



# Data Parallel Essentials For Python

## *Interfacing oneAPI and Python*

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# Agenda



Duration	Topics
5 minutes	Goals
20 minutes	Current ecosystem and core packages
5 minutes	Q&A

# Data Parallel Essentials for Python

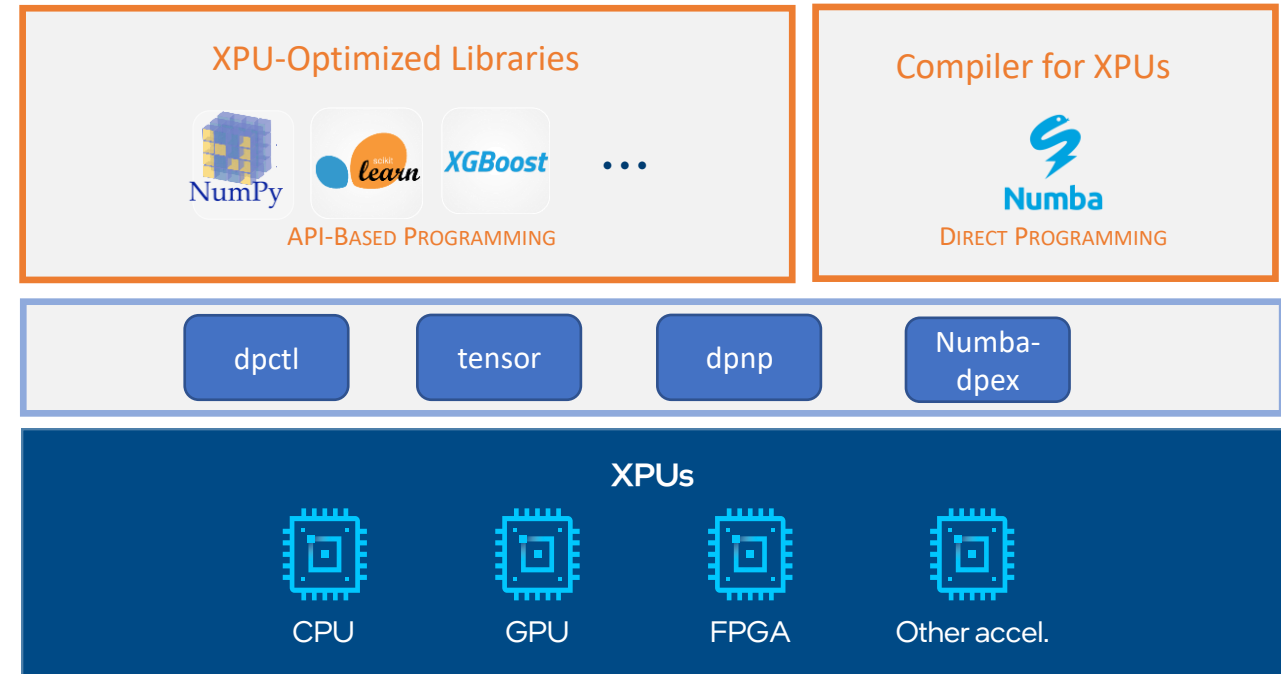


Fostering a oneAPI/SYCL-  
based ecosystem for PyDATA

PyData Ecosystem

Data Parallel  
Essentials for Python

oneAPI + SYCL



# Core Goals



- Prescribe a Pythonic offload model and interoperability API
  - offload model (compute follows data)
  - data interchange and interoperation specification
- Building blocks to foster a SYCL-based ecosystem in Python
  - SYCL USM-based Python array library (Array API standard)
  - Compilation of Python bytecode to SPIR-V for SYCL/DPC++
  - SYCL-based drop-in replacement for NumPy
- Ease Python native extension development for oneAPI and SYCL libraries

# Programming Model Goals



## Offload Model

- Pythonic offload model following array API spec (<https://data-apis.org/array-api/latest/>)
- Offload happens where data currently resides (“compute follows data”)

```
X = dp.array([1,2,3])  
Y = X * 4
```

executed on default device

```
X = dp.array([1,2,3], device="gpu:0")  
Y = X * 4
```

executed on “gpu:0” device

```
X = dp.array([1,2,3], device="gpu:0")  
Y = dp.array([1,2,3], device="gpu:1")  
Z = X + Y
```

Error! Arrays are on different devices

## Interoperability

Native extensions

- Extend the dlpack standard (<https://github.com/dmlc/dlpack>)

Pure Python modules

- Define a protocol like NumPy’s `__array_interface__` and CuPy’s `__cuda_array_interface__`

# Current Ecosystem



Scikit-learnx

Scikit-learn extension for XPU

Wider ecosystem

3

dpnp

Drop in NumPy replacement

Numba-dpex

JIT Compiler for NumPy, Kernel programming

User-level libraries

2

dpctl.tensor

Math

Relational

Stats

Python Data API compliant array library based on USM

Data Parallel Essentials for Python

1

dpctl

SYCL Wrapper classes

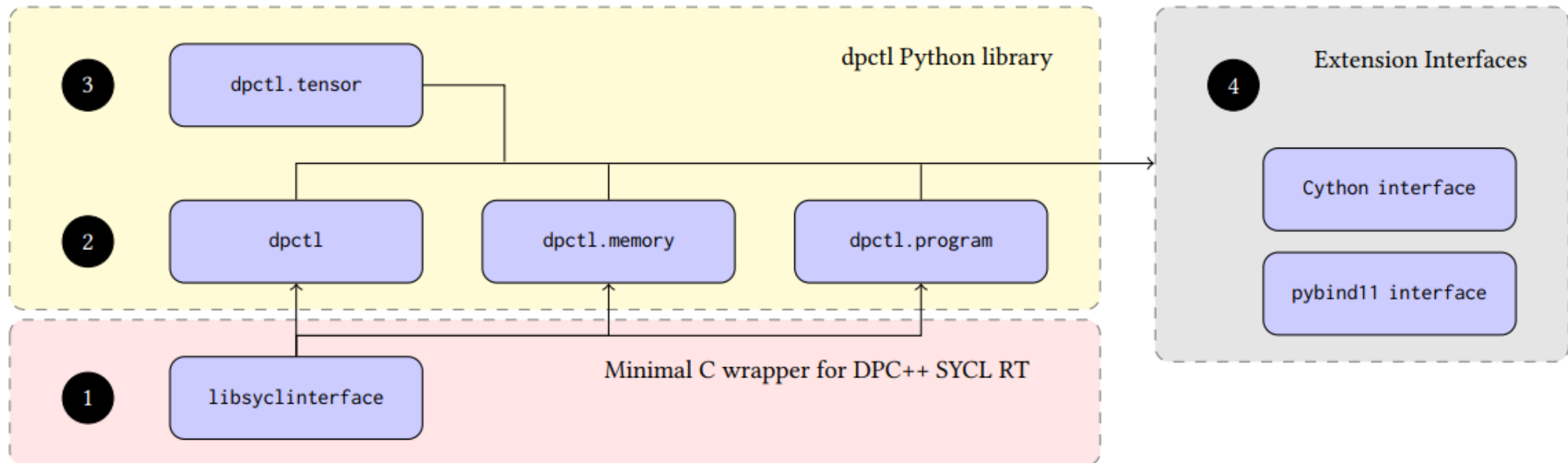
USM allocators

Cython, Pybind11 iface

Python bindings for subset of SYCL

DPC++

# dpctl – Data parallel control



1 Library providing a minimal C API for the main DPC++ SYCL runtime classes

2 Python modules exposing SYCL runtime classes, USM allocators, and kernel bundle

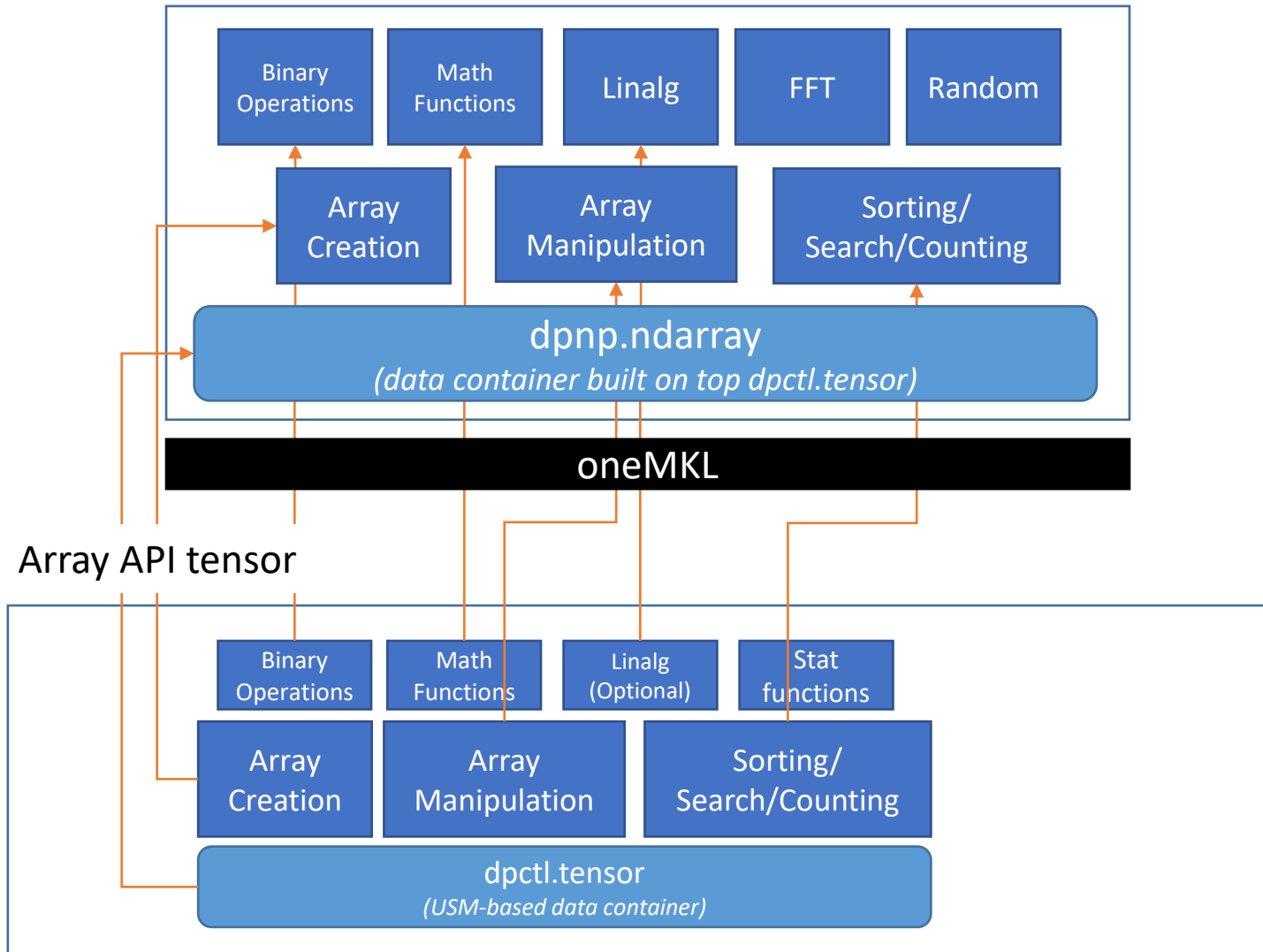
3 A data API standard compliant array library supporting USM allocated memory

4 Native API to use dpctl objects in Cython and pybind11 extensions modules

# Array Libraries



## Data Parallel Numeric Python (dnpnp)



Original CPU script

```
import numpy as np

x = np.array([[1, 1], [1, 1]])
y = np.array([[1, 1], [1, 1]])

res = np.matmul(x, y)
```

Modified XPU script

```
import dnpnp as dp

x = dp.array([[1, 1], [1, 1]], device="gpu")
y = dp.array([[1, 1], [1, 1]], device="gpu")

res = dp.matmul(x, y) # res resides on gpu
```



# Extension Interfaces



```
#include "dpctl4pybind11.hpp"
#include <CL/sycl.hpp>
#include <oneapi/mkl.hpp>
#include <pybind11/pybind11.h>
#include <pybind11/stl.h>

void gemv_blocking(sycl::queue q,
                  dpt::usm_ndarray m,
                  dpt::usm_ndarray v,
                  dpt::usm_ndarray r,
                  const std::vector<sycl::event> &deps = {})
{
    auto n = m.get_shape(0);
    auto m = m.get_shape(1);
    int mat_tynenum = m.get_tynenum();
    /* various legality checks omitted */
    sycl::event res_ev;

    if (mat_tynenum == UAR_DOUBLE) {
        auto *mat_ptr = m.get_data<double>();
        auto *v_ptr = v.get_data<double>();
        auto *r_ptr = r.get_data<double>();
        res_ev = oneapi::mkl::blas::row_major::gemv(
            q, oneapi::mkl::transpose::nontrans, n, m, 1,
            mat_ptr, m, v_ptr, 1, 0, r_ptr, 1, depends);
    }
    else
        throw std::runtime_error("unsupported");

    res_ev.wait();
}

PYBIND11_MODULE(_onemkl, m)
{
    // Import the dpctl extensions
    import_dpctl();
    m.def("gemv_blocking", &gemv_blocking, "oneMKL gemv wrapper");
}
```

- Create a Python ext. to call `onemkl::gemv` in < 40 loc (fits on a slide)
- Invoke it seamless from Python using `dpctl`, `dpctl.tensor`

```
import dpctl;
import numpy as np
import dpctl.tensor as dpt
import onemkl4py

# Programmatically select a device
d = select_device()
# Create an execution queue for the selected device
q = dpctl.SyclQueue(d)
# Allocate matrices and vectors objects using NumPy
Mnp, vnp = np.random.randn(5, 3), np.random.randn(3)
# Copy data to a USM allocation
M = convert_numpy_to_tensor(Mnp, q)
v = convert_numpy_to_tensor(vnp, q)
r = dpt.empty((5,), dtype="d", sycl_queue=q)
# Invoke a binding for the oneMKL gemv kernel.
onemkl4py.gemv_blocking(M.sycl_queue, M, v, r, [])
```

# Numba-dpex



## Array-style programming

```
@njit(parallel=True)
def l2_distance(a, b, c)
    return np.sum((a-b)**2)
```

NumPy (array) style programming. Requires minimum code changes to compile existing Numpy code for XPU. Nvidia cuPy offers this programming model with JIT fusion capabilities via `cupy.fuse()`

## Explicit prange (parfor) loops

```
@njit(parallel=True)
def l2_distance(a, b, c)
    s = 0.0
    for i in prange(len(a))
        s += (a[i]-b[i])**2
    return s
```

Parfor-style programming. Preferred by some users when iteration space requires complex indexing. Unique for CPU. Intel extends to XPU via numba-dpex. No CUDA alternatives to date

## OpenCL-style kernel programming

```
@kernel(access_type={"read_only": ["a", "b"], write_only: ["c"]})
def l2_distance(a, b, c)
    i = numba_dpex.get_global_id(0)
    j = numba_dpex.get_global_id(1)
    sub = a[i,j] - b[i,j]
    sq = sub ** 2
    atomic.add(c, 0, sq)
```

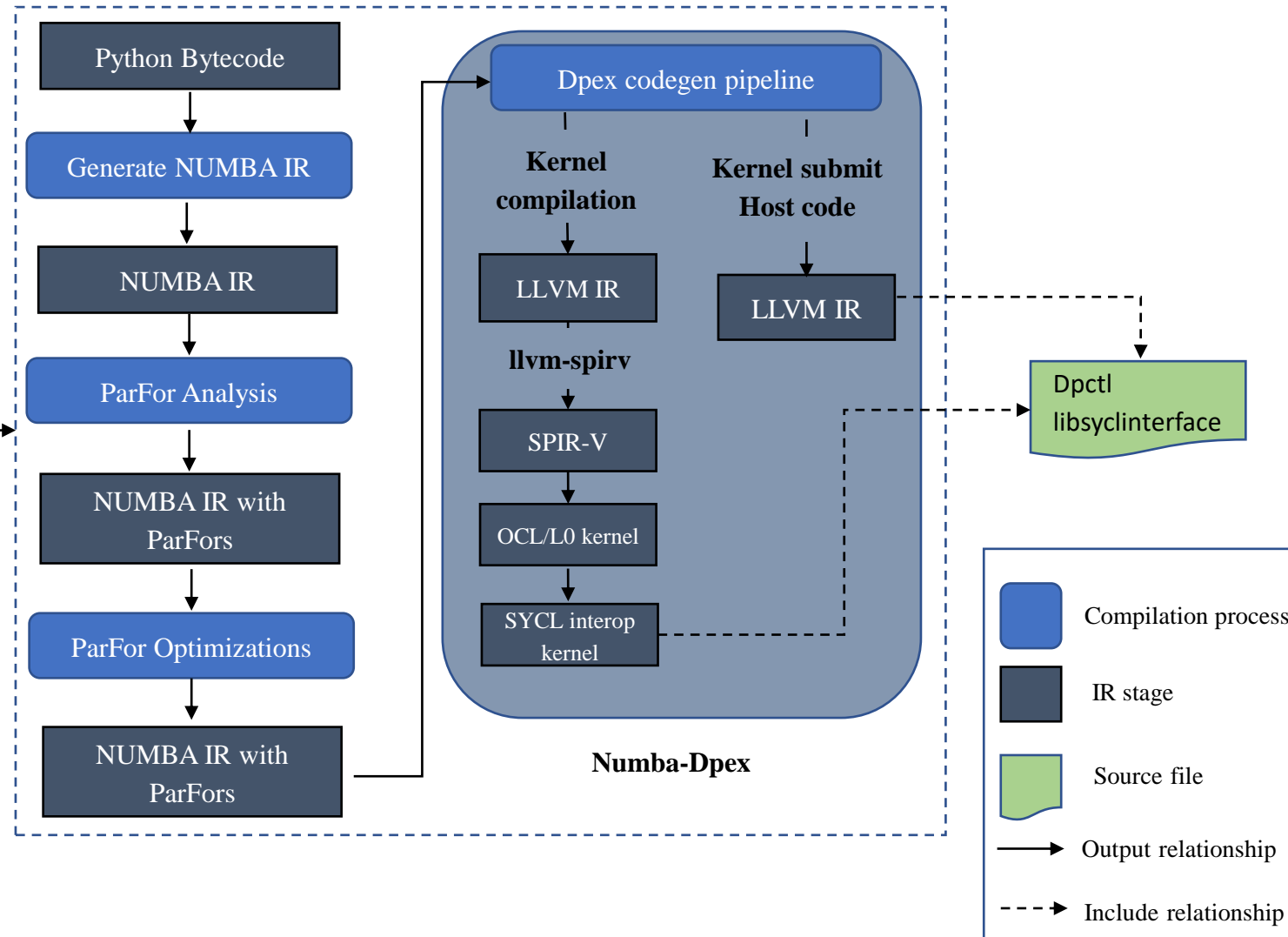
Most advanced programming model. Recommended to get highest performance on XPU yet avoiding DPC++. Nvidia `@cuda.jit` offers this programming model in Numba

# Numba-dpex codegen



@njit

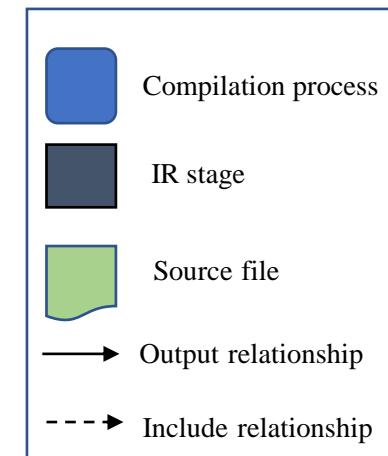
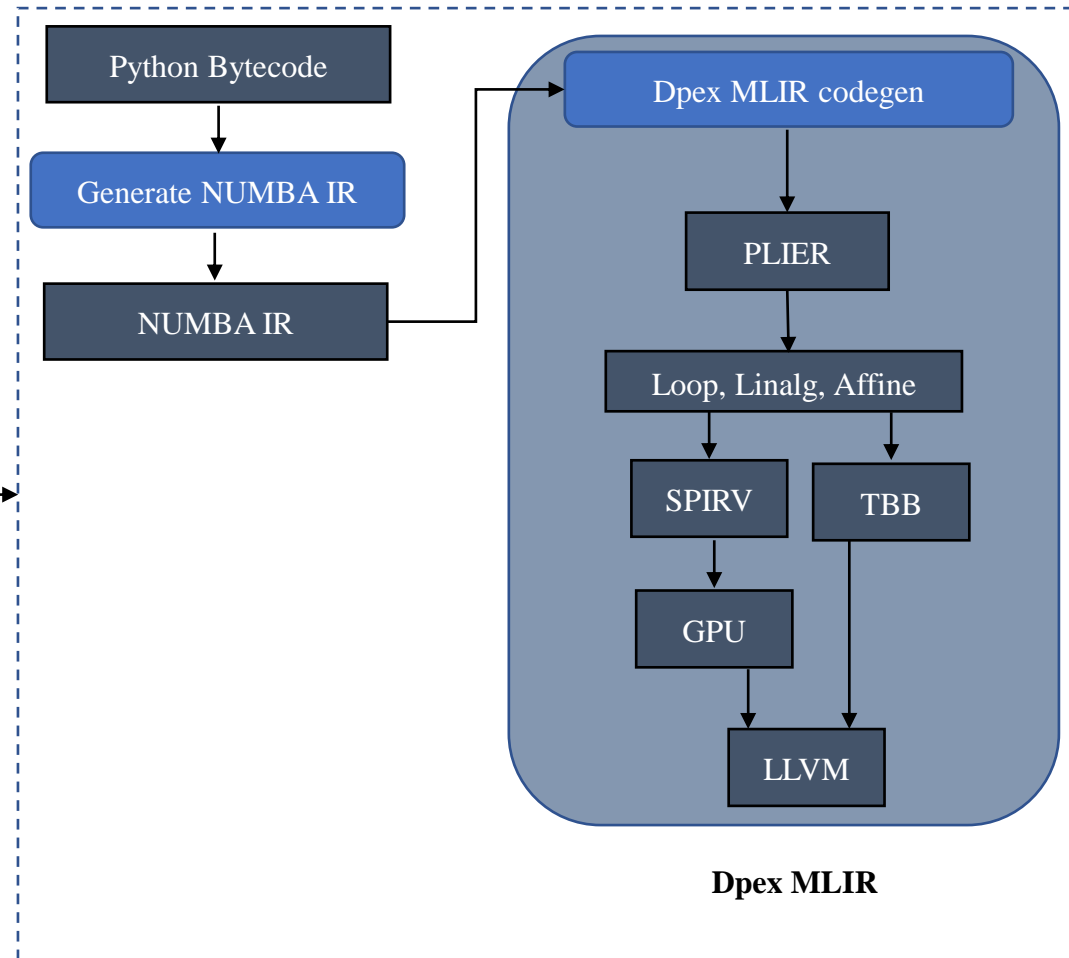
@njit function



# Numba-dpex codegen (MLIR)

@njit

@njit function



# Current Status



- Included in oneAPI Basekit and Intel Distribution for Python\* (IDP)
- Open-source development on [github.com/IntelPython](https://github.com/IntelPython)
- Packages available from Anaconda cloud and PyPi

# Programming Model



## Compute Follows Data

- Pythonic offload model following array API spec
- Explicit control over execution based on data placement

## Interoperability

- `__sycl_usm_array_interface__` modeled after NumPy's `__array_interface__`
- Dlpack for exchanging data across native extensions

```
import dpnp as dp
# Case 1
# Allocate X on the default device
X = dp.array([1,2,3])
# scaling of X executed on device of X, result
# placed into Y
Y = X * 4
# Case 2
# Allocate X on "gpu:1"
X = dp.array([1,2,3], device="gpu:1")
# Executed on "gpu:1"
Y = X * 4
# Case 3
X1 = dp.array([1,2,3], device="gpu:1")
X2 = dp.array([1,2,3], device="gpu:0")
# error!
Y = X1 + X2

# Arrays can be associated with another device
# (copy is performed if needed)
X1a = X1.to_device(device=dev)
```