Spark and Matrix Factorization

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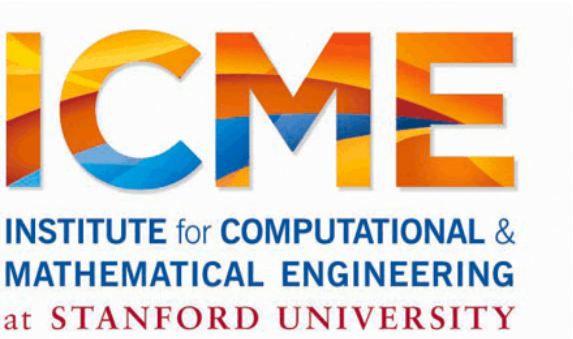


Problem

Data growing faster than processing speeds

Only solution is to parallelize on large clusters

» Wide use in both enterprises and web industry

How do we program these things?

Traditional Network Programming

Message-passing between nodes (e.g. MPI)

Very difficult to do at scale:

- How to split problem across nodes?
  - Must consider network & data locality
- How to deal with failures? (inevitable at scale)
- Even worse: stragglers (node not failed, but slow)
- Ethernet networking not fast
- Have to write programs for each machine

Rarely used in commodity datacenters

Spark Computing Engine

Extends a programming language with a distributed collection data-structure

- » “Resilient distributed datasets” (RDD)

Open source at Apache

- » Most active community in big data, with 50+ companies contributing

Clean APIs in Java, Scala, Python, R

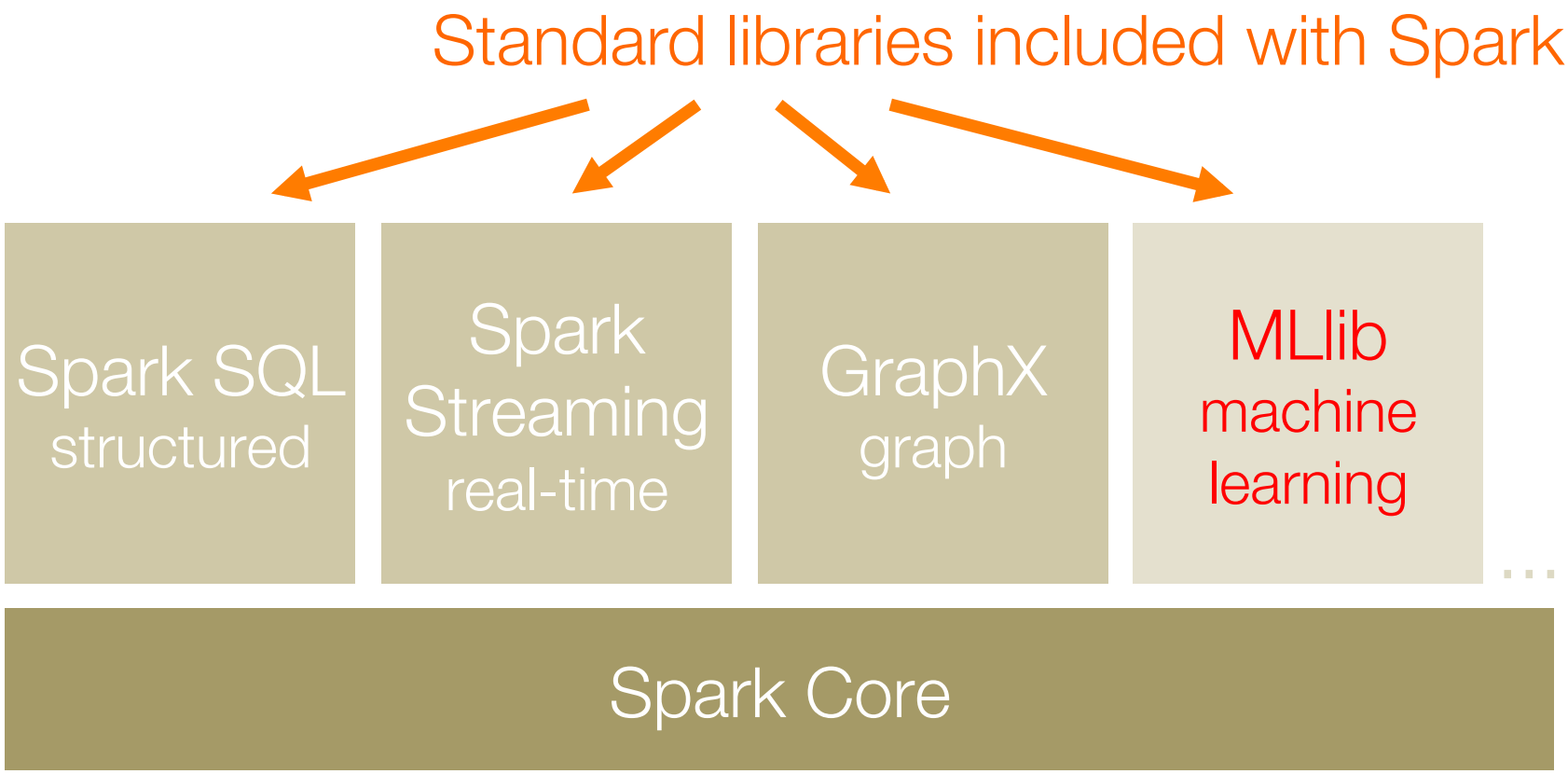
Key Idea

Resilient Distributed Datasets (RDDs)

- » Collections of objects across a cluster with user controlled partitioning & storage (memory, disk, ...)
- » Built via parallel transformations (map, filter, …)
- » The world only lets you make make RDDs such that they can be:

Automatically rebuilt on failure

A General Platform



Benefit of iterations: Optimization

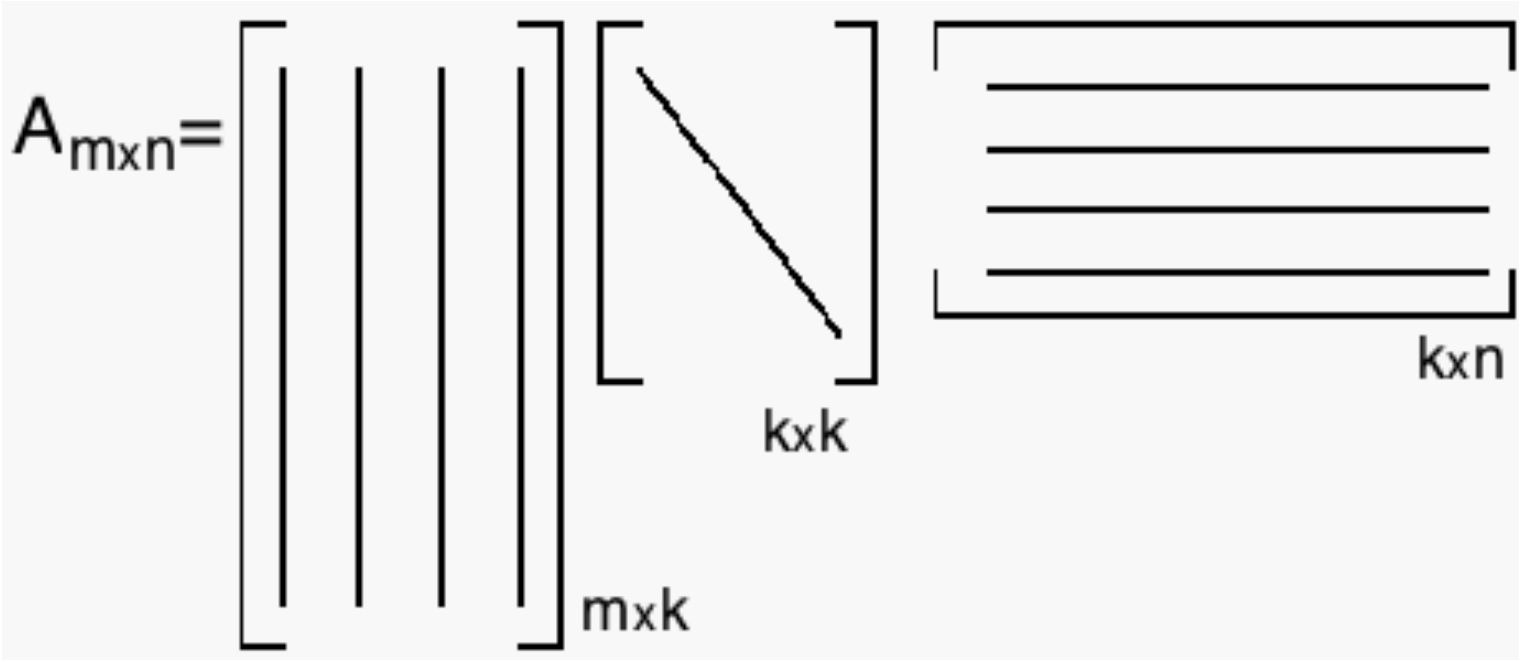
Optimization

At least two large classes of optimization problems humans can solve:

- Convex Programs
- Spectral Problems (SVD)

Deep Dive: Singular Value Decomposition

Singular Value Decomposition



Singular Value Decomposition

Two cases: Tall and Skinny vs roughly Square

computeSVD function takes care of which one to call, so you don’t have to.

Tall and Skinny SVD

- Given $m \times n$ matrix A, with $m \gg n$.
- We compute $A^T A$.
- $A^T A$ is $n \times n$, considerably smaller than A.
- $A^T A$ is dense.
- Holds dot products between all pairs of columns of A.

$$A = U\Sigma V^T \qquad\qquad A^T A = V\Sigma^2 V^T$$

Tall and Skinny SVD

$$A^T A = V \Sigma^2 V^T$$

Gets us V and the singular values

$$A = U \Sigma V^T$$

Gets us U by one matrix multiplication

Square SVD via ARPACK

Very mature Fortran77 package for computing eigenvalue decompositions

JNI interface available via netlib-java

Distributed using Spark

Square SVD via ARPACK

Only needs to compute matrix vector multiplies to build Krylov subspaces

$$K_n = \begin{bmatrix} b & Ab & A^2b & \cdots & A^{n-1}b \end{bmatrix}$$

The result of matrix-vector multiply is small

The multiplication can be distributed

All pairs Similarity

All pairs Similarity

All pairs of similarity scores between n vectors

Compute via DIMSUM:

“Dimension Independent Similarity Computation using MapReduce”

Will be in Spark 1.2 as a method in RowMatrix

All-pairs similarity computation

- Given $m \times n$ matrix A, with $m \gg n$.

$$A = \begin{pmatrix} a_{1,1} & a_{1,2} & \cdots & a_{1,n} \\ a_{2,1} & a_{2,2} & \cdots & a_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m,1} & a_{m,2} & \cdots & a_{m,n} \end{pmatrix}$$

- A is tall and skinny, example values $m = 10^{12}$, $n = 10^6$
- A has sparse *rows*, each row has at most L nonzeros.
- A is stored across hundreds of machines and cannot be streamed through a single machine.

Intuition

Sample columns that have many non-zeros with lower probability.

On the flip side, columns that have fewer non-zeros are sampled with higher probability.

Spark implementation

```scala
// Load and parse the data file.
val rows = sc.textFile(filename).map { line =>
  val values = line.split(' ').map(_.toDouble)
  Vectors.dense(values)
}
val mat = new RowMatrix(rows)

// Compute similar columns perfectly, with brute force.
val simsPerfect = mat.columnSimilarities()

// Compute similar columns with estimation using DIMSUM
val simsEstimate = mat.columnSimilarities(threshold)
```

Future of MLlib

General Linear Algebra

CoordinateMatrix

RowMatrix

BlockMatrix

Local and distributed versions.
Operations in-between.

Goal: version 1.3

Spark and ML

Spark has all its roots in research, so we hope to keep incorporating new ideas!