Choose the Best Accelerated Technology

Intel® Acceleration for Classical Machine Learning

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Agenda

- Recap: Intel AI Analytics Toolkit
- Intel Distribution for Python
- Intel Distribution of Modin
- Intel(R) Extension for Scikit-learn
- XGBoost Optimization
- Data Parallel Python

Intel® AI Analytics Toolkit

Powered by oneAPI

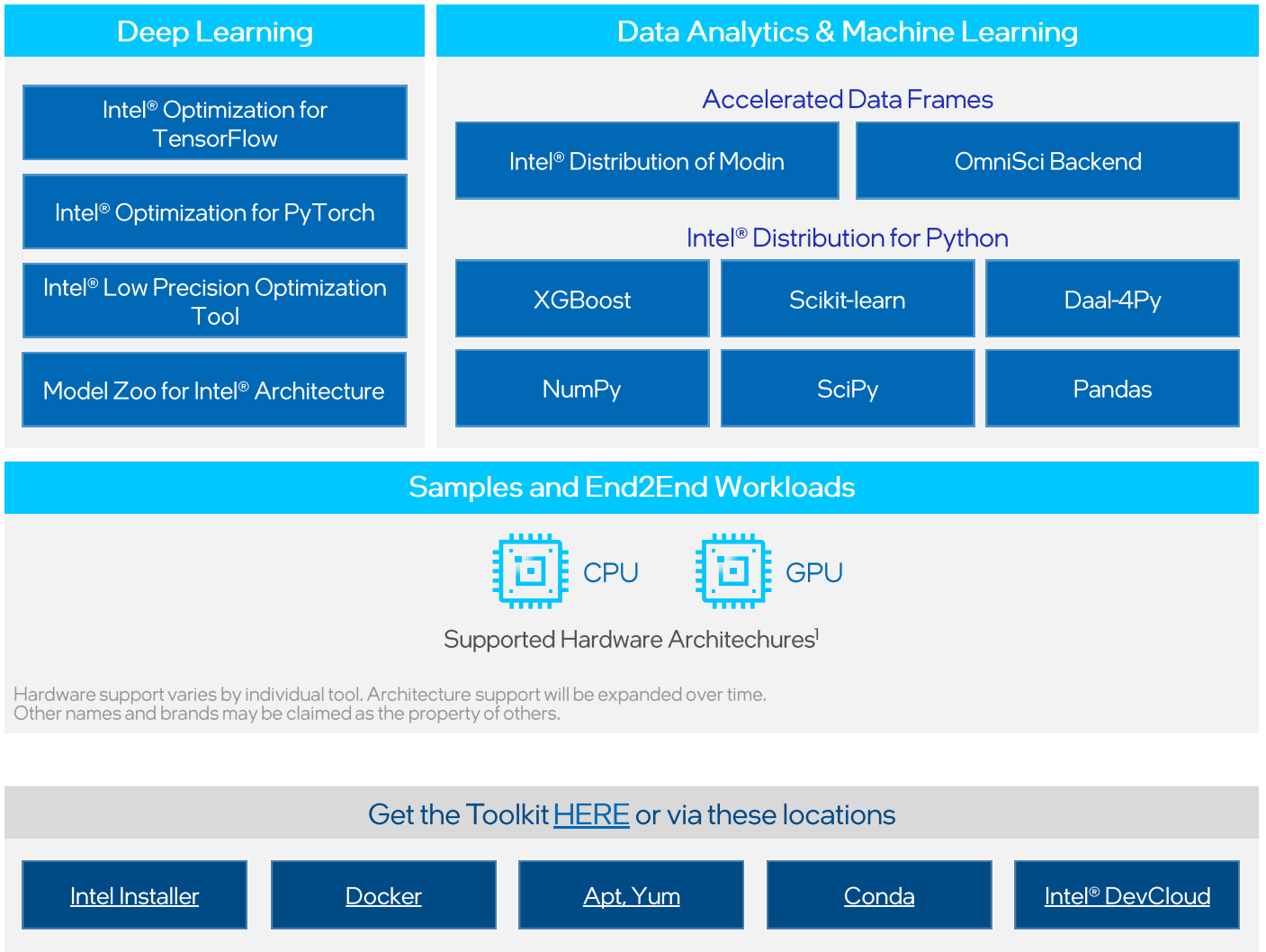
Accelerate end-to-end AI and data analytics pipelines with libraries optimized for Intel® architectures

Who Uses It?

Data scientists, AI researchers, ML and DL developers, AI application developers

Top Features/Benefits

- Deep learning performance for training and inference with Intel optimized DL frameworks and tools
- Drop-in acceleration for data analytics and machine learning workflows with compute-intensive Python packages

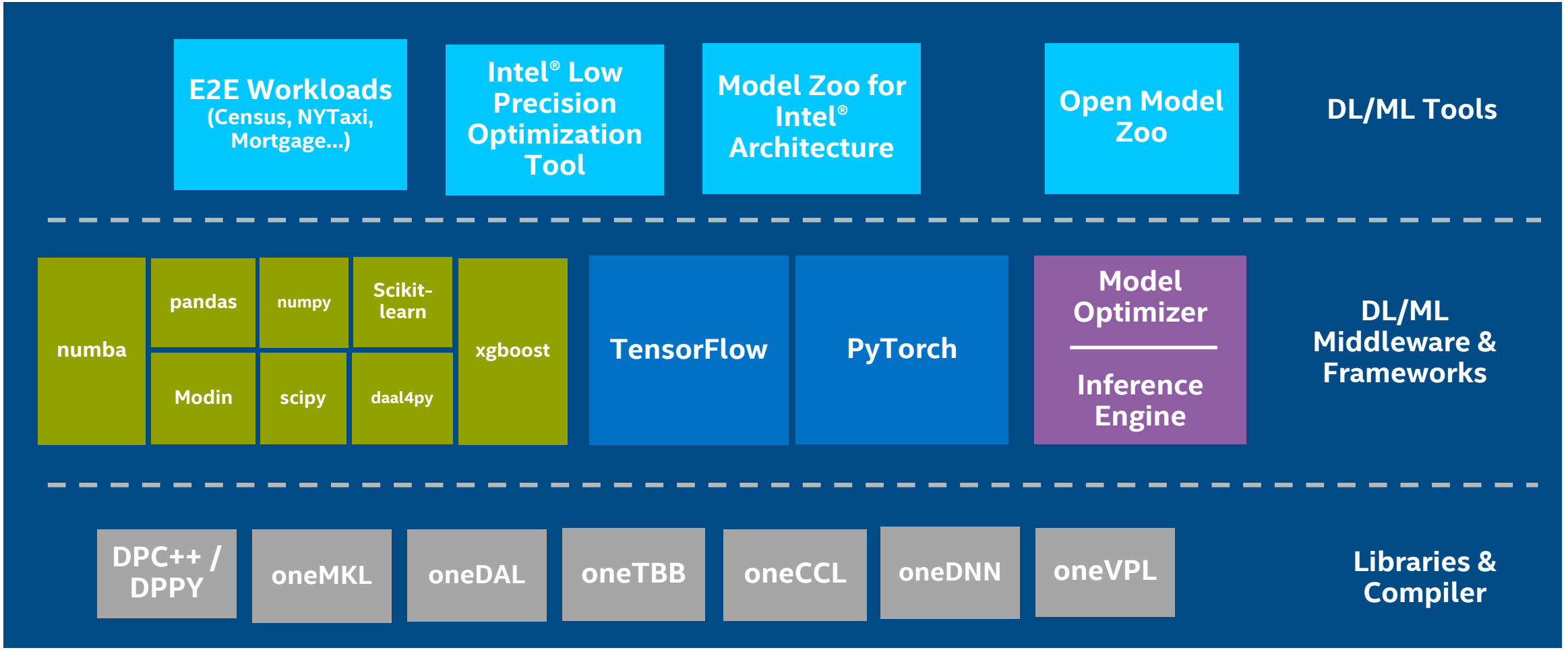


Learn More: software.intel.com/oneapi/ai-kit

Back to Domain-specific Toolkits for Specialized Workloads

AI Software Stack for Intel® XPUs

Intel offers a robust software stack to maximize performance of diverse workloads



AI Software Stack for Intel® XPUs

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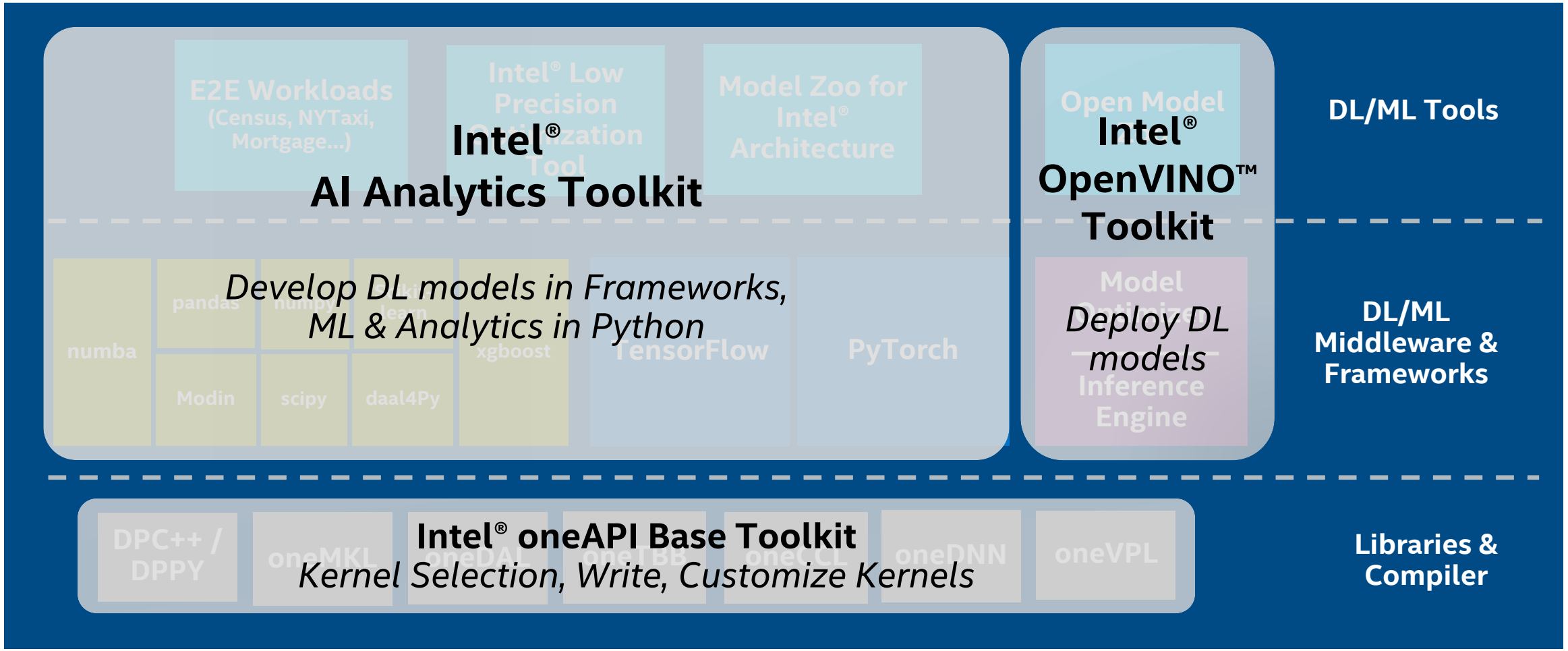
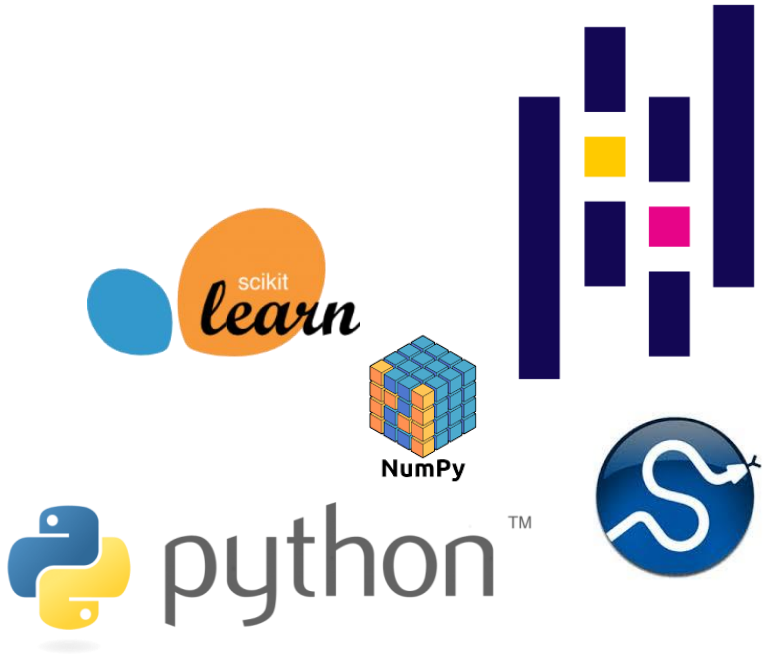


Full Set of AI ML and DL Software Solutions Delivered with Intel's oneAPI Ecosystem

Executive Summary

- Intel® Distribution for Python covers major usages in HPC and Data Science
- Achieve faster Python application performance — right out of the box — with minimal or no changes to a code
- Accelerate NumPy*, SciPy*, and scikit-learn* with integrated Intel® Performance Libraries such as Intel® oneMKL (Math Kernel Library) and Intel® oneDAL (Data Analytics Library)
- Access the latest vectorization and multithreading instructions, Numba* and Cython*, composable parallelism with Threading Building Blocks, and more

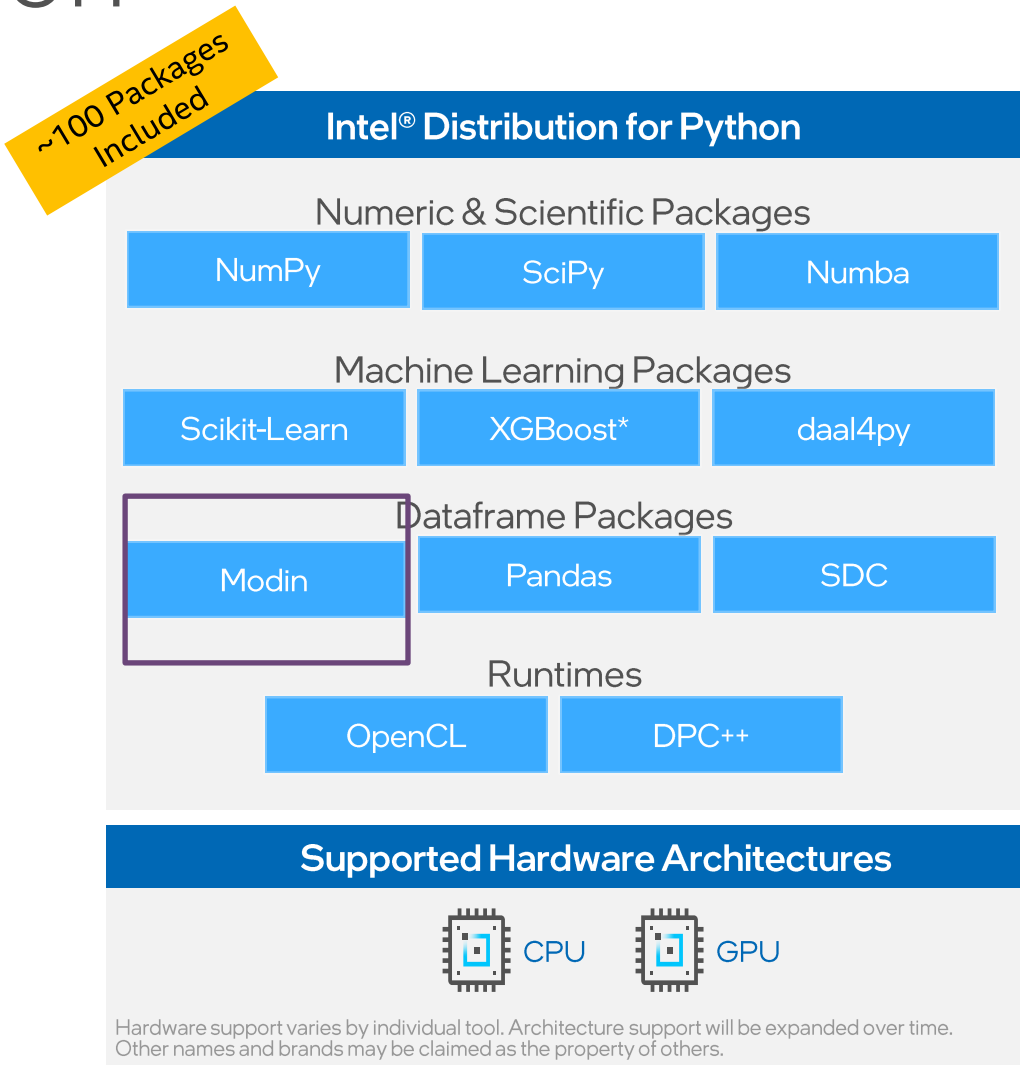


- Analysts
- Data Scientists
- Machine Learning Developers

Intel® Distribution for Python

oneAPI Powered

Develop fast, performant Python code with this set of essential computational packages

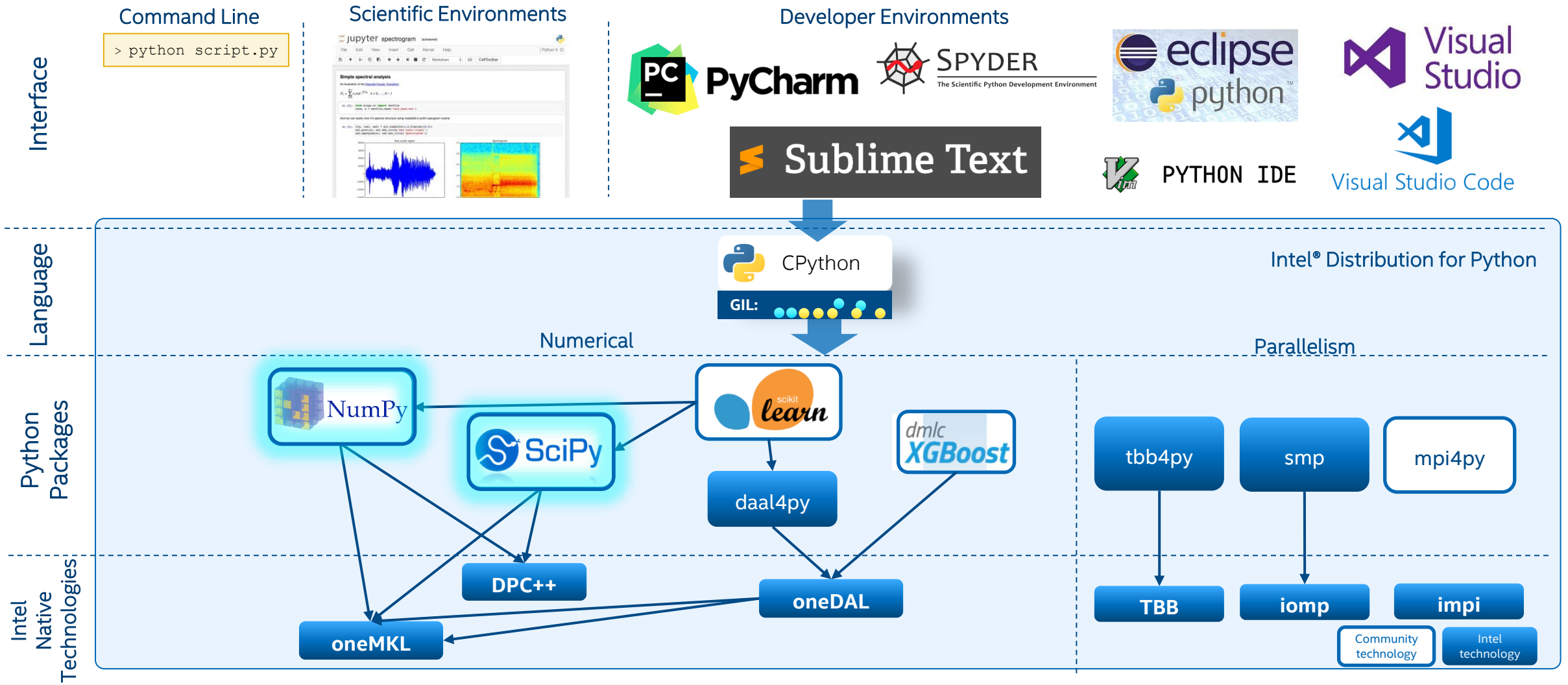


Who Uses It?

- Machine Learning Developers, Data Scientists, and Analysts can implement performance-packed, production-ready scikit-learn algorithms
- Numerical and Scientific Computing Developers can accelerate and scale the compute-intensive Python packages NumPy, SciPy, and mpi4py
- High-Performance Computing (HPC) Developers can unlock the power of modern hardware to speed up your Python applications

Initial GPU support enabled with Data Parallel Python

Intel® Distribution for Python Architecture



Intel® Distribution for Python

Developer Benefits

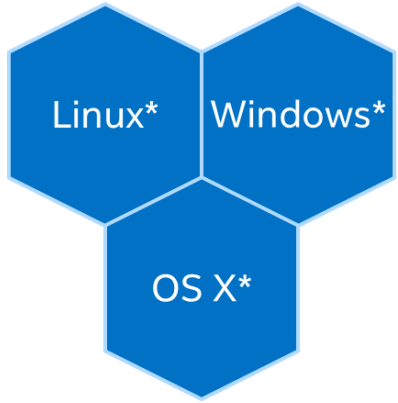
Maximize Performance	Minimize Development Cost	Vast Ecosystem
Performance Libraries, Parallelism, Multithreading, Language Extensions	**Drop-in Python Replacement**	**Familiar usage and compatibility**
Near-native performance comes through acceleration of core Python numerical packages Accelerated NumPy/SciPy/scikit-learn with oneMKL & oneDAL Data analytics, machine learning & deep learning with scikit-learn, XGBoost, Modin, daal4py Scale with Numba*, Cython*, tbb4py, mpi4py, SDC Optimized for latest Intel® architectures	Prebuilt optimized packages for numerical computing, machine/deep learning, HPC, & data analytics Data-Parallel Python provides cross-architecture XPU support Conda build recipes included in packages Free download & free for all uses including commercial deployment	Supports Python 3 Supports conda & pip package managers Packages available via conda, pip YUM/APT, Docker image on DockerHub Commercial support through the Intel® oneAPI Base Toolkit

Operating Systems: Windows*, Linux*, MacOS[1]*

Intel® Architecture Platforms 

Choose Your Download Option

Python Solutions	Download Options
Tools and frameworks to accelerate end-to-end data science and analytics pipelines	Intel® AI Analytics Toolki
Develop fast, performant Python code with essential computational packages	Intel® Distribution for Python
Optimized Python packages from package managers and containers	Conda | YUM | APT | Docker
Develop in the Cloud	Intel® DevCloud



* Also available in the Intel® oneAPI Base Toolkit

Modin

Data Science Landscape: Today

Tools efficient for O(1MB)

Usable but not scalable

pandas

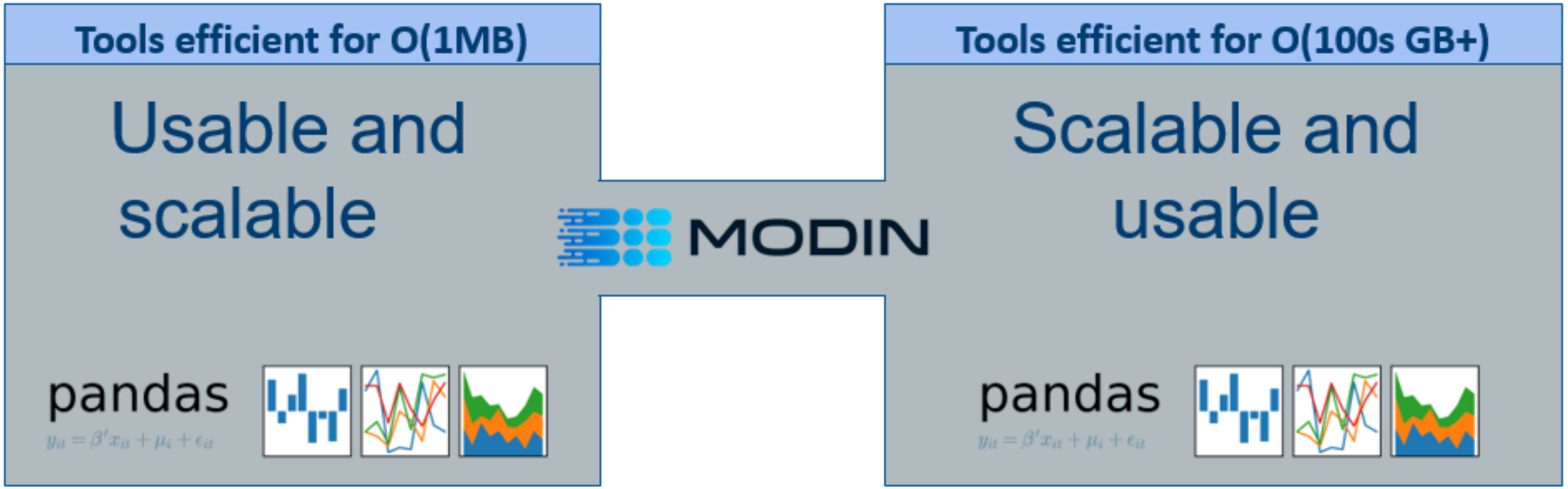
$y_{it} = \beta' x_{it} + \mu_i + \epsilon_{it}$

Tools efficient for O(100s GB+)

Scalable but not usable

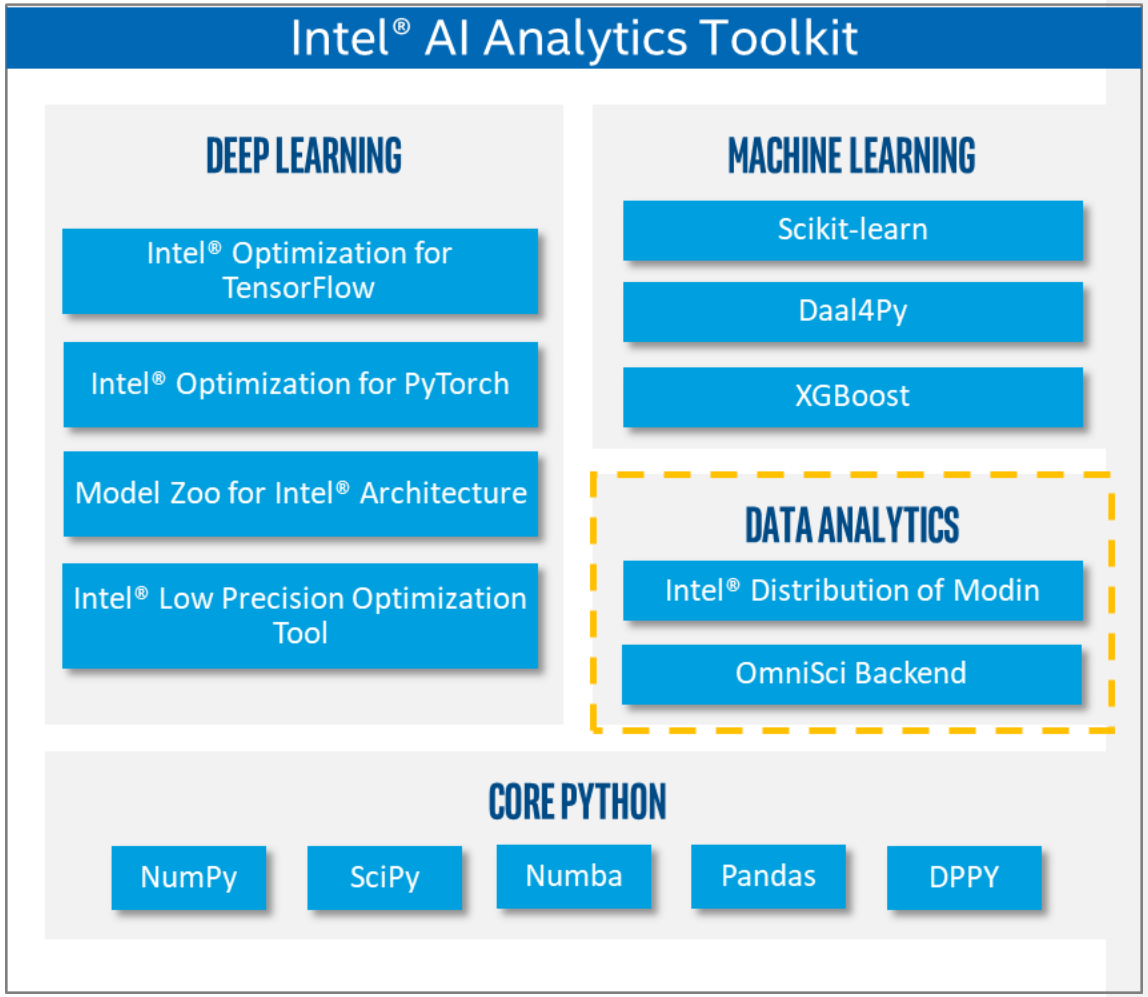
APACHE Spark™

Data Science Landscape: Today



Intel distribution of Modin

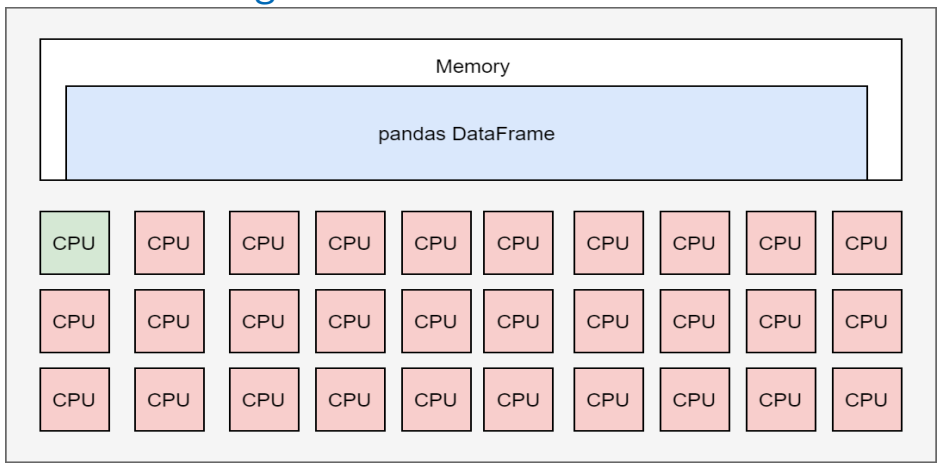
- Accelerate your Pandas* workloads across multiple cores and multiple nodes
- No upfront cost to learning a new API
  - import modin.pandas as pd
- In the backend, Intel Distribution of Modin is supported by Omnisci*, a performant framework for end-to-end analytics that has been optimized to harness the computing power of existing and emerging Intel® hardware



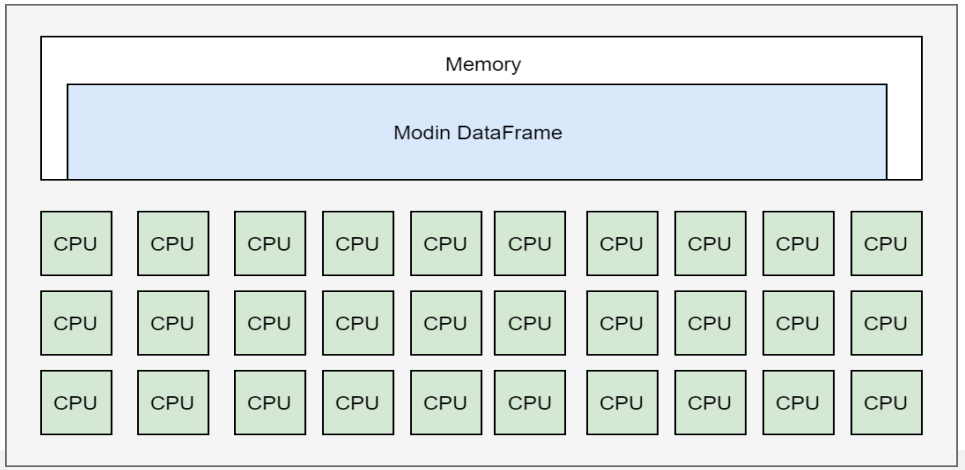
Intel distribution of Modin

- Recall: No upfront cost to learning a new API
  - import modin.pandas as pd
- Integration with the Python* ecosystem
- Integration with Ray*/Dask *clusters (Run on what you have, even on laptop!)
- To use Modin, you do not need to know how many cores your system has, and you do not need to specify how to distribute the data

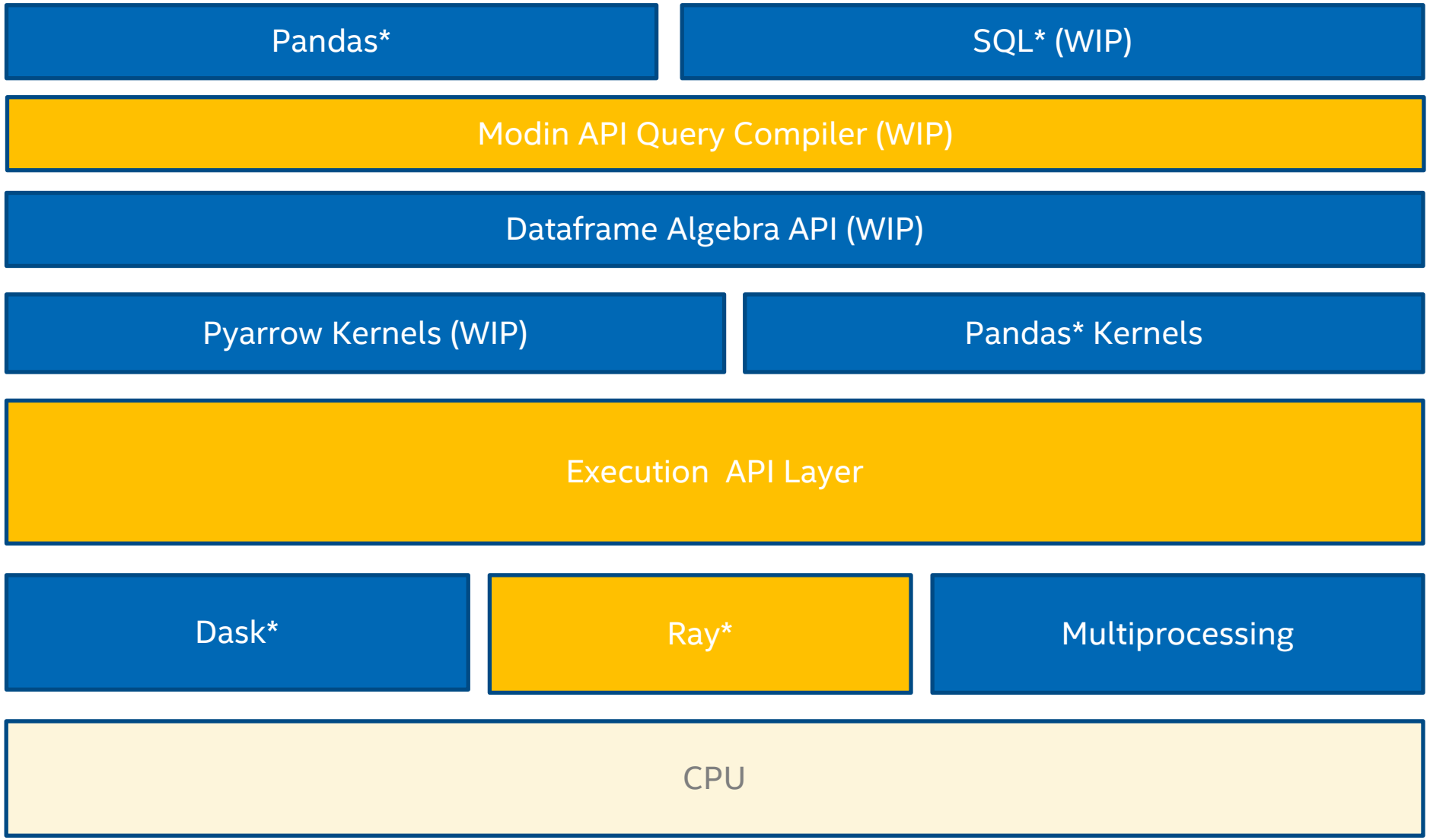
Pandas* on Big Machine



Modin on Big Machine

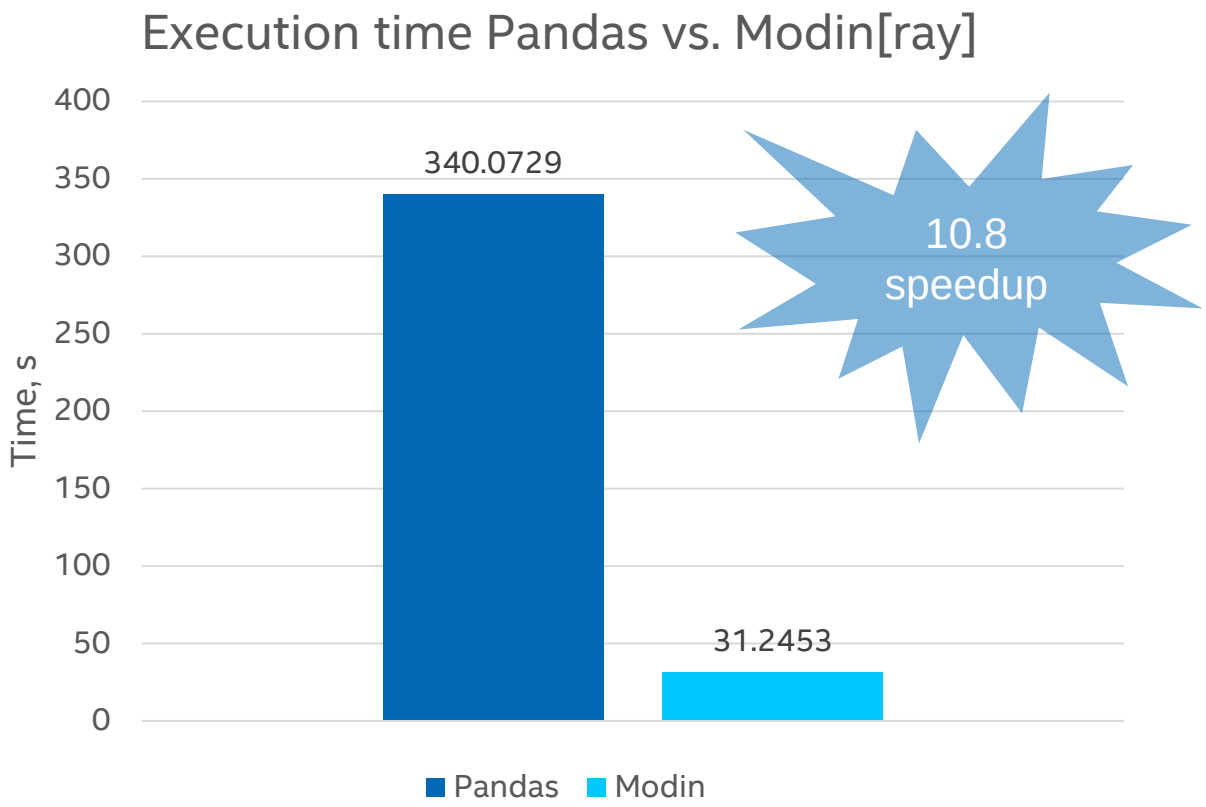


MODIN LAYERED ARCHITECTURAL DIAGRAM - NOW



Modin

```
import modin.pandas as pd
import numpy as np


def run_etl():

    def cat_converter(x):
        if x is '':
            return np.int32(0)
        else:
            return np.int32(int(x, 16))

    names = [f"column_{i}" for i in range(40)]
    converter= {names[i]: cat_converter for i in range(14, 40)}

    df = pd.read_csv('data.csv', delimiter='\t', names=names,
                     converters=converter)

    count_y = df.groupby("column_0")["0"].count()

    return df, count_y


df, count_y = run_etl()
```

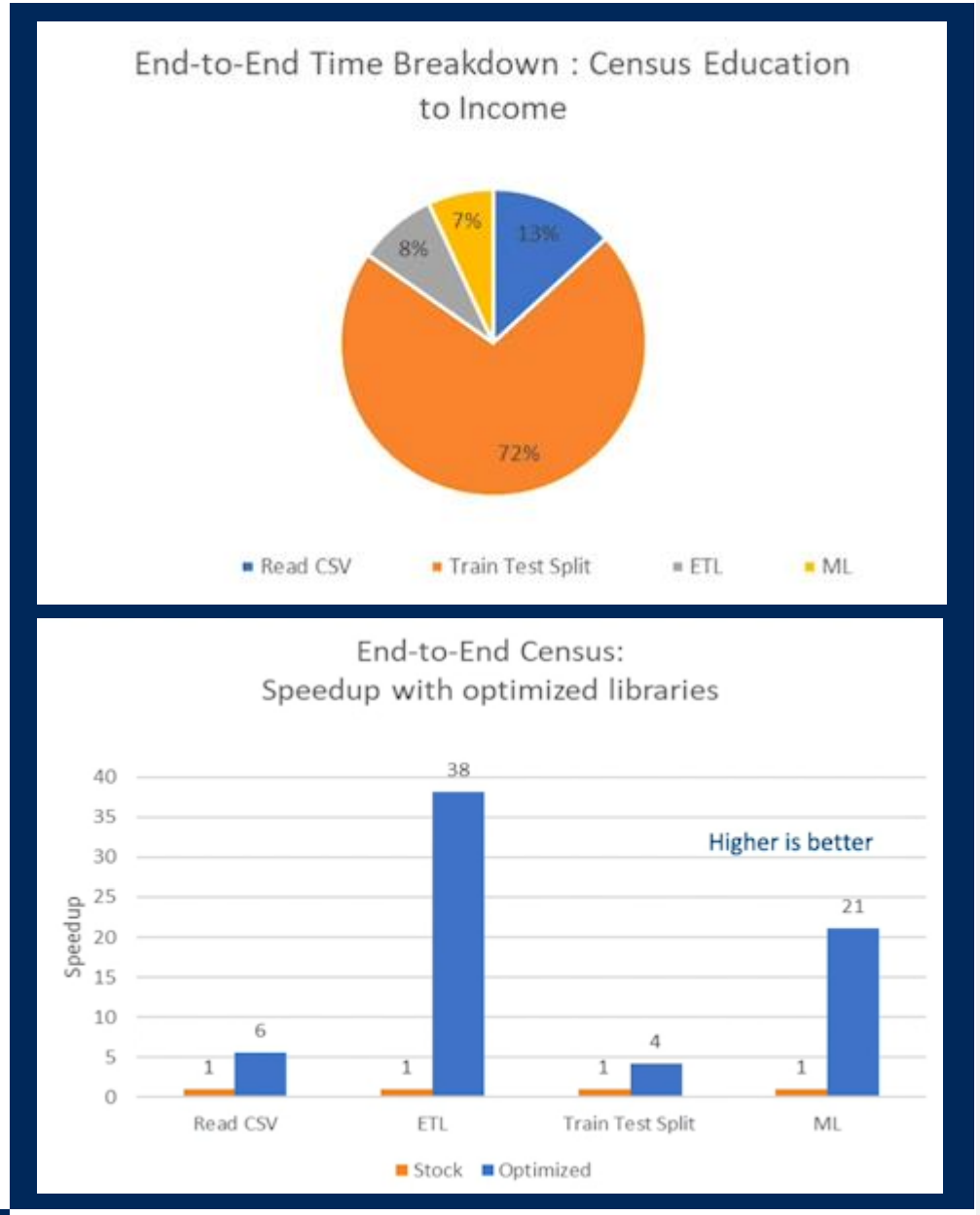


Intel® Xeon™ Gold 6248 CPU @ 2.50GHz, 2x20 cores

- Dataset size: 2.4GB

End-to-End Data Pipeline Acceleration

- **Workload:** Train a model using 50yrs of Census dataset from IPUMS.org to predict income based on education
- **Solution:** Intel Modin for data ingestion and ETL, Daal4Py and Intel scikit-learn for model training and prediction
- **Perf Gains:**
  - Read_CSV (Read from disk and store as a dataframe) : **6x**
  - ETL operations : **38x**
  - Train Test Split : **4x**
  - ML training (fit & predict) with Ridge Regression : **21x**



Demo

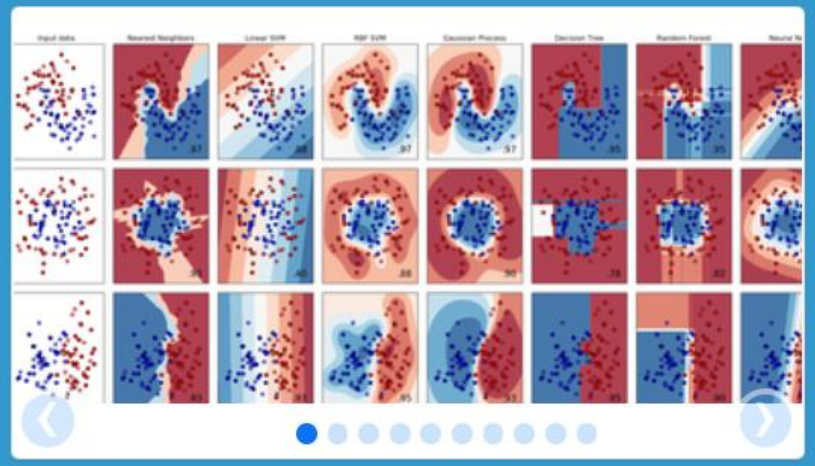
Intel(R) Extension for Scikit-learn

THE MOST POPULAR ML PACKAGE FOR PYTHON*

scikit learn

Home Installation Documentation Examples

Google Custom Search Search



scikit-learn

Machine Learning in Python

- Simple and efficient tools for data mining and data analysis
- Accessible to everybody, and reusable in various contexts
- Built on NumPy, SciPy, and matplotlib
- Open source, commercially usable - BSD license

Classification

Identifying to which category an object belongs to.

Applications: Spam detection, Image recognition.
Algorithms: SVM, nearest neighbors, random forest, … — Examples

Regression

Predicting a continuous-valued attribute associated with an object.

Applications: Drug response, Stock prices.
Algorithms: SVR, ridge regression, Lasso, … — Examples

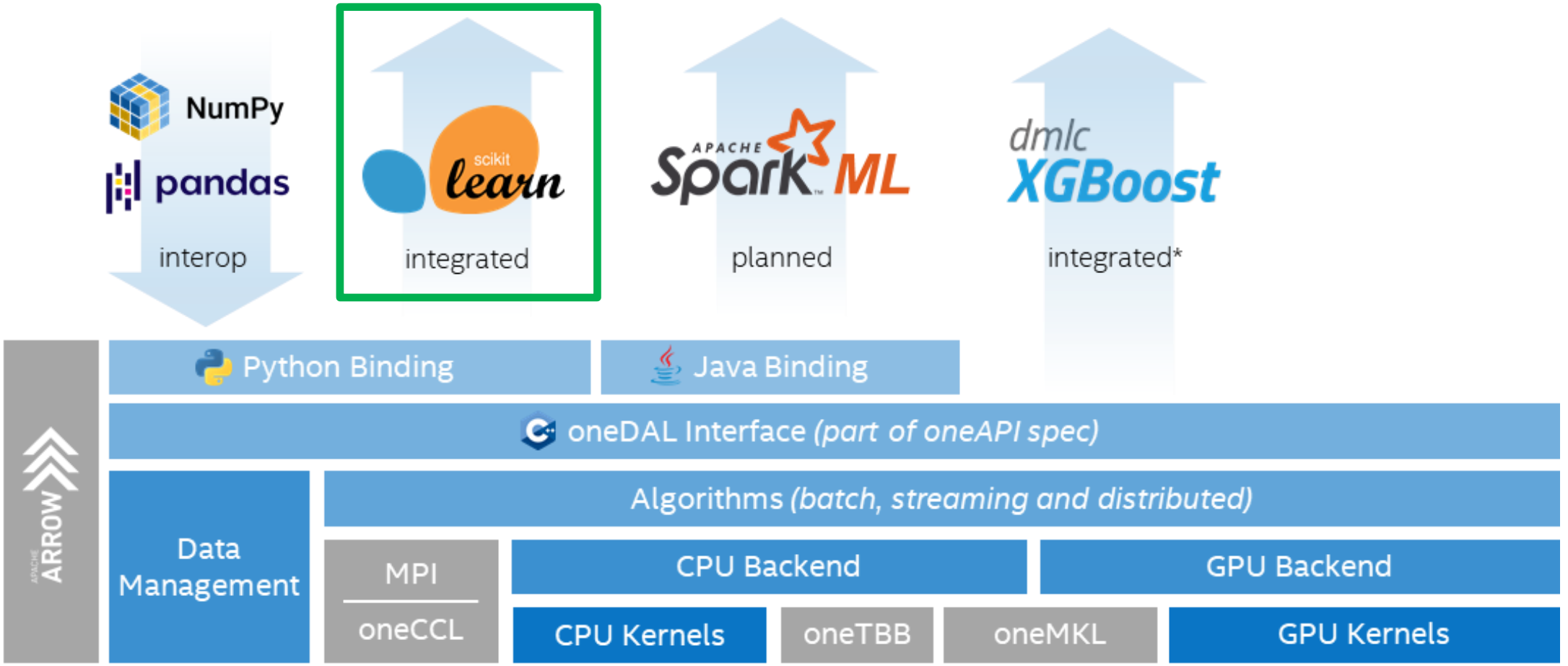
Clustering

Automatic grouping of similar objects into sets.

Applications: Customer segmentation, Grouping experiment outcomes
Algorithms: k-Means, spectral clustering, mean-shift, … — Examples

oneAPI Data Analytics Library (oneDAL)

Optimized building blocks for all stages of data analytics on Intel Architecture



GitHub: https://github.com/oneapi-src/oneDAL

Intel(R) Extension for Scikit-learn

Common Scikit-learn

```
from sklearn.svm import SVC

X, Y = get_dataset()


clf = SVC().fit(X, y)
res = clf.predict(X)
```

Scikit-learn mainline

Scikit-learn with Intel CPU opts

```
import daal4py as d4p
d4p.patch_sklearn()
from sklearn.svm import SVC

X, Y = get_dataset()


clf = SVC().fit(X, y)
res = clf.predict(X)
```

Available through Intel conda
(conda install daal4py –c intel)

```
> python -m daal4py <your-scikit-learn-script>
```

Monkey-patch any scikit-learn*
on the command-line

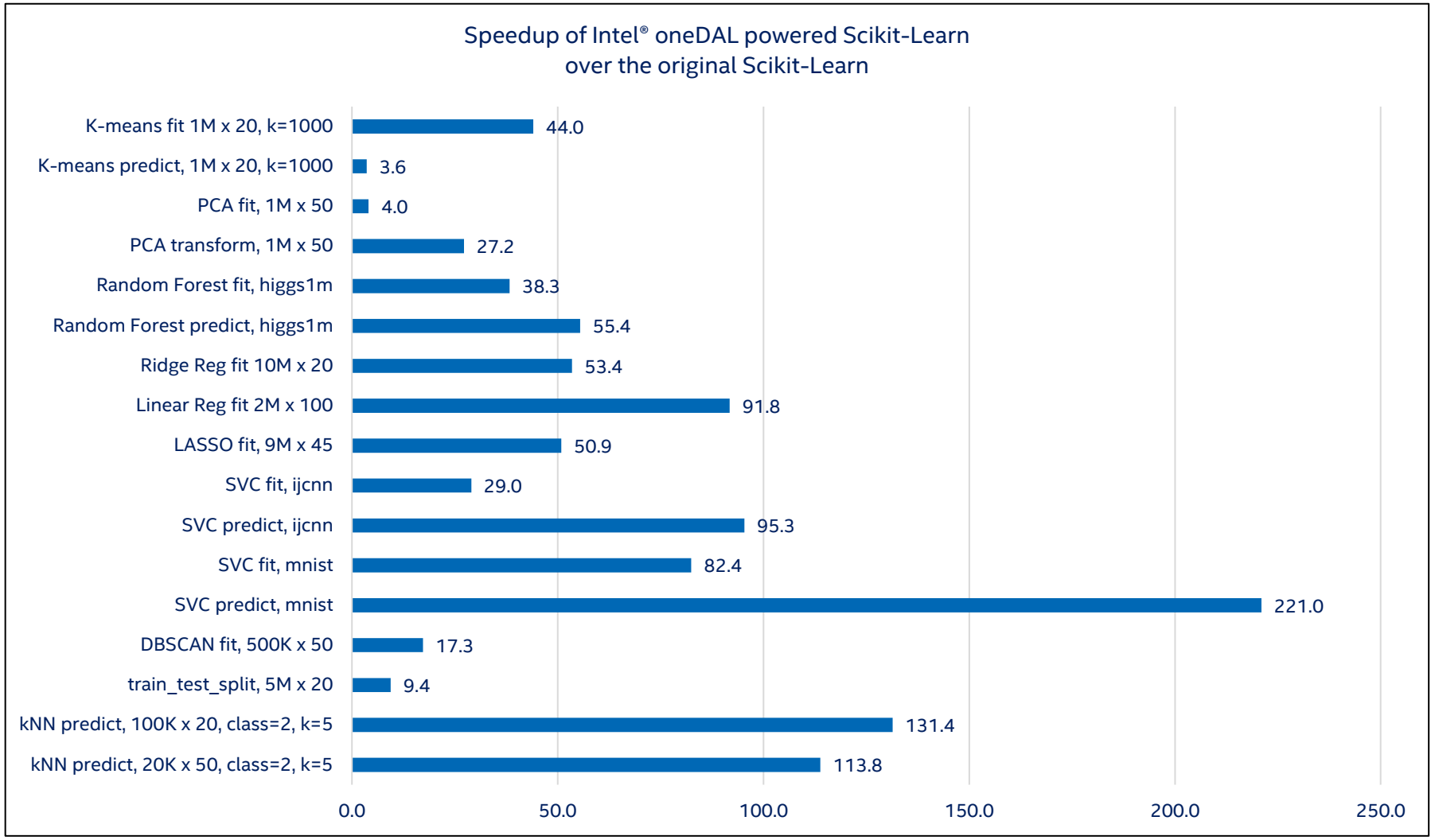
Same Code,
Same Behavior

- Scikit-learn, not scikit-learn-*like*
- Scikit-learn conformance (mathematical equivalence) defined by Scikit-learn Consortium, continuously vetted by public CI

Available algorithms

- Accelerated IDP Scikit-learn algorithms:
  - Linear/Ridge Regression
  - Logistic Regression
  - ElasticNet/LASSO
  - PCA
  - K-means
  - DBSCAN
  - SVC
  - train_test_split(), assume_all_finite()
  - Random Forest Regression/Classification - DAAL 2020.3
  - kNN (kd-tree and brute force) - DAAL 2020.3

Intel optimized Scikit-Learn



Same Code, Same Behavior

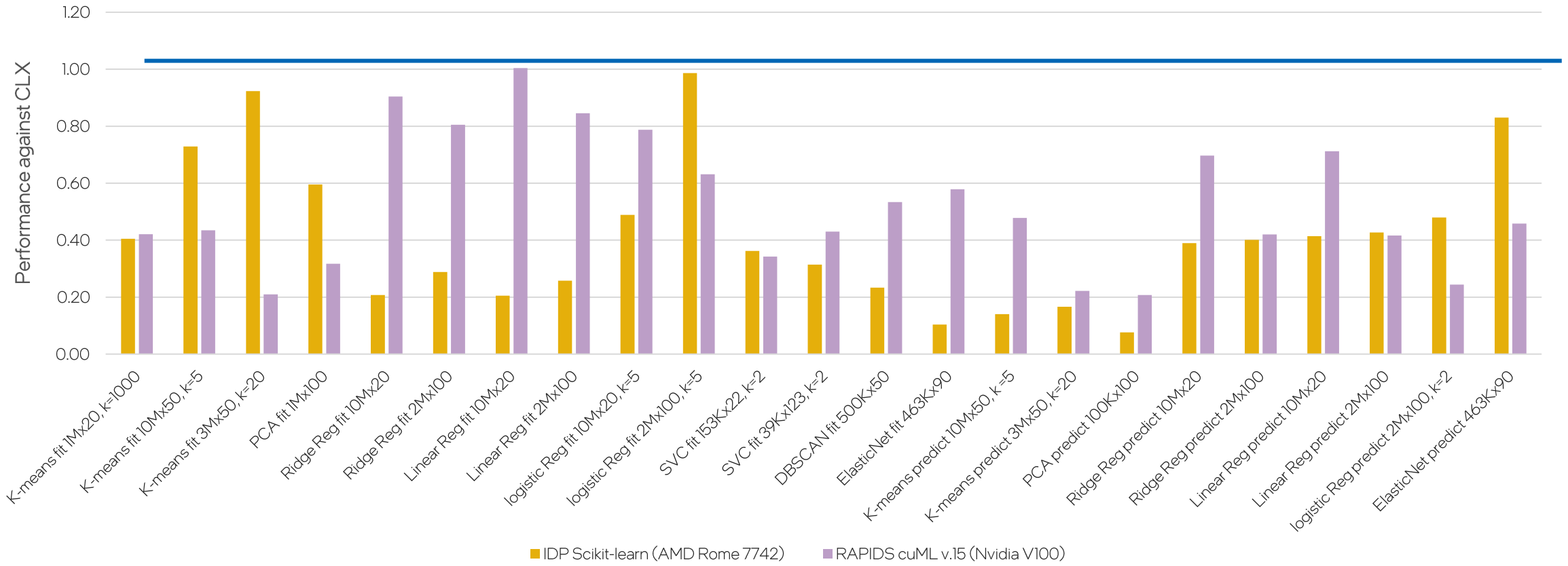
PASSED

- Scikit-learn, not scikit-learn-*like*
- Scikit-learn conformance (mathematical equivalence) defined by Scikit-learn Consortium, continuously vetted by public CI

HW: Intel Xeon Platinum 8276L CPU @ 2.20GHz, 2 sockets, 28 cores per socket;
Details: https://medium.com/intel-analytics-software/accelerate-your-scikit-learn-applications-a06cacf44912

Competitor's Relative Performance vs. Intel® Distribution for Python* (IDP) with Scikit-learn* from the Intel® AI Analytics Toolkit

(Intel = 1)



Testing Date: Performance results are **based on testing by Intel as of October 23, 2020** and may not reflect all publicly available security updates.

Configuration Details and Workload Setup: Intel® oneDAL beta10, Scikit-learn 0.23.1, Intel® Distribution for Python 3.7, Intel® AI Analytics Toolkit 2021.1, Intel(R) Xeon(R) Platinum8280 CPU @ 2.70GHz, 2 sockets, 28 cores per socket, microcode: 0x4003003, total available memory 376 GB, 12X32GB modules, DDR4. AMD Configuration: AMD Rome 7742 @2.25 GHz, 2 sockets, 64 cores per socket, microcode: 0x8301038, total available memory 512 GB, 16X32GB modules, DDR4, Intel® oneDAL beta10, Scikit-learn 0.23.1, Intel® Distribution for Python 3.7. NVIDIA Configuration: Nvidia Tesla V100-16Gb, total available memory 376 GB, 12X32GB modules, DDR4, Intel(R) Xeon(R) Platinum 8280 CPU @ 2.70GHz, 2 sockets, 28 cores per socket, microcode: 0x5003003, cuDF 0.15, cuML 0.15, CUDA 10.2.89, driver 440.33.01, Operation System: CentOS Linux 7 (Core), Linux 4.19.36 kernel.

Demo

XGBoost

Gradient Boosting - Overview

Gradient Boosting:

- Boosting algorithm (Decision Trees - base learners)
- Solve many types of ML problems (classification, regression, learning to rank)
- Highly-accurate, widely used by Data Scientists
- Compute intensive workload
- Known implementations: XGBoost*, LightGBM*, CatBoost*, Intel® oneDAL, …

Gradient Boosting Acceleration – gain sources

Pseudocode for XGBoost* (0.81) implementation

```
def ComputeHist(node):
  hist = []
  for i in samples:
    for f in features:
      bin = bin_matrix[i][f]
      hist[bin].g += g[i]
      hist[bin].h += h[i]
  return hist

def BuildLvl:
  for node in nodes:
    ComputeHist(node)

  for node in nodes:
    for f in features:
      FindBestSplit(node, f)

  for node in nodes:
    SamplePartition(node)
```

Memory prefetching to mitigate irregular memory access

Usage uint8 instead of uint32

SIMD instructions instead of scalar code

Nested parallelism

Advanced parallelism, reducing seq loops

Usage of AVX-512, vcompress instruction (from Skylake)

Pseudocode for Intel® oneDAL implementation

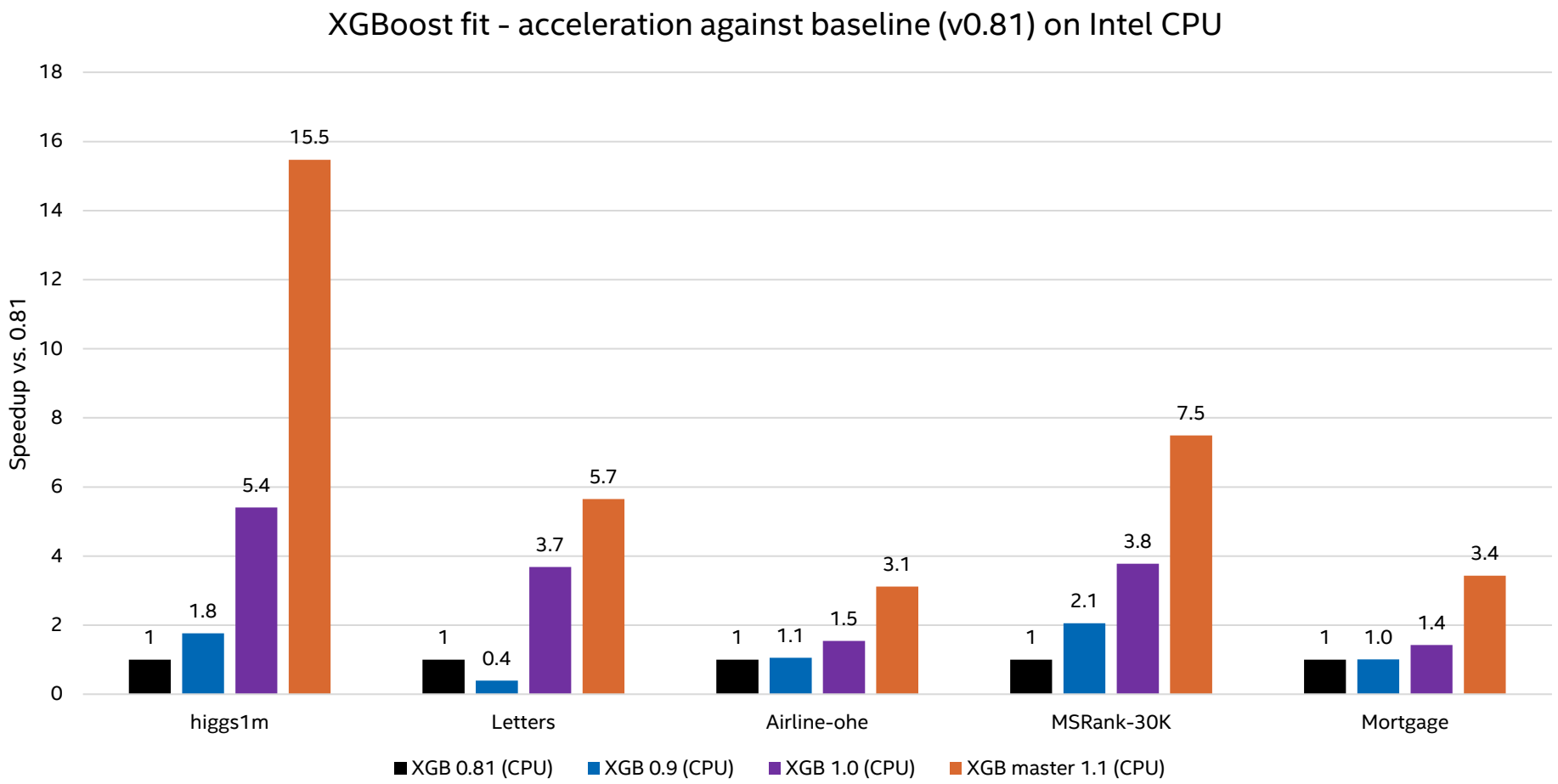
```
def ComputeHist(node):
  hist = []
  for i in samples:
    prefetch(bin_matrix[i + 10])
    for f in features:
      bin = bin_matrix[i][f]
      bin_value = load(hist[2*bin])
      bin_value = add(bin_value, gh[i])
      store(hist[2*bin], bin_value)
  return hist


def BuildLvl:
  parallel_for node in nodes:
    ComputeHist(node)

  parallel_for node in nodes:
    for f in features:
      FindBestSplit(node, f)

  parallel_for node in nodes:
    SamplePartition(node)
```

Training stage

Legend:

- Moved from Intel® oneDAL to XGBoost (v1.3)
- Already available in Intel® DAAL, potential optimizations for XGBoost*

XGBoost* fit CPU acceleration (“hist” method)

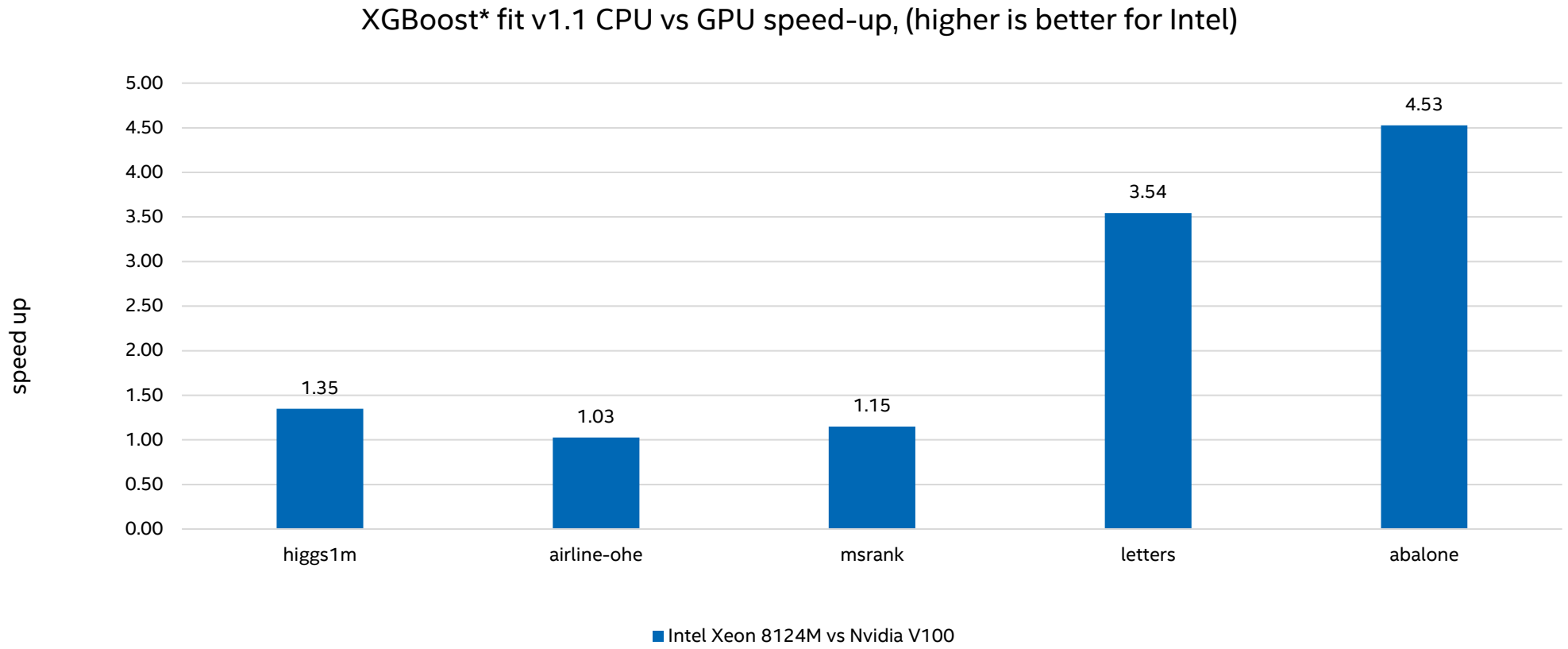


+ Reducing memory consumption

memory, Kb	Airline	Higgs1m
Before	28311860	1907812
#5334	16218404	1155156
reduced:	1.75	1.65

CPU configuration: c5.24xlarge AWS Instance, CLX 8275 @ 3.0GHz, 2 sockets, 24 cores per socket, HT:on, DRAM (12 slots / 32GB / 2933 MHz)

XGBoost* CPU vs. GPU



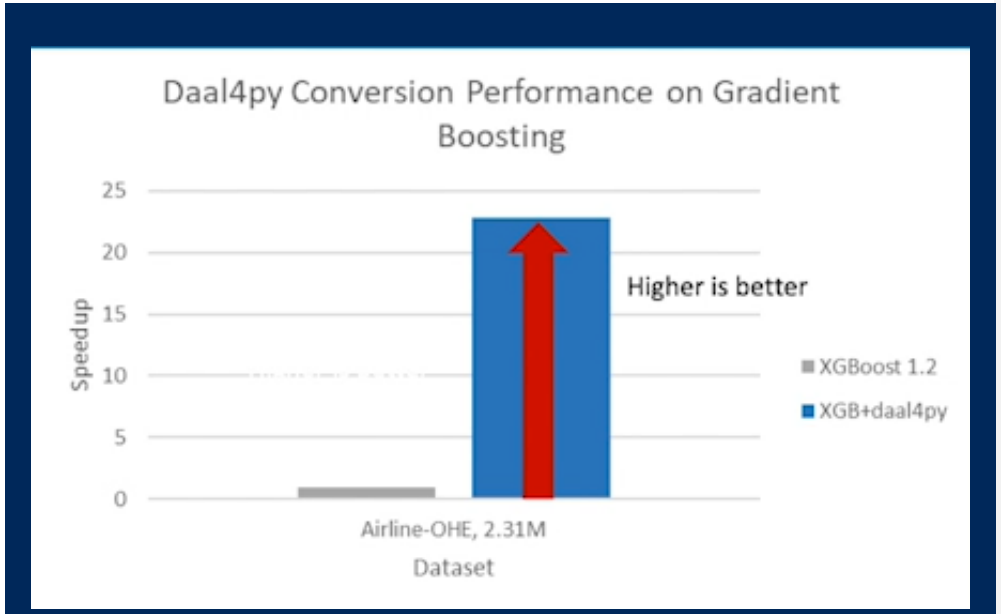
Details: https://medium.com/intel-analytics-software/new-optimizations-for-cpu-in-xgboost-1-1-81144ea21115
CPU: c5.18xlarge AWS Instance (2 x Intel® Xeon Platinum 8124M @ 18 cores, OS: Ubuntu 20.04.2 LTS, 193 GB RAM.
GPU: p3.2xlarge AWS Instance (GPU: NVIDIA Tesla V100 16GB, 8 vCPUs), OS: Ubuntu 18.04.2 LTS, 61 GB RAM.
SW: XGBoost 1.1:build from sources. compiler – G++ 7.4, nvcc 9.1. Intel DAAL: 2019.4 version, downloaded from conda. Python env: Python 3.6, Numpy 1.16.4, Pandas 0.25, Scikit-lean 0.21.2.
Testing Date: 5/18/2020

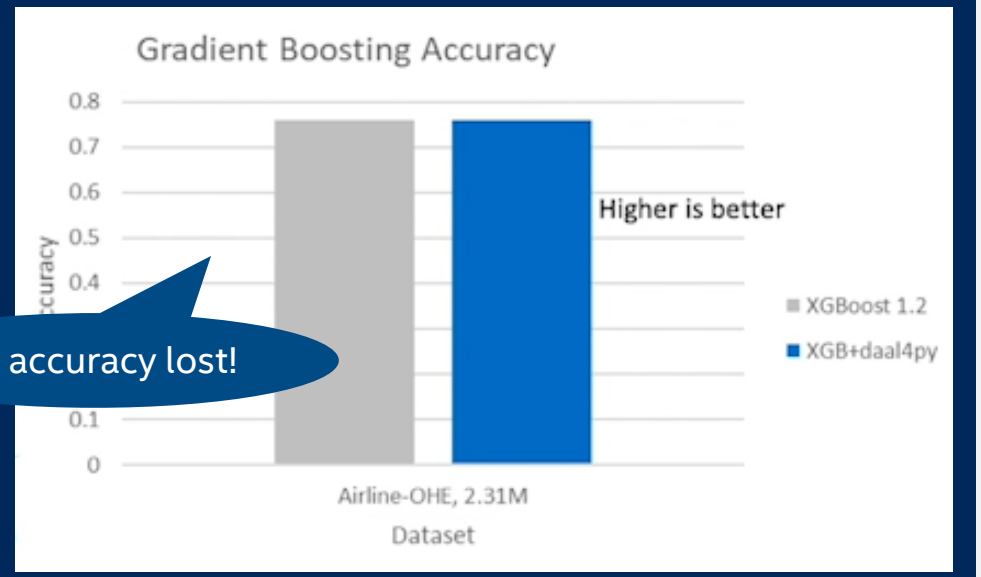
XGBoost* and LightGBM* Prediction Acceleration with Daal4Py

- Custom-trained XGBoost* and LightGBM* Models utilize Gradient Boosting Tree (GBT) from Daal4Py library for performance on CPUs
- No accuracy loss; 23x performance boost by simple model conversion into daal4py GBT:

```
# Train common XGBoost model as usual
xgb_model = xgb.train(params, X_train)

import daal4py as d4p

# XGBoost model to DAAL model
daal_model = d4p.get_gbt_model_from_xgboost(xgb_model)

# make fast prediction with DAAL
daal_prediction = d4p.gbt_classification_prediction(...).compute(X_test, daal_model)
```

- Advantages of daal4py GBT model:
  - More efficient model representation in memory
  - Avx512 instruction set usage
  - Better L1/L2 caches locality





For more complete information about performance and benchmark results, visit www.intel.com/benchmarks.
See backup for configuration details.

Demo

Envision a GPU-enabled Python Library Ecosystem Data Parallel Python

Extending PyData ecosystem for XPU

numpy → *dpnp*

ndarray → *dparray*

host memory → *unified shared mem*

CPU → *XPU*

Unified Python Offload Programming Model

with device_context("gpu"):

```
a_dparray = dpnp.random.random(1024, 3)
X_dparray = numba.njit(compute_embedding)(a_dparray)
res_dparray = daal4py.kmeans().compute(X_dparray)
```

Optimized Packages for Intel CPUs & GPUs

NumPy · scikit learn · XGBoost · TensorFlow · PyTorch · • • •

Jit Compilation

Numba

```
@njit(parallel=True)
def foo(x, y):
    return np.matmul(x, y)
```

Unified Data & Execution Infrastructure

zero-copy USM array interface

common device execution queues

DPC++ RUNTIME

OpenCL | Level 0 | CUDA

Scikit-Learn on XPU

Stock on Host:

```
from sklearn.svm import SVC

X, Y = get_dataset()


clf = SVC().fit(X, y)
res = clf.predict(X)
```

Optimized on Host:

```
import daal4py as d4p
d4p.patch_sklearn()

from sklearn.svm import SVC

X, Y = get_dataset()


clf = SVC().fit(X, y)
res = clf.predict(X)
```

Offload to XPU:

```
import daal4py as d4p
d4p.patch_sklearn()
import dpctl

from sklearn.svm import SVC

X, Y = get_dataset()

with dpctl.device_context("gpu"):
    clf = SVC().fit(X, y)
    res = clf.predict(X)
```

SAME NUMERIC BEHAVIOR

as defined by Scikit-learn Consortium

& continuously validated by CI

QnA

Backup slides

INSTALLING INTEL® DISTRIBUTION FOR PYTHON* 2021

Anaconda.org
https://anaconda.org/intel/packages

```
> conda create -n idp -c intel intelpython3_core python=3.x
> conda activate idp
> conda install intel::numpy
```

YUM/APT

https://software.intel.com/content/www/us/en/develop/articles/installing-intel-free-libs-and-python-apt-repo.html
https://software.intel.com/content/www/us/en/develop/articles/installing-intel-free-libs-and-python-yum-repo.html

Docker Hub

```
docker pull intelpython/intelpython3_full
```

oneAPI

https://software.intel.com/content/www/us/en/develop/tools/oneapi/ai-analytics-toolkit.html

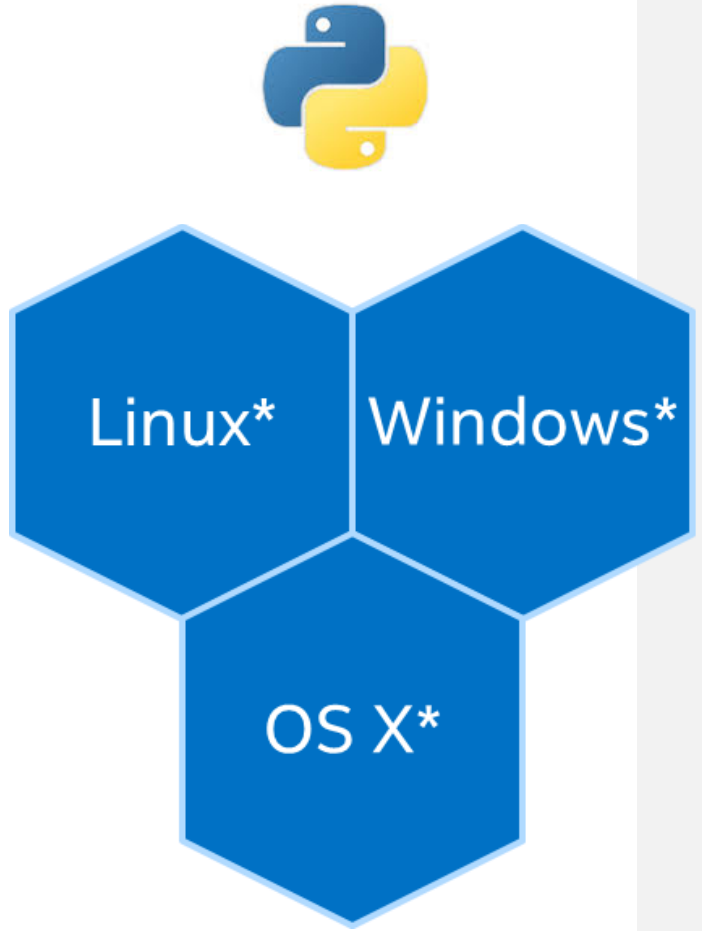
Standalone Installer

https://software.intel.com/content/www/us/en/develop/articles/oneapi-standalone-components.html#python

PyPI

```
> pip install intel-numpy
> pip install intel-scipy
> pip install mkl_fft
> pip install mkl_random
```

+ Intel library Runtime packages
+ Intel development packages



New Additions to Numba's Language Design

@dppy.kernel

```
import dpctl
import numba_dppy as dppy
import numpy as np


@dppy.kernel
def sum(a,b,c):
    i = dppy.get_global_id[0]
    c[i] = a[i] + b[i]
a = np.ones(1024 dtype=np.float32)
b = np.ones(1024, dtype=np.float32)
c = np.zeros_like(a)
with dpctl.device_context("gpu"):
    sum[1024, dppy. DEFAULT_LOCAL_SIZE](a, b, c)
```

Explicit kernels, Low-level kernel programming for expert ninjas

@njit

```
from numba import njit
import numpy as np
import dpctl

@njit
def f1(a, b):
    c = a + b
    return c

a = np.ones(1024 dtype=np.float32)
b = np.ones(1024, dtype=np.float32)
with dpctl.device_context("gpu"):
    c = f1(a, b)
```

NumPy-based array programming, auto-offload, high-productivity

Seamless interoperability and sharing of resources

```
import dpctl, numba, dpnp, daal4py

@numba.njit
def compute(a):
    ...

with dpctl.device_context("gpu"):
    a_dparray   = dpnp.random.random(1024, 3)
    X_dparray   = compute(a_dparray)
    res_dparray = daal4py.kmeans().compute(X_dparray)
```

▸ Numba function

▸ daal4py function

- Different packages share same execution context
- Data can be exchanged without extra copies and kept on the device

Portability Across Architectures

```
import numba
import numpy as np
import math

@numba.vectorize(nopython=True)
def cndf2(inp):
    out = 0.5 + 0.5 * math.erf((math.sqrt(2.0) / 2.0) * inp)
    return out

@numba.njit(parallel={"offload": True}, fastmath=True)
def blackscholes(sptprice, strike, rate, volatility, timev):
    logterm = np.log(sptprice / strike)
    powterm = 0.5 * volatility * volatility
    den = volatility * np.sqrt(timev)
    d1 = (((rate + powterm) * timev) + logterm) / den
    d2 = d1 - den
    NofXd1 = cndf2(d1)
    NofXd2 = cndf2(d2)
    futureValue = strike * np.exp(-rate * timev)
    c1 = futureValue * NofXd2
    call = sptprice * NofXd1 - c1
    put = call - futureValue + sptprice
    return put
```

```
# Runs on CPU by default
blackscholes(...)

# Runs on GPU
with dpctl.device_context("gpu"):
    blackscholes(...)

# In future
with dpctl.device_context(“cuda:gpu"):
    blackscholes(...)
```