

Apache Mahout's new DSL for Distributed Machine Learning

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Overview

- Apache Mahout: Past & Future
- A DSL for Machine Learning
- Example
- Under the covers
- Distributed computation of X^TX

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Apache Mahout: History

- library for scalable machine learning (ML)
- started six years ago as ML on MapReduce



- focus on popular ML problems and algorithms
 - Collaborative Filtering *"find interesting items for users based on past behavior"*
 - Classification

"learn to categorize objects"

Clustering

"find groups of similar objects"

Dimensionality Reduction

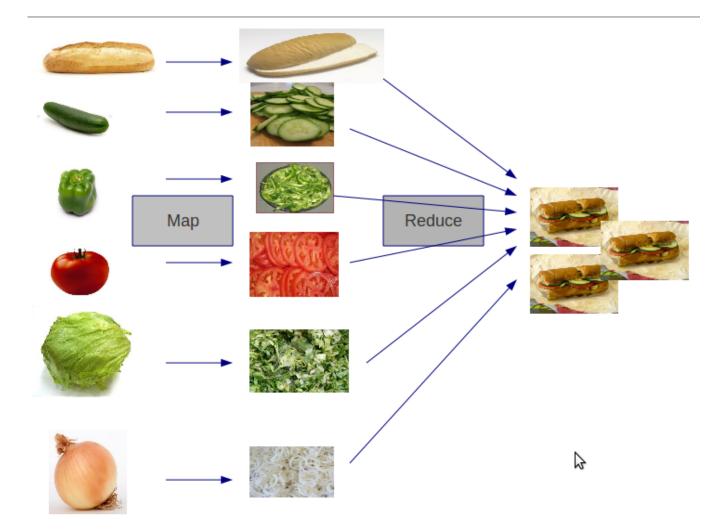
"find a low-dimensional representation of the data"

 large userbase (e.g. Adobe, AOL, Accenture, Foursquare, Mendeley, Researchgate, Twitter)

Background: MapReduce

- simple paradigm for distributed processing (proposed by Google)
- user implements two functions map and reduce
- system executes program in parallel, scales to clusters with thousands of machines
- popular open source implementation:
 Apache Hadoop

Background: MapReduce



Apache Mahout: Problems

MapReduce not well suited for ML

- slow execution, especially for iterations
- constrained programming model makes code hard to write, read and adjust
- lack of declarativity
- lots of handcoded joins necessary

→ Abandonment of MapReduce

- will reject new MapReduce implementations
- widely used "legacy" implementations will be maintained
- → "Reboot" with a new DSL

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Requirements for an ideal ML environment

1. R/Matlab-like semantics

type system that covers linear algebra and statistics

2. Modern programming language qualities

- functional programming
- object oriented programming
- scriptable and interactive

3. Scalability

 automatic distribution and parallelization with sensible performance

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Scala DSL

- Scala as programming/scripting environment
- R-like DSL :

$$G = BB^{T} - C - C^{T} + \xi^{T} \xi s_{q}^{T} s_{q}$$

val G = B^{**} B.t - C - C.t + (ksi dot ksi) * (s_q cross s_q)

- Declarativity!
- Algebraic expression optimizer for distributed linear algebra
 - provides a translation layer to distributed engines
 - currently supports Apache Spark only
 - might support Apache Flink in the future

Data Types

- Scalar real values
- In-memory vectors
 - dense
 - 2 types of sparse
- In-memory matrices
 - sparse and dense
 - a number of specialized matrices

val x = 2.367

val v = dvec(1, 0, 5)

val w =
 svec((0 -> 1)::(2 -> 5):: Nil)

val A = dense(
$$(1, 0, 5)$$
,
(2, 1, 4),
(4, 3, 1))

val drmA = drmFromHDFS(...)

- Distributed Row Matrices (DRM)
 - huge matrix, partitioned by rows
 - lives in the main memory of the cluster
 - provides small set of parallelized operations
 - lazily evaluated operation execution

Features (1)

• Matrix, vector, scalar operators: in-memory, out-of-core

- Slicing operators
- Assignments (in-memory only)
- Vector-specific
- Summaries

drmA %*% drmB
A %*% x
A.t %*% drmB
A * B
A(5 until 20, 3 until 40)
A(5, ::); A(5, 5); x(a to b)

A(5, ::) := x A *= B A -=: B; 1 /:= x x dot y; x cross y

A.nrow; x.length; A.colSums; B.rowMeans x.sum; A.norm

Features (2)

- solving linear systems
 val x = solve (A, b)
- in-memory decompositions

val (inMemQ, inMemR) = qr(inMemM)
val ch = chol(inMemM)
val (inMemV, d) = eigen(inMemM)
val (inMemU, inMemV, s) = svd(inMemM)

- out-of-core decompositions
 val (drmQ, inMemR) = thinQR(drmA)
 val (drmU, drmV, s) =
 dssvd(drmA, k = 50, q = 1)
- caching of DRMs val drmA cached = drmA.checkpoint()

drmA_cached.uncache()

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Cereals

Name	protein	fat	carbo	sugars	rating
Apple Cinnamon Cheerios	2	2	10.5	10	29.509541
Cap'n'Crunch	1	2	12	12	18.042851
Cocoa Puffs	1	1	12	13	22.736446
Froot Loops	2	1	11	13	32.207582
Honey Graham Ohs	1	2	12	11	21.871292
Wheaties Honey Gold	2	1	16	8	36.187559
Cheerios	6	2	17	1	50.764999
Clusters	3	2	13	7	40.400208
Great Grains Pecan	3	3	13	4	45.811716

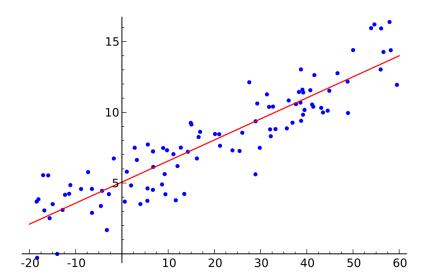
http://lib.stat.cmu.edu/DASL/Datafiles/Cereals.html

Linear Regression

 Assumption: target variable y generated by linear combination of feature matrix X with parameter vector β, plus noise ε

 $y = X\beta + \varepsilon$

- Goal: find **estimate of the parameter vector β** that explains the data well
- Cereals example
 - X = weights of **ingredients**
 - y = customer rating



Data Ingestion

• Usually: load dataset as DRM from a distributed filesystem:

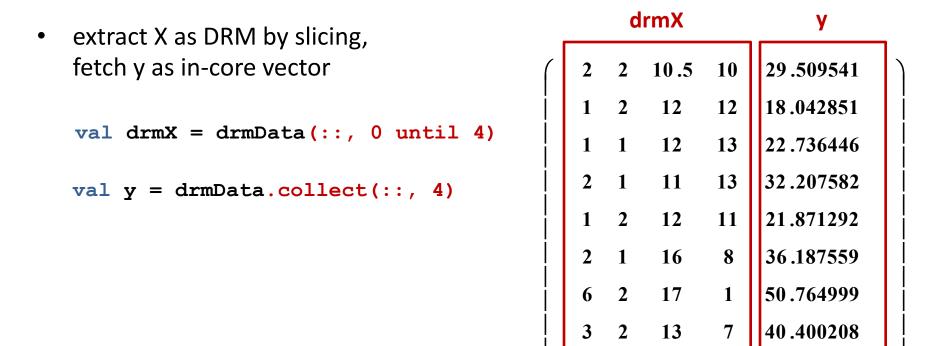
```
val drmData = drmFromHdfs(...)
```

• ,Mimick' a large dataset for our example:

```
val drmData = drmParallelize(dense(
  (2, 2, 10.5, 10, 29.509541),  // Apple Cinnamon Cheerios
  (1, 2, 12, 12, 18.042851),  // Cap'n'Crunch
  (1, 1, 12, 13, 22.736446),  // Cocoa Puffs
  (2, 1, 11, 13, 32.207582),  // Froot Loops
  (1, 2, 12, 11, 21.871292),  // Honey Graham Ohs
  (2, 1, 16, 8, 36.187559),  // Wheaties Honey Gold
  (6, 2, 17, 1, 50.764999),  // Cheerios
  (3, 2, 13, 7, 40.400208),  // Clusters
  (3, 3, 13, 4, 45.811716)),  // Great Grains Pecan
  numPartitions = 2)
```

Data Preparation

 Cereals example: target variable y is customer rating, weights of ingredients are features X



3

3

13

4

45.811716

Estimating β

- Ordinary Least Squares: minimizes the sum of residual squares between true target variable and prediction of target variable
- Closed-form expression for estimation of ß as

 $\hat{\boldsymbol{\beta}} = (\boldsymbol{X}^T \boldsymbol{X})^{-1} \boldsymbol{X}^T \boldsymbol{y}$

• Computing **X^TX** and **X^Ty** is as simple as typing the formulas:

val drmXtX = drmX.t %*% drmX

val drmXty = drmX %*% y

Estimating β

- Solve the following linear system to get least-squares estimate of ß $X^{T}X \hat{\beta} = X^{T}y$
- Fetch X^TX and X^Ty onto the driver and use an in-core solver
 - assumes X^TX fits into memory
 - uses analogon to R's solve() function

val XtX = drmXtX.collect
val Xty = drmXty.collect(::, 0)

val betaHat = solve(XtX, Xty)

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→ We have implemented distributed linear regression! (would need to add a bias term in a real implementation)

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Underlying systems

- currently: prototype on Apache Spark
 - fast and expressive cluster computing system
 - general computation graphs, in-memory primitives, rich API, interactive shell



- future: add Apache Flink
 - database-inspired distributed processing engine
 - emerged from research by TU Berlin, HU Berlin, HPI
 - functionality similar to Apache Spark, adds data flow optimization and efficient out-of-core execution



Runtime & Optimization

- Execution is deferred, user composes logical operators
- Computational actions implicitly trigger optimization (= selection of physical plan) and execution

val C = X.t %*% X

I.writeDrm(path);

val inMemV =
 (U %*% M).collect

• Optimization factors: size of operands, orientation of operands, partitioning, sharing of computational paths

• Computation of X^TX in example

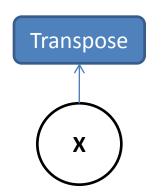
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Naïve execution

1st pass: transpose X (requires repartitioning of X)



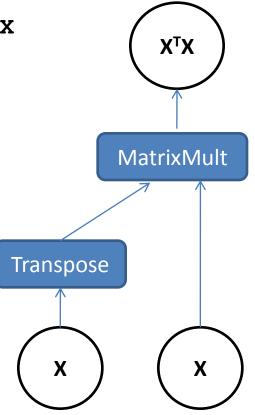
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val drmXtX = drmX.t %*% drmX

• Naïve execution

1st pass: transpose X (requires repartitioning of X)

2nd pass: multiply result with X (expensive, potentially requires repartitioning again)



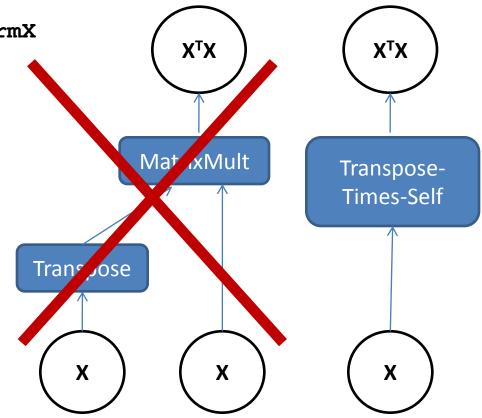
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- Naïve execution

 1st pass transpore X (requires reparationing of X)
 2nd pass: multiply result with X (expensive, potentially requires reparationing again).
- Logical optimization

Optimizer rewrites plan to use specialized logical operator for *Transpose-Times-Self* matrix multiplication



- Mahout computes X^TX via **row-outer-product** formulation
 - executes in a single pass over row-partitioned X

$$X^T X = \sum_{i=0}^m x_{i \bullet} x_{i \bullet}^T$$

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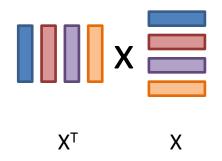
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XΤ

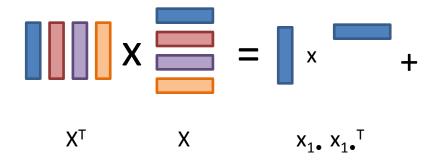
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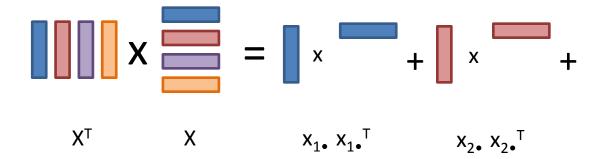
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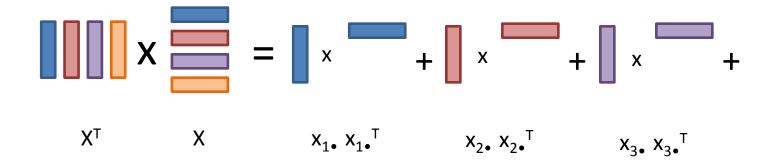
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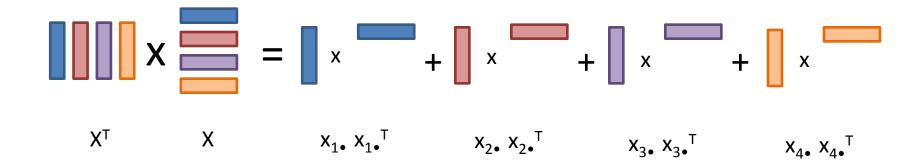
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Tranpose-Times-Self

- Mahout computes X^TX via **row-outer-product** formulation
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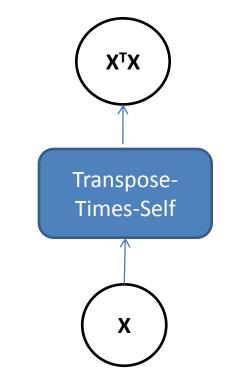


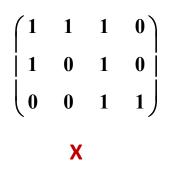
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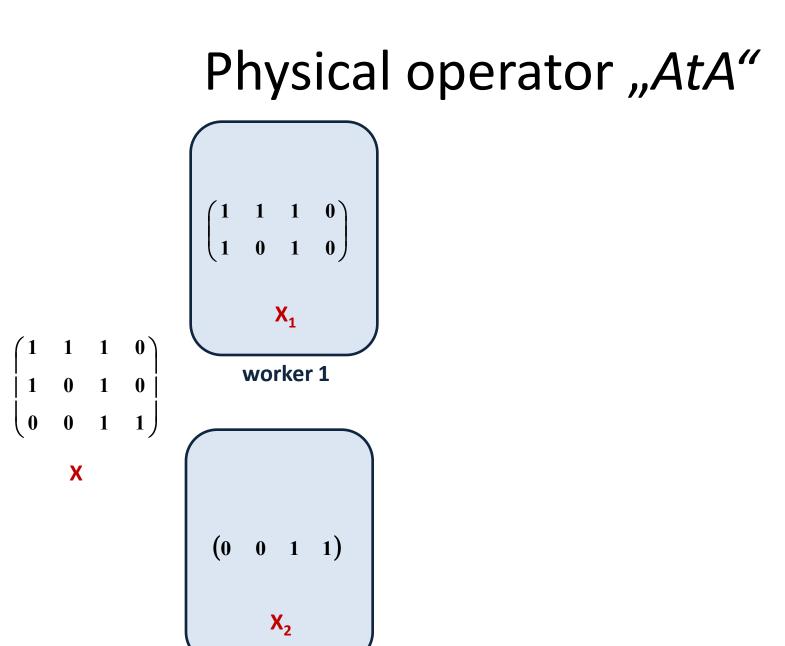
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Physical operators for Transpose-Times-Self

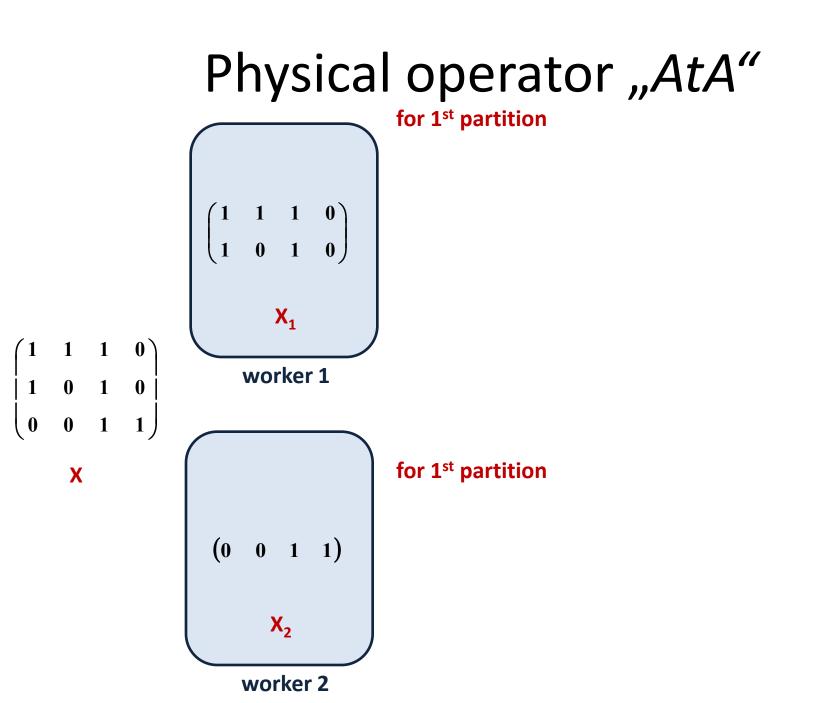
- Two physical operators (concrete implementations) available for *Transpose-Times-Self* operation
 - standard operator "AtA"
 - operator "AtA_slim", specialized implementation for "tall & skinny" matrices (many rows, few columns)
- Optimizer must choose
 - currently: depends on user-defined threshold for number of columns
 - ideally: cost based decision, dependent on estimates of intermediate result sizes

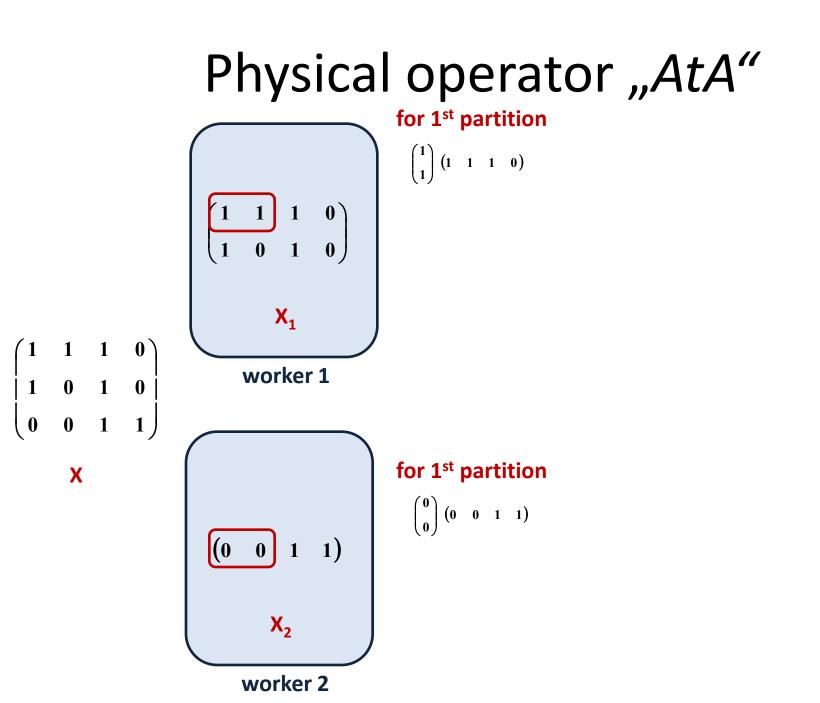


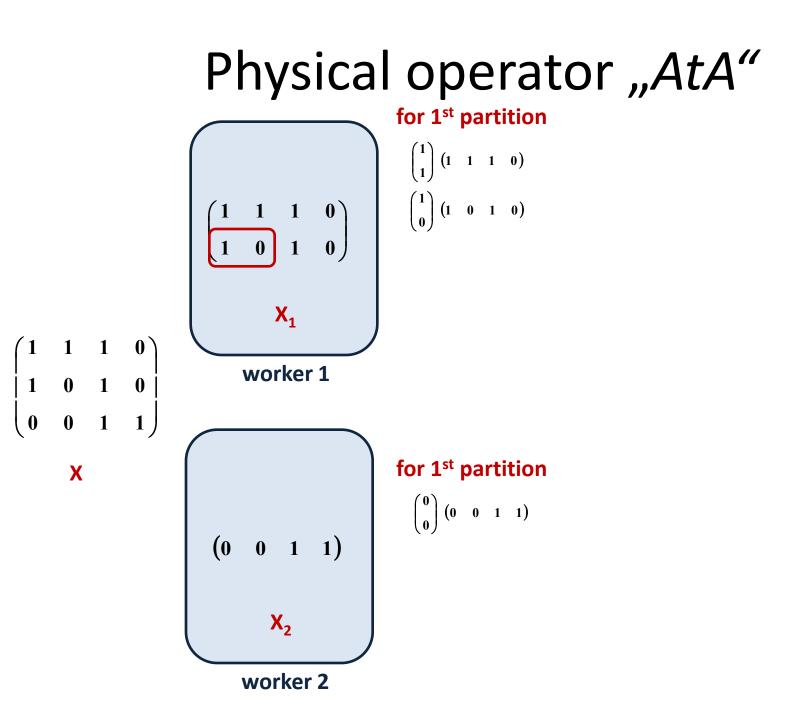


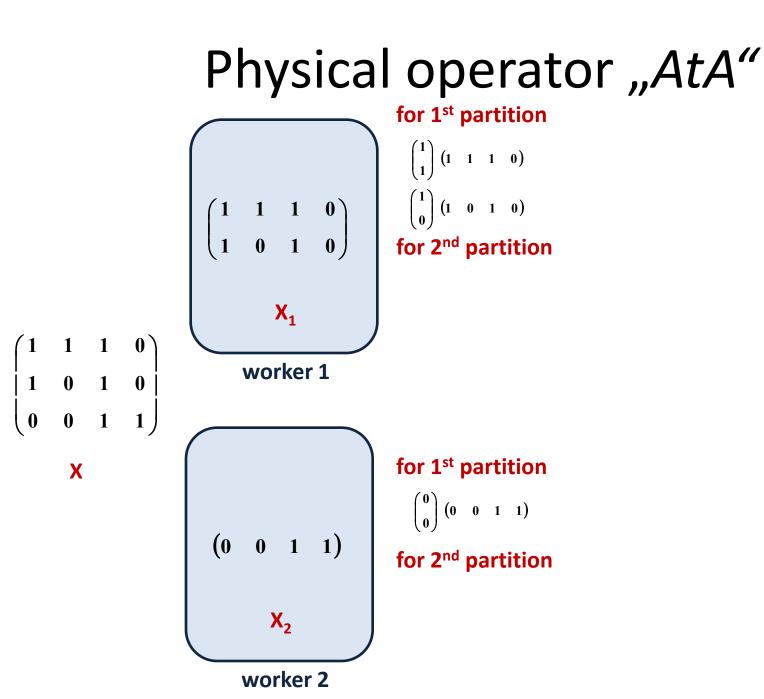


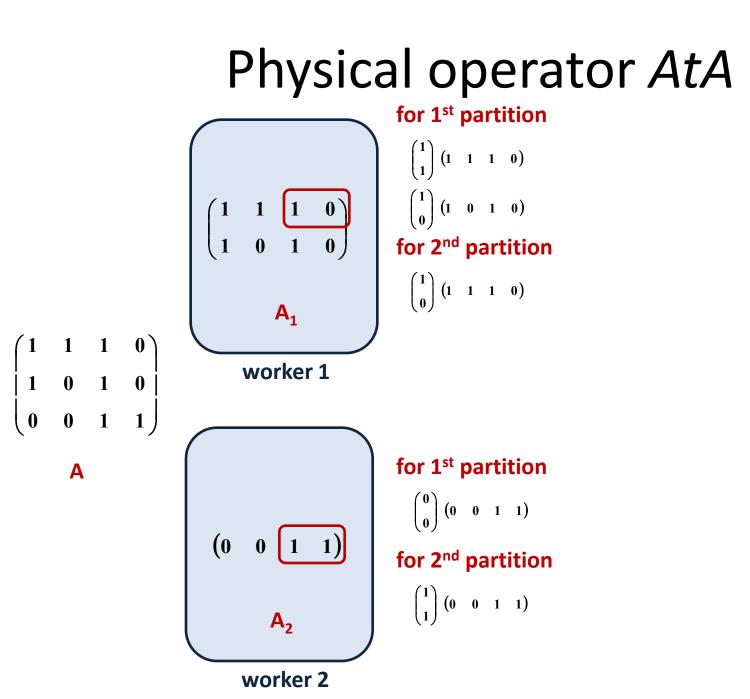
worker 2

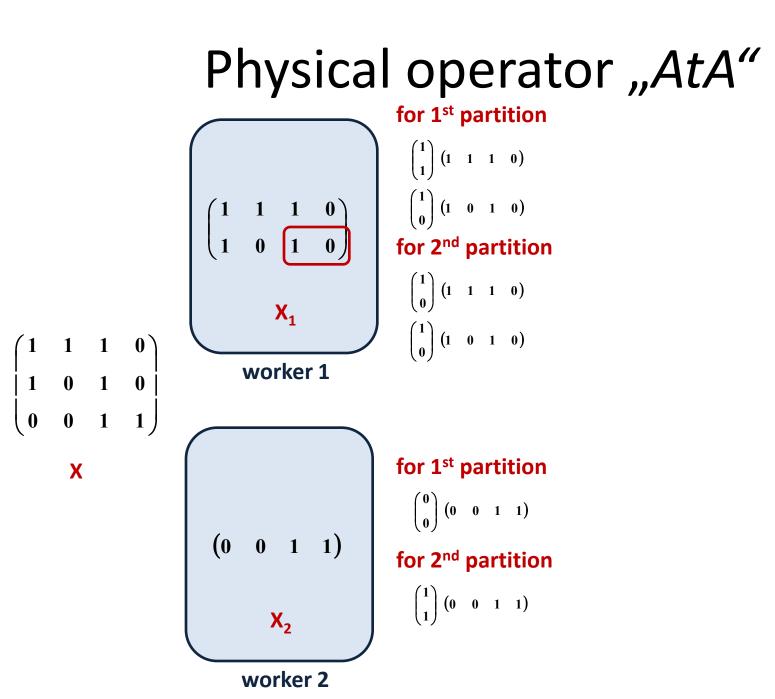


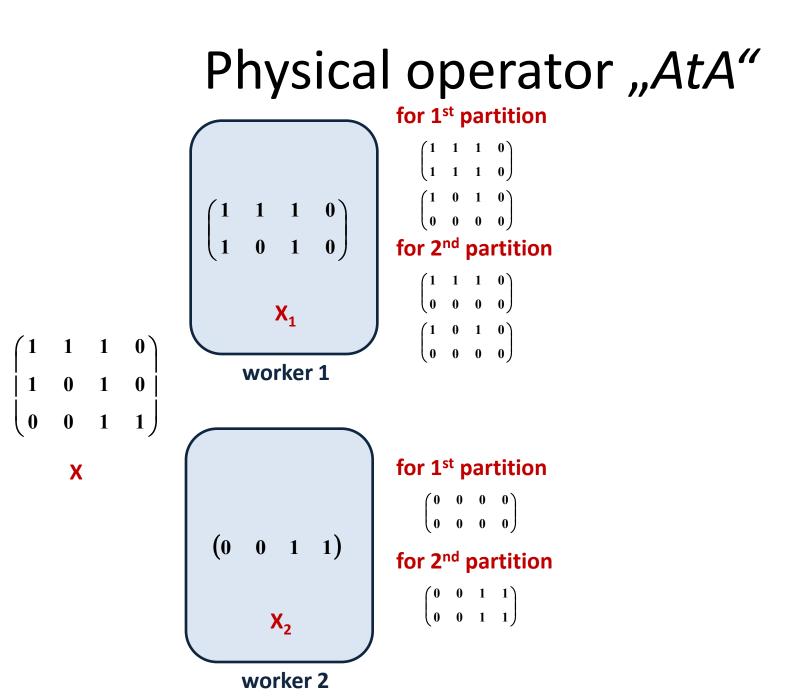


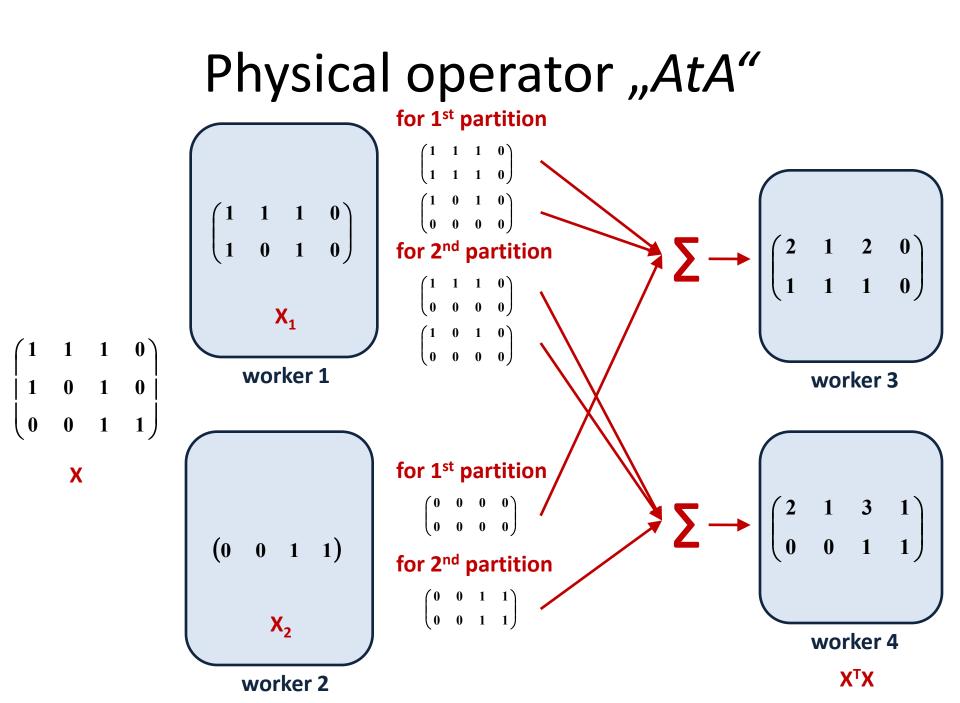


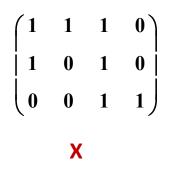


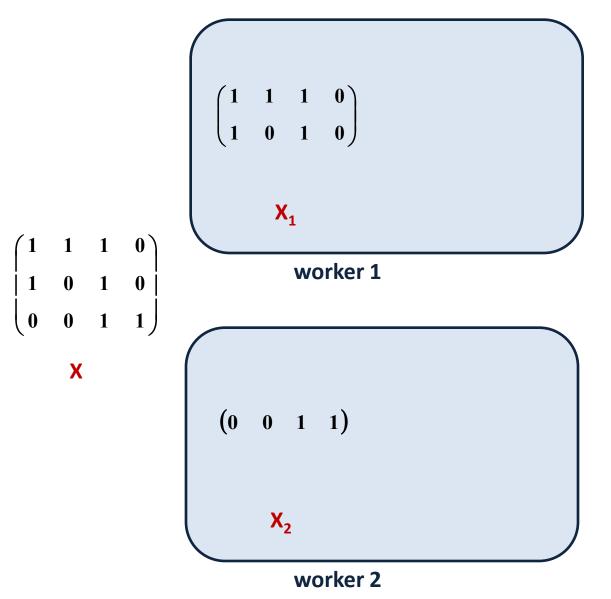


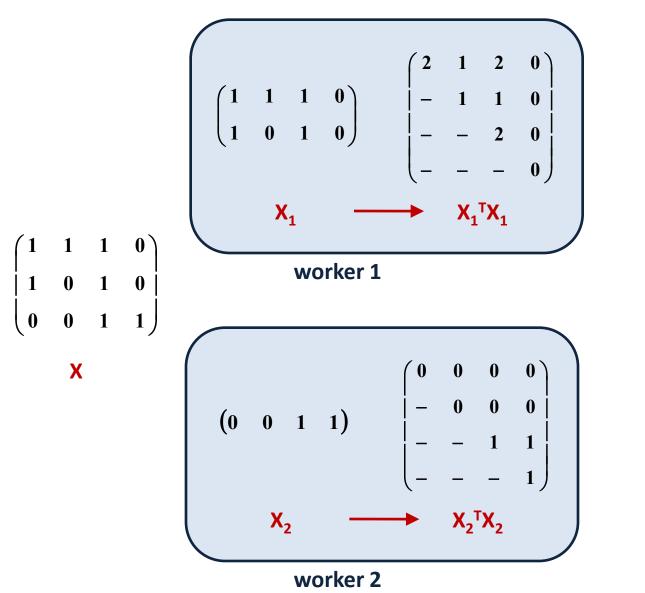


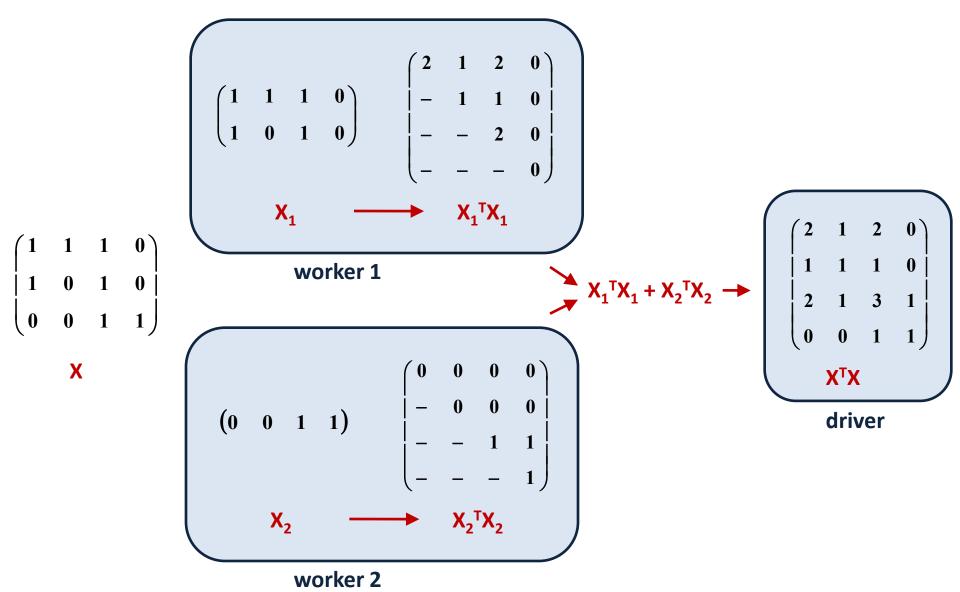












Summary

- MapReduce outdated as abstraction for distributed machine learning
- R/Matlab-like DSL for declarative implementation of algorithms
- Automatic compilation, optimization and parallelization of programs written in this DSL
- Execution on novel distributed engines like
 Apache Spark and Apache Flink

Thank you. Questions?

Tutorial for playing with the new Mahout DSL: http://mahout.apache.org/users/sparkbindings/play-with-shell.html

Apache Flink Meetup in Berlin: http://www.meetup.com/Apache-Flink-Meetup/

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