HPC and Data Analytics

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SuperComputing Applications and Innovation Department

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Learning Algorithm

Definition of Learning Algorithm [Mitchell 1997][1]

A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E.

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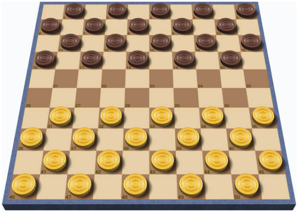
Example: checkers game



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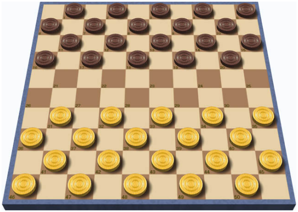

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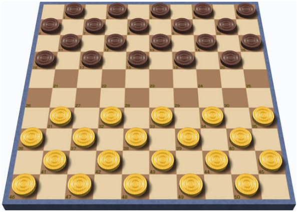

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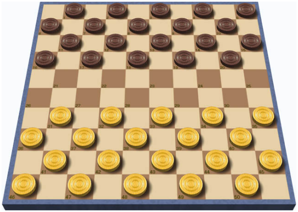

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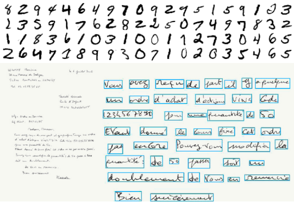

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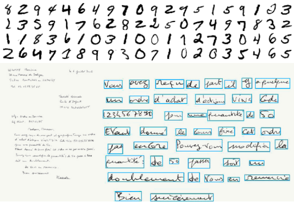

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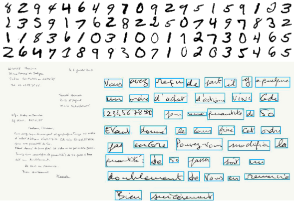

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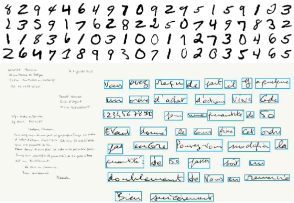

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Example: supervised learning

- **training experience E:** a number of traininig examples $E = \{z_1, z_2, z_3 \dots\}$
  each example is a (input,target) pair: $Z_i = (X_i, Y_i)$

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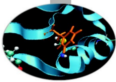

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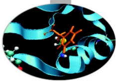

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Examples:

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  - X is a real-valued scalar or vector
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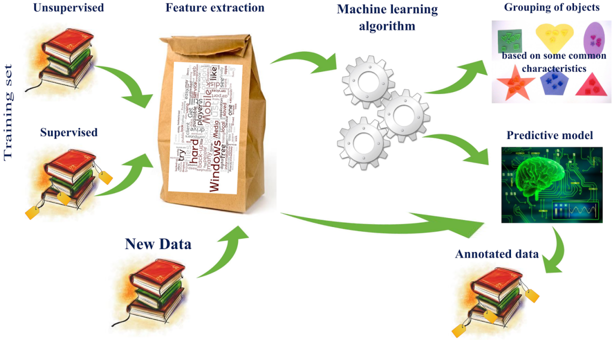
- classification
  - X is a real-valued scalar or vector (features)
  - Y is an integer (label) corresponding to a class index
  - f is able to provide the probability of X_i being in class Y_i
  - L is usually the negative log-likelihood

Machine Learning



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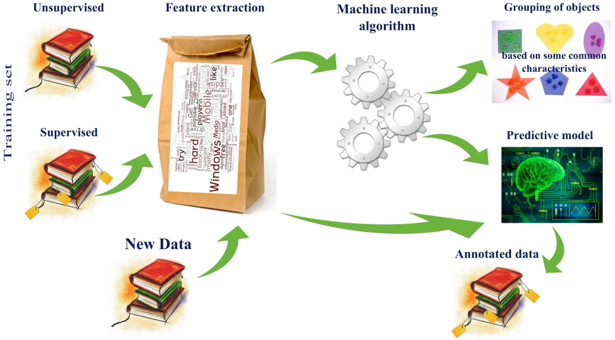

- Application of computer-enabled algorithm to a data set to find a pattern

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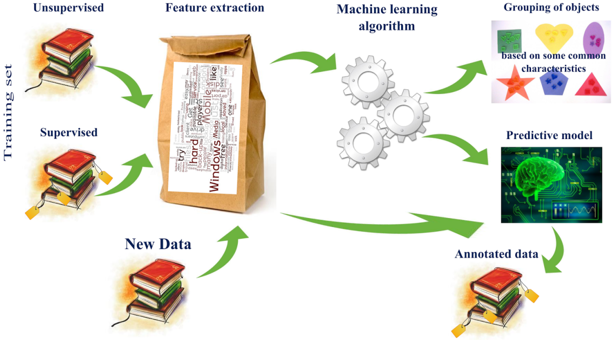

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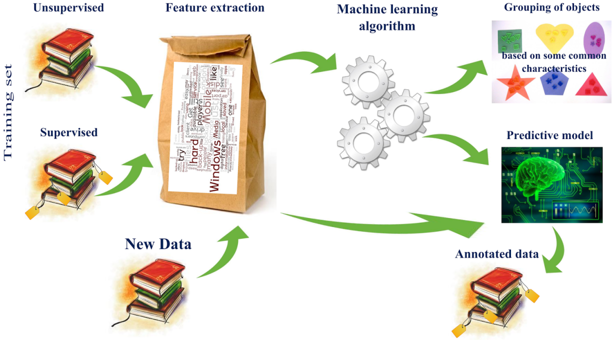
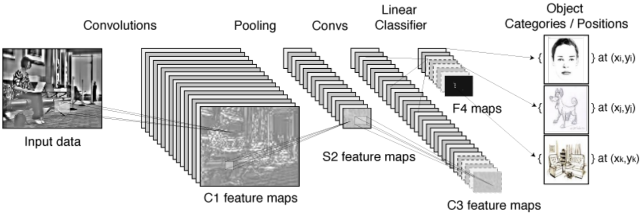


- Application of computer-enabled algorithm to a data set to find a pattern
- Wide range of tasks: segmentation. classification, clustering, supervised/unsupervised learning
- Various algorithms: association rules, decision trees, SVM

Deep Learning



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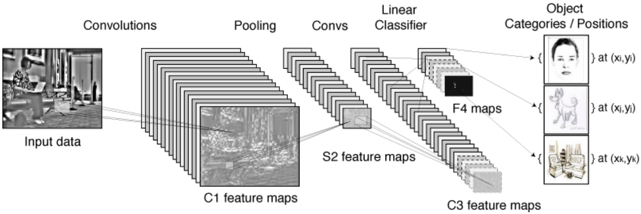

- Application of an Artificial Neural Network to a data set to find a pattern

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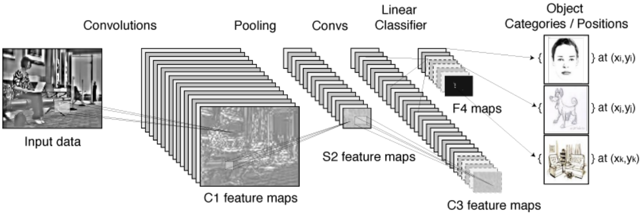

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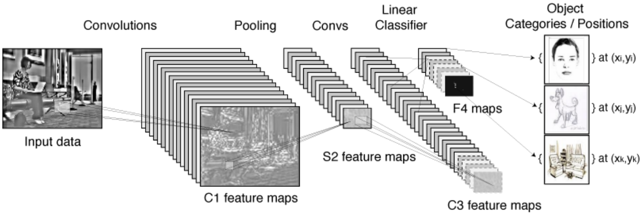

- Application of an Artificial Neural Network to a data set to find a pattern
- Multiple hidden layers (to mimic human brain processes associated to vision/hearing)
- Big data sets and relevant number of variables

Framework desired features

We are interested in:

- classical machine learning algorithms
- deep learning approach (especially convolutional neural network)

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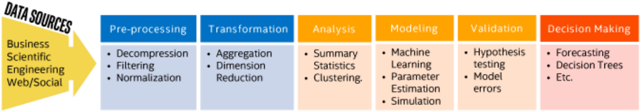
- integration with existing pipelines
- multi-core CPU and/or many-core GPU support

Intel Data Analytics Acceleration Library (DAAL)



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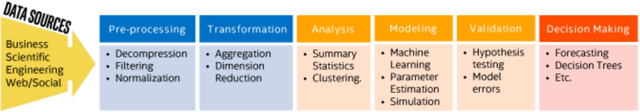

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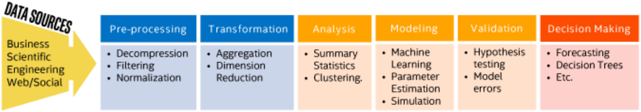

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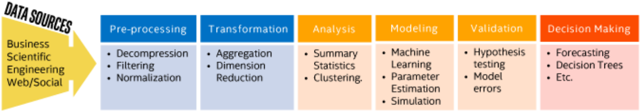

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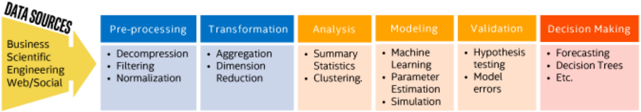

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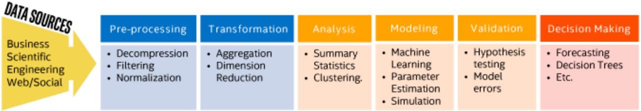

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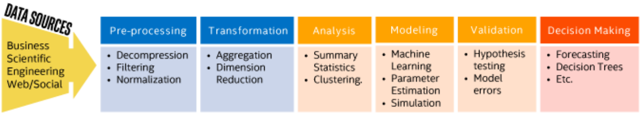

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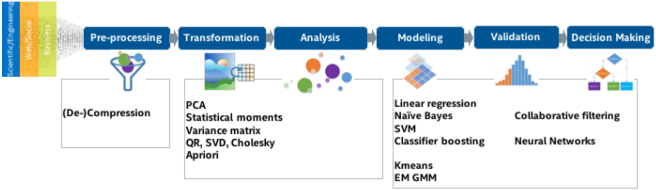
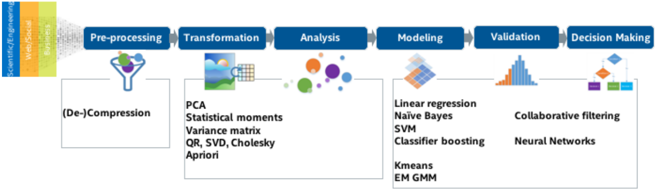
Algorithms


Scientific/Engineering
Web/Social
Business
Pre-processing
Transformation
Analysis
Modeling
Validation
Decision Making
(De-)Compression
PCA
Statistical moments
Variance matrix
QR, SVD, Cholesky
Apriori
Linear regression
Naïve Bayes
SVM
Classifier boosting
Kmeans
EM GMM
Collaborative filtering
Neural Networks

Algorithms



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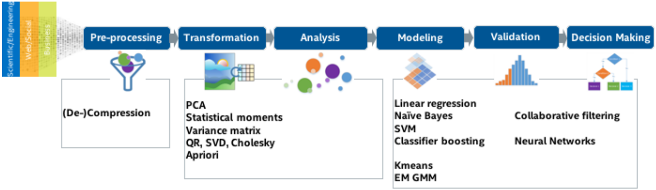

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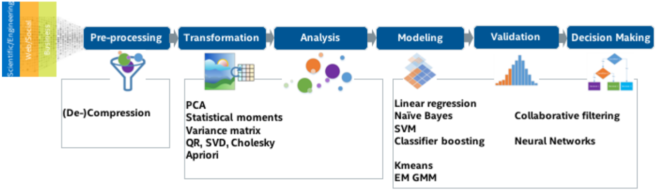

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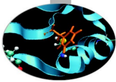

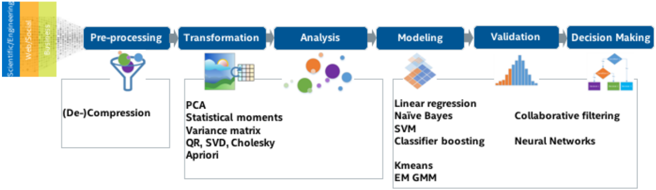

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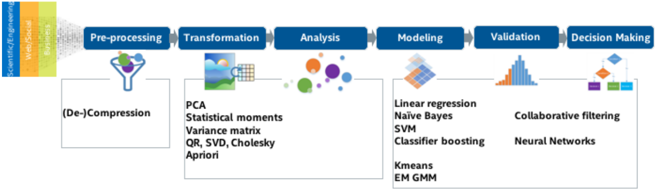

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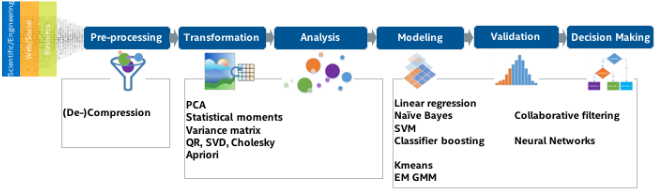

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Clustering: K-Means, EM for GMM

Processing Modes

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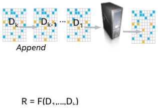

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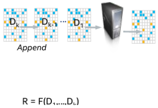

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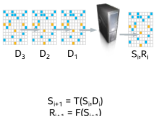

Streaming processing

All data does not fit in memory, or when data is arriving piece by piece. Intel DAAL can process data chunks individually and combine all partial results at the finalizing stage.

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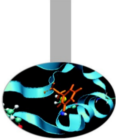

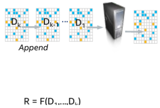

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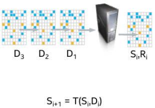

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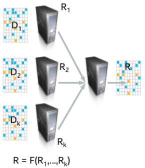
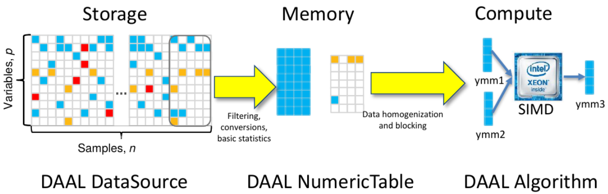


Distributed processing

Intel DAAL supports a model similar to MapReduce. Slaves in a cluster process local data (map stage), and then the master process collects and combines partial results from slaves (reduce stage).

SuperComputing Applications and Innovation

DAAL data flow



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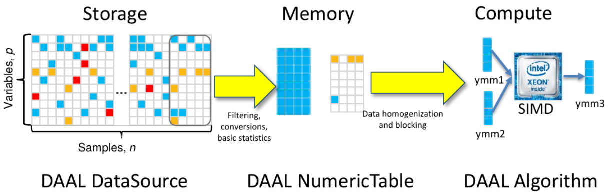

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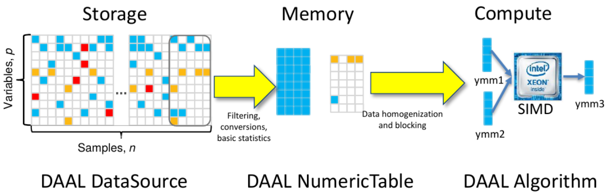

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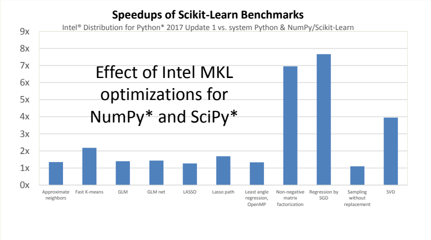
Data structures:

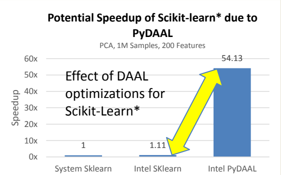
- numeric tables
  - homogeneous data: dense, sparse, packed, triangular matrix, symmetric matrix
  - heterogeneous data: SOA vs AOS
- tensors (n-dimensional matrices)

Official Intel benchmark results (I)

Skt-Learn* Optimizations With Intel® MKL… And Intel® DAAL



Intel® Distribution for Python* ships Intel® Data Analytics Acceleration Library with Python interfaces, a.k.a. pyDAAL



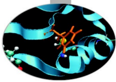
System info: 32x Intel® Xeon® CPU E5-2698 v3 @ 2.30GHz, disabled HT, 64GB RAM; Intel® Distribution for Python* 2017 Gold; Intel® MKL 2017.0.0; Ubuntu 14.04.4 LTS; Numpy 1.11.1; scikit-learn 0.17.1.

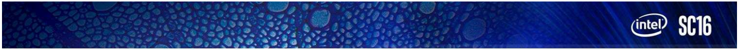
Software and workloads used in performance tests may have been optimized for performance only on Intel microprocessors. Performance tests, such as SYSmark and MobileMark, are measured using specific computer systems, components, software, operations and functions. Any change to any of those factors may 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

Optimization Notice: Intel's compilers may or may not optimize to the same degree for non-Intel microprocessors for optimizations that are not unique to Intel microprocessors. These optimizations include SSE2, SSE3, and SSSE3 instruction sets and other optimizations. Intel does not guarantee the availability, functionality, or effectiveness of any optimization on microprocessors not manufactured by Intel. Microprocessor-dependent optimizations in this product are intended for use with Intel microprocessors. Certain optimizations not specific to Intel microarchitecture are reserved for Intel microprocessors. Please refer to the applicable product User and Reference Guides for more information regarding the specific instruction sets covered by this notice. Notice revision #20110804 .

[Supercomputing 2016 (SC16), November 13-18, 2016, Salt Lake City]

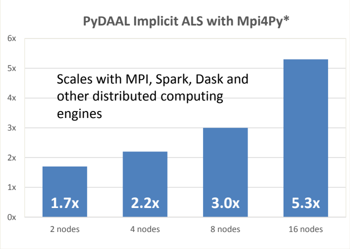
Official Intel benchmark results (II)





Distributed Parallelism

- Intel® MPI* accelerates Intel® Distribution for Python (mpi4py*, ipyparallel*)
- Intel Distribution for Python also supports
  - PySpark* - Python* interfaces for Spark*, an engine for large-scale data processing
  - Dask* - flexible parallel computing library for numerical computing



Configuration Info: Hardware (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.

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pyDAAL installation

Requirements:

- Intel Math Kernel Library (MKL): for BLAS and LAPACK
- Integrated Performance Primitives (IPP) for data compression/decompression
- Threading Building Blocks (TBB) for multicore and many-core parallelism

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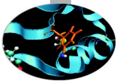
Installation methods:

1. anaconda Intel channel (Linux)
2. Intel distribution (Windows, Linux, OS X)
3. build from source



SVM multiclass classification in 11 steps

```
import numpy as np

# load digits dataset
from sklearn import datasets
digits = datasets.load_digits()

# define training set size
n_samples = len(digits.images)
n_training = int( 0.9 * n_samples )

data = np.ascontiguousarray( digits.data, dtype=np.double )
labels = np.ascontiguousarray( digits.target.reshape(n_samples, 1),
                               dtype=np.double )

from daal.data_management import HomogenNumericTable

train_data = HomogenNumericTable( data[:n_training] )
train_labels = HomogenNumericTable( labels[:n_training] )

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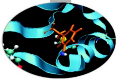
3. create instances of HomogenNumericTable

training algorithm setup



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from daal.algorithms.svm import training as svm_training
from daal.algorithms.svm import prediction as svm_prediction
from daal.algorithms.multi_class_classifier import training as
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from daal.algorithms.classifier import training as training_params

kernel = rbf.Batch_Float64DefaultDense()
kernel.parameter.sigma = 0.001

# Create two class svm classifier
# training alg
twoclass_train_alg = svm_training.Batch_Float64DefaultDense()
twoclass_train_alg.parameter.kernel = kernel
twoclass_train_alg.parameter.C = 1.0
# prediction alg
twoclass_predict_alg = svm_prediction.Batch_Float64DefaultDense()
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# Create a multiclass classifier object (training)
train_alg = multiclass_training.Batch_Float64OneAgainstOne()
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4. define kernel and kernel parameters
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6. create multi class svm classifier (training)

training phase

```
# Pass training data and labels
train_alg.input.set(training_params.data, train_data)
train_alg.input.set(training_params.labels, train_labels)

# training
model = train_alg.compute().get(training_params.model)
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7. set input data and labels
8. start training and get model

prediction algorithm setup

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9. create multi class svm classifier (prediction)

prediction phase

```
# Pass a model and input data
predict_alg.input.setModel(prediction_params.model, model)
predict_alg.input.setTable(prediction_params.data, test_data)

# Compute and return prediction results
results = predict_alg.compute().get(prediction_params.prediction)
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10. set input model and data
11. start prediction and get labels

Benchmark results

- Test description: 1797 samples total (90% training set, 10% test set), 64 features per sample
- Platform description: Intel Core i5-6300U CPU @ 2.40GHz

	sklearn	pyDAAL	speedup
training time [s]	0.161	0.018	8.9
test time [s]	0.017	0.004	4.3

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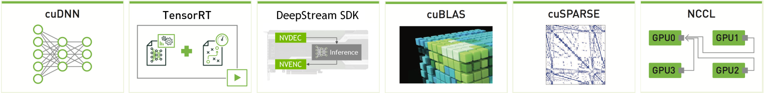
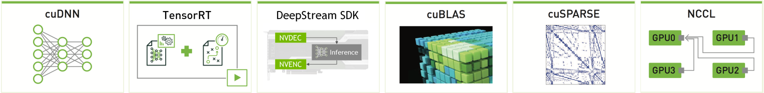
- ✗ Python interface still in development phase
  - not all neural network layers parameters are accessible/modifiable

NVIDIA Deep Learning Software



Tools and libraries for designing and deploying GPU-accelerated deep learning applications.

NVIDIA Deep Learning Software



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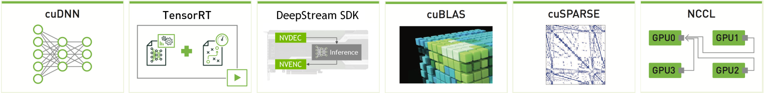

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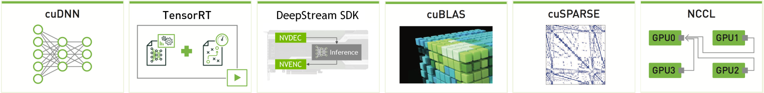

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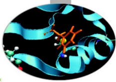

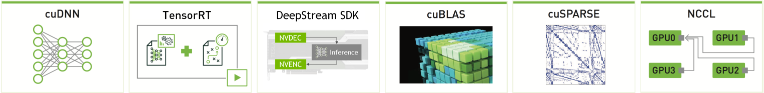

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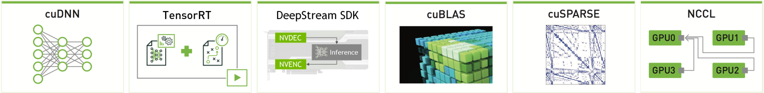

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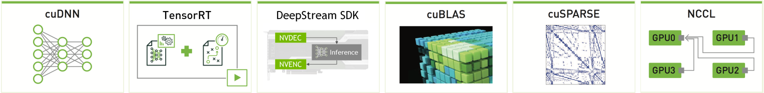

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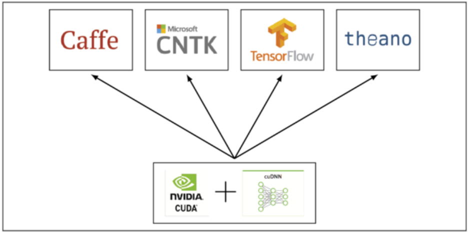
- **Multi-GPU Communications (NCCL, pronounced "Nickel")** optimized primitives for collective multi-GPU communication;

NVIDIA based frameworks



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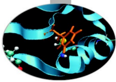
Linear regression (I)



```python
import tensorflow as tf
import numpy as np
import matplotlib.pyplot as plt

# Set up the data with a noisy linear relationship between X and Y.
num_examples = 50
X = np.array([np.linspace(-2, 4, num_examples), np.linspace(-6, 6,
     num_examples)])
X += np.random.randn(2, num_examples)
x, y = X
x_with_bias = np.array([(1., a) for a in x]).astype(np.float32)

losses = []
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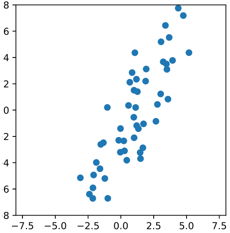

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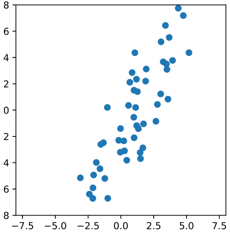

1. generate noisy input data
2. set slack variables and fix algorithm parameters

Linear regression (II)

```
# Start of graph description
# Set up all the tensors, variables, and operations.
A = tf.constant(x_with_bias)
target = tf.constant(np.transpose([y]).astype(np.float32))
weights = tf.Variable(tf.random_normal([2, 1], 0, 0.1))

yhat = tf.matmul(A, weights)
yerror = tf.sub(yhat, target)
loss = tf.nn.l2_loss(yerror)

update_weights =
  tf.train.GradientDescentOptimizer(learning_rate).minimize(loss)

sess = tf.Session()
sess.run( tf.global_variables_initializer() )
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Linear regression (II)

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# Set up all the tensors, variables, and operations.
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target = tf.constant(np.transpose([y]).astype(np.float32))
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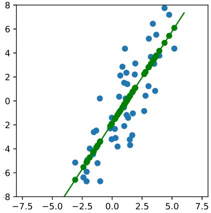

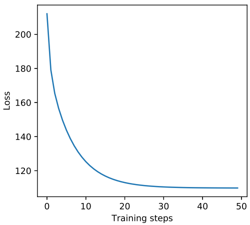

Benchmark results

- MNIST dataset of handwritten digits:
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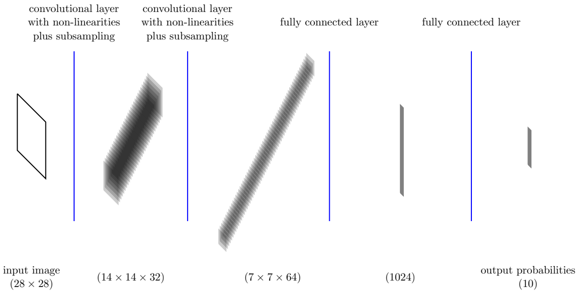
- Convolutional NN: two conv. layers, two fully conn. layers (plus reg.) ≈ 3m variables



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- stochastic gradient descent (batch size: 50 examples)
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Same code achieves 3.8x when running in 1 GALILEO node and 17.2x on a single GPU (training phase).

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SuperComputing Applications and Innovation

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- ✗ lower level than pyDAAL (?)