BUILDING FASTER DATA APPLICATIONS ON SPARK* CLUSTERS USING INTEL® DAAL

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Agenda

Overview - Apache Spark™

What is Intel® DAAL?

Intel® DAAL in the context of Spark

Speeding up Spark MLlib with Intel® DAAL
  - Data conversion
  - Programming model of Intel® DAAL distributed processing
  - Example: PCA
  - Example: Linear regression

Performance

Future of Intel® DAAL
Overview of Apache Spark™

A fast and general engine for large-scale data processing*.

- Providing more operations than MapReduce
- Increasing developer productivity
- Running on Hadoop, Mesos, as a standalone, or in the cloud
- Fault-tolerant distributed data structures (RDD)
- A stack of powerful libraries

* Source: Apache Spark website (http://spark.apache.org)
Intel® Data Analytics Acceleration Library (Intel® DAAL)

An industry leading Intel® Architecture based data analytics acceleration library of fundamental algorithms covering all machine learning stages.

- (De-)Compression
  - PCA
  - Statistical moments
  - Variance matrix
  - QR, SVD, Cholesky
  - Apriori

- Transformation
  - Linear regression
  - Naive Bayes
  - SVM
  - Classifier boosting
  - Collaborative filtering
  - Neural Networks

- Analysis
  - Kmeans
  - EM GMM

- Modeling
  - Pre-processing
  - Transformation
  - Analysis
  - Modeling
  - Validation

- Decision Making
  - Scientific/Engineering
  - Web/Social
  - Business
What’s in the Package?

- Support IA-32 and Intel64 architectures
- Support Linux, Windows, and OS X*
- C++ and Java API. Python support is coming soon.
- Static and dynamic linking.
- A standalone library, and also bundled in Intel® Parallel Studio XE 2016.
- Also available as part of the **Intel Performance Libraries Community Edition** (free).
- An open source Intel DAAL will soon be available on Github.

Note: Bundled version is not available on OS* X.
Where Intel DAAL Fits?

- **Optimization Notice**
- **Limited performance**
  - Many layers of dependencies
  - Low ROI on HW investment

**Big data frameworks:** Hadoop, Spark, Cassandra, etc.

- **Spark**
- **MLLib**
- **Breeze**
- **Netlib-Java**
- **JVM**
- **JNI**
- **Netlib BLAS**

**Connectors**

- **All data sources**
  - Finance
  - Social media
  - CRM
  - Marketing
  - Sensors, devices
  - Ad campaigns
  - Manufacturing

- **SQL stores**
- **NoSQL stores**
- **In-memory stores**
Where Intel DAAL Fits?

Big data analytics

- Run on state-of-art hardware
- Single library to cover all stages of data analytics
- Fully optimized for underlying hardware

Optimized performance
Simpler development/deployment
High ROI on HW investment

Big data frameworks: Hadoop, Spark, Cassandra, etc.
Where Intel DAAL Fits?

Intel® Data Analytics Acceleration Library

- **Analysis**
  - PCA
  - Low order moments
  - Matrix factorization
  - Outlier detection
  - Distances
  - Association rules

- **Machine learning**
  - Regression
    - Linear regression
  - Classification
    - SVM
    - Naïve Bayes
    - Boosting algorithms
  - Recommendation
    - ALS
  - Clustering
    - K-Means
    - EM for GMM

- **Programming languages**
  - C++
  - Java

- **Processing modes**
  - Batch processing
  - Distributed processing
  - Online processing

- **Utilities**
  - Data compression
  - Serialization
  - Model import/output

- **Big data frameworks**: Hadoop, Spark, Cassandra, etc.

Intel DAAL fits in various domains such as:

- **All data sources**
  - Finance
  - Social media
  - CRM
  - Marketing
  - Sensors, devices
  - Ad campaigns
  - Manufacturing

- **SQL stores**
  - Connectors

- **In-memory stores**

- **Batch processing**
- **Distributed processing**
- **Online processing**
Intel® DAAL Distributed Processing

Conceptual Model

Master -> Partial results collection -> Local processing

Input -> Local processing

Partial result

Final result

Input

Partial result
Intel DAAL in the Context of Spark

SparkContext

- Driver Program
- Master
- Final result
- Partial results collection

Executor

- Input
- Local processing
- Partial result
- Final result

Worker Node

- Cluster Manager

Executor

- Input
- Local processing
- Partial result

Worker Node
Intel DAAL Numeric Tables

Heterogeneous – AOS
- Observations are stored in contiguous memory buffers.

Heterogeneous – SOA
- Features are stored in contiguous memory buffers.

Homogeneous – Dense matrix
- 2D matrix: $n$ rows (observations), $p$ columns (features)

Homogeneous – Sparse matrix (CSR)
- Support both 0-based indexing and 1-based indexing.

$m$-by-$n$ homogenous

\[
\begin{bmatrix}
    x_{00} & x_{01} & \ldots & x_{0(n-1)} \\
    x_{10} & x_{11} & \ldots & x_{1(n-1)} \\
    \vdots & \vdots & \ddots & \vdots \\
    x_{m0} & x_{m1} & \ldots & x_{m(n-1)} \\
\end{bmatrix}
\]
Numeric Tables and RDD

JavaRDD<NumericTable>

```
public class NumericTableWithIndex implements java.io.Serializable {
    private Tuple2<Long, NumericTable> tup;
    private long nRows;
    private long nCols;
}
```
Handle MLlib Distributed Data Structures

JavaRDD<Vector>  
RowMatrix

User-defined conversion methods

JavaRDD<NumericTable>
Data Conversion: RDD<Vector> to RDD<NumericTable>

JavaPairRDD<Vector, Long> vecrddWithIds = vecrdd.zipWithIndex();

JavaRDD<NumericTableWithIndex> jntrdd = vecrddWithIds.mapPartitions(
    new FlatMapFunction<Iterator<Tuple2<Vector, Long>>, NumericTableWithIndex>() {
        public List<NumericTableWithIndex> call(Iterator<Tuple2<Vector, Long>> it) {
            DalContext context = new DalContext();
            ArrayList<NumericTableWithIndex> tables = new ArrayList<NumericTableWithIndex>();
            int cursize = 0;
            int nrows = 0;
            double[] data = new double[0];
            while (it.hasNext()) {
                Tuple2<Vector, Long> tup = it.next();
                double[] row = tup._1().toArray();
                data = ArrayUtils.addAll(data, row);
                cursize += row.length;
                nrows++;
                if (nrows == maxRowsPerTable || !it.hasNext()) {
                    NumericTableWithIndex part = new NumericTableWithIndex(
                        tup._2() - nrows + 1,
                        new HomogenNumericTable(context, data, cursize/nrows, nrows)).
                        tables.add(part);
                    cursize = 0;
                    nrows = 0;
                }
            }
            return tables;
        }
    }.

return new DistributedNumericTable(jntrdd, vecrdd.count(), ncols);
Data Conversion: RDD<NumericTable> to RDD<Vector>

```java
return distNT.numTables.flatMap(
    new FlatMapFunction<NumericTableWithIndex, Vector>() {
        public List<Vector> call(NumericTableWithIndex nt) {
            DaalContext context = new DaalContext();
            NumericTable table = nt.getTable(context);
            double[] data = (table instanceof HomogenNumericTable) ? ((HomogenNumericTable) table).getDoubleArray() : null;
            if (data == null) {
                throw new IllegalArgumentException("Invalid NumericTable type");
            }
            long begin = 0;
            long end = nt.numOfCols();
            ArrayList<Vector> veclist = new ArrayList<Vector>();
            while (begin < data.length) {
                double[] row = ArrayUtils.subarray(data, (int)begin, (int)end);
                DenseVector dv = new DenseVector(row);
                veclist.add(dv);
                begin = end;
                end += nt.numOfCols();
            }
            context.dispose();
            return veclist;
        }
    });
```
Local processing algorithms abstractions:

- **Package:** com.intel.daal.algorithms
  - pca.DistributedStep1Local
  - linear_regression.Training.TrainingDistributedStep1Local
  - …

Partial results abstractions:

- pca.PartialResult
- linear_regression.Training.PartialResult
- …

For each `table` in `JavaRDD<NumericTable>`:

```java
// Local processing algorithm and params
DistributedStep1Local alg =
    new DistributedStep1Local(......);

// Set input
alg.input.set(Input.data, table);

// Compute and access partial result
PartialResult ret = alg.compute();
...
Programming Model of Distributed Processing

Master Side

Master side algorithms abstractions:

- **Package**: com.intel.daal.algorithms
  - pca.DistributedStep2Master
  - linear_regression.Training.TrainingDistributedStep2Master
  - …

Final results abstractions:

- pca.Result
- linear_regression.Training.TrainingResult
- …

```java
// Collect partial results from all slaves
List<PartialResult> partsList = parts.collect();

// Master side processing algorithms and params
DistributedStep2Master alg =
    new DistributedStep2Master(......);

// Set master side processing input
for (PartialResult val : partsList) {
    ..... 
    alg.input.add(MasterInputId.partialResults, val);
}

// Compute
alg.compute();

// Get final result
Result result = alg.finalizeCompute();
```
Example: Intel DAAL PCA on Spark

Intel DAAL provides two computation methods:
- Correlation method (*default*)
- SVD method

Input in the form of NumericTables:
- Non-normalized data, or
- Normalized data ($\mu = 0, \sigma = 1$), or
- Correlation matrix

Output:
- Scores (*A $1 \times p$ NumericTable* with eigenvalues, largest to smallest)
- Loadings (*A $p \times p$ NumericTable* with corresponding eigenvectors)
PCA - Slave Side

```java
final Broadcast<Tuple2<Class<? extends Number>, PCAMethod>> configBcast = sc.broadcast(config);
// Local processing on all slaves
JavaRDD<PartialResult> partsrdd = nTables.map(
    new Function<NumericTableWithIndex, PartialResult>() {
      public PartialResult call(NumericTableWithIndex table) {
        DaalContext context = new DaalContext();
        // Create algorithm to calculate PCA decomposition using Correlation method on local nodes
        DistributedStep1Local pcaLocal = new DistributedStep1Local(
          context,
          configBcast.value()._1(),
          configBcast.value()._2().getMethod());

        // Set input data on local node
        pcaLocal.input.set(InputId.data, table.getTable(context));

        // Compute PCA on local node
        PartialResult pres = pcaLocal.compute();
        pres.pack();
        context.dispose();
        return pres;
      }
    }).cache();
```
PCA – Master Side

```java
// Finalize on master
List<PartialResult> partsCollection = partsrdd.collect();
DistributedStep2Master pcaMaster = new DistributedStep2Master(dc, config._1(), config._2().getMethod());
for (PartialResult value : partsCollection) {
    value.unpack(dc);
    pcaMaster.input.add(MasterInputId.partialResults, value);
}
pcaMaster.compute();
Result daalresult = pcaMaster.finalizeCompute();

return new PCAResult(daalresult.get(ResultId.eigenValues),
                      daalresult.get(ResultId.eigenVectors));
```
Example: Intel DAAL Linear Regression on Spark

Training – distributed processing

- Computation methods:
  - Normal equation method
  - QR method

- Input:
  - An \( nxp \) NumericTable of independent variables
  - An \( nxk \) NumericTable of corresponding known responses

- Output:
  - A Model object (the intercept, coefficients)

Prediction – batch processing, on master side only

- Input:
  - A Model
  - An \( mxp \) NumericTable of unseen data

- Output:
  - An \( mkx \) NumericTable of predicted responses
Training Data Representation

JavaPairRDD<
NumericTable, NumericTable>

Local

\[ \begin{align*}
\text{Independent variables} & \quad \text{Responses} \\
\end{align*} \]

Local

\[ \begin{align*}
\end{align*} \]

\[ \begin{align*}
\end{align*} \]
Linear Regression Model Training – Slave Side

```java
final Broadcast<Tuple2<Class<? extends Number>, Method>> config = sc.broadcast(trConfig);
// Local processing on all slaves
JavaRDD<PartialResult> partsrdd = dataWithLabels.map(
    new Function<Tuple2<NumericTable, NumericTable>, PartialResult>() {
        public PartialResult call(Tuple2<NumericTable, NumericTable> tup) {
            DaalContext context = new DaalContext();

            // Create algorithm to train a model
            TrainingDistributedStep1Local training = new TrainingDistributedStep1Local(
                context, config.value()._1(), config.value()._2().getMethod());
            // Set input data on local node
            tup._1().unpack(context);
            tup._2().unpack(context);
            training.input.set(TrainingInputId.data, tup._1());
            training.input.set(TrainingInputId.dependentVariable, tup._2());
            // Compute on local node
            PartialResult pres = training.compute();
            pres.pack();
            context.dispose();
            return pres;
        }
    });
).cache();
```
// Finalizing on master
List<PartialResult> partscollection = partsrdd.collect();
TrainingDistributedStep2Master master =
    new TrainingDistributedStep2Master(dc, trConfig._1(), trConfig._2().getMethod());
for (PartialResult value : partscollection) {
    value.unpack(dc);
    master.input.add(MasterInputId.partialModels, value);
}
master.compute();
TrainingResult result = master.finalizeCompute();
return result.get(TrainingResultId.model);
Linear Regression Prediction

```java
// Linear Regression prediction only works with batch mode.
// Prediction algorithm
PredictionBatch predict = new PredictionBatch(dc, predictFpType, predictMethod);
// Set input
predict.input.set(PredictionInputId.data, testData);
// Set model
predict.input.set(PredictionInputId.model, model);
return predict.compute();
```
PCA Performance Boosts Using Intel® DAAL vs. Spark* MLLib on Intel® Architectures

PCA (correlation method) on an 8-node Hadoop* cluster based on Intel® Xeon® Processors E5-2699 v3

Table size

<table>
<thead>
<tr>
<th>Table size</th>
<th>1M x 200</th>
<th>1M x 400</th>
<th>1M x 600</th>
<th>1M x 800</th>
<th>1M x 1000</th>
</tr>
</thead>
<tbody>
<tr>
<td>Speedup</td>
<td>4X</td>
<td>6X</td>
<td>6X</td>
<td>7X</td>
<td>7X</td>
</tr>
</tbody>
</table>

Configuration Info - Versions: Intel® Data Analytics Acceleration Library 2016, CDH v5.3.1, Apache Spark* v1.2.0; Hardware: Intel® Xeon® Processor E5-2699 v3, 2 Eighteen-core CPUs (45MB LLC, 2.3GHz), 128GB of RAM per node; Operating System: CentOS 6.6 x86_64.

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DAAL 2017 Key New Features

Neural Networks

Python API (a.k.a. PyDAAL)

Open source project on Github

Join the Beta program today
https://softwareproductsurvey.intel.com/f/150587/1103/
## Intel® DAAL Neural Networks Components

### Layers

<table>
<thead>
<tr>
<th>Common layers</th>
<th>Activation</th>
<th>Normalization</th>
</tr>
</thead>
<tbody>
<tr>
<td>Convolutional</td>
<td>Logistic</td>
<td>Z-score</td>
</tr>
<tr>
<td>Pooling (max, average, stochastic, spatial)</td>
<td>Hyperbolic tangent</td>
<td>Batch</td>
</tr>
<tr>
<td>Fully connected</td>
<td>ReLU, pReLU, soft ReLU</td>
<td>Local response</td>
</tr>
<tr>
<td>Locally connected</td>
<td>Softmax</td>
<td>Local contrast</td>
</tr>
<tr>
<td>Dropout</td>
<td>Abs</td>
<td></td>
</tr>
</tbody>
</table>

### Optimization solvers

**Supported objective functions**
- MSE (mean squared errors)

**Supported solvers**
- SGD
- Mini-batch gradient descent
- Stochastic LBFGS
- Adagrad
Python API (a.k.a. PyDAAL)

Stick closely with DAAL’s overall design
  - Object-oriented, namespace hierarchy, plug&play

Seamless interfacing with NumPy Anaconda package
  - http://anaconda.org/intel/

```python
... 
# Create a Numpy array as our input
a = np.array([[1,2,4],
              [2,1,23],
              [4,23,1]])

# create a DAAL Matrix using our numpy array
m = daal.Matrix(a)

# Create algorithm objects for cholesky decomposition computing using default method
algorithm = cholesky.Batch()

# Set input arguments of the algorithm
algorithm.input.set(cholesky.data, m)

# Compute Cholesky decomposition
res = algorithm.compute()

# Get computed Cholesky decomposition
tbl = res.get(choleskyFactor)

# get and print the numpy array
print tbl.getArray()
```
Open Source Project

Co-exists with the proprietary version

Apache 2.0 license

Lives on github.com
Resources

Product Links

- Intel® Data Analytics Acceleration Library
- User forum
- Community licensing program
  - https://software.intel.com/sites/campaigns/nest

Code Modernization Links

- Modern Code Developer Community
  - software.intel.com/modern-code
- Intel Code Modernization Enablement Program
  - software.intel.com/code-modernization-enablement
- Intel Parallel Computing Centers
  - software.intel.com/ipcc
- Technical Webinar Series Registration
- Intel Parallel Universe Magazine
  - software.intel.com/intel-parallel-universe-magazine
Call to Action

Download the code samples and try it out on your Spark cluster


Join the 2017 Beta program

- Intel DAAL is part of Intel Parallel Studio XE 2017 Beta
- Registration link
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Notice revision #20110804
Intel DAAL Processing modes

**Batch Processing**

\[ R = F(D_1, \ldots, D_k) \]

**Online Processing**

\[ S_{i+1} = T(S_i, D_i) \]
\[ R_{i+1} = F(S_{i+1}) \]

**Distributed Processing**

\[ R = F(D_1, \ldots, D_k) \]
\[ R = F(R_1, \ldots, R_k) \]
<table>
<thead>
<tr>
<th>Algorithms</th>
<th>Batch</th>
<th>Distributed</th>
<th>Online</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Descriptive statistics</strong></td>
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<td></td>
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</tr>
<tr>
<td>Low order moments</td>
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<tr>
<td>SVD</td>
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