TRADITIONAL MACHINE LEARNING WITH ONEDAL AND XGBOOST*

Rachel Oberman – AI Technical Consulting Engineer

INTRODUCING
oneAPI

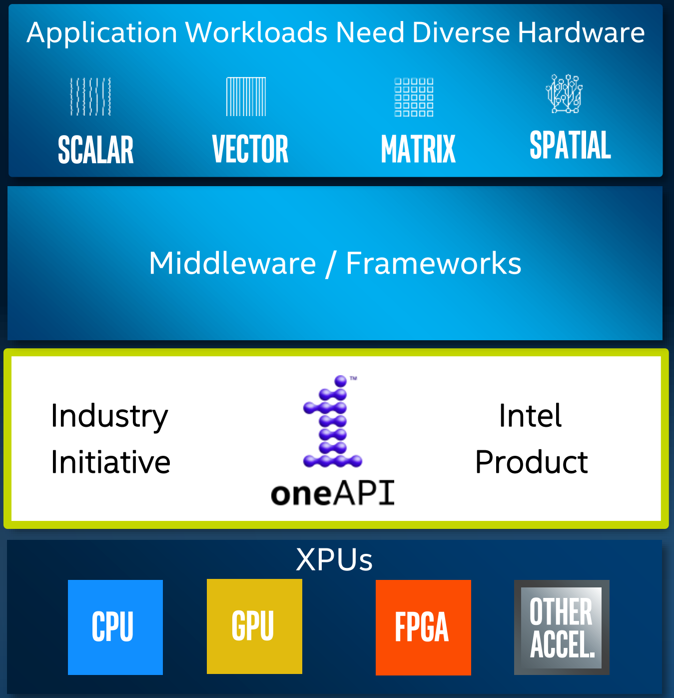
Unified programming model to simplify development across diverse architectures

Unified and simplified language and libraries for expressing parallelism

Uncompromised native high-level language performance

Based on industry standards and open specifications

Interoperable with existing HPC programming models



INTEL® ONEAPI TOOLKITS(BETA)

TOOLKITS TAILORED TO YOUR NEEDS

Domain-specific sets of tools to get your job done quickly.

Intel® oneAPI Base Toolkit

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

Learn More

Intel® oneAPI HPC Toolkit

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

Learn More

Intel® oneAPI IoT Toolkit

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

Learn More

Intel® oneAPI DL Framework Developer Toolkit

Tools for developers & researchers who build deep learning frameworks or customize existing ones so applications run faster

Learn More

Intel® oneAPI Rendering Toolkit

Powerful rendering libraries to create high-performance, high-fidelity visualization applications

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Toolkits Powered by oneAPI

Intel® System Bring-Up Toolkit

Tools to debug & tune power & performance in pre- & post-silicon development

Learn More

Intel® Distribution of OpenVINO™ Toolkit

Tools to build high performance deep learning inference & computer vision applications (production-level tool)

Learn More

Intel® AI Analytics Toolkit

Tools to build applications that leverage machine learning & deep learning models

Learn More

SPEED UP DEVELOPMENT
WITH OPEN AI SOFTWARE

MODEL

	MACHINE LEARNING				DEEP LEARNING
TOOLKITS App Developers					ANALYTICS ZOO · MODEL ZOO · OpenVINO[1]
LIBRARIES Data Scientists	Intel® Data Analytics Acceleration Library (DAAL)	Intel® Distribution for Python* (Sklearn*, Pandas*)	R (Cart, Random Forest, e1071)	Distributed (MlLib on Spark, Mahout)	Intel Optimized Frameworks: TensorFlow*, BigDL, Caffe, ONNX, mxnet, PyTorch. *More framework optimizations in progress…*
KERNELS Library Developers	Intel® Math Kernel Library (Intel® MKL)				Intel® oneAPI Collective Communication Library (Intel® oneCCL); Deep Neural Networks Library (Intel® oneDNN)

CPU ▪ GPU

Visit: www.intel.ai/technology

1 An open source version is available at: 01.org/openvinotoolkit

*Other names and brands may be claimed as the property of others.

Developer personas show above represent the primary user base for each row, but are not mutually-exclusive

All products, computer systems, dates, and figures are preliminary based on current expectations, and are subject to change without notice.

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MACHINE LEARNING | DEEP LEARNING

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Intel Optimized Frameworks

TensorFlow* BigDL Caffe ONNX mxnet PyTorch

More framework optimizations in progress…

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Accelerate libraries with Intel® Distribution for Python*

High Performance Python* for Scientific Computing, Data Analytics, Machine Learning

FASTER PERFORMANCE

Performance Libraries, Parallelism, Multithreading, Language Extensions

Accelerated NumPy*/SciPy*/scikit-learn* with oneMKL[1] & oneDAL[2]

Data analytics, machine learning with scikit-learn, daal4py

Optimized run-times Intel MPI®, Intel® TBB

Scale with Numba* & Cython*

Includes optimized mpi4py, works with Dask* & PySpark*

Optimized for latest Intel® architecture

GREATER PRODUCTIVITY

Prebuilt & Accelerated Packages

Prebuilt & optimized packages for numerical computing, machine/deep learning, HPC & data analytics

Drop-in replacement for existing Python*

Usually NO code changes required!

Conda build recipes included in packages

Free download & free for all uses including commercial deployment

ECOSYSTEM COMPATIBILITY

Supports Python* 2.7 & 3.6, & 3.7 conda, pip

Compatible & powered by Anaconda*, supports conda & pip

Distribution & individual optimized

oneMKL accelerated NumPy*, and SciPy now in Anaconda*!

Optimizations upstreamed to main Python* trunk

Commercial support through Intel® Parallel Studio XE

Intel® Architecture Platforms

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

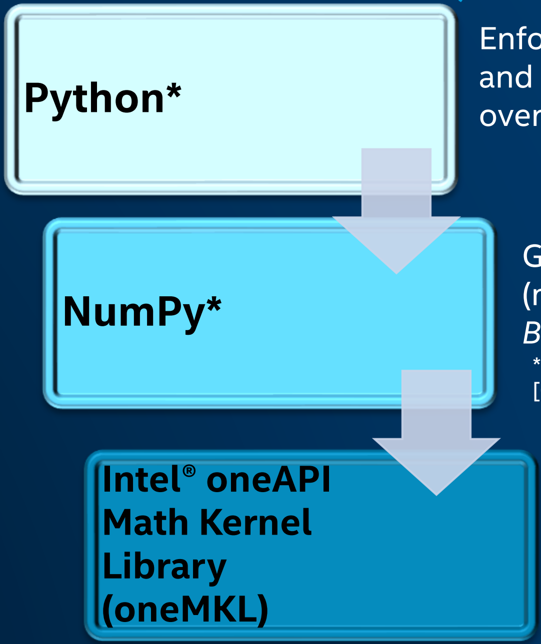
[1]Intel® oneAPI Math Kernel Library
[2]Intel® oneAPI Data Analytics Library

Performance Optimization:

Introduction to Python Performance, cont.*

The layers of quantitative Python*

- The Python* language is interpreted and has many type checks to make it flexible
- Each level has various tradeoffs; *NumPy** value proposition is immediately seen
- For best performance, escaping the Python* layer early is best method



Enforces *Global Interpreter Lock* (GIL) and is single-threaded, abstraction overhead. No advanced types.

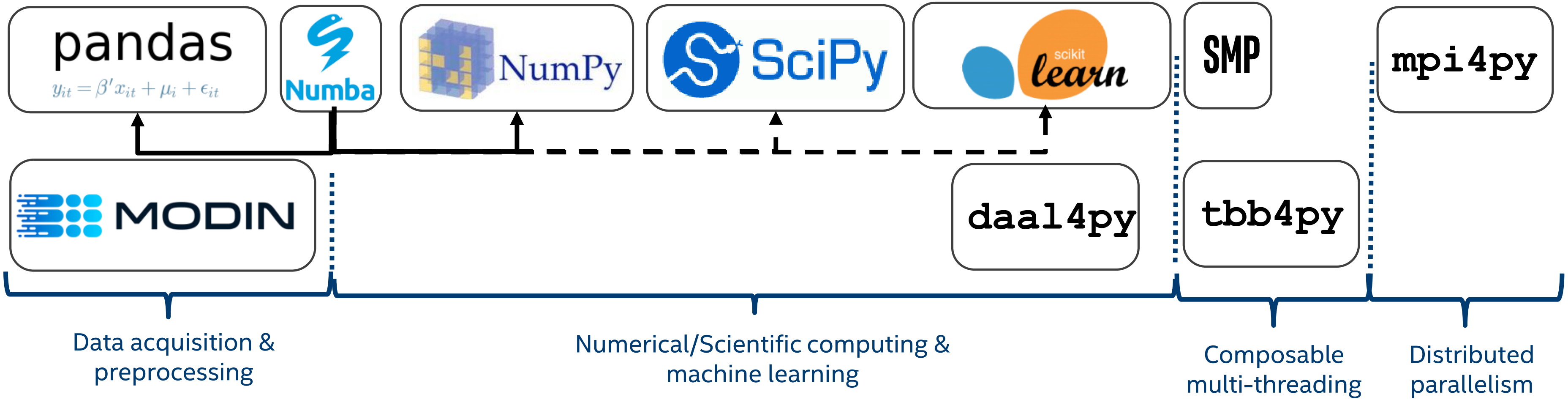
Gets around the GIL (multi-thread and multi-core)
BLAS API can be the bottleneck
*Basic Linear Algebra Subprograms (BLAS) [CBLAS]

Gets around BLAS API bottleneck
Much stricter typing
Fastest performance level
Dispatches to hardware vectorization

Intel® oneMKL included with Anaconda* standard bundle; is Free for Python*

Productivity with Performance via Intel® Distribution for Python*

Intel® Distribution for Python*



Learn More: software.intel.com/distribution-for-python

https://www.anaconda.com/blog/developer-blog/parallel-python-with-numba-and-parallelaccelerator/

Intel Distribution of Modin with OmnisciDB backend

- A lightweight DataFrame to seamlessly scale Pandas workflows across multi-nodes, multi-cores
- Pandas compatible API - No upfront cost to learning a new API.
  - Only add one line: 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
- In the backend, Modin is supported by OmnisciDB, a performant framework for end-to-end analytics that has been optimized to harness the computing power of existing and emerging Intel® hardware

Installing Intel® Distribution for Python* 2020

Standalone Installer

Download full installer from
https://software.intel.com/en-us/intel-distribution-for-python

Anaconda.org
Anaconda.org/intel channel

```
> conda config --add channels intel
> conda install intelpython3_full
> conda install intelpython3_core
```

PyPI

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

+ Intel library Runtime packages
+ Intel development packages

Docker Hub

```
docker pull intelpython/intelpython3_full
```

YUM/APT

Access for yum/apt:
https://software.intel.com/en-us/articles/installing-intel-free-libs-and-python

2.7 & 3.6 & 3.7

Linux*

Windows*

OS X*

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with open AI software

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Speed-up Machine Learning and Analytics with Intel® oneAPI Data Analytics Library (oneDAL)

Boost Machine Learning & Data Analytics Performance

- Helps applications deliver better predictions faster
- Optimizes data ingestion & algorithmic compute together for highest performance
- Supports offline, streaming & distributed usage models to meet a range of application needs
- Split analytics workloads between edge devices and cloud to optimize overall application throughput

Learn More: software.intel.com/daal

What's New in the 2020 Release

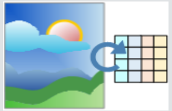
New Algorithms:

- Probabilistic classification and variable importance computation for gradient boosted trees
- Classification stump with information gain and Gini index split methods
- Regression stump with the Mean Squared Error (MSE) algorithm split method

Pre-processing

Decompression, Filtering, Normalization

Transformation



Aggregation, Dimension Reduction

Analysis

Summary Statistics Clustering, etc.

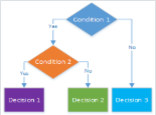
Modeling

Machine Learning (Training) Parameter Estimation Simulation

Validation

Hypothesis Testing Model Errors

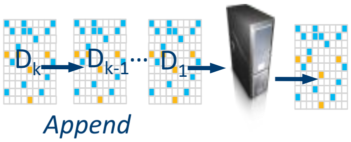
Decision Making



Forecasting Decision Trees, etc.

Processing Modes

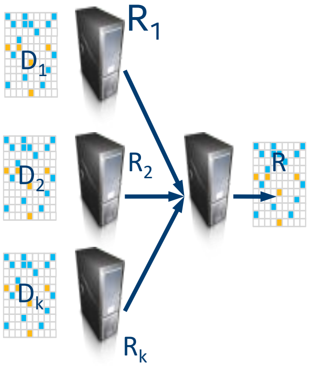
Batch Processing



$R = F(D_1,\ldots,D_k)$

```
d4p.kmeans_init(10, method="plusPlusDense")
```

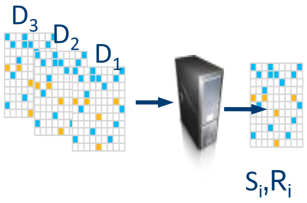
Distributed Processing



$R = F(R_1,\ldots,R_k)$

```
d4p.kmeans_init(10, method="plusPlusDense“,
distributed=“True”)
```

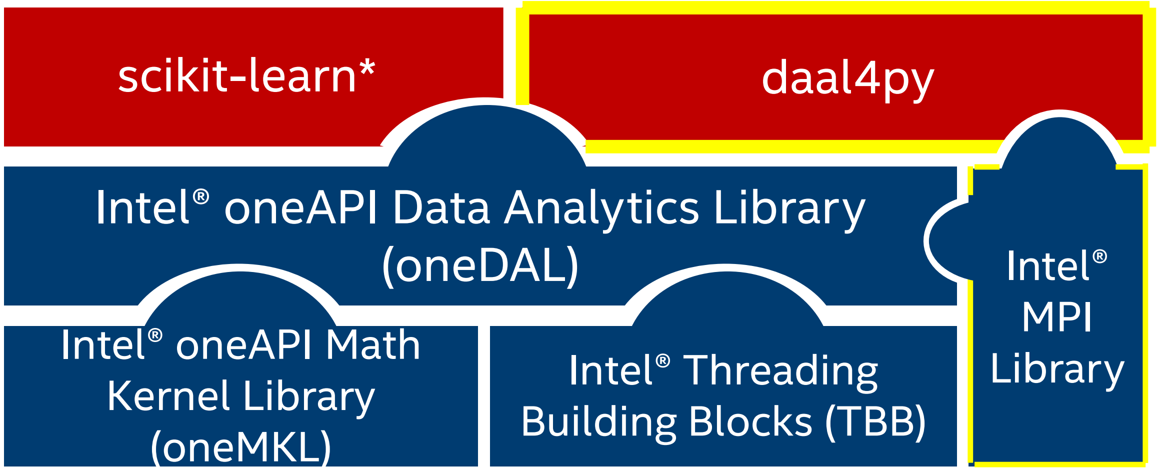
Online Processing



$S_{i+1} = T(S_i,D_i)$
$R_{i+1} = F(S_{i+1})$

```
d4p.kmeans_init(10, method="plusPlusDense“,
streaming=“True”)
```

Scaling Machine Learning Beyond a Single Node



Simple Python* API
Powers scikit-learn*

Powered by Intel® oneDAL

Scalable to multiple nodes

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

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

```
import daal4py.sklearn
daal4py.sklearn.patch_sklearn()
```

Monkey-patch any scikit-learn* programmatically

https://intelpython.github.io/daal4py/sklearn.html#

oneAPI Data Analytics Library (oneDAL)

PCA
KMeans
LinearRegression
Ridge
SVC
pairwise_distances
logistic_regression_path

Scikit-Learn* Equivalents
USE_DAAL4PY_SKLEARN=YES

Scikit-Learn* API Compatible

KNeighborsClassifier
RandomForestClassifier
RandomForestRegressor

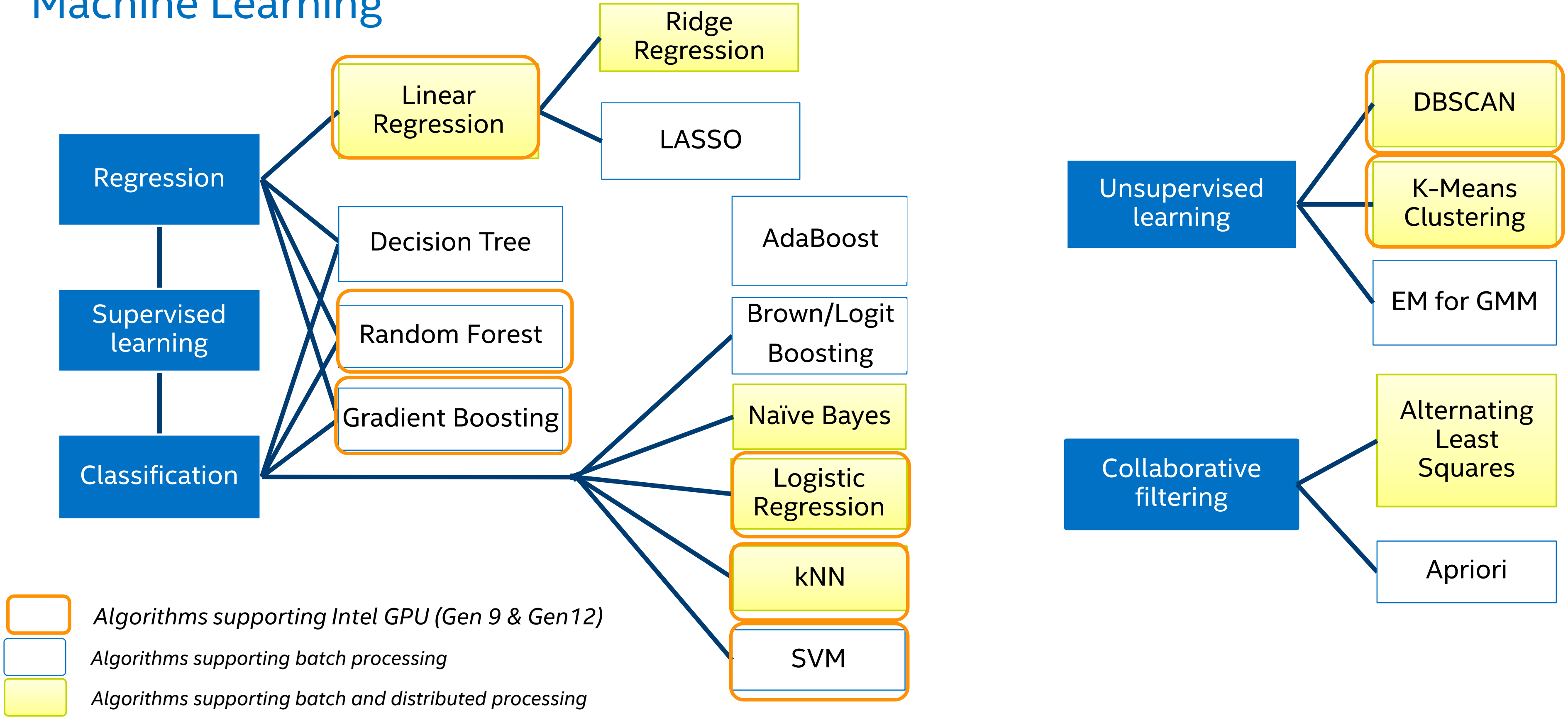
Use directly for
- Scaling to multiple nodes
- Streaming data
- Non-homogeneous dataframes

daal4py

Intel® oneDAL

Intel® oneAPI Data Analytics Library(beta) (oneDAL) Algorithms

Machine Learning



Intel® oneAPI Data Analytics Library(beta) (oneDAL) algorithms
Data Transformation and Analysis

- **Basic statistics for datasets**
  - Low order moments
  - Quantiles
  - Order statistics
- **Correlation and dependence**
  - Cosine distance
  - Correlation distance
  - Variance-Covariance matrix
- **Matrix factorizations**
  - SVD
  - QR
  - Cholesky
  - tSVD
- **Dimensionality reduction**
  - PCA
- **Outlier detection**
  - Univariate
  - Multivariate

Association rule mining (Apriori)

Optimization solvers (SGD, AdaGrad, lBFGS, CD)

Math functions (exp, log,...)

Algorithms supporting batch processing Intel GPU (Gen 9 & Gen12)

Algorithms supporting batch processing

Algorithms supporting batch, online and/or distributed processing

Intel® Distribution for Python* Scikit-learn* Optimizations, cont.

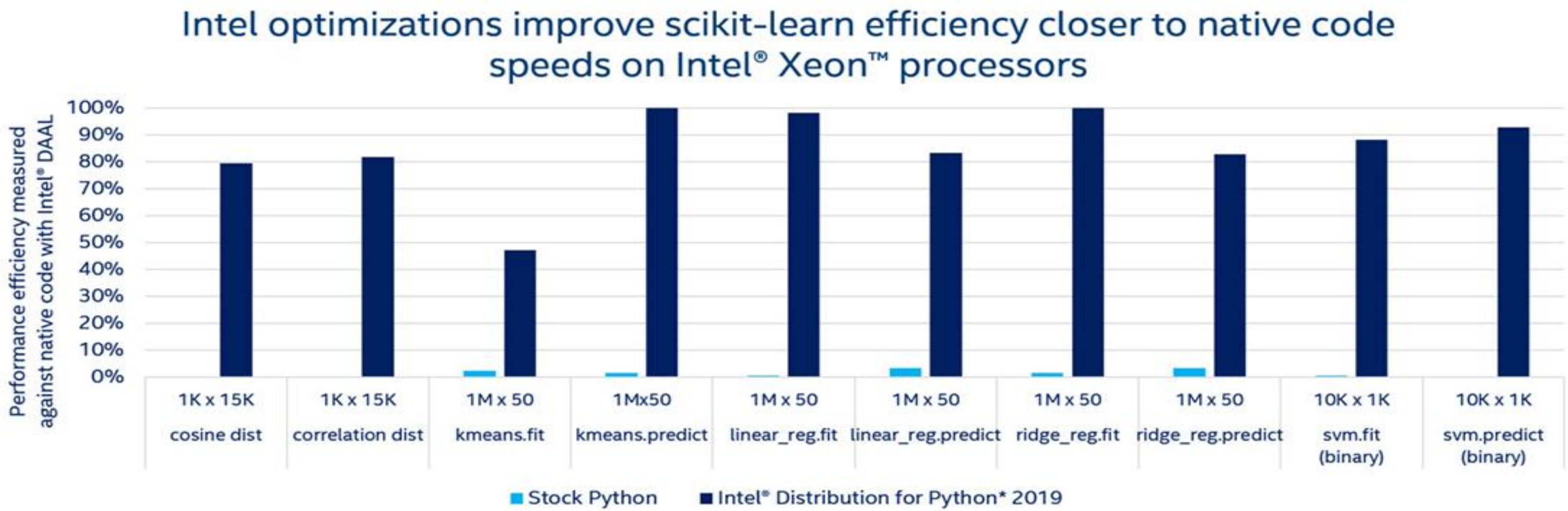


Figure 1**

Figure 1 Performance results are based on testing as of **July 9, 2018** and may not reflect all publicly available security updates. See configuration disclosure for details. No product can be absolutely secure. Software and workloads used in performance tests may have been optimized for performance only on Intel microprocessors. Performance tests, such as SYSmark and MobileMark, are measured using specific computer systems, components, software, operations and functions. Any change to any of those factors may cause the results to vary. You should consult other information and performance tests to assist you in fully evaluating your contemplated purchases, including the performance of that product when combined with other products. For more complete information, see Performance Benchmark Test Disclosure.

Testing by Intel as of July 9, 2018. Configuration: Stock Python: python 3.6.6 hc3d631a_0 installed from conda, numpy 1.15, numba 0.39.0, llvmlite 0.24.0, scipy 1.1.0, scikit-learn 0.19.2 installed from pip; Intel Python: Intel® Distribution for Python* 2019 Gold: python 3.6.5 intel_11, numpy 1.14.3 intel_py36_5, mkl 2019.0 intel_101, mkl_fft 1.0.2 intel_np114py36_6,mkl_random 1.0.1 intel_np114py36_6, numba 0.39.0 intel_np114py36_0, llvmlite 0.24.0 intel_py36_0, scipy 1.1.0 intel_np114py36_6, scikit-learn 0.19.1 intel_np114py36_35; OS: CentOS Linux 7.3.1611, kernel 3.10.0-514.el7.x86_64; Hardware: Intel(R) Xeon(R) Gold 6140 CPU @ 2.30GHz (2 sockets, 18 cores/socket, HT:off), 256 GB of DDR4 RAM, 16 DIMMs of 16 GB@2666MHz

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Strong & Weak Scaling via daal4py

Hardware	Intel(R) Xeon(R) Gold 6148 CPU @ 2.40GHz, EIST/Turbo on
	2 sockets, 20 Cores per socket
	192 GB RAM
	16 nodes connected with Infiniband
Operating System	Oracle Linux Server release 7.4
Data Type	double

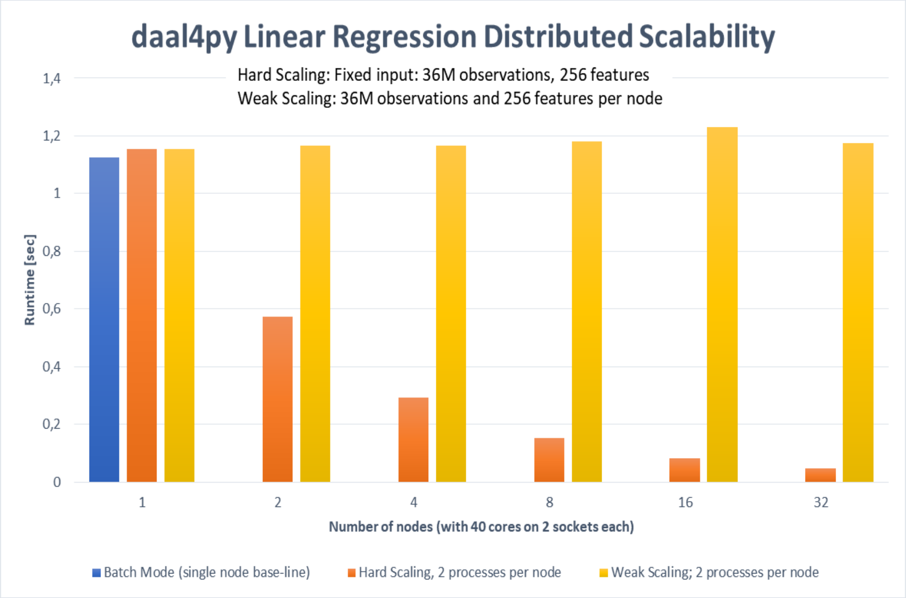


Figure 2**

On a 32-node cluster (1280 cores) daal4py computed linear regression of 2.15 TB of data in 1.18 seconds and 68.66 GB of data in less than 48 milliseconds.

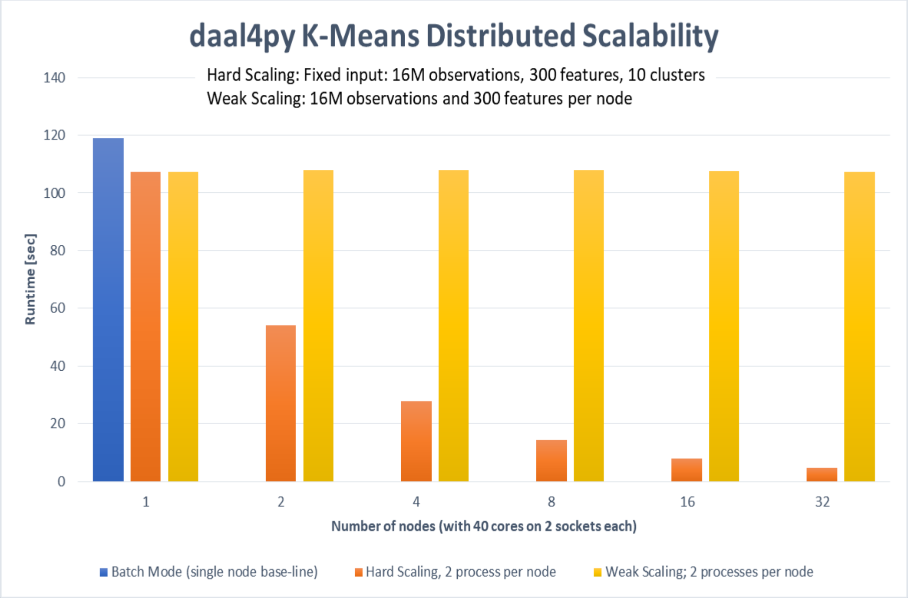
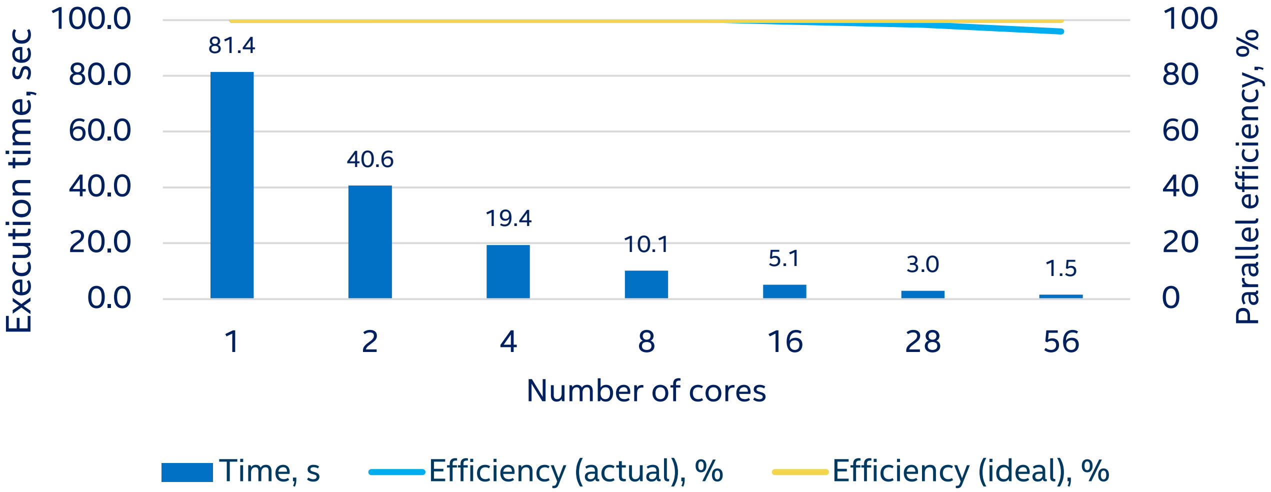


Figure 3**

On a 32-node cluster (1280 cores) daal4py computed K-Means (10 clusters) of 1.12 TB of data in 107.4 seconds and 35.76 GB of data in 4.8 seconds.

Intel® DAAL 2020 K-means fit, cores scaling

(10M samples, 10 features, 100 clusters, 100 iterations, float32)



Intel technologies' features and benefits depend on system configuration and may require enabled hardware, software or service activation. Learn more at intel.com, or from the OEM or retailer. Performance results are based on testing as of **11/11/2019** and may not reflect all publicly available security updates. See configuration disclosure for details. No product can be absolutely secure.

Software and workloads used in performance tests may have been optimized for performance only on Intel microprocessors. Performance tests, such as SYSmark and MobileMark, are measured using specific computer systems, components, software, operations and functions. Any change to any of those factors may cause the results to vary. You should consult other information and performance tests to assist you in fully evaluating your contemplated purchases, including the performance of that product when combined with other products. For more complete information visit www.intel.com/benchmarks.

Configuration: Testing by Intel as of **11/11/2019**. Intel® Data Analytics Acceleration Library 2019.3 (Intel® DAAL); Intel(R) Xeon(R) Platinum 8180 CPU @ 2.50GHz, 2 sockets, 28 cores per socket, 10M samples, 10 features, 100 clusters, 100 iterations, float32

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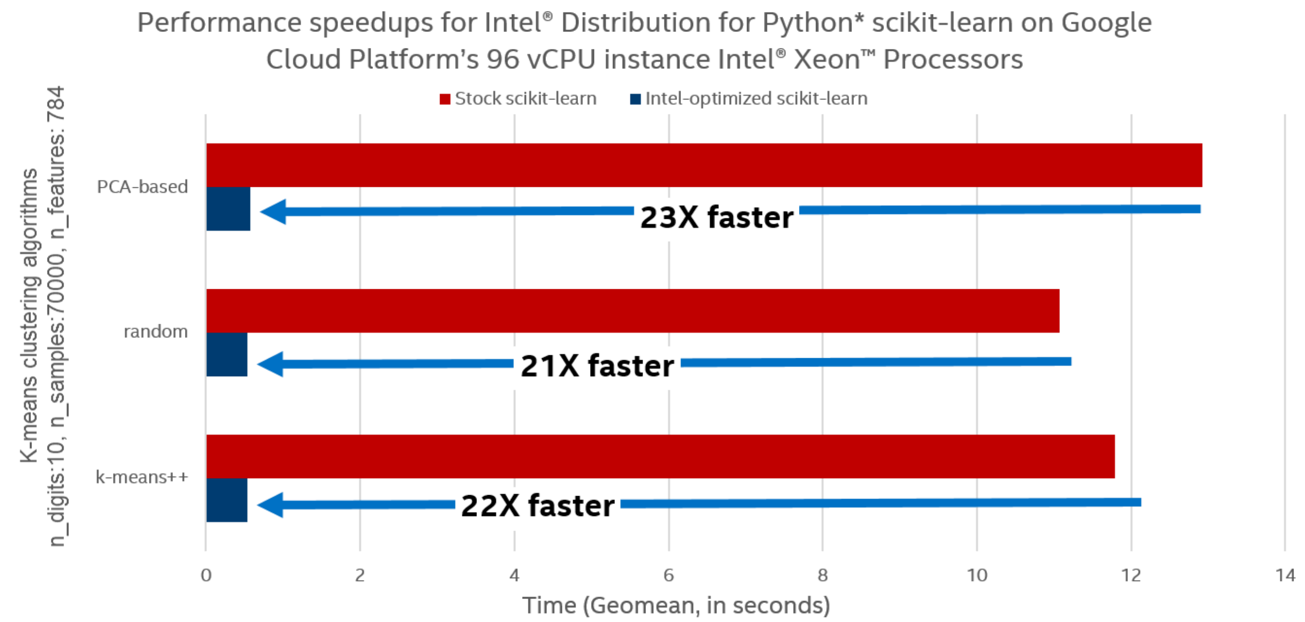
Accelerating K-Means



System Configuration: GCP VM, zone us-central1-c; 96 vCPU, Intel Skylake; 360 GB memory. Ubuntu 16.04.3 LTS; Linux instance-1 4.10.0-38-generic #42~16.04.1-Ubuntu SMP Tue Oct 10 16:32:20 UTC 2017 x86_64 x86_64 x86_64 GNU/Linux; Intel® Distribution for Python* from Docker image intelpython/intelpython3_full:latest (created 2017-09-12T20:10:42.862965559Z); Stock Python*: pip install scikit-learn

https://cloudplatform.googleblog.com/2017/11/Intel-performance-libraries-and-python-distribution-enhance-performance-and-scaling-of-Intel-Xeon-Scalable-processors-on-GCP.html

K-Means using daal4py

```
import daal4py as d4p

# daal4py accepts data as CSV files, numpy arrays or pandas dataframes
# here we let daal4py load process-local data from csv files
data = "kmeans_dense.csv"

# Create algob object to compute initial centers
init = d4p.kmeans_init(10, method="plusPlusDense")
# compute initial centers
ires = init.compute(data)
# results can have multiple attributes, we need centroids
centroids = ires.centroids
# compute initial centroids & kmeans clustering
result = d4p.kmeans(10).compute(data, centroids)
```

Distributed K-Means using daal4py

```
import daal4py as d4p

# initialize distributed execution environment
d4p.daalinit()

# daal4py accepts data as CSV files, numpy arrays or pandas dataframes
# here we let daal4py load process-local data from csv files
data = "kmeans_dense_{}.csv".format(d4p.my_procid())

# compute initial centroids & kmeans clustering
init = d4p.kmeans_init(10, method="plusPlusDense", distributed=True)
centroids = init.compute(data).centroids
result = d4p.kmeans(10, distributed=True).compute(data, centroids)
```

```
mpirun -n 4 python ./kmeans.py
```

Streaming data (linear regression) using daal4py

```
import daal4py as d4p

# Configure a Linear regression training object for streaming
train_algo = d4p.linear_regression_training(interceptFlag=True, streaming=True)

# assume we have a generator returning blocks of (X,y)...
rn = read_next(infile)

# on which we iterate
for chunk in rn:
    algo.compute(chunk.X. chunk.y)

# finalize computation
result = algo.finalize()
```

GRADIENT BOOSTING ACCELERATION – GAIN SOURCES

Pseudocode for XGBoost* (0.81)

```
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® DAAL 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® DAAL to XGBoost (v1.0) | Already available in Intel® DAAL, potential optimizations for XGBoost

Intel-optimized XGBoost*

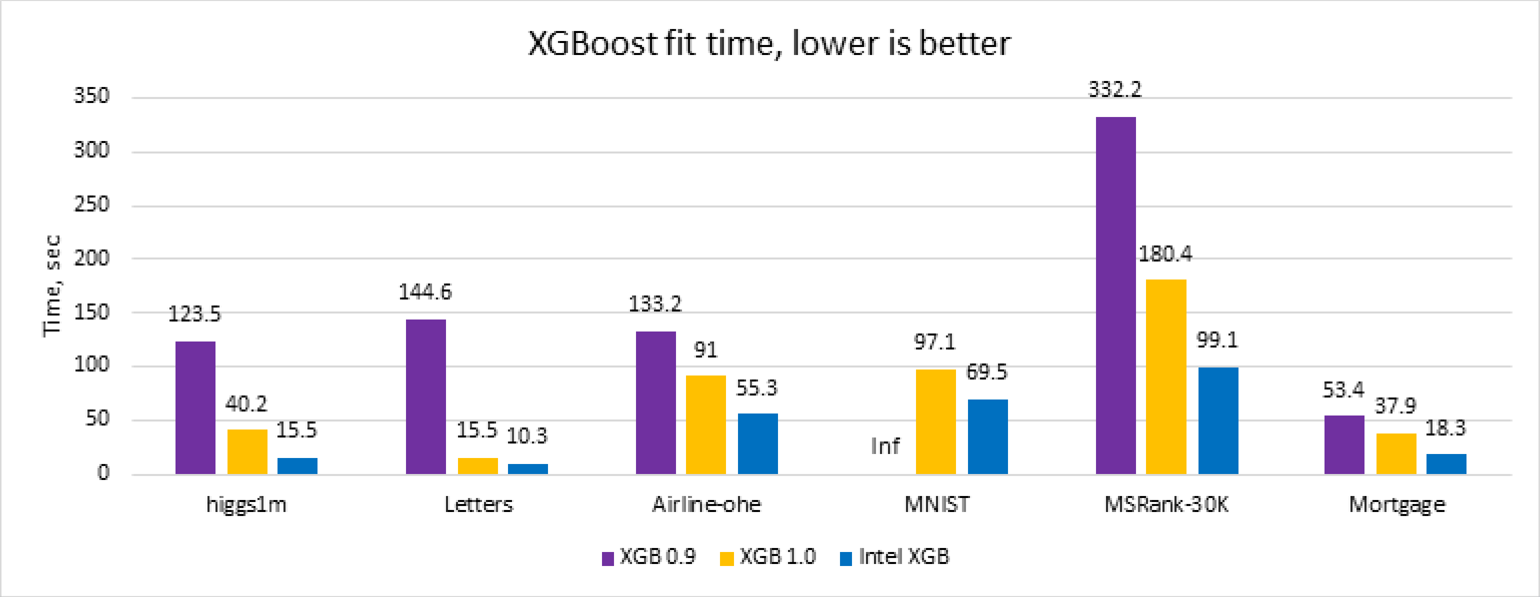


Figure 4**

1) XGBoost* 0.9 – w/ no Intel optimizations
2) XGBoost* 1.0 – the latest official XGBoost
3) XGBoost* from Intel channel

(we expect that XGBoost* 1.1 official will have similar performance).

[Intel XGB 0.9](#)

conda install xgboost –c intel

SPEED UP DEVELOPMENT

WITH OPEN AI SOFTWARE

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MACHINE LEARNING | DEEP LEARNING

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- MODEL ZOO & QUANTIZATION TOOLS
- OpenVINO

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CPU ▪ GPU

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