

INTEL PERFORMANCE LIBRARIES FOR MACHINE LEARNING AND DEEP LEARNING

Feb, 2017 Gennady.Fedorov@intel.com

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Notice revision #20110804

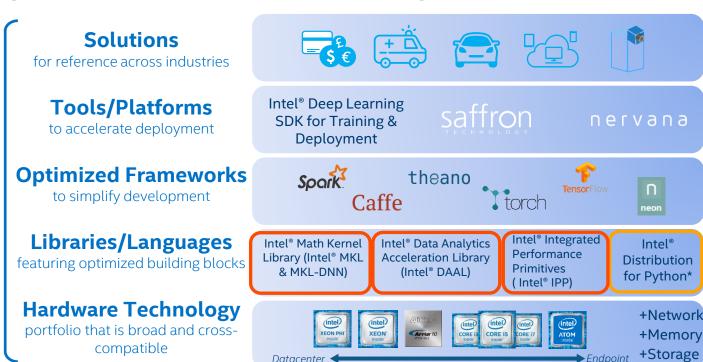


Machine Learning: Your Path to Deeper Insight

Driving increasing innovation and competitive advantage across industries



provides the foundation for success using Al



Datacenter ·

Agenda

- Intel® Math Kernel Library (Intel® MKL)
 - Overview, what's new in Intel MKL v.2017
 - Intel® MKL for machine learning
 - Neural network primitives in Intel MKL 2017 for deep learning
 - Introduction to open source Intel MKL-DNN
- Intel® Data Analytics Acceleration Library (Intel® DAAL)
- Intel[®] DAAL Case Studies



Intel MKL v.2017

Fast Fourier Summary Deep Neural Vector Math Linear Algebra And More... **Transforms Statistics** Networks • BLAS Multidimensional Trigonometric Kurtosis Splines Convolution LAPACK FFTW interfaces Hyperbolic Variation Interpolation Pooling coefficient ScaLAPACK Cluster FFT Exponential Trust Region Normalization Sparse BLAS • Log Order Fast Poisson ReLU Sparse Power statistics Solver Softmax Solvers(SMP • Min/max Root & for Vector RNGs Variance-Clusters) covariance

Iterative

Intel MKL v.2017 - what's New

- Introduced optimizations for the Intel[®] Xeon Phi[™] processor x200
- Introduced Deep Neural Networks (DNN) primitives
- Introduced new packed matrix multiplication interfaces
- Added fully distributed reordering step to Parallel Direct Sparse Solver for Clusters
- Included the latest LAPACK v3.6 enhancements
- Improved LU factorization, solve, and inverse (?GETR?) performance for very small sizes (<16).
- SparseQR & Largest or smallest EV problem Prototype Packages
- Many others

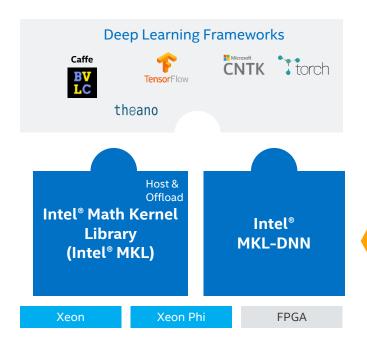


Intel® MKL for machine learning

- BLAS and Lapack
 - Packed gemm, batch gemm
 - Small matrix multiply enhancements
 - gemmt for calculating U/L triangular part of C = alpha*A*B + beta*C
 - QR, SVD, Cholesky
 - Equation solvers
- Vector Statistics
 - Random Number Generation, Summary Statistics, Convolution
- Vector Mathematical Functions
- Sparse matrix operations
 - Sparse BLAS inspector-executor API
- Deep Neural Network primitives



Intel® MKL - Intel®MKL-DNN



Deep Learning frameworks

Intel MKL-DNN is an open source IA optimized DNN APIs, combined with Intel® MKL and build tools designed for scalable, high-velocity integration with ML/DL frameworks.

- Includes open source implementations of new DNN functionality
- Delivers new algorithms ahead of MKL releases
- Open for community contributions

Intel MKL is commercial SW Performance Library to extract max Intel HW performance and provide a common interface to all Intel processors and accelerators.

Intel libraries as path to bring optimized ML/DL frameworks to Intel hardware

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



Intel MKL 2017- Deep Neural Network (DNN) Primitives

	Functionality		
Convolution	Direct (3-D); Fully connected		
Pooling	Max; Min; Average		
Activation	ReLU + variants		
Normalization	LRN; Batched		
Auxiliary	Conversion; Sum; Scale; Concat; Split		
Topologies	AlexNet; ResNet; GoogleNet v1 & v2; VGG		

Intel MKL v.2017: Deep Learning Framework Optimization

	MKL	MKL-DNN	
Functionality	BLAS, LAPACK, FFT, Sparse Solvers, Vector Math & Statistics, DNN , & more	DNN	
API	С	C, C++	
Product type	Proprietary commercial grade software Binary/Free/paid support	Open source + (GEMM binary*)	
License	EULA	Apache 2.0	
Distribution	Intel Registration Center	<u>Github</u>	
Source code	Not available	Available (less GEMM*)	
Maturity	Production	Tech preview	
Release schedule	quarterly updates	incremental weekly updates	

^{*} GEMM matrix multiply building blocks are binary

Deep learning with Intel® MKL-DNN

Intel® MKL-DNN Programming Model

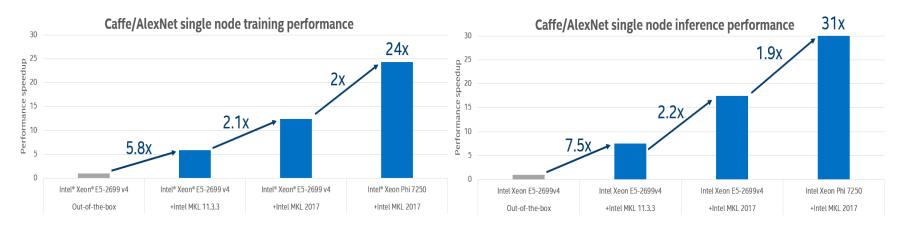
- Primitive any operation (convolution, data format re-order, memory)
 - Operation/memory descriptor - convolution parameters, memory dimensions
 - Descriptor complete description of a primitive
 - Primitive a specific instance of a primitive relying on descriptor
- Engine execution device (e.g., CPU)
- Stream execution context

```
/* Initialize CPU engine */
auto cpu engine = mkldnn::engine(mkldnn::engine::cpu, 0);
/* Create a vector of primitives */
std::vector<mkldnn::primitive> net;
/* Allocate input data and create a tensor structure that describes it */
std::vector<float> src(2 * 3 * 227 * 227);
mkldnn::tensor::dims conv src dims = {2, 3, 227, 227};
/* Create memory descriptors, one for data and another for convolution input */
auto user src md = mkldnn::memory::desc({conv src dims},
mkldnn::memory::precision::f32, mkldnn::memory::format::nchw);
auto conv src md = mkldnn::memory::desc({conv src dims},
mkldnn::memory::precision::f32, mkldnn::memory::format::any);
/* Create convolution descriptor */
auto conv desc = mkldnn::convolution::desc(
mkldnn::prop kind::forward, mkldnn::convolution::direct,
conv src md, conv weights md, conv bias md, conv dst md,
{1, 1}, {0, 0}, mkldnn::padding kind::zero);
/* Create a convolution primitive descriptor */
auto conv pd = mkldnn::convolution::primitive desc(conv desc, cpu engine);
/* Create a memory descriptor and primitive */
auto user src memory descriptor
= mkldnn::memory::primitive desc(user src md, engine);
auto user src memory = mkldnn::memory(user src memory descriptor, src);
/* Create a convolution primitive and add it to the net */
auto conv = mkldnn::convolution(conv pd, conv input, conv weights memory,
conv user bias memory, conv dst memory);
net.push back(conv);
/* Create a stream, submit all primitives and wait for completion */
mkldnn::stream().submit(net).wait();
```

Intel MKL v.2017- DNN Primitives, Performance

Brings IA-optimized performance to popular image recognition topologies:

AlexNet, Visual Geometry Group (VGG), GoogleNet, and ResNet



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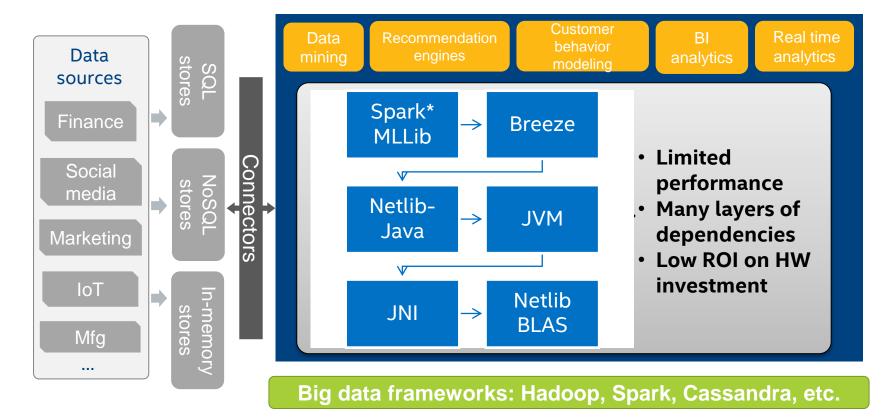
2 socket system with Intel® Xeon® Processor E5-2699 v4 (22 Cores, 2.2 GHz.), 128 GB memory, Red Hat® Enterprise Linux 6.7, <u>BVLC Caffe, Intel Optimized Caffe framework</u>, Intel® MKL 11.3.3, Intel® MKL 2017
 Intel® Xeon Phi™ Processor 7250 (68 Cores, 1.4 GHz, 166B MCDRAM), 128 GB memory, Red Hat® Enterprise Linux 6.7, <u>Intel® Optimized Caffe framework</u>, Intel® MKL 2017
 All numbers measured without taking data manipulation into account.



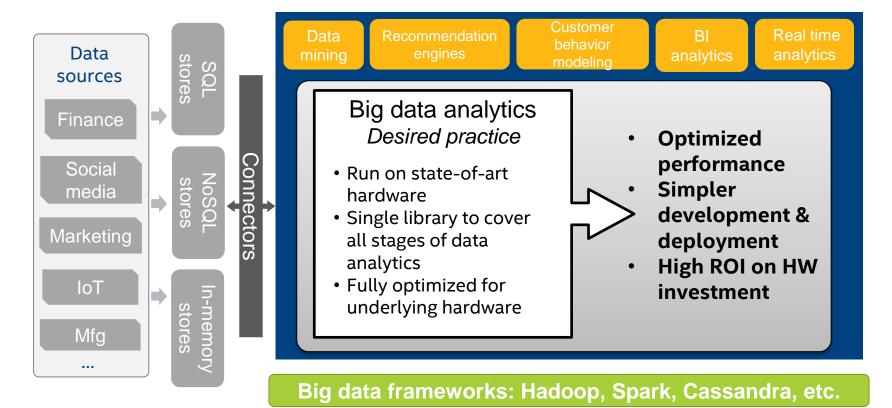
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- Intel[®] DAAL Case Studies

Problem Statement

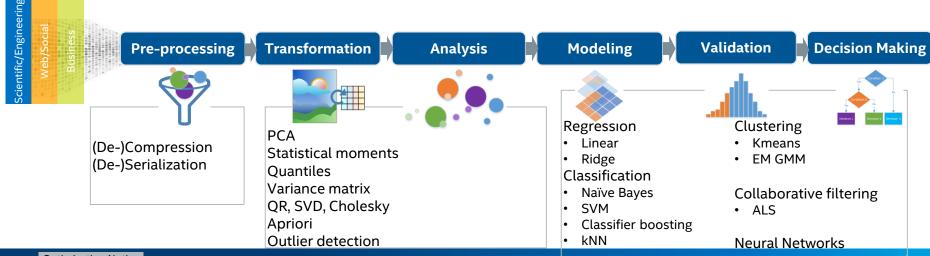


Desired Solution



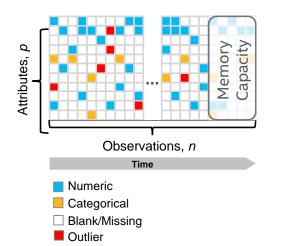
Intel® Data Analytic Acceleration Library

- Targets both data centers (Intel® Xeon® and Intel® Xeon Phi™) and edge-devices (Intel® Atom)
- Perform analysis close to data source (sensor/client/server) to optimize response latency, decrease network bandwidth utilization, and maximize security
- Offload data to server/cluster for complex and large-scale analytics

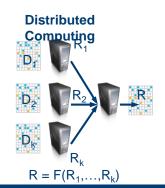




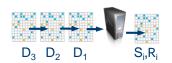
Intel® Data Analytics Acceleration Library



Big Data Attributes	Solution
Volume: Huge data not fitting into node/device memory/distributed across nodes	Distributed computing (e.g. communication-avoiding algorithms), streaming algorithms
Velocity: • Data arriving in time	Data buffering, streaming algorithms
Variety: • Non-homogeneous/sparse/missing/noisy data	 Categorical→Numeric (counters, histograms, etc) Homogeneous numeric data kernels Conversions, Indexing, Repacking Sparse data algorithms Recovery methods (bootstrapping, outlier correction)



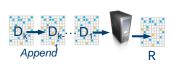
Streaming Computing



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

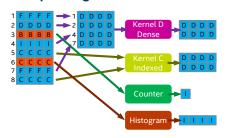
 $R_{i+1} = F(S_{i+1})$

Batch Computing

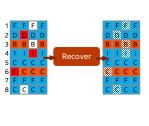


$$R = F(D_1, ..., D_k)$$

Converts, Indexing, Repacking



Data Recovery



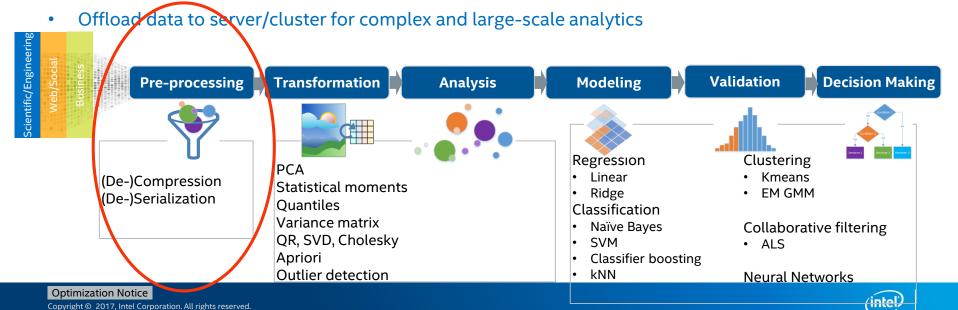
Intel® Data Analytics Acceleration Library

	Algorithms	Batch	Distributed	Online
Descriptive statistics	Low order moments	√	✓	√
	Quantiles/sorting	√		
Statistical relationships	Correlation / Variance-Covariance	√	√	✓
	(Cosine, Correlation) distance matrices	√		
Matrix decomposition	SVD	√	✓	√
	Cholesky	√		
	QR	√	√	√
Regression	Linear/ridge regression	✓	✓	✓
Classification	Multinomial Naïve Bayes	√	✓	✓
	SVM (two-class and multi-class)	√		
	Boosting (Ada, Brown, Logit)	√		
Unsupervised learning	Association rules mining (Apriori)	√		
	Anomaly detection (uni-/multi-variate)	√		
	PCA	√	✓	√
	KMeans	√	√	
	EM for GMM	√		
Recommender systems	ALS	√	√	
Deep learning	Fully connected, convolution, normalization, activation layers, model, NN, optimization solvers,	√		

Intel® Data Analytic Acceleration Library

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- Perform analysis close to data source (sensor/client/server) to optimize response latency, decrease network bandwidth utilization, and maximize security



Intel® Integrated Performance Primitives, v.2017

Image Processing

- Geometry transformations
- Linear and non-linear filtering
- Linear transforms
- Statistics and analysis
- Color models

Data Compression

- LZSS
- LZ77(ZLIB)
- LZO
- Bzip2

Computer Vision

- Feature detection
- Objects tracking
- Pyramids functions
- Segmentation, enhancement
- Camera functions
- And more

Cryptography

- Symmetric cryptography
- Hash functions
- Data authentication
- Public key

Signal Processing

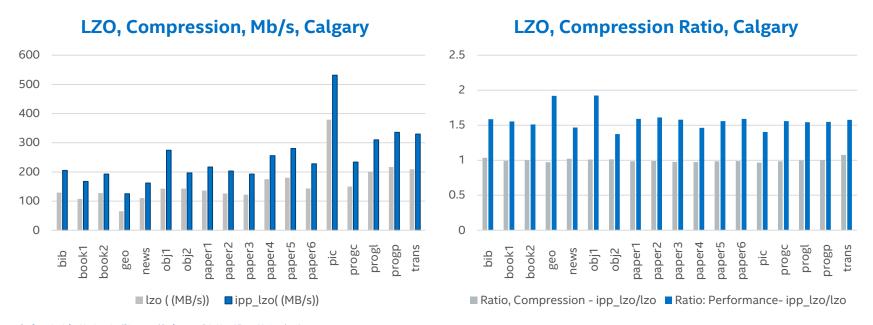
- Transforms
- Convolution, Cross-Correlation
- Signal generation
- Digital filtering
- Statistical

String Processing

- String Functions: Find, Insert, Remove, Compare, etc.
- Regular expression



Intel® IPP v.2017 update 2, LZO optimization

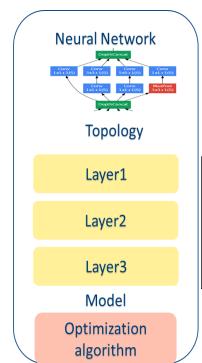


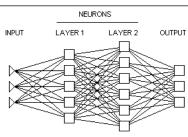
Configuration Info - Versions: Intel® Integrated Performance Primitives Library 2017 update 2;
Hardware: Intel® Xeon® Processor E5-2699 v.3, 2 Eighteen-core CPUs (45MB LLC, 2.3HEB) ELC, 2.3HEB LLC, 2.3HEB LLC, 2.3HEB LLC, 2.3HEB LLC, 2.3HEB LLC, 2.3HEB of RAM per node; Operating System: CentOS 6.6 x86_64.
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. **Other brands and names are the property of their respective owners. Benchmark Source: Intel Corporation

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Intel® Data Analytics Acceleration Library 2017

- Major new functionality Python APIs
 - Python APIs (in addition to existing C++ and Java APIs)
- Support building neural networks for deep learning applications
 - Layers: convolution, pooling, fully connected, locally connected, dropout, etc.
 - Activation functions: logistic regression, hyperbolic tangent, ReLU, pReLU, soft ReLU, etc.
 - Function optimizations: SGD, L-BFGS, minibatch, Adagrad, etc.
 - Support more types of data sources (Attribute-Relation File Format, PostgreSQL, asynchronous)
- Open source version under Apache 2.0 license





Agenda

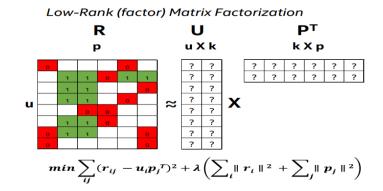
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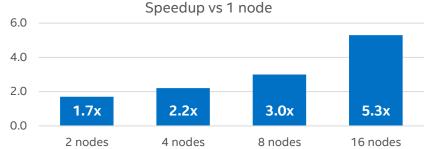
Intel®DAAL::Alternating Least Square (ALS) Algorithm 1/2

Alternating Least Square algorithm

- Moves to low-dimensional latent feature space and factorize: R = U x P^T
 - U matrix of size u x k, association (user, feature)
 - P matrix of size p x k, association (product, feature)
- Iterative algorithm minimizing least square error
 - Initializes U with random data, calculates P
 - Fixes P and calculates U
 - Matrix decompositions and linear solvers
- Computation: Matrix Factorization, Linear Solvers, Dot-Products and

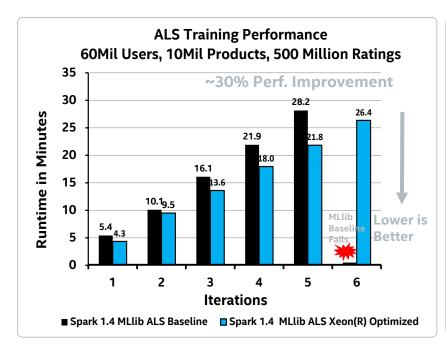


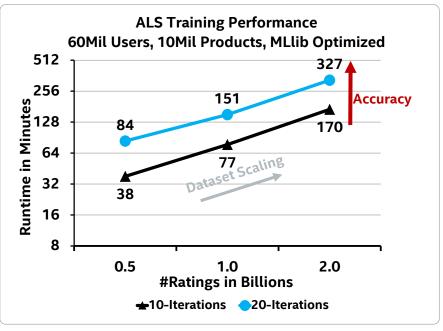
Intel® DAAL ALS in distributed computing mode.



Configuration Info: HW (each node): Intel(R) Xeon(R) CPU E5-2697 v4 @ 2.30GHz, 2x18 cores, HT is ON, RAM 128GB; Versions: Oracle Linux Server 6.6, Intel® DAAL 2017 Gold, Intel® MPI 5.1.3; Interconnect: 1 GB Ethernet. 10M users, 10M items, 100M ratings, 10 factors 15 iterations

Intel® DAAL::Alternating Least Square (ALS) Algorithm 2/2



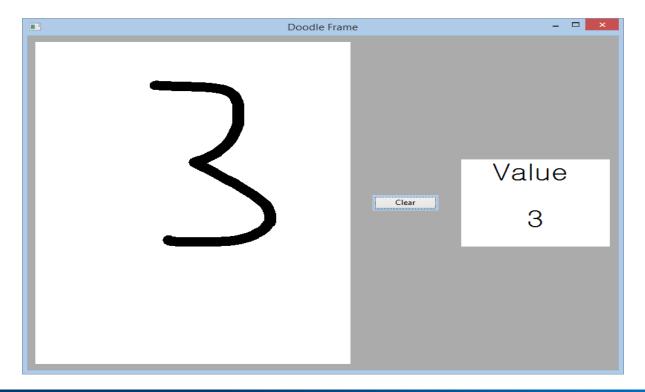


Significant performance & scalability with Cluster HW, Application & Spark optimization

Linear dataset scalability and accuracy

Optimizations achieve good performance improvement and linear dataset scalability

Intel® DAAL - Handwritten Digit Recognition



Intel® DAAL - Handwritten Digit Recognition

Training multi-class SVM for 10 digits recognition.

3,823 pre-processed training data.

available at http://archive.ics.uci.edu/ml/datasets/Optical+Recognition+of+Handwritten+Digits

99.6% accuracy with 1,797 test data from the same data provider.

```
Confusion matrix:
177,000 0.000
                 0.000
                         0.000
                                 1.000
                                         0.000
                                                 0.000
                                                          0.000
                                                                  0.000
                                                                          0.000
0.000
       181.000 0.000
                         0.000
                                 0.000
                                         0.000
                                                 0.000
                                                          0.000
                                                                  1.000
                                                                          0.000
0.000
       2.000
               173,000 0.000
                                 0.000
                                         0.000
                                                 0.000
                                                          1.000
                                                                  1.000
                                                                          0.000
0.000
       0.000
               0.000
                       176.000 0.000
                                         1.000
                                                 0.000
                                                          0.000
                                                                 3.000
                                                                          3.000
0.000
       1.000
               0.000
                       0.000
                                179.000
                                        0.000
                                                 0.000
                                                          0.000
                                                                  1.000
                                                                          0.000
0.000
       0.000
               0.000
                       0.000
                                0.000
                                        180.000 0.000
                                                          0.000
                                                                 0.000
                                                                          2.000
0.000
               0.000
       0.000
                       0.000
                                0.000
                                        0.000
                                                180.000 0.000
                                                                 1.000
                                                                          0.000
       0.000
               0.000
                       0.000
                                0.000
                                        0.000
0.000
                                                0.000
                                                        170,000
                                                                 1.000
                                                                          8.000
0.000
       3.000
               0.000
                       0.000
                                0.000
                                        0.000
                                                0.000
                                                        0.000
                                                                166.000
                                                                          5.000
0.000
       0.000
               0.000
                       2.000
                                0.000
                                        1.000
                                                0.000
                                                        0.000
                                                                2.000
                                                                        175,000
```

Average accuracy: 0.996 Error rate: 0.004 Micro precision: 0.978 Micro recall: 0.978 Micro F-score: 0.978 Macro precision: 0.978 Macro recall: 0.978 Macro F-score: 0.978



Training Handwritten Digits

```
Create a numeric
void trainModel()
                                                                               table
        /* Initialize FileDataSource<CSVFeatureManager> to retrieve input data from .csv file */
        FileDataSource(CSVFeatureManager> trainDataSource(trainDatasetFileName,
                DataSource::doAllocateNumericTable, DataSource::doDictionaryFromContext);
        /* Load data from the data files */
        trainDataSource.loadDataBlock(nTrainObservations);
                                                                         Create an alg. Obj.
        /* Create algorithm object for multi-class SVM training */
        multi class classifier::training::Batch<> algorithm;
        algorithm.parameter.nClasses = nClasses;
        algorithm.parameter.training = training;
                                                                           Set input and
                                                                            parameters
        /* Pass training dataset and dependent values to the algorithm
        algorithm.input.set(classifier::training::data,trainDataSource.getNumericTable());
        /* Build multi-class SVM model */
                                                                             Compute
        algorithm.compute();
        /* Retrieve algorithm results */
        trainingResult = algorithm.getResult();
                                                                            Serialize the
        /* Serialize the learned model into a disk file */
                                                                           learned model
        ModelFileWriter writer("./model");
        writer.serializeToFile(trainingResult->get(classifier::training::model));
```

Handwritten Digit Prediction

```
void testDigit()
       /* Initialize FileDataSource<CSVFeatureManager> to retrieve the test data
from .csv file */
       FileDataSource<CSVFeatureManager> testDataSource(testDatasetFileName,
              DataSource::doAllocateNumericTable, DataSource::doDictionaryFromContext);
       testDataSource.loadDataBlock(1):
       /* Create algorithm object for prediction of multi-class SVM values */
       multi class classifier::prediction::Batch<> algorithm;
       algorithm.parameter.prediction = prediction;
                                                                             Deserialize
       /* Deservalize a model from a disk file */
       ModelFileReader reader("./model");
                                                                            learned model
       services::SharedPtr<multi_class_classifier::Model> pModel(new
multi class classifier::Model());
       reader.deserializeFromFile(pModel);
       /* Pass testing dataset and trained model to the algorithm */
       algorithm.input.set(classifier::prediction::data,
testDataSource.getNumericTable());
       algorithm.input.set(classifier::prediction::model, pModel);
       /* Predict multi-class SVM values */
       algorithm.compute();
       /* Retrieve algorithm results */
       predictionResult = algorithm.getResult();
       /* Retrieve predicted labels */
       predictedLabels = predictionResult->get(classifier::prediction::prediction);
```

Summary

- Intel® DAAL+Intel® MKL+Intel® IPP = Complementary Big Data Libraries
 Solution
- Intel MKL, Intel DAAL and Intel IPP provide high performance and optimized building blocks for data analytics and machine learning algorithms on Intel platforms.
- Deep learning applications can benefit from DNN primitives in Intel MKL 2017 and Neural Networks API in Intel DAAL 2017



Intel® MKL Resources

Intel® MKL website, forum, benchmarks

- https://software.intel.com/en-us/intel-mkl
- https://software.intel.com/en-us/forums/intel-math-kernel-library
- https://software.intel.com/en-us/intel-mkl/benchmarks#

Intel® MKL link line advisor

http://software.intel.com/en-us/articles/intel-mkl-link-line-advisor/

Intel® MKL-DNN

https://01.org/mkl-dnn

Intel[®] IA optimized frameworks

- https://github.com/intel/caffe
- https://github.com/intel/theano



Intel® DAAL Resources

Intel® Machine Learning

http://www.intel.com/content/www/us/en/analytics/machine-learning/overview.html

Intel® DAAL website

https://software.intel.com/en-us/intel-daal

Intel® DAAL forum

https://software.intel.com/en-us/forums/intel-data-analytics-acceleration-library

Intel® DAAL blogs

- https://software.intel.com/en-us/blogs/daal
- https://01.org/daal/blogs/kmoffat/2016/intel%C2%AE-daal-and-intel%C2%AE-mkl-%E2%80%93-complementary-high-performance-machine-learning



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