(intel) INTRODUCTION TO INTEL® DATA **ANALYTICS ACCELERATION LIBRARY AND** INTEL[®] DISTRIBUTION OF PYTHON

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Intel Architecture Graphics and Software (IAGS)

SPEED UP DEVELOPMENT WITH OPEN AI SOFTWARE



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LIBR Data Scier	ARIES ntists	Intel® Data Analytics Acceleration Library (DAAL)	Intel® Distribution for Python* (Sklearn*, Pandas*)	R (Cart, Random Forest, e1071)	Distributed (MlLib on Spark, Mahout)	Intel Or FensorFlow Big More framew	timized Fran Caffe t OPyTo work optimization	mework	(S NNX 'ss
KER Libra Deve	NELS ary elopers	Intel [®] Math Kernel Library (Intel [®] MKL)		Intel® o Commu I (Ir	neAPI Collec Inication Lib Intel® oneCCL)	ctive rary I	Deep Neural Networks Library (Intel® oneDNN)		

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.



SPEED UP DEVELOPMENT 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

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



Learn More: software.intel.com/daal

Processing Modes

Batch Processing



 $\mathsf{R}=\mathsf{F}(\mathsf{D}_1,...,\mathsf{D}_k)$

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

Distributed Processing R₁ Dι R_k $\mathsf{R} = \mathsf{F}(\mathsf{R}_1, \dots, \mathsf{R}_k)$

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

-0

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")



Intel[®] oneAPI Data Analytics Library_(beta) (oneDAL) Algorithms Machine Learning



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Intel[®] oneAPI Data Analytics Library_(beta) (oneDAL) algorithms Data Transformation and Analysis



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

Algorithms supporting batch, online and/or distributed processing

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oneAPI Data Analytics Library (oneDAL)

PCA KMeans LinearRegression Ridge SVC pairwise_distances logistic_regression_path

Scikit-Learn* Equivalents

Scikit-Learn* API Compatible

KNeighborsClassifier RandomForestClassifier RandomForestRegressor

Use directly for

- Scaling to multiple nodes
- Streaming data
- Non-homogeneous
 dataframes

daal4py

Intel[®] oneDAL



What makes Intel[®] oneDAL faster?



Accelerate libraries with Intel[®] Distribution for Python*

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

FASTER PERFORMANCE	GREATER PRODUCTIVITY	ECOSYSTEM COMPATIBILITY				
Performance Libraries, Parallelism, Multithreading, Language Extensions	Prebuilt & Accelerated Packages	Supports Python* 2.7 & 3.6, & 3.7 conda, pip				
Accelerated NumPy*/SciPy*/scikit-learn* with oneMKL ¹ & oneDAL ² Data analytics, machine learning with scikit-	Prebuilt & optimized packages for numerical computing, machine/deep learning, HPC & data analytics	Compatible & powered by Anaconda*, supports conda & pip Distribution & individual optimized				
learn, daal4py Optimized run-times Intel MPI®, Intel® TBB	Drop-in replacement for existing Python* Usually NO code changes required!	oneMKL accelerated NumPy*, and SciPy now in Anaconda*!Optimizations upstreamed to main Python* trunkCommercial support through Intel® Parallel Studio XE				
Includes optimized mpi4py, works with Dask* & PySpark* Optimized for latest Intel® architecture	Conda build recipes included in packages Free download & free for all uses including commercial deployment					
Intel [®] Architecture Platforms		CORE 13 CORE 13 CORE 13 CORE 15 CORE 17 Inside CORE 17 Inside CORE 15 Inside				

Operating System: Windows*, Linux*, MacOS1*

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

Performance Optimization: Introduction to Python* Performance, cont. The layers of quantitative

Enforces Global Interpreter Lock (GIL) and is single-threaded, abstraction Python* overhead. No advanced types. The Python* language is interpreted and has many type checks to make it flexible Gets around the GIL Each level has various tradeoffs; NumPy* (multi-thread and multi-core) NumPy* value proposition is immediately seen BLAS API can be the bottleneck *Basic Linear Algebra Subprograms (BLAS) [CBLAS] For best performance, escaping the Python* layer early is best method Intel[®] oneAPI Gets around BLAS API bottleneck Much stricter typing Math Kernel Fastest performance level Library Dispatches to hardware (oneMKL) vectorization

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

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® 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 <u>www.intel.com/benchmarks</u>.

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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Intel[®] Distribution for Python* Scikit-learn* Optimizations



Intel optimizations improve scikit-learn efficiency closer to native code speeds on Intel[®] Xeon[™] processors

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.

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Figure 1Software 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 <u>Performance Benchmark Test Disclosure</u>.

Testing by Intel as of July 9, 2018. Configuration: Stock Python: python 3.6.6 hca3631a_0 installed from conda, numpy 1.15, numba 0.390, llvmlite 0.24.0, scipy 1.1.0, scilit-learn 0.192, listalled 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_fit 1.0.2 intel_np114py36_6, scikl-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:0ft), 256 GB of DDR4 RAM, 16 DIMRA RAM,

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Software

Strong & Weak Scaling via daal4py

	Intel(R) Xeon(R) Gold 6148 CPU @ 2.40GHz, EIST/Turbo on
Hardware	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

daal4py Linear Regression Distributed Scalability Hard Scaling: Fixed input: 36M observations, 256 features 1,4 Weak Scaling: 36M observations and 256 features per node 1,2 1 **Runtime [sec]** 0'0 0.4 0,2 2 16 32 Number of nodes (with 40 cores on 2 sockets each) Batch Mode (single node base-line) Hard Scaling, 2 processes per node Weak Scaling: 2 processes per node

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.

daal4py K-Means Distributed Scalability



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.

Accelerating K-Means



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

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Software

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()
```

Intel-optimized XGBoost*



XGBoost* 0.9 – w/ no Intel optimizations

- 2) XGBoost* 1.0 the latest official XGBoost
- 3) XGBoost* from Intel channel

1)

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

Figure 4** Intel XGB 0.9

conda install xgboost –c intel

Demo



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Scikit-Learn Sample with oneDAL

Original image (96,615 colors)



Quantized image (64 colors, K-Means)





More Resources

Intel® Distribution for Python

- Product page overview, features, FAQs...
- <u>Training materials</u> movies, tech briefs, documentation, evaluation guides...
- <u>Support</u> forums, secure support...





Footnotes and Disclaimers

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