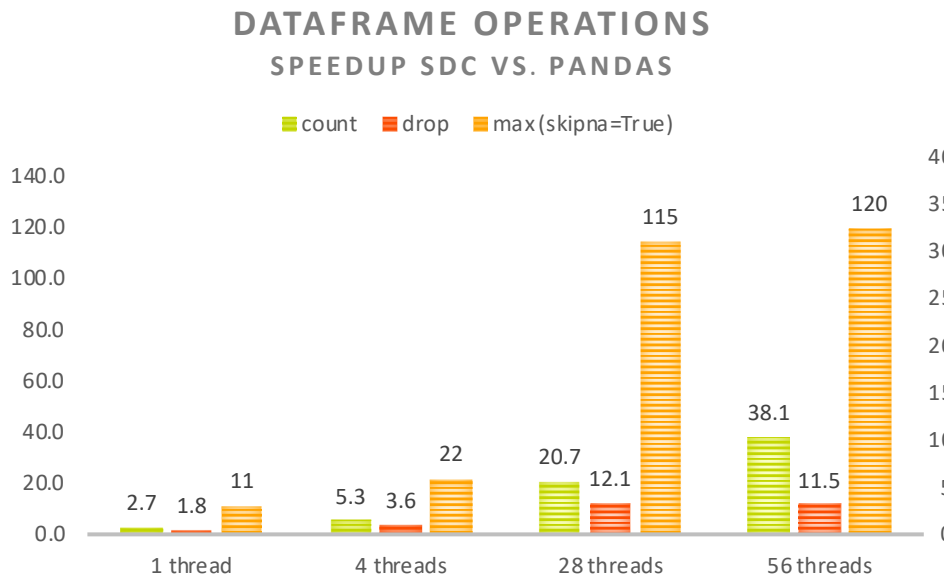


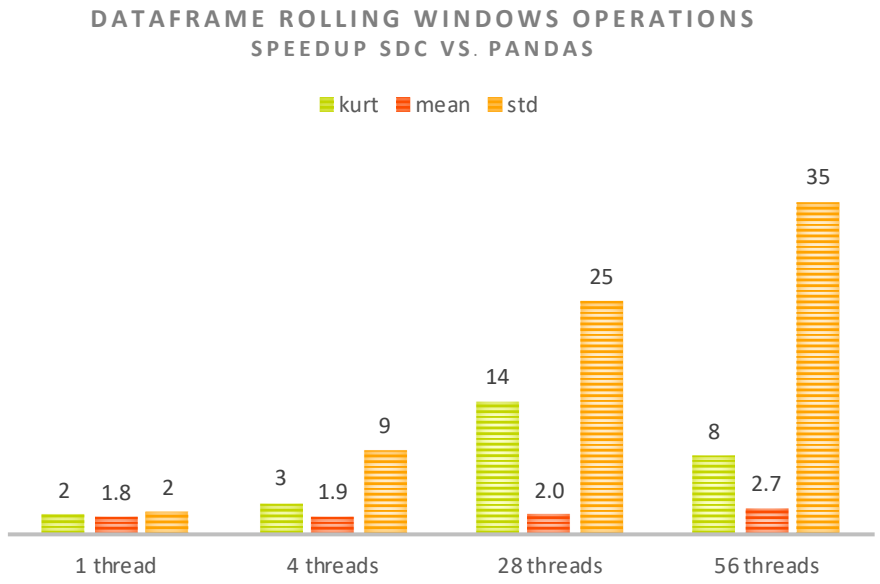
Intel SDC Performance – read_csv



Intel® SDC Beta, Numba* 0.48, Pandas* 0.25.3
Intel® Xeon™ Platinum 8280L, 2.7 GHz, 2x28 cores, Hyperthreading=on, Turbo Mode=on

Intel SDC Performance – Dataframes





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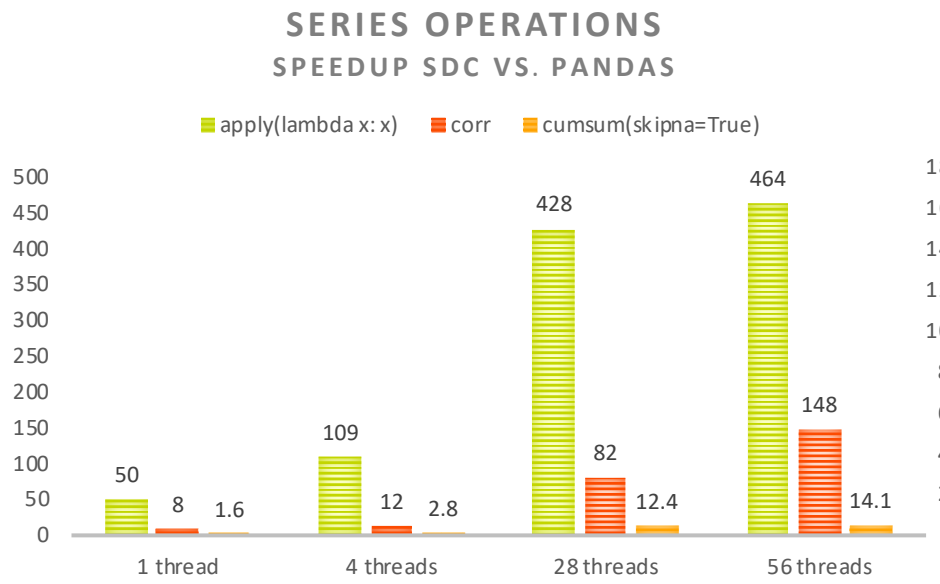
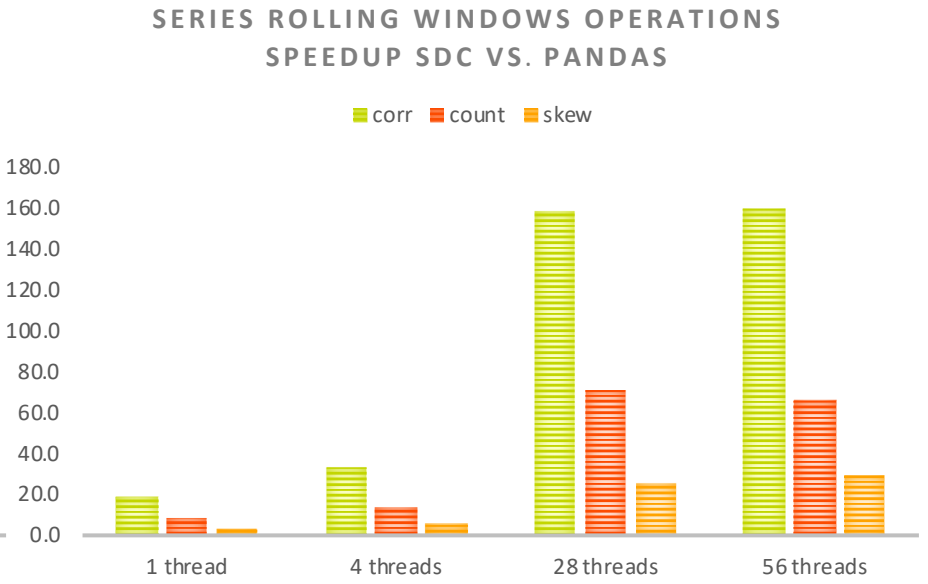
Intel SDC Performance – Series





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Intel® Xeon™ Platinum 8280L, 2.7 GHz, 2x28 cores, Hyperthreading=on, Turbo Mode=on

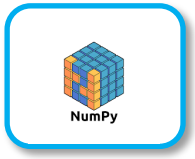
DPPY and Numba

Extending Numba* to support Intel accelerators

Envision a GPU-enabled Python Library Ecosystem

Say Hello to DPPY!!!

Data Parallel Python (DPPY)



daal4p
y

Your GPU-enabled library!

Intel is working to enable core Numpy* ecosystem with DPPY

- Lightweight Python wrapper for the SYCL runtime
- An interface for queues, events, buffers, USM, and kernels
- USM and sycl::buffer backed containers
- Allows different Python libraries to share SYCL runtime objects

Where does DPPY help me?

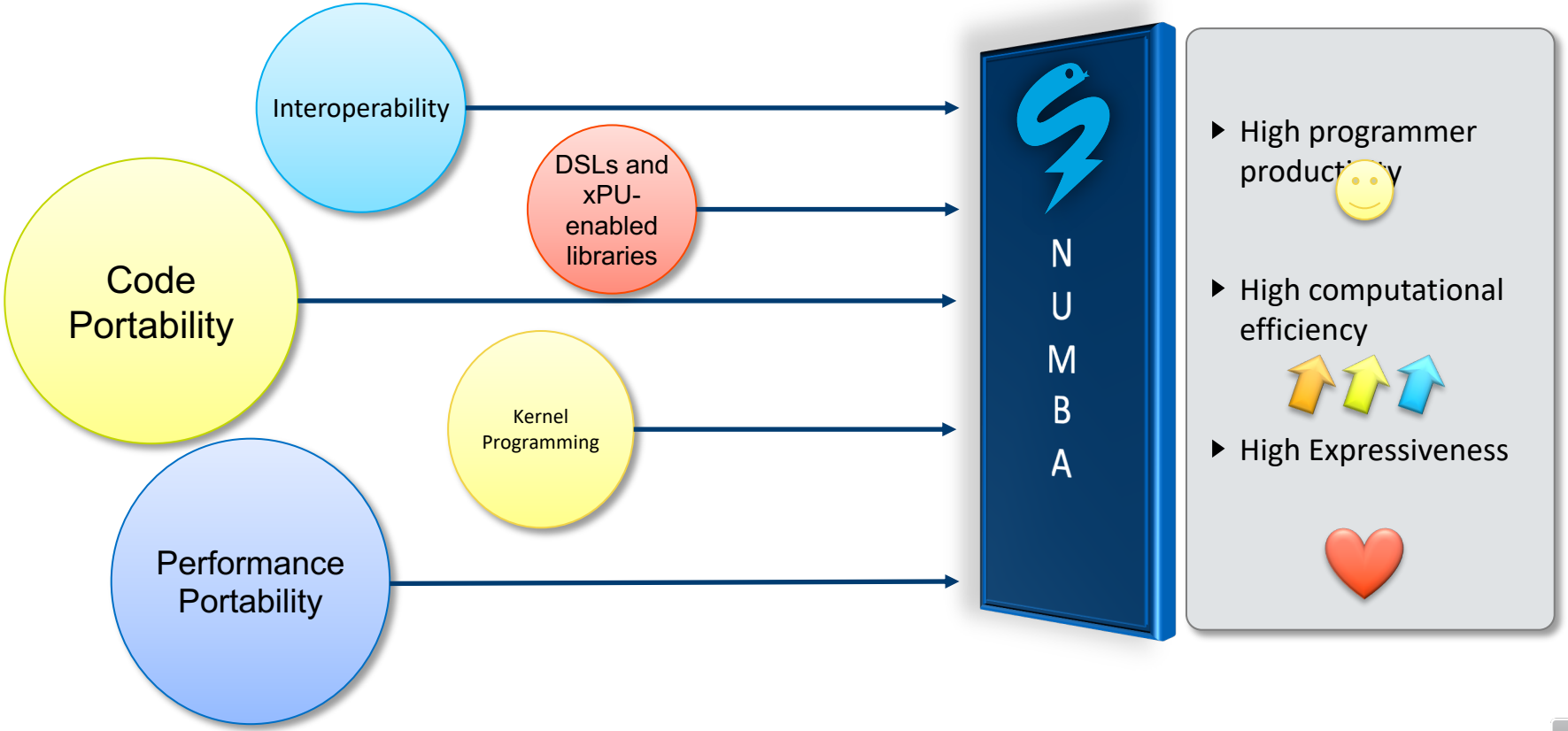
Seamless interoperability and sharing of resources

```
1  from dppy import device_context, DeviceArr
2  import daal4py as d4p
3  from numba import njit
4  import numpy as np
5
6  @njit
7  def numba_foo(a):
8      ...
9
10 a = np.array(np.random.random(1024), dtype=float32)
11
12 with device_context(gpu,0):
13     d_a = DeviceArr(a)
14     d_a = numba_foo(d_a)
15     d_a = d4p.bar(d_a)
16     a = d_a.asarray()
17
```

- Numba function
- daal4py function

Data remains on the device across different library calls!

Extending Numba* for tomorrow's Intel xPU



New Additions to Numba's Language Design

dppy.kernel

```
1  @dppy.kernel
2  def data_parallel_sum(a, b, c):
3      i = dppy.get_global_id(0)
4      c[i] = a[i] + b[i]
```

- Low-level kernel programming for expert ninjas

njit (target=dppy)

```
1  @njit(parallel=True, target=dppy.igpu)
2  def f1(a, b):
3      c = a + b
4      return c
```

- Domain-specific data-parallel code generation
- Compiler optimizations: kernel fusion, data movement optimizations
- Same code works for multiple devices and programming model (just change the target)

Let’s take an example

```
1   @numba.vectorize(nopython=True)
2   def cndf2(inp):
3       out = 0.5 + 0.5 * math.erf((math.sqrt(2.0)/2.0) * inp)
4       return out
5
6   @numba.njit(parallel=True, fastmath=True)
7   def blackscholes(sptprice, strike, rate, volatility, timev):
8       logterm = np.log(sptprice / strike)
9       powterm = 0.5 * volatility * volatility
10      den = volatility * np.sqrt(timev)
11      d1 = (((rate + powterm) * timev) + logterm) / den
12      d2 = d1 - den
13      NofXd1 = cndf2(d1)
14      NofXd2 = cndf2(d2)
15      futureValue = strike * np.exp(- rate * timev)
16      c1 = futureValue * NofXd2
17      call = sptprice * NofXd1 - c1
18      put  = call - futureValue + sptprice
19      return put
```

Blackscholes formula with Numba auto-parallelization on CPU using “parallel=True”

Default Numba behavior (added previously by Intel)

- **Fusion of all NumPy operations**
- **Auto-parallelization of the fused operation on CPUs using OpenMP**

Let’s take an example

```
1   @numba.vectorize(nopython=True)
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19      return put
```

Blackscholes formula with Numba auto-parallelization on CPU using “parallel=True”

Now let us make the same code work on Intel’s Gen9 GPUs…

… multiple options

Just change a decorator option

```
1   @numba.vectorize(nopython=True)
2   def cndf2(inp):
3       out = 0.5 + 0.5 * math.erf((math.sqrt(2.0)/2.0) * inp)
4       return out
5
6   @numba.njit(parallel=True, target=dppy.igpu)
7   def blackscholes(sptprice, strike, rate, volatility, timev):
8       logterm = np.log(sptprice / strike)
9       powterm = 0.5 * volatility * volatility
10      den = volatility * np.sqrt(timev)
11      d1 = (((rate + powterm) * timev) + logterm) / den
12      d2 = d1 - den
13      NofXd1 = cndf2(d1)
14      NofXd2 = cndf2(d2)
15      futureValue = strike * np.exp(- rate * timev)
16      c1 = futureValue * NofXd2
17      call = sptprice * NofXd1 - c1
18      put  = call - futureValue + sptprice
19      return put
```

- "target=dppy.igpu" triggers GPU code-generation and execution
- All other goodness like kernel fusion work out of the box!
- Numba handles all host-side control code (buffer creation, kernel enqueuing, data movement)

More power to the programmer

Type-driven JIT compilation

```
1   @numba.njit(parallel=True)
2   def blackscholes(sptprice, strike, rate, volatility, timev):
3
4   with device_context(gpu,0):
5       d_SP = DeviceArr(sptprice)
6       d_S = DeviceArr(strike)
7       d_R = DeviceArr(rate)
8       d_V = DeviceArr(volatility)
9       d_T = DeviceArr(timev)
10      blackscholes(d_SP, d_S, d_R, d_V, d_T)
11
```

- No change to njit options
- Define a GPU execution context
- Explicitly allocate memory (DeviceArr) on the GPU
- Since DeviceArr is passed in, Numba infers programmer wants GPU code

What about us ninjas?

Blackscholes dppy.kernel edition

```
@dppy.kernel
def black_scholes_dppy(callResult, putResult, S, X, T, R, V):
    i = dppy.get_global_id(0)
    if i >= S.shape[0]:
        return
    sqrtT = math.sqrt(T[i])
    d1 = (math.log(S[i] / X[i]) + (R + 0.5 * V * V) * T[i]) / (V * sqrtT)
    d2 = d1 - V * sqrtT

    K = 1.0 / (1.0 + 0.2316419 * math.fabs(d1))
    cndd1 = (RSQRT2PI * math.exp(-0.5 * d1 * d1) *
             (K * (A1 + K * (A2 + K * (A3 + K * (A4 + K * A5))))))
    if d1 > 0:
        cndd1 = 1.0 - cndd1

    K = 1.0 / (1.0 + 0.2316419 * math.fabs(d2))
    cndd2 = (RSQRT2PI * math.exp(-0.5 * d2 * d2) *
             (K * (A1 + K * (A2 + K * (A3 + K * (A4 + K * A5))))))
    if d2 > 0:
        cndd2 = 1.0 - cndd2

    expRT = math.exp((-1. * R) * T[i])
    callResult[i] = (S[i] * cndd1 - X[i] * expRT * cndd2)
    putResult[i] = (X[i] * expRT * (1.0 - cndd2) - S[i] * (1.0 - cndd1))

```

and Python*

The breadth of Intel technologies for entire Python ecosystem

Industry Initiative

oneAPI

Intel Product

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A core set of high-performance tools for building Data Parallel C++ applications and oneAPI library based applications

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Everything HPC developers need to deliver fast C++, Fortran, & OpenMP* applications that scale

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Tools for building high-performing, efficient, reliable solutions that run at the network's edge

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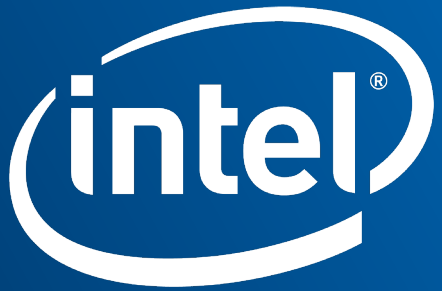

Software

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