MLlib & MLbase

Distributed Machine Learning on Spark

Evan Sparks
UC Berkeley

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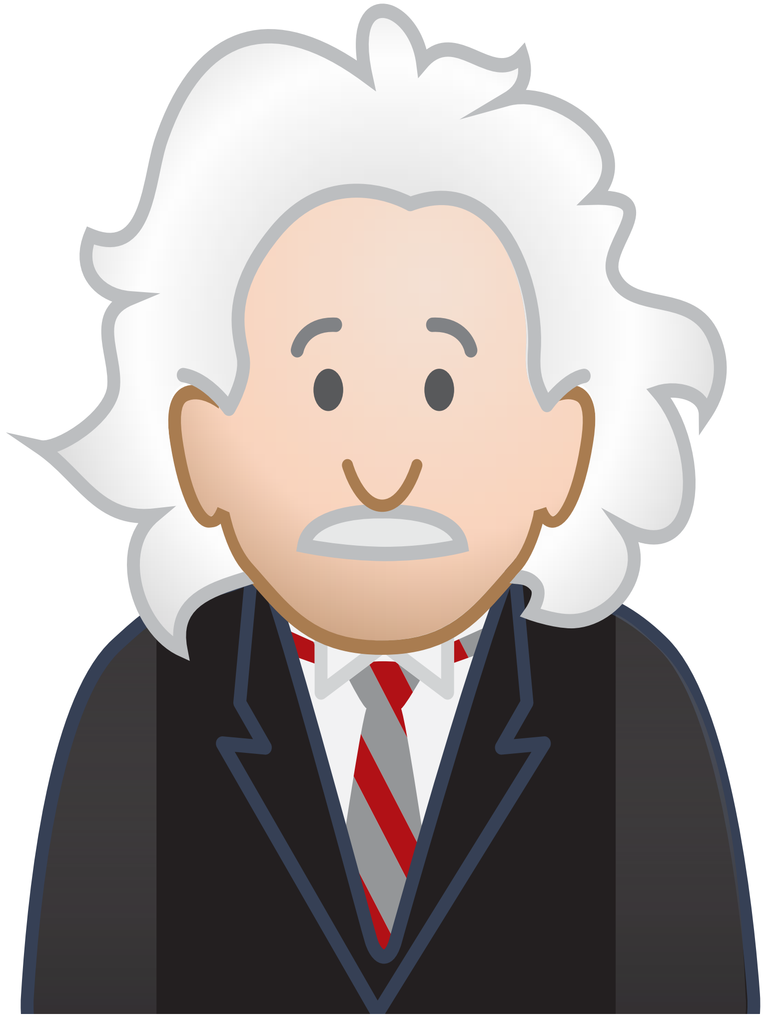
Problem: Scalable implementations *difficult* for ML Developers…



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MATLAB
The Language of Technical Computing

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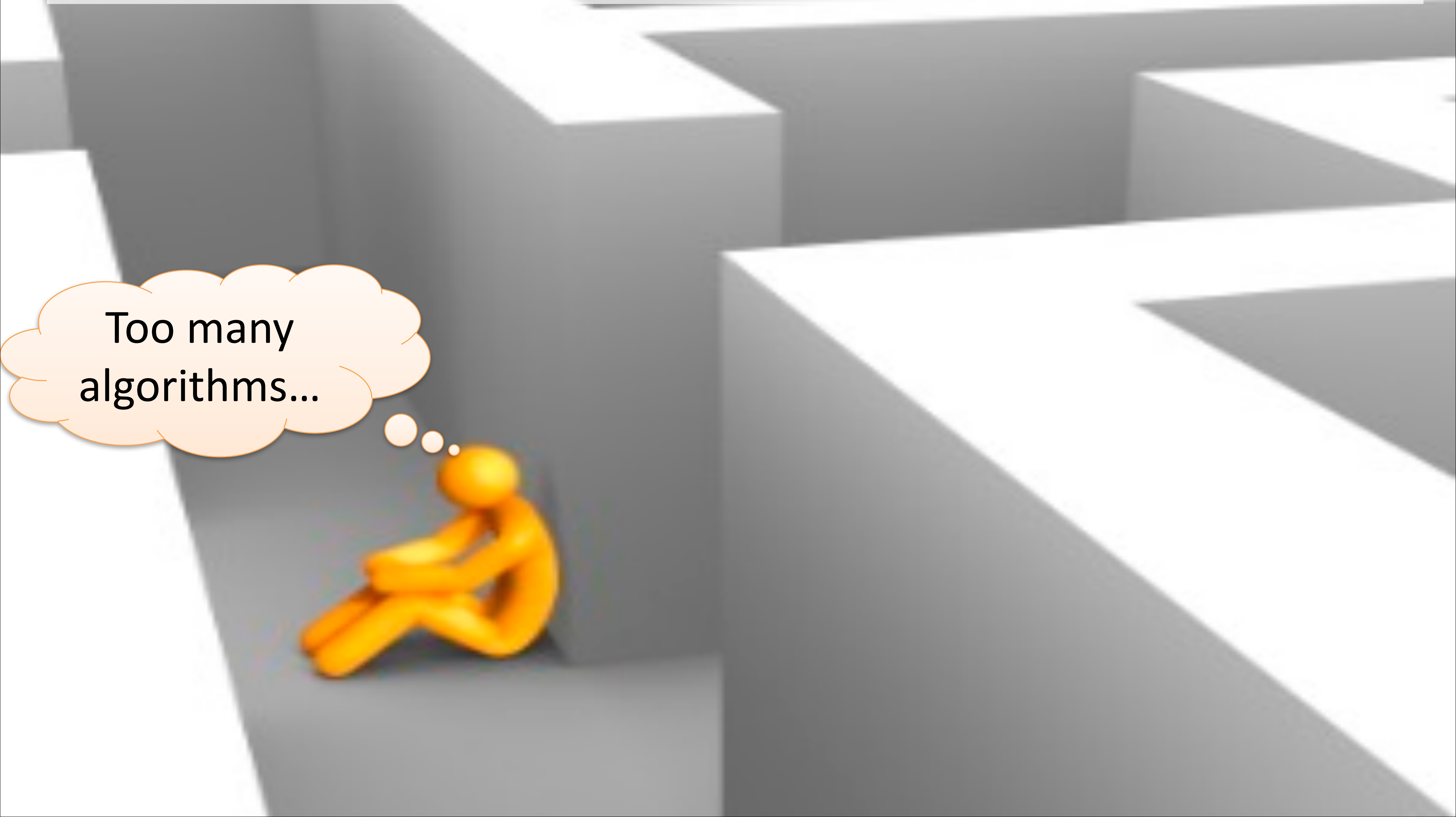

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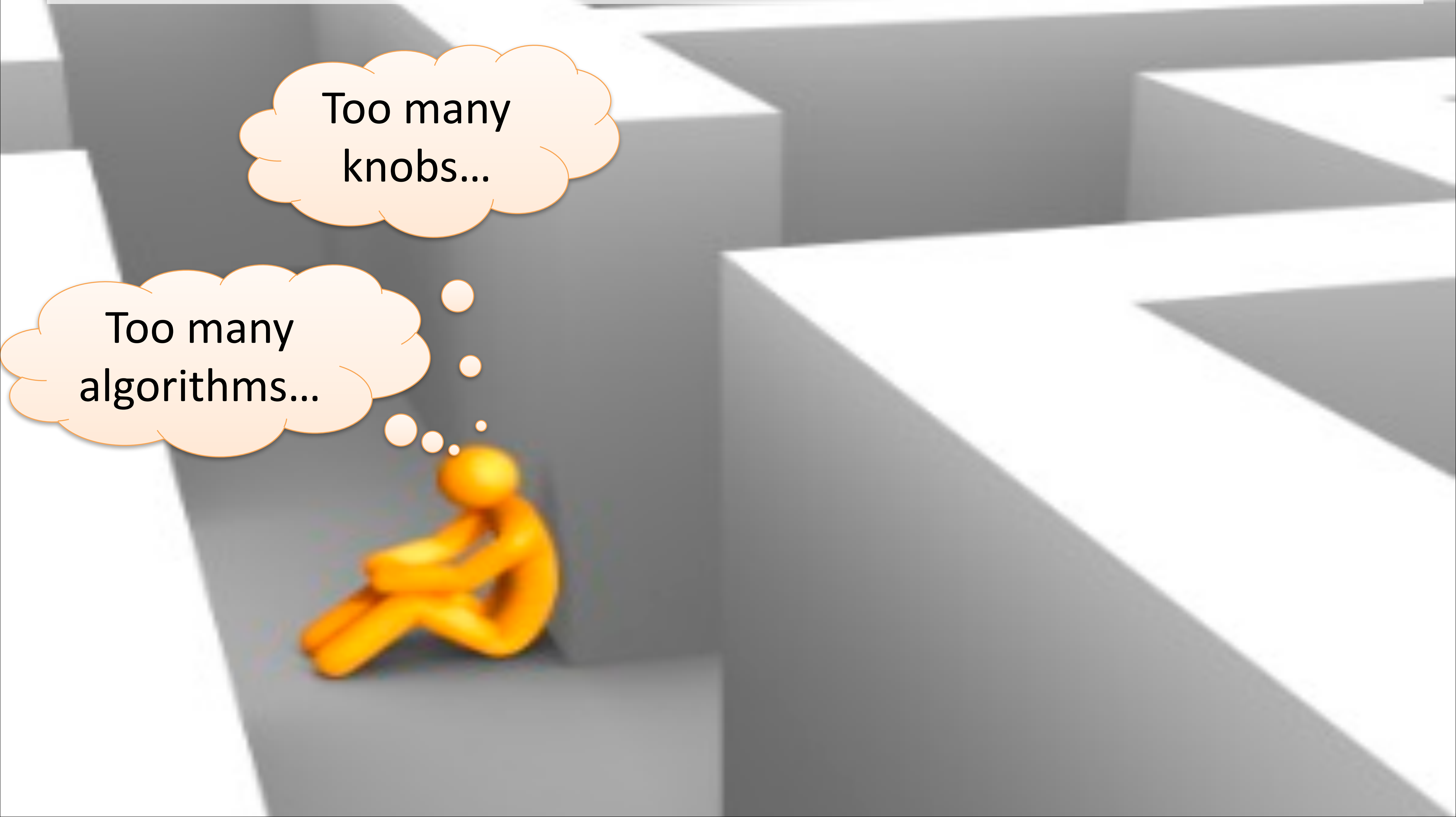

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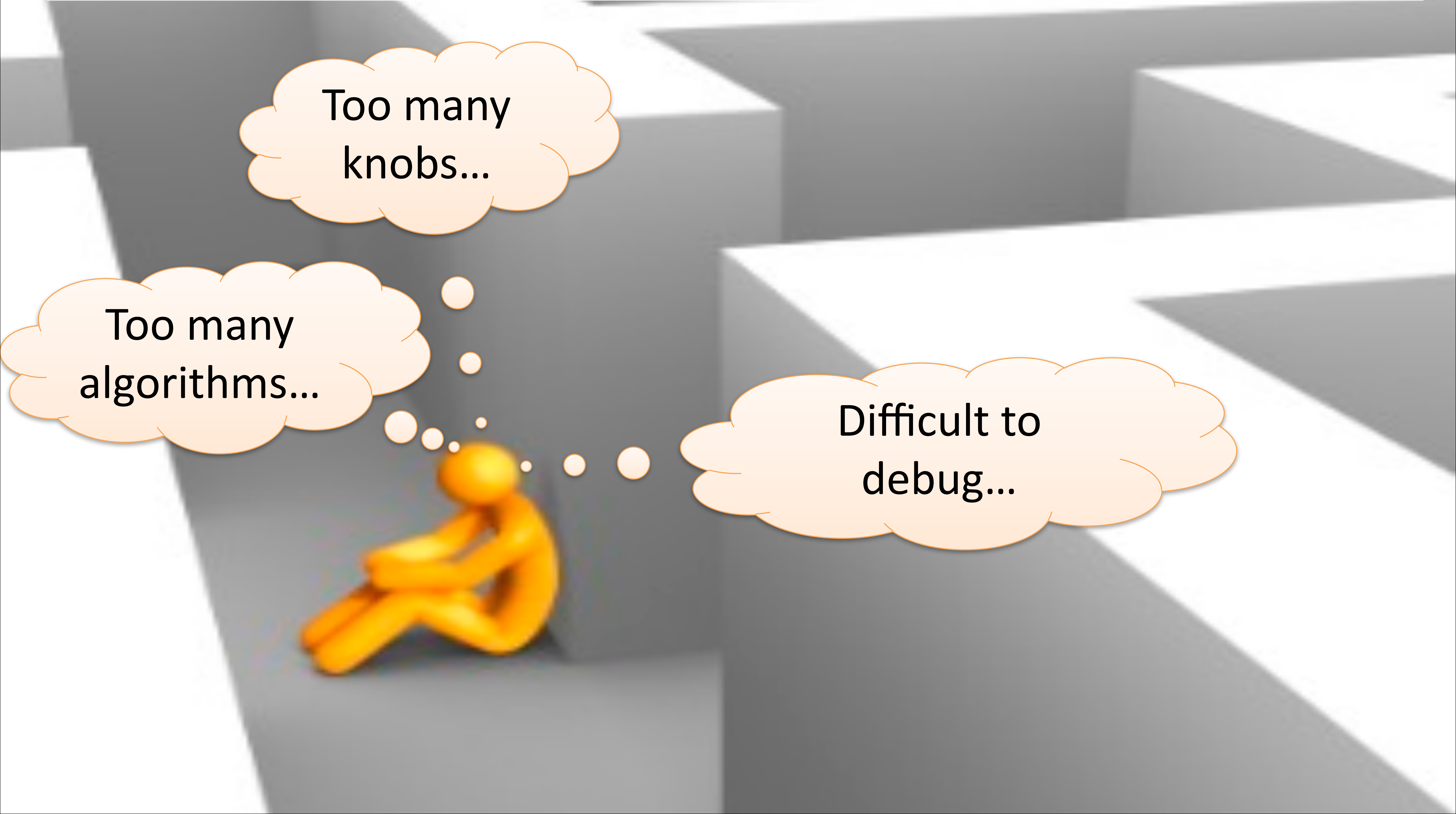

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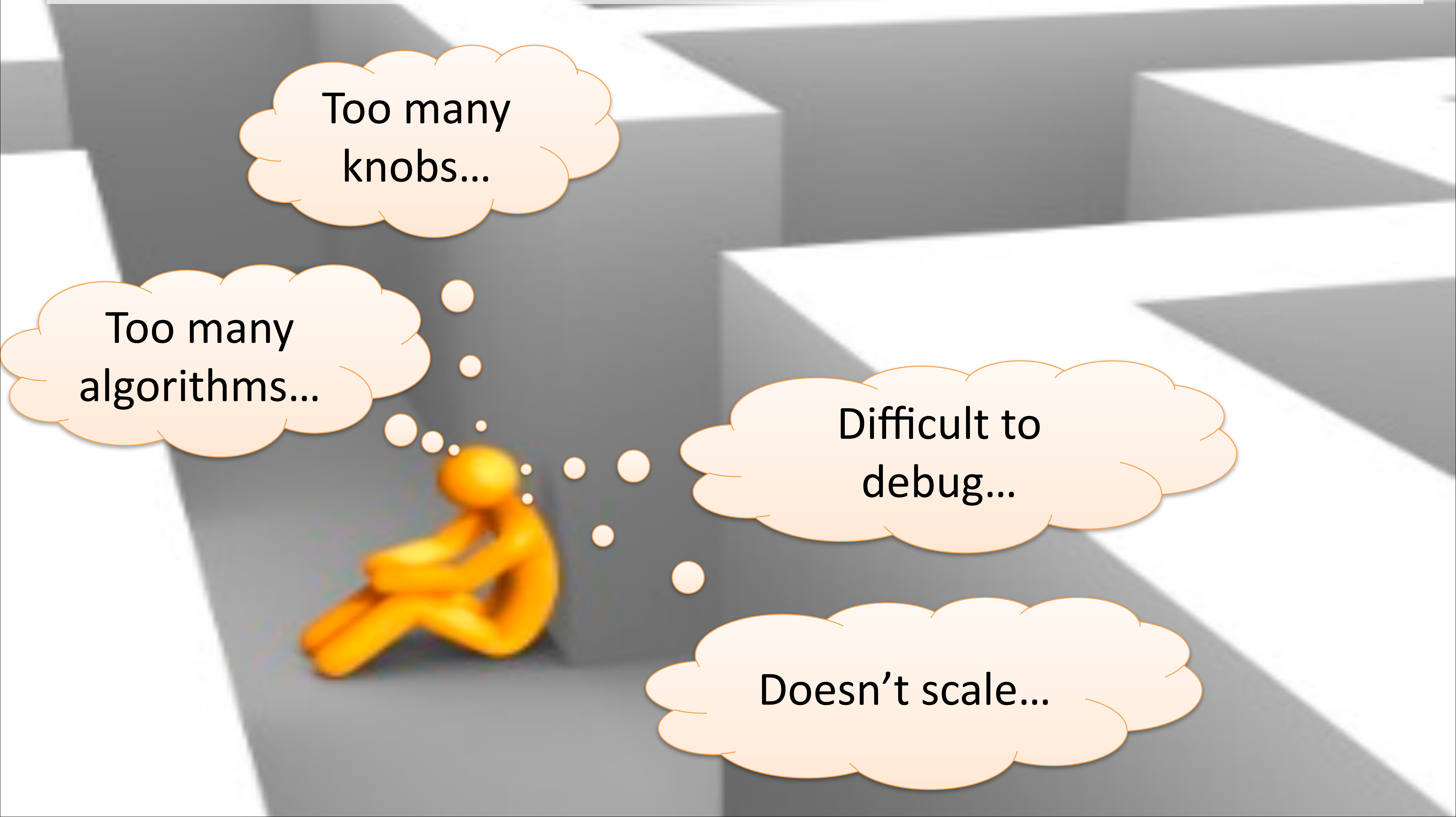

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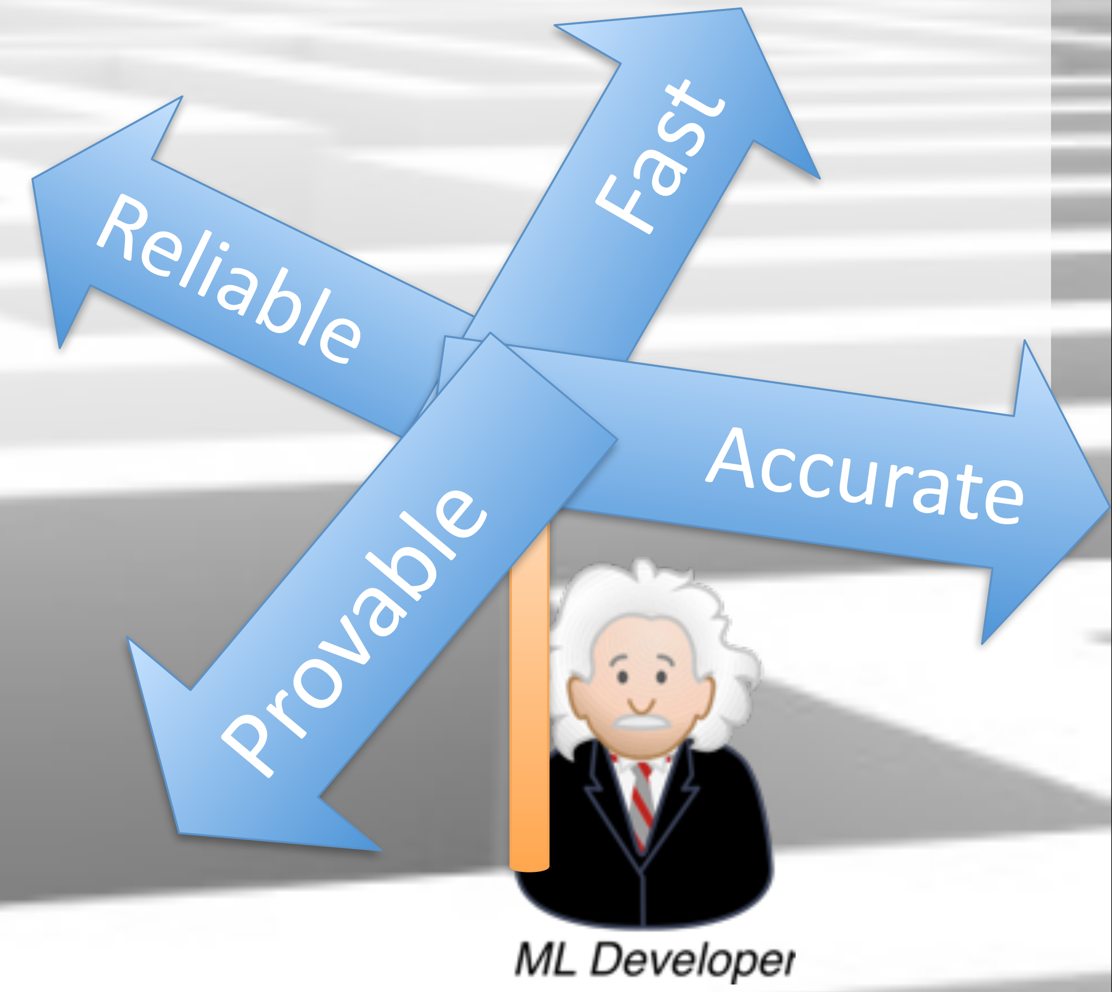
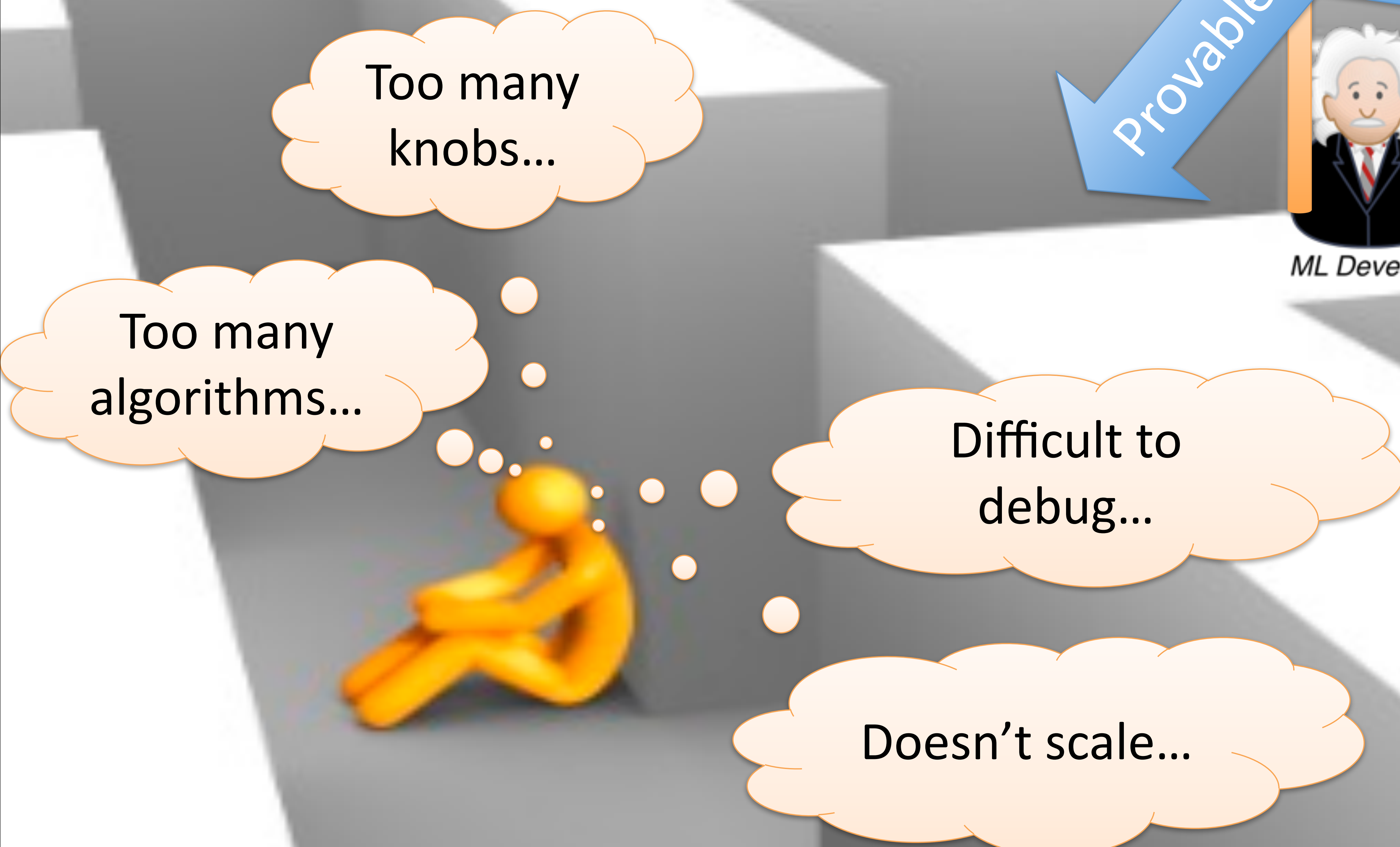
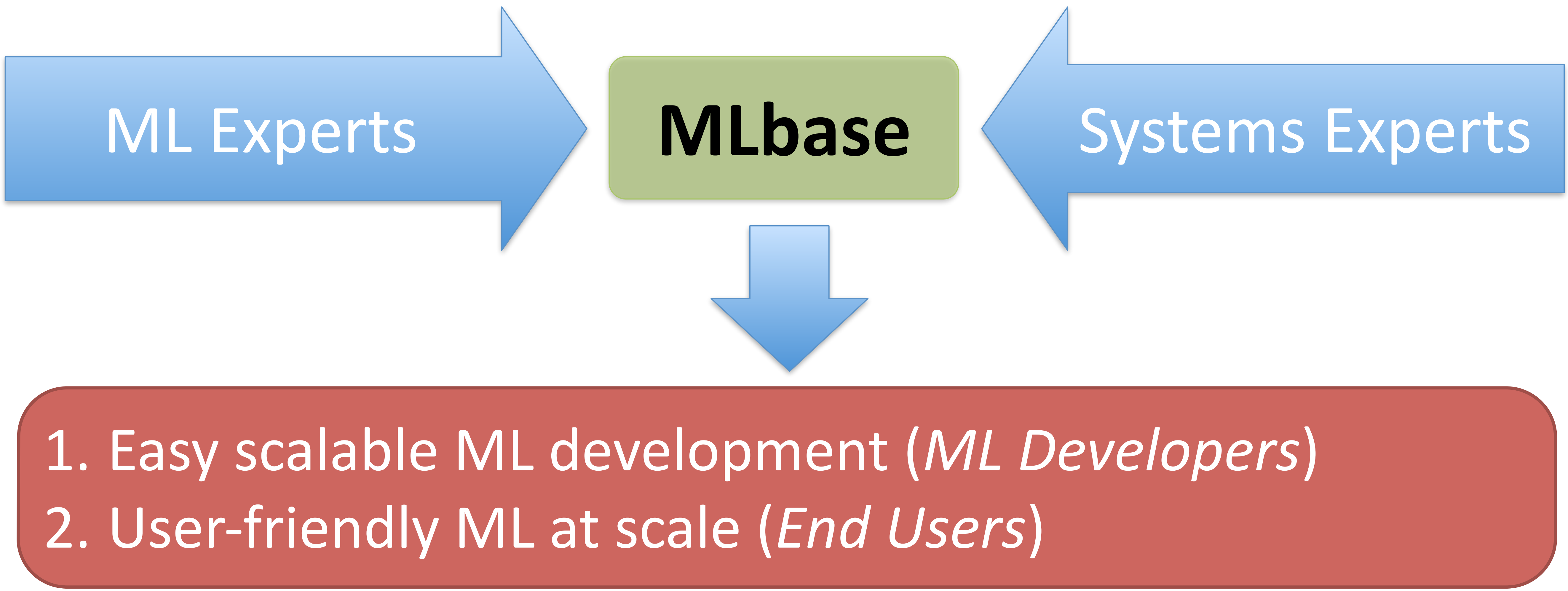





ML Experts
MLbase
Systems Experts

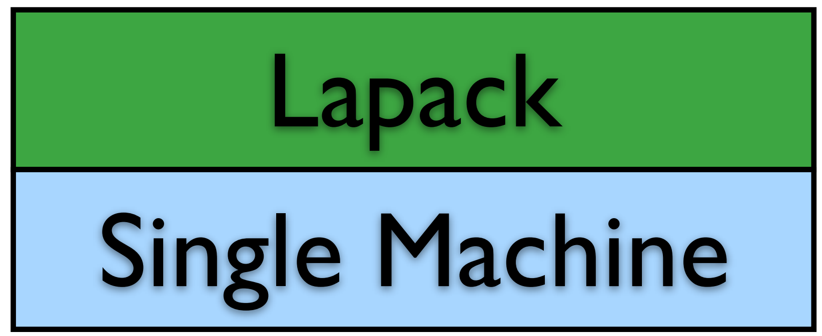

ML Experts
MLbase
Systems Experts
1. Easy scalable ML development (*ML Developers*)
2. User-friendly ML at scale (*End Users*)

Matlab Stack

Matlab Stack

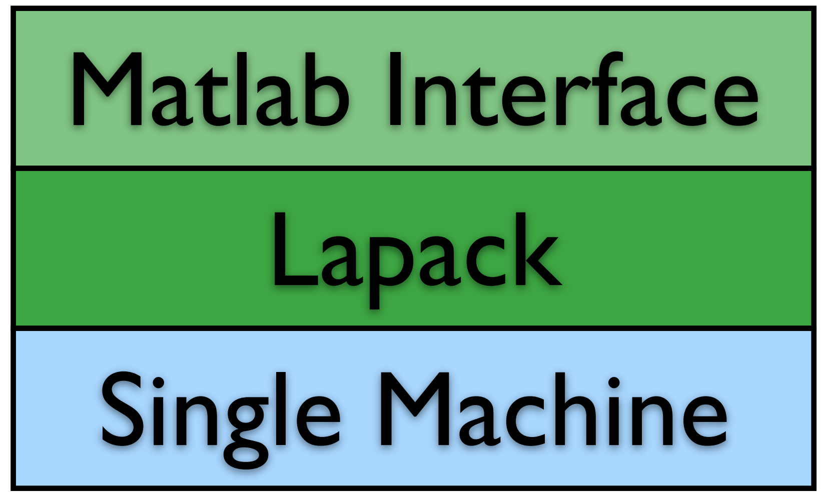
Single Machine

Matlab Stack



- Lapack: low-level Fortran linear algebra library

Matlab Stack



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- Matlab Interface
  - Higher-level abstractions for data access / processing
  - More extensive functionality than Lapack
  - Leverages Lapack whenever possible

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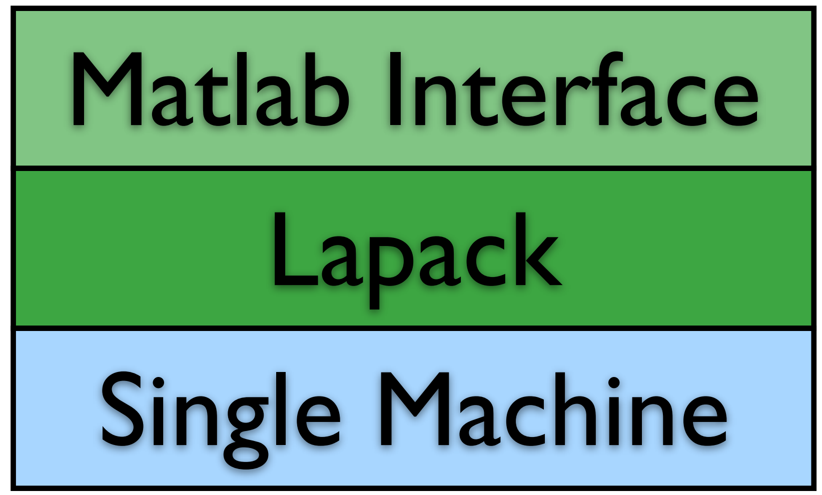

- Lapack: low-level Fortran linear algebra library
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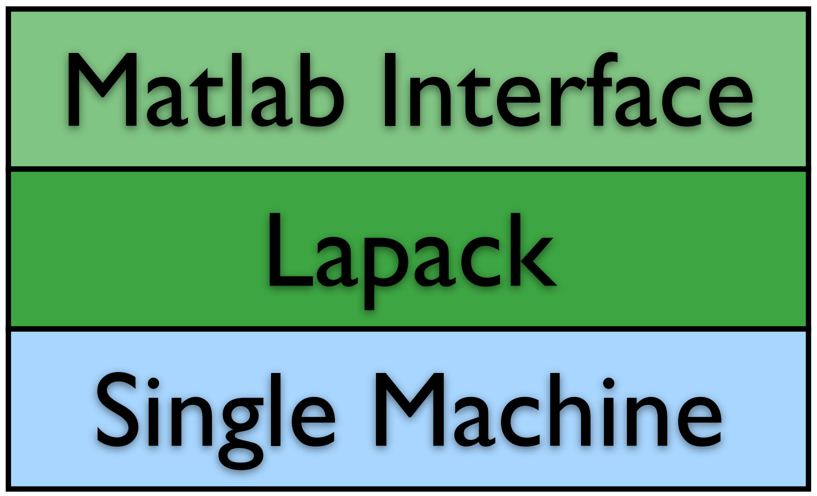
  - Higher-level abstractions for data access / processing
  - More extensive functionality than Lapack
  - Leverages Lapack whenever possible
- Similar stories for R and Python

MLbase Stack



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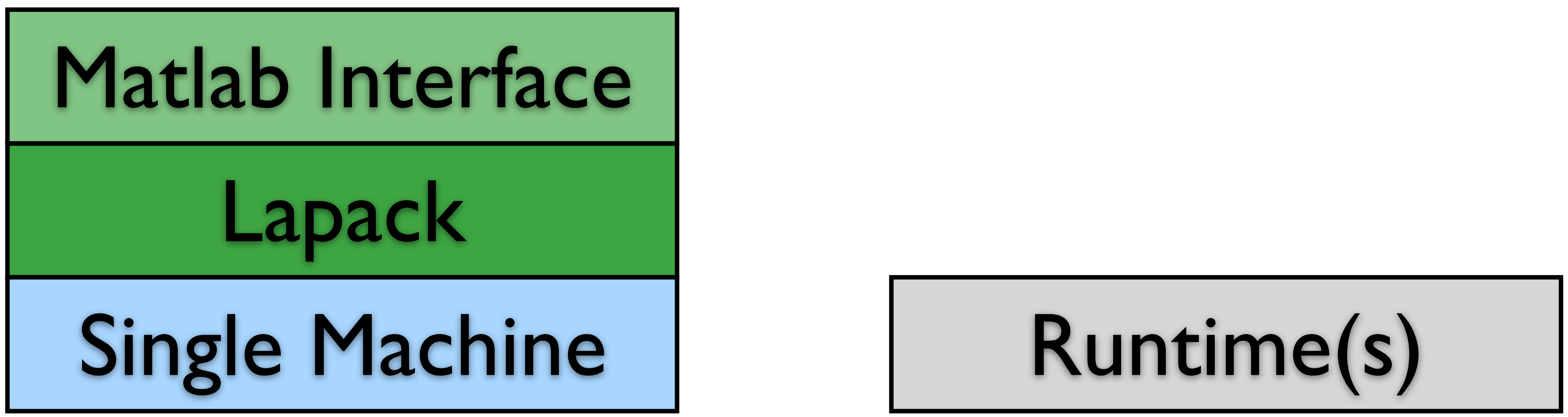

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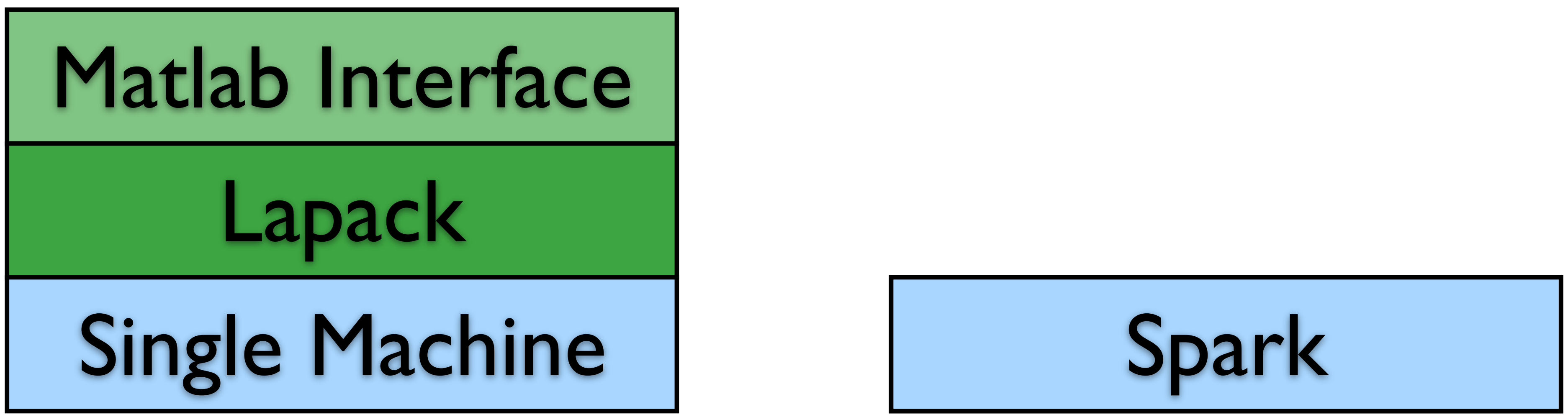
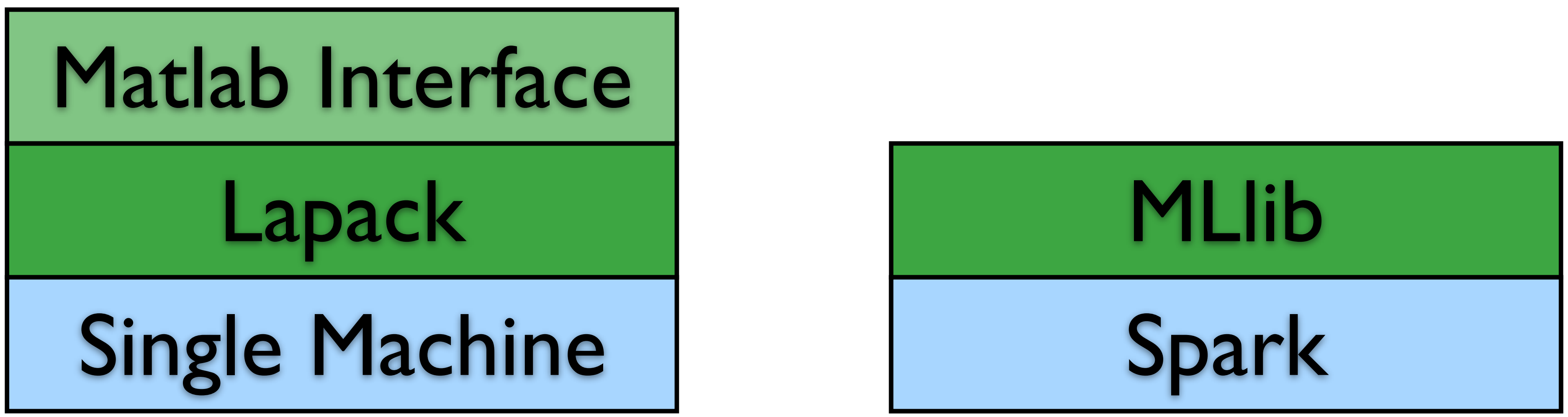


Spark: cluster computing system designed for iterative computation

MLbase Stack



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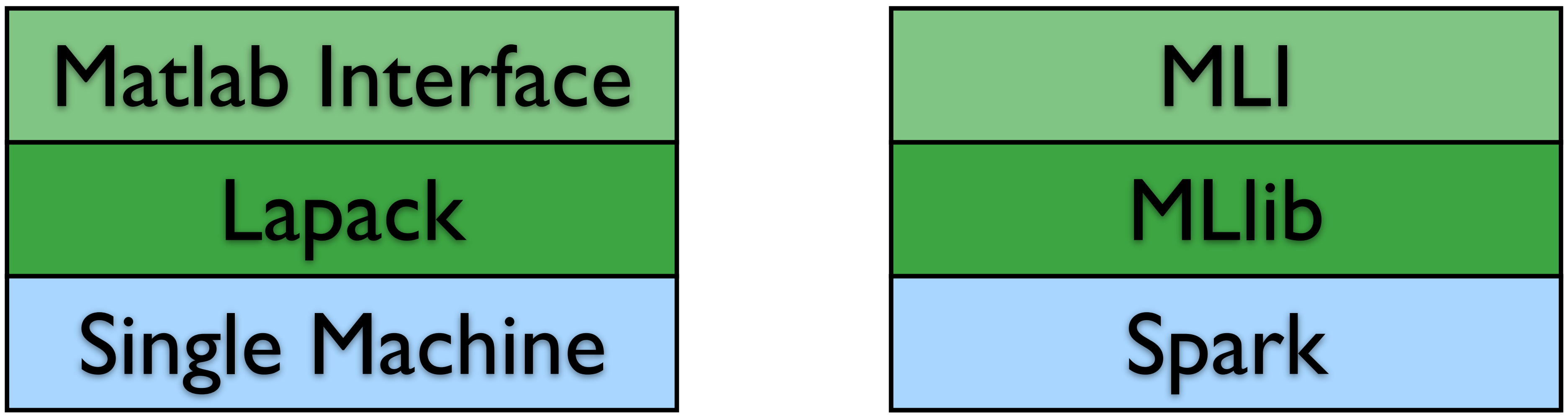

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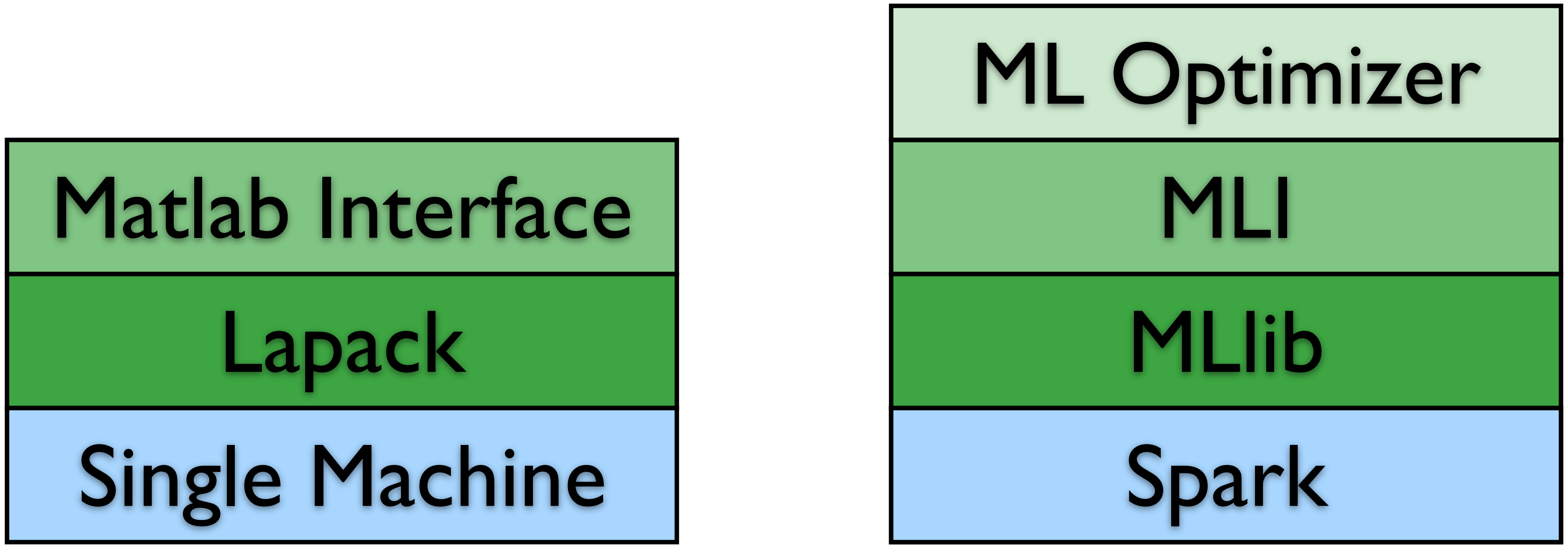

Spark: cluster computing system designed for iterative computation

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ML Optimizer: a declarative layer to simplify access to large-scale ML

Overview

MLlib

Collaborative Filtering

ALS Details

MLlib

Classification: Logistic Regression, Linear SVM (+L1, L2), Decision Trees, Naive Bayes

Regression: Linear Regression (+Lasso, Ridge)

Collaborative Filtering: Alternating Least Squares

Clustering / Exploration: K-Means, SVD

Optimization Primitives: SGD, Parallel Gradient

Interoperatility: Scala, Java, PySpark (0.9)

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Included within Spark codebase

- Unlike Mahout/Hadoop
- Part of Spark 0.8 release
- Continued support via Spark project
- Community involvement has been terrific: ALS with implicit feedback (0.8.1), Naive Bayes (0.9), SVD (0.9), Decision Trees (soon!)

MLlib Performance

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- **EC2 Experiments**
  - m2.4xlarge instances, up to 32 machine clusters

Logistic Regression - Weak Scaling

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- Full dataset: 200K images, 160K dense features

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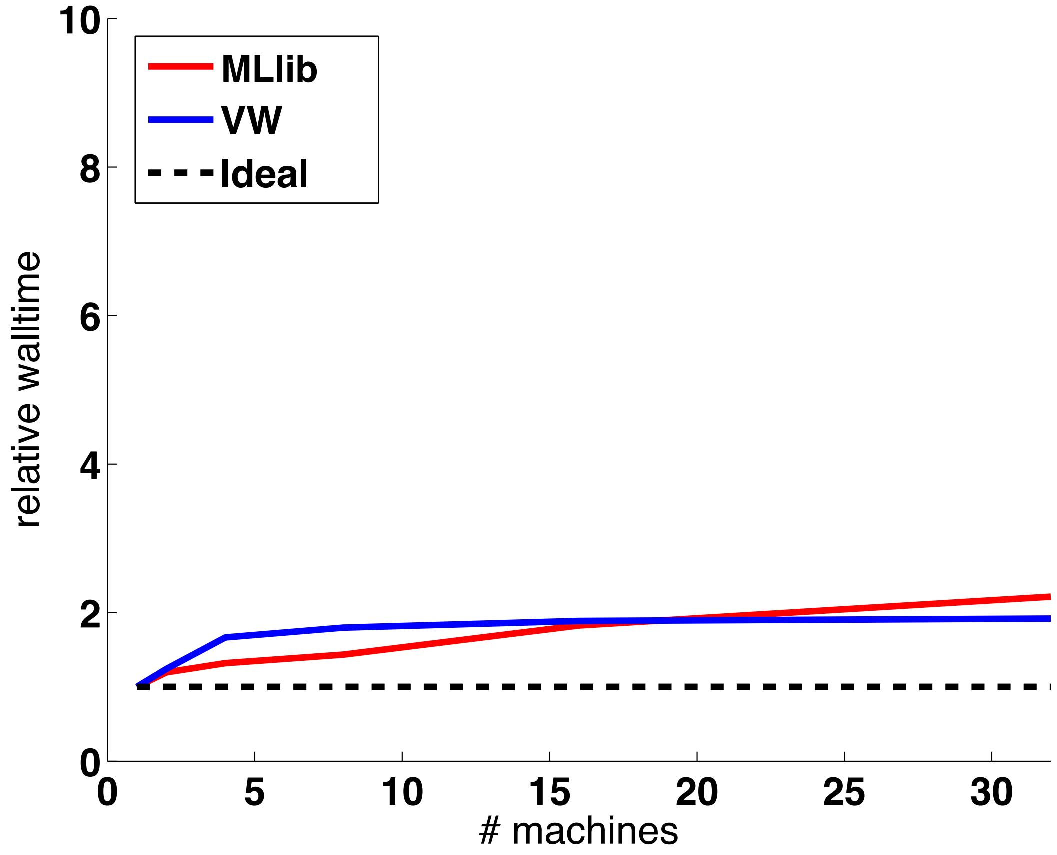

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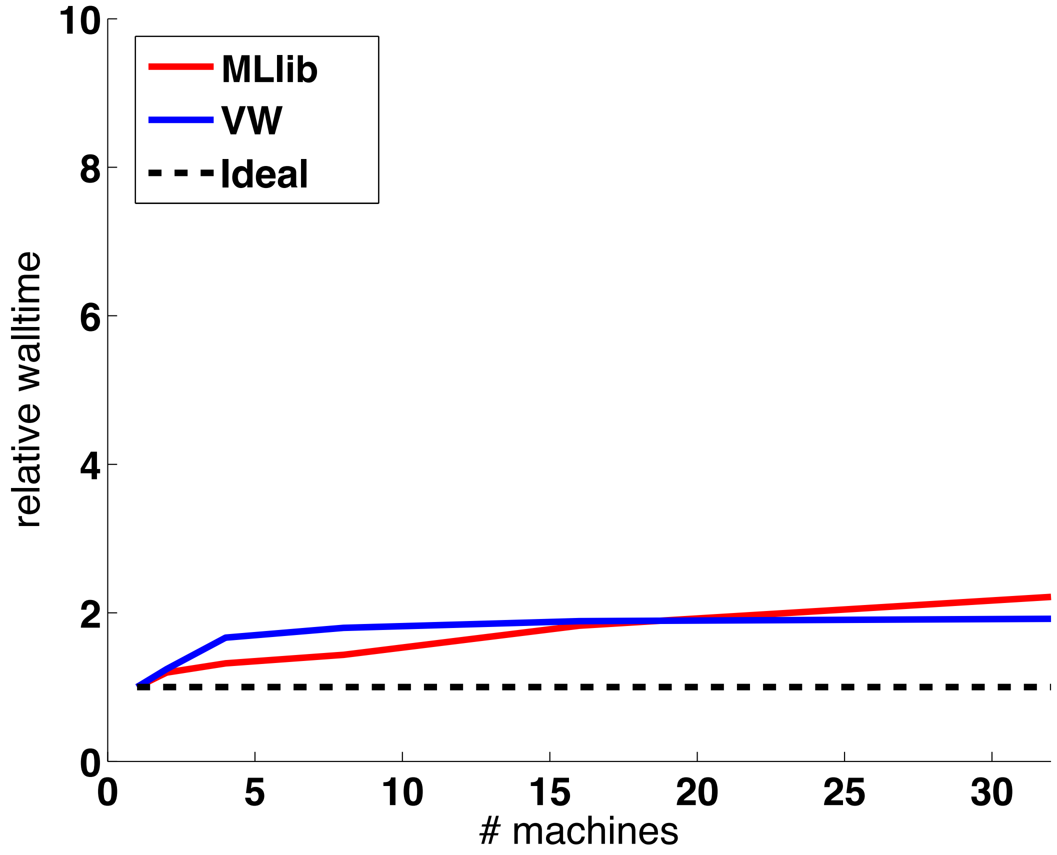

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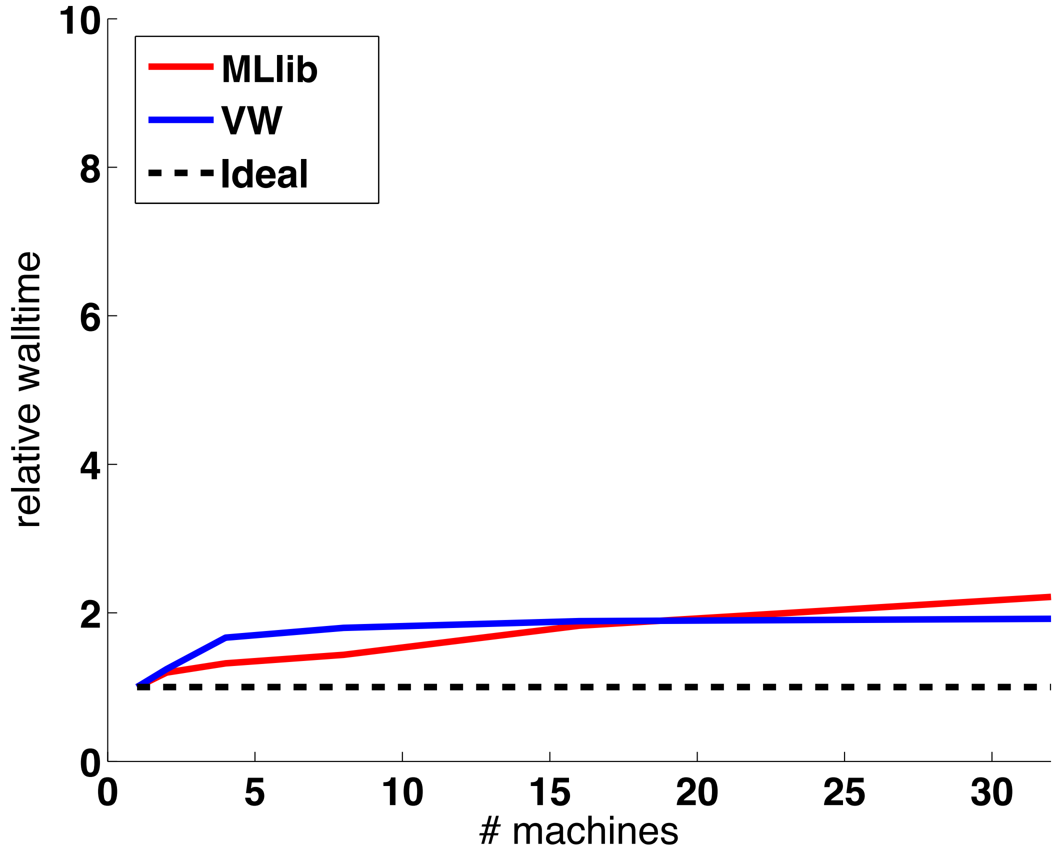

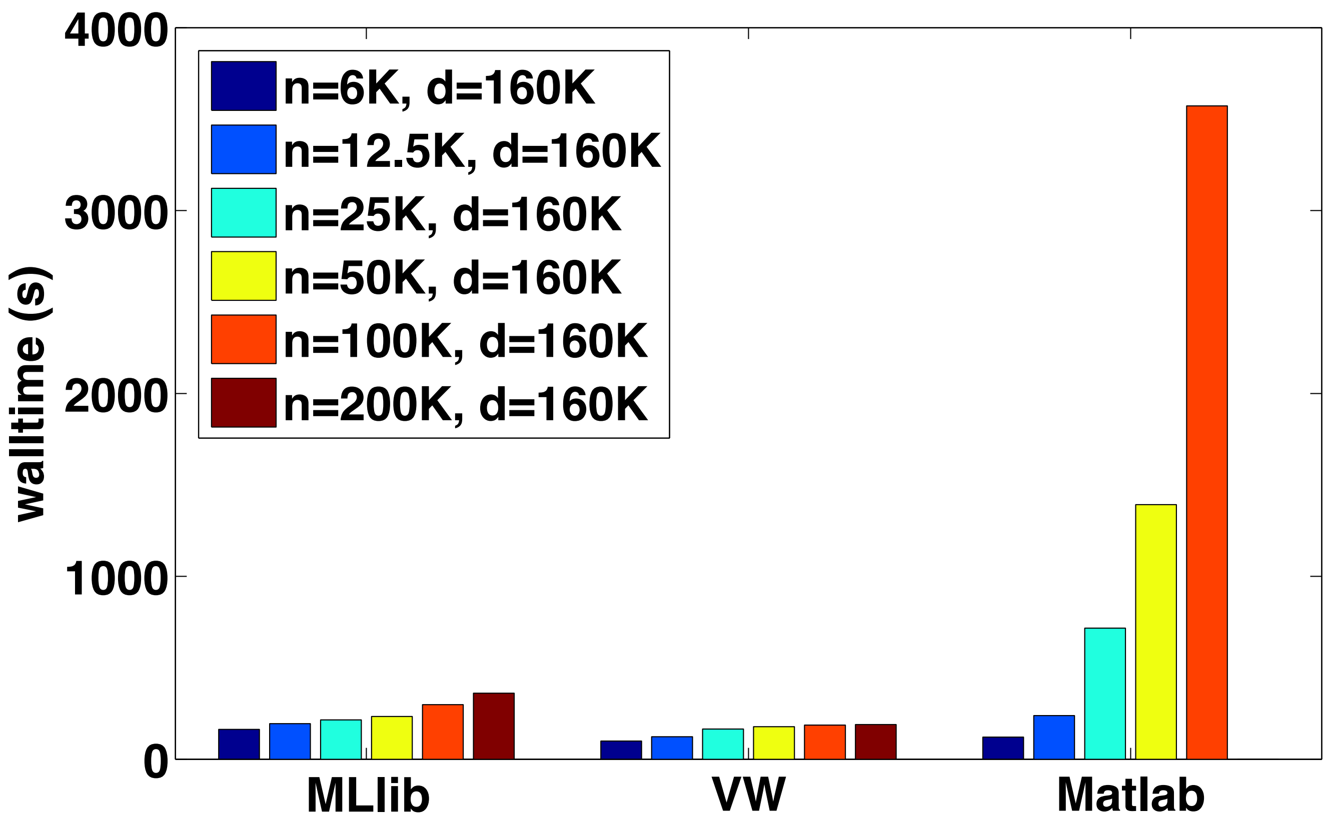

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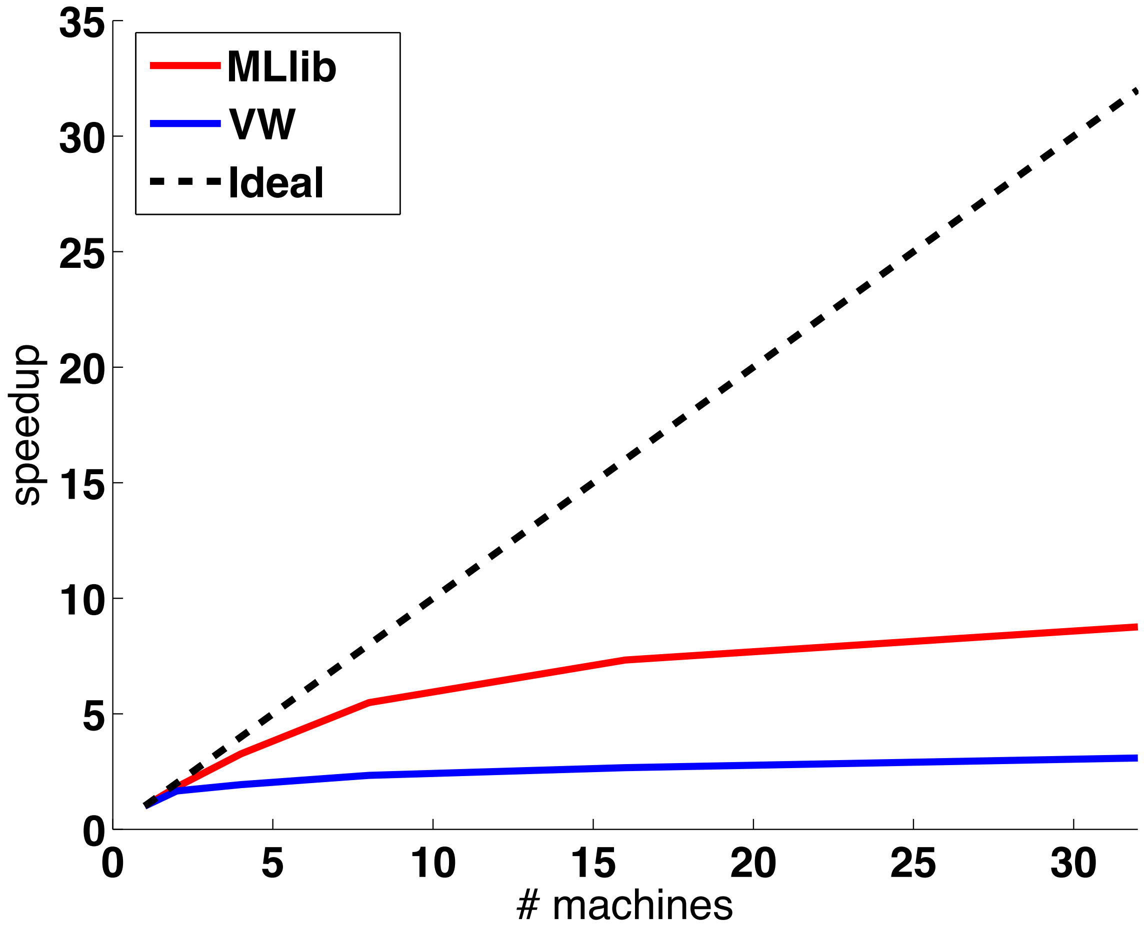

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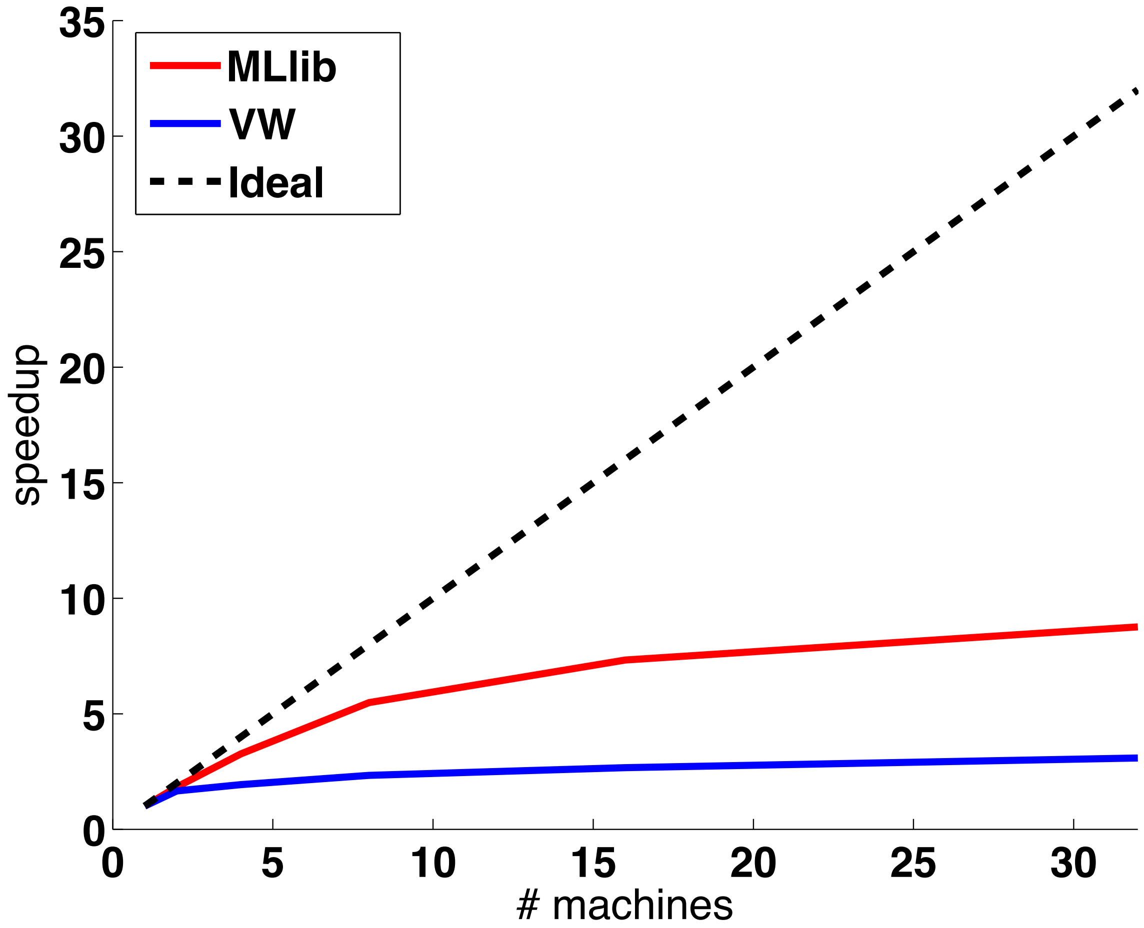

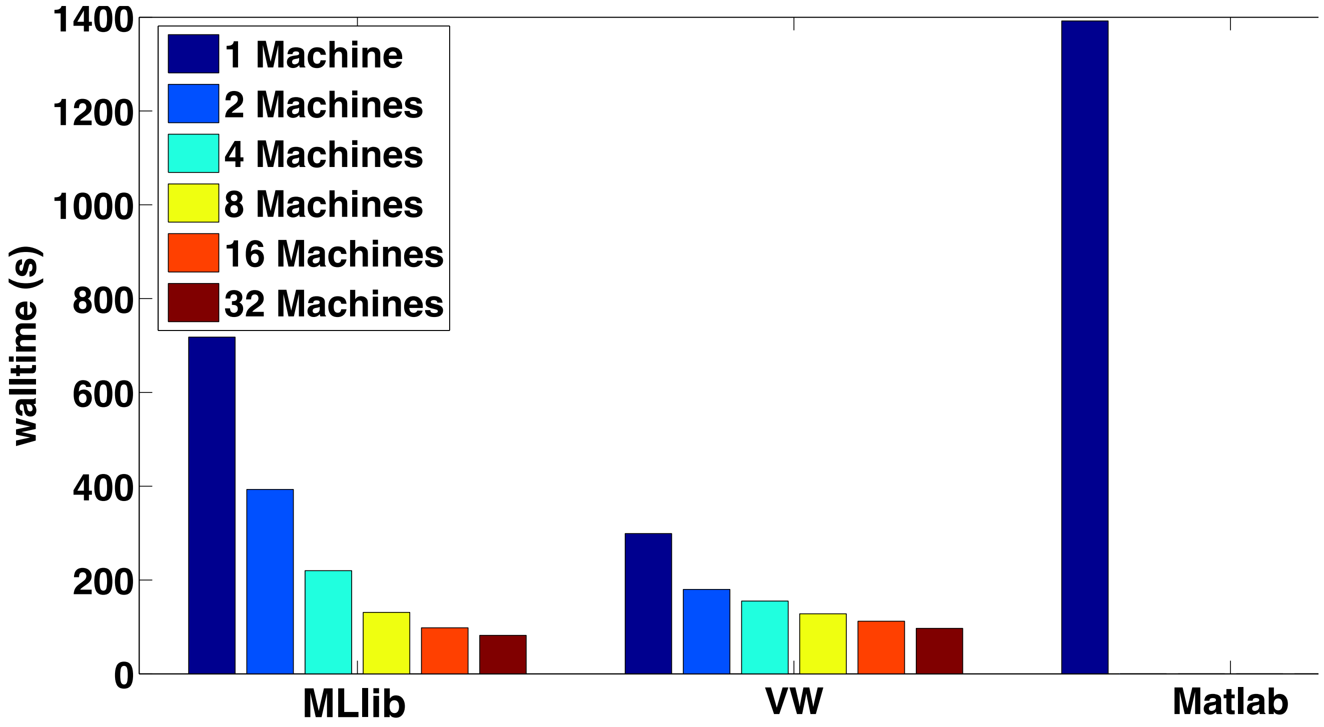

- Fixed Dataset: 50K images, 160K dense features
- MLlib exhibits better scaling properties
- MLlib faster than VW with 16 and 32 machines

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- **Part of Spark's 'swiss army knife' ecosystem**
  - Shark, Spark Streaming, Graph-X, BlinkDB, etc.

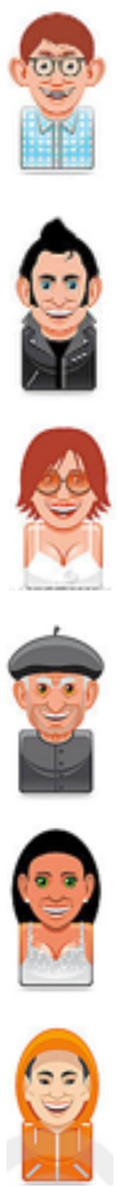
Vision

MLlib

Collaborative Filtering

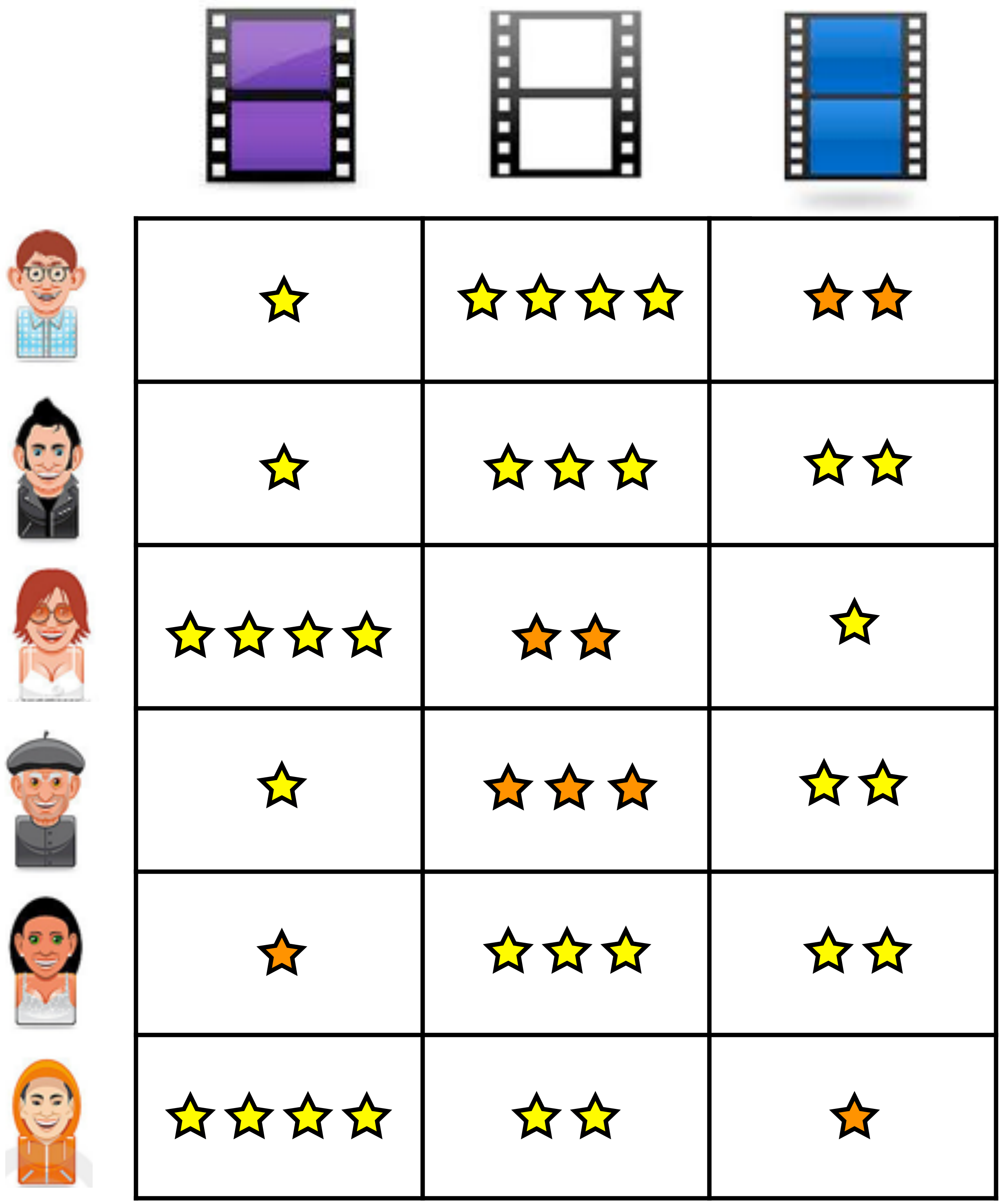
ALS Details

Matrix Completion



★	★★★★	
★	★★★	★★
★★★★		★
★		★★
	★★★	★★
★★★★	★★	

Matrix Completion



Goal: Recover a matrix from a subset of its entries

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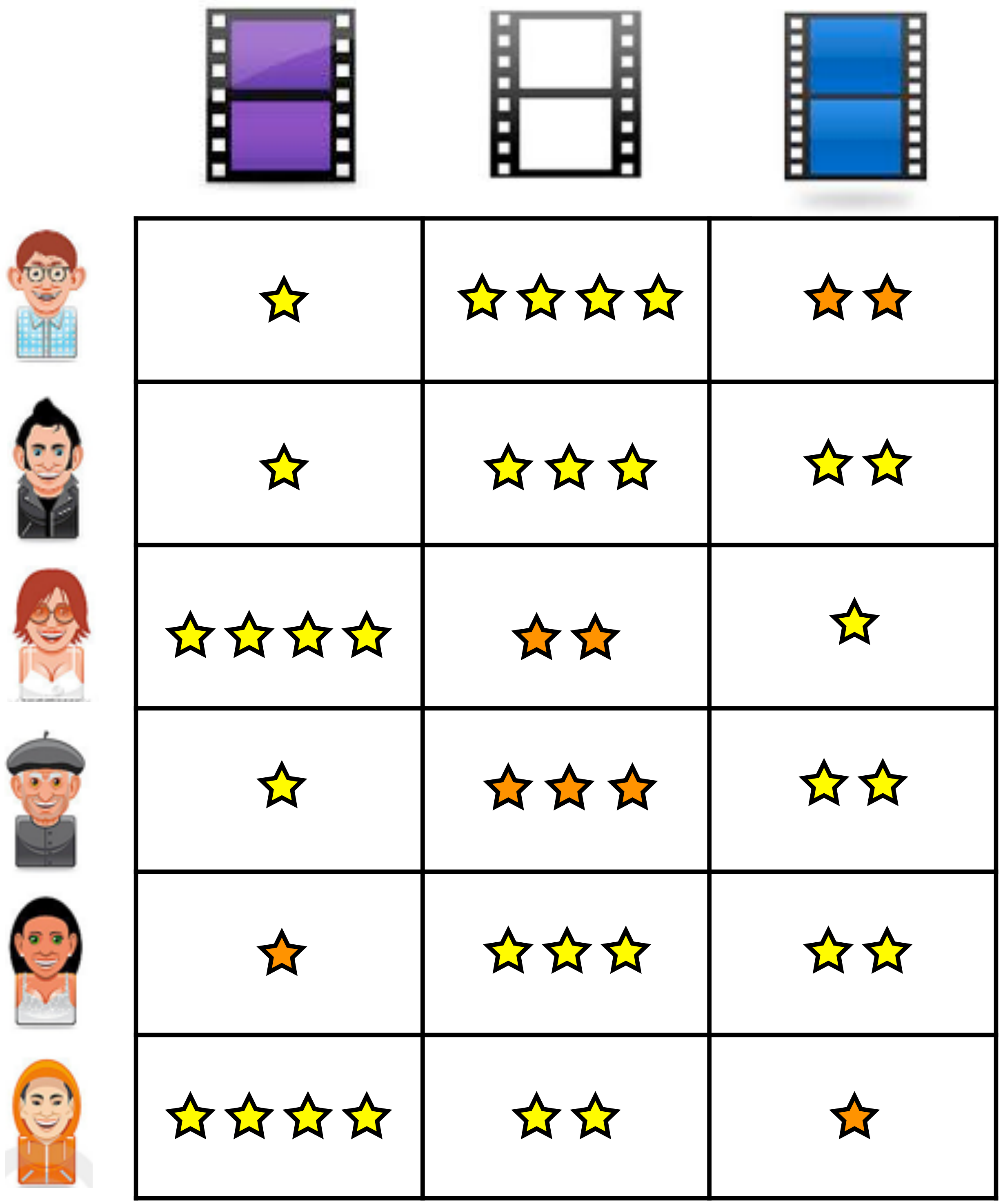

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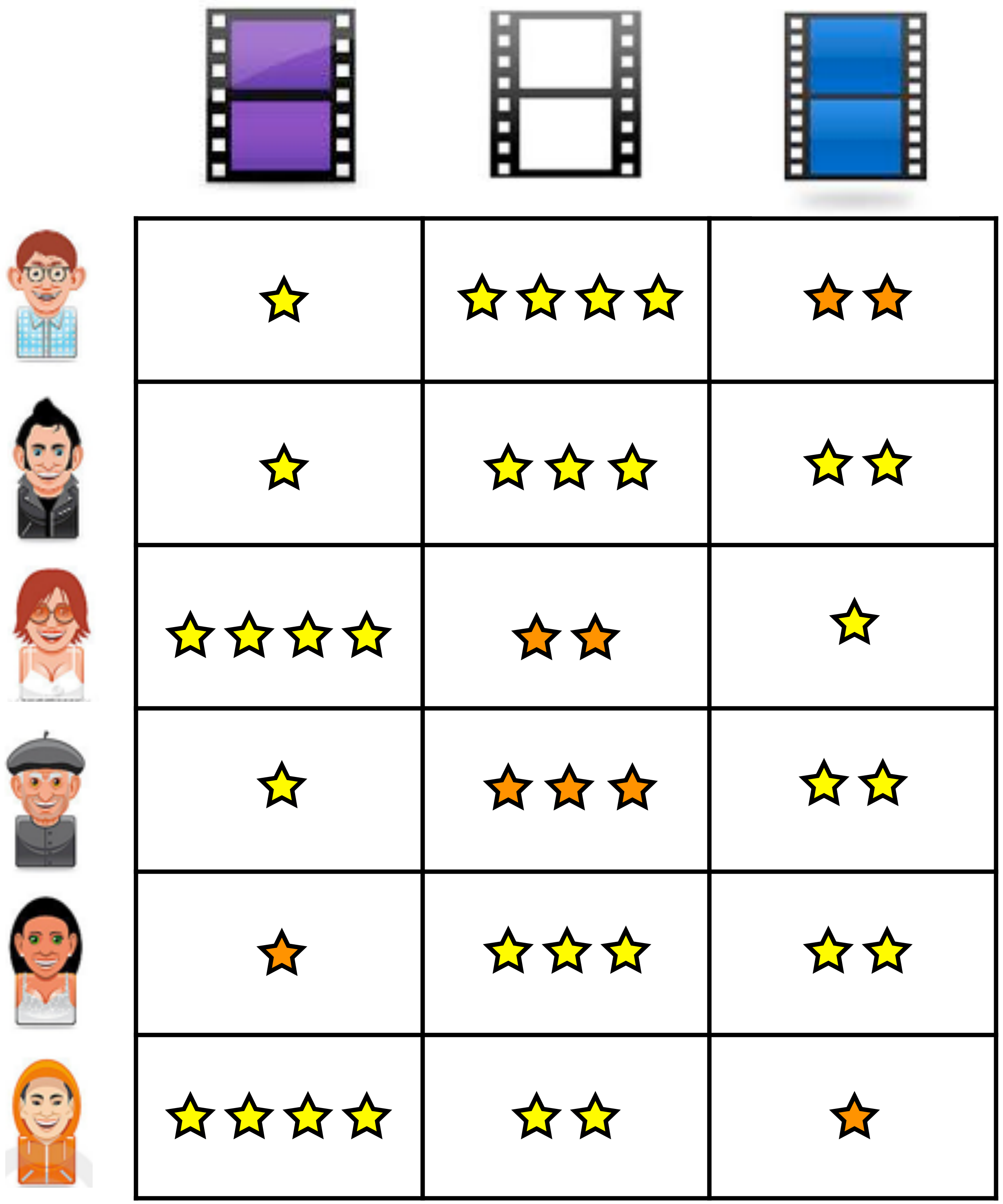

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Reducing Degrees of Freedom

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★★★★		★
★		★★
	★★★	★★
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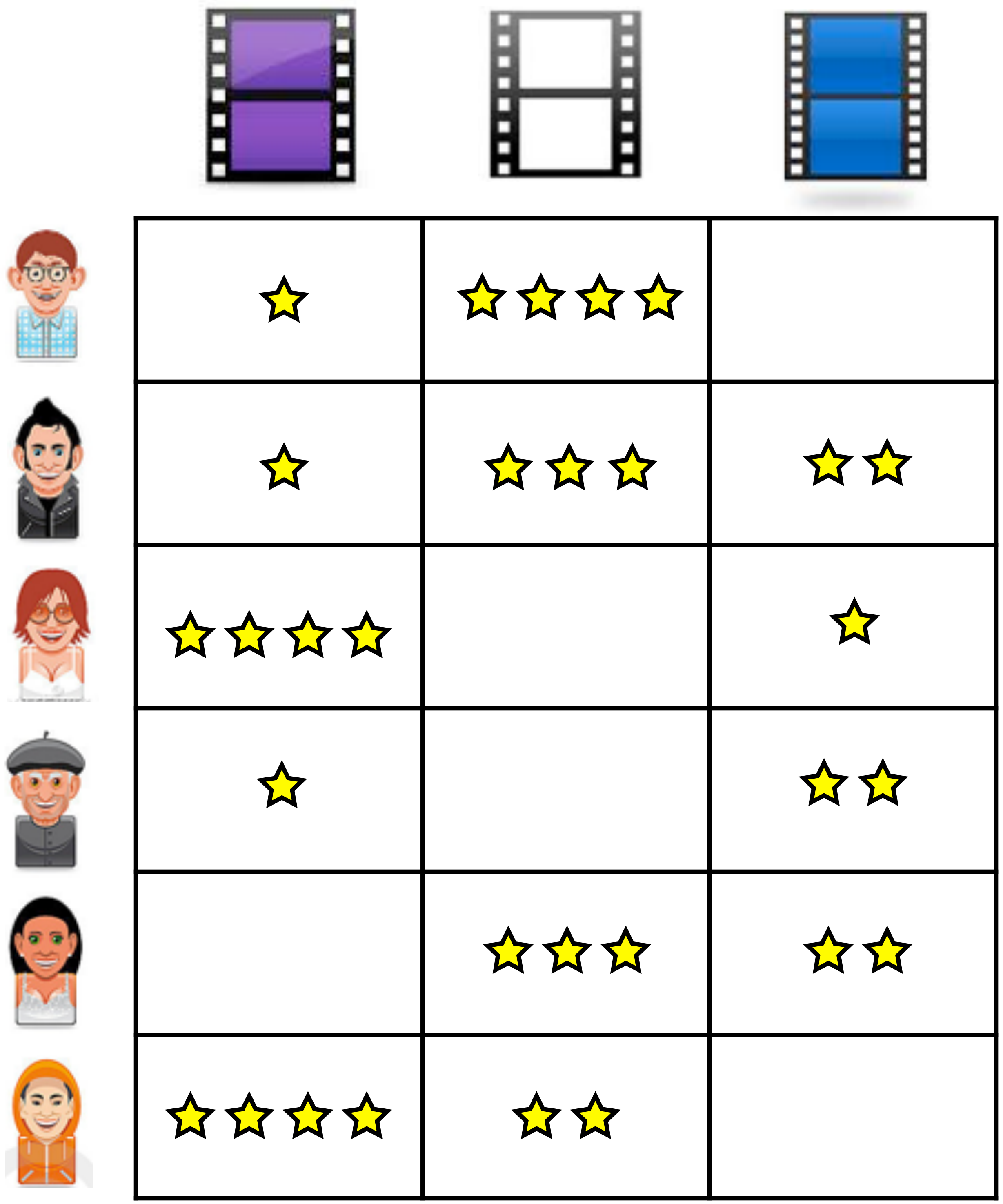
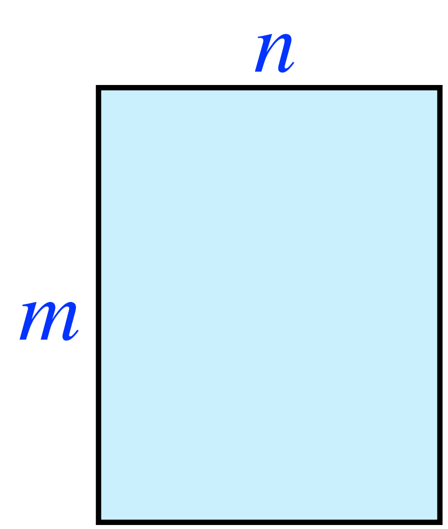


- Problem: Impossible without additional information



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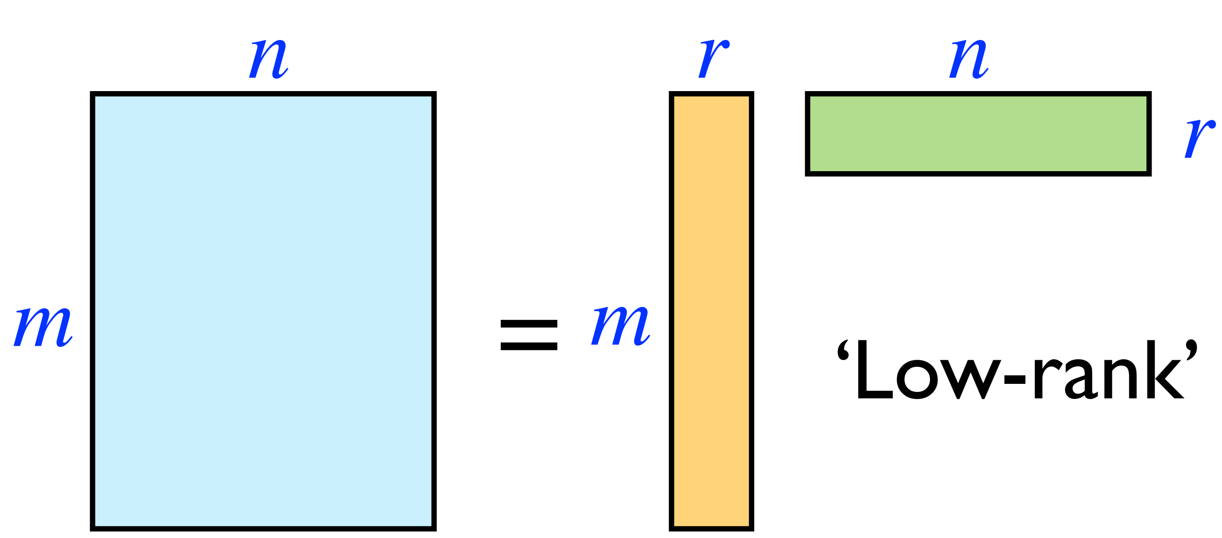

Reducing Degrees of Freedom

★	★★★★	
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★★★★		★
★		★★
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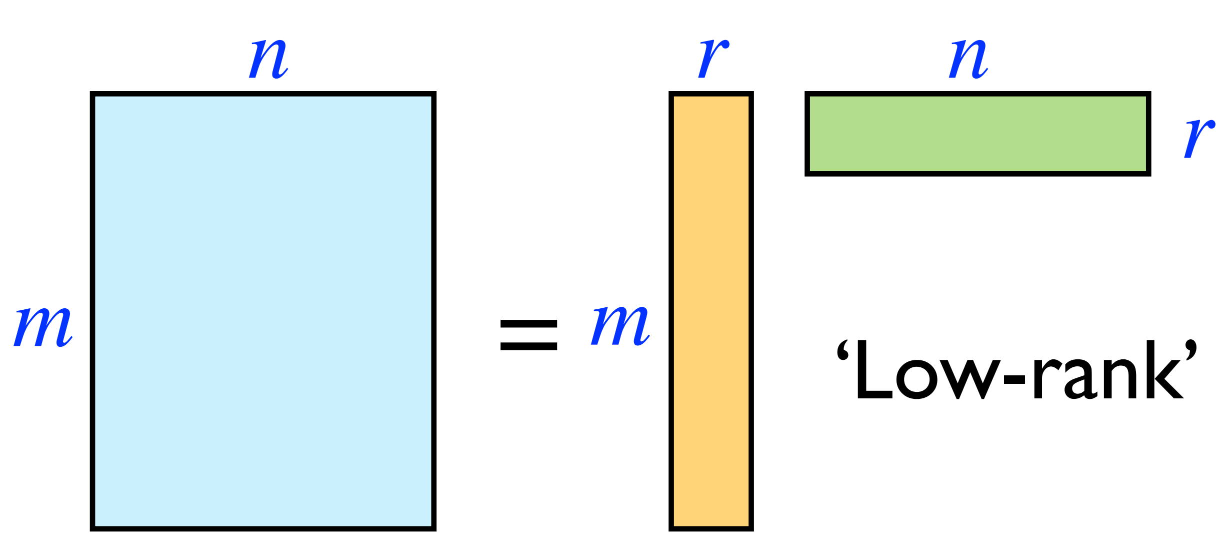
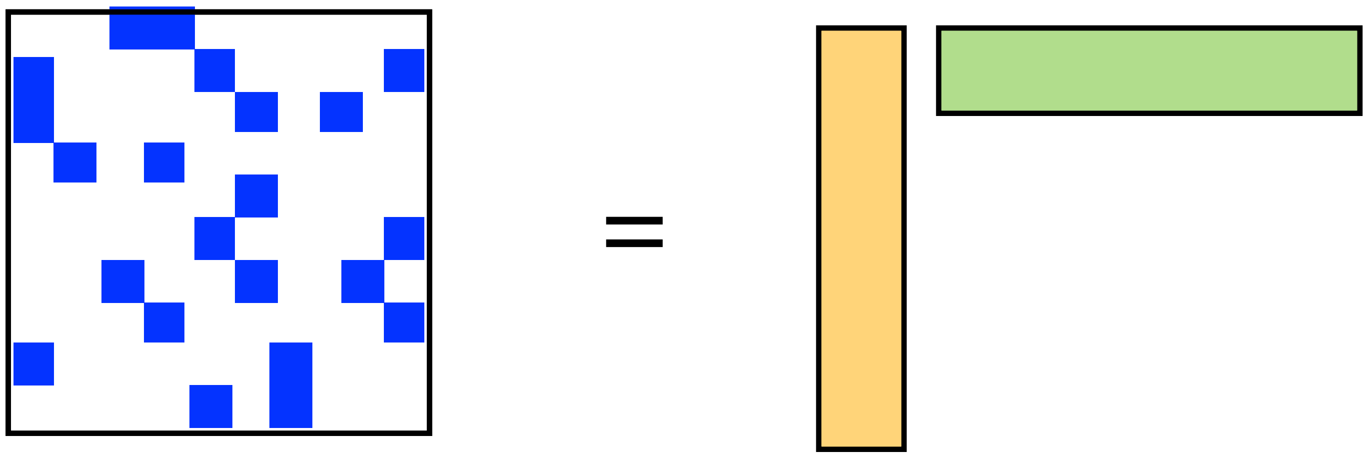
- **Problem**: Impossible without additional information
  - mn degrees of freedom
- **Solution**: Assume small # of factors determine preference
  - $O(m+n)$ degrees of freedom



Alternating Least Squares



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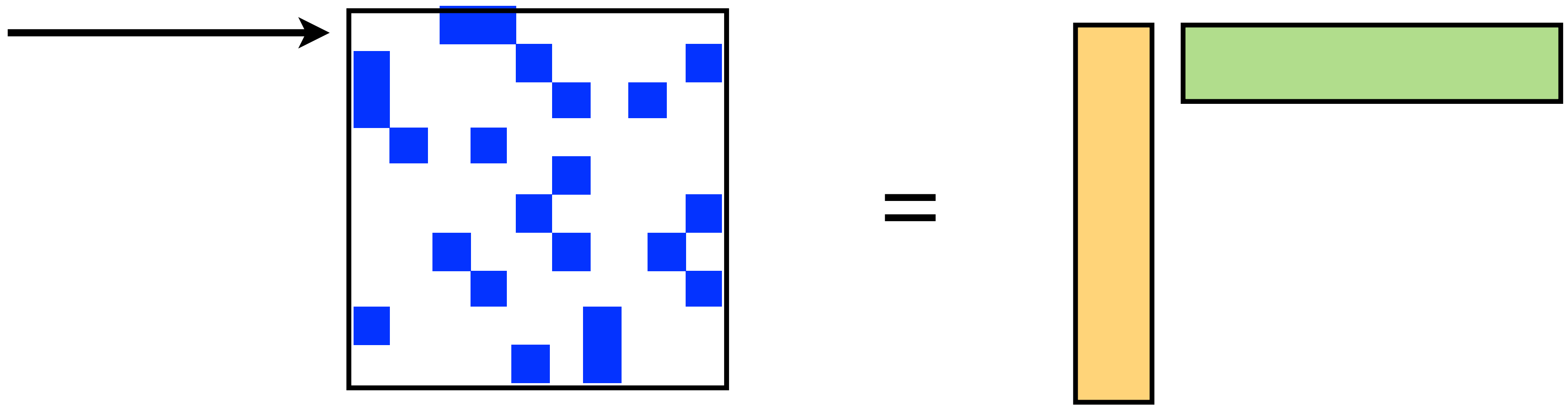

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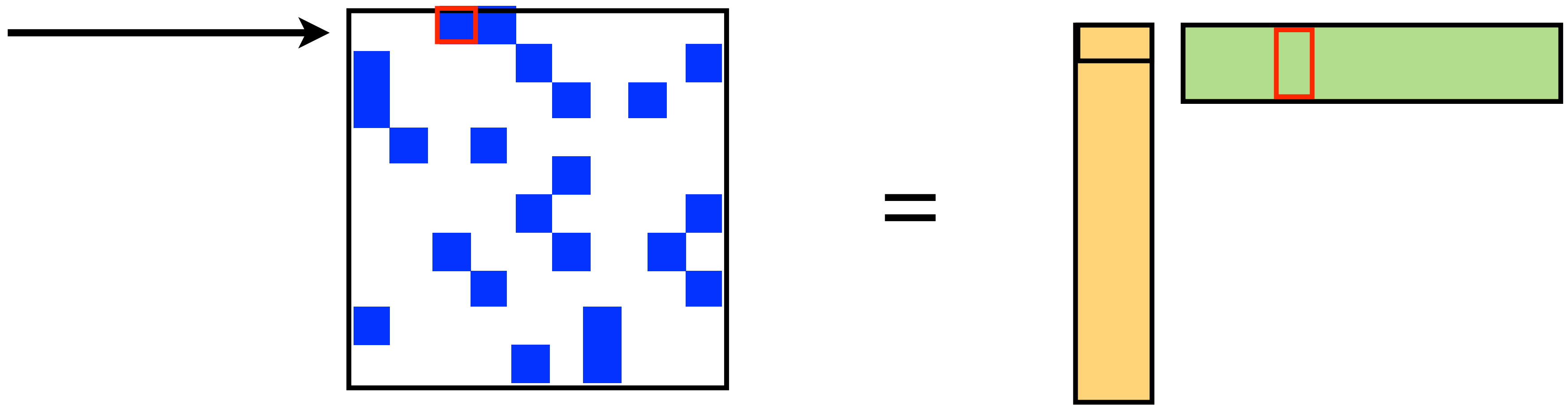

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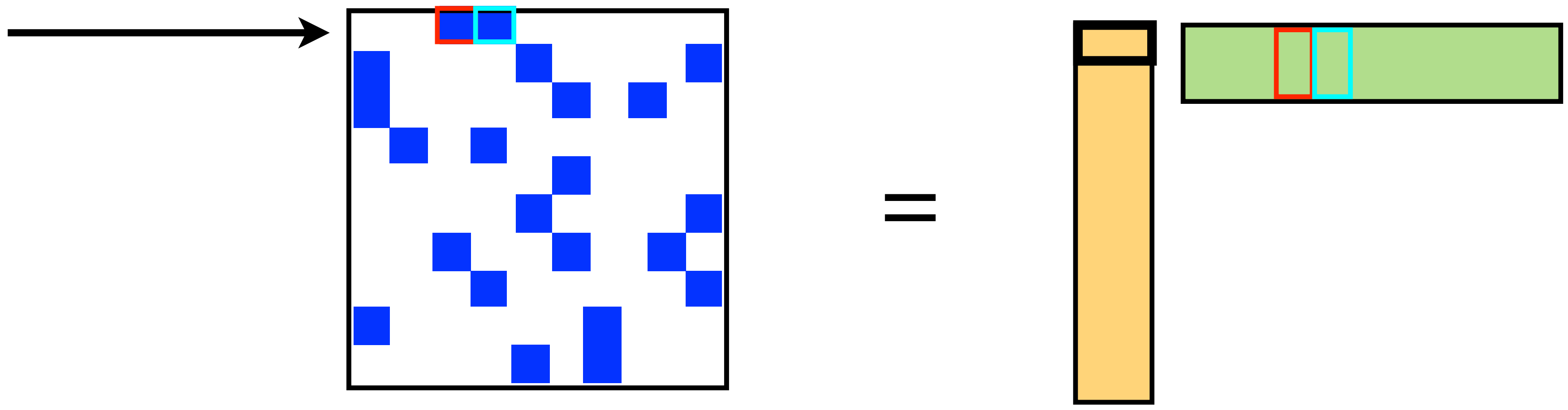

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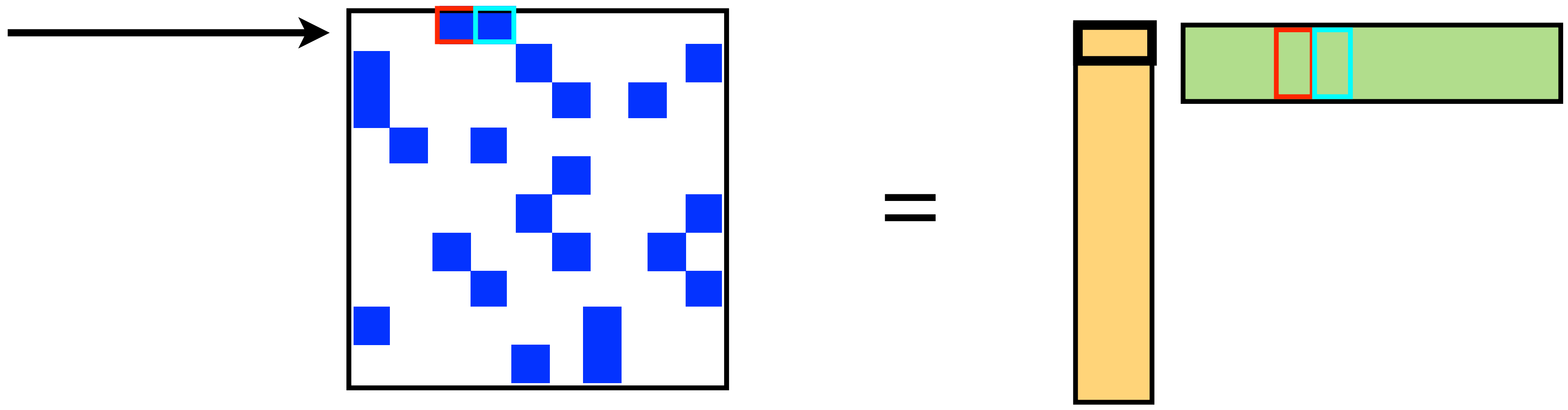

training error for first user = (-) + (-)

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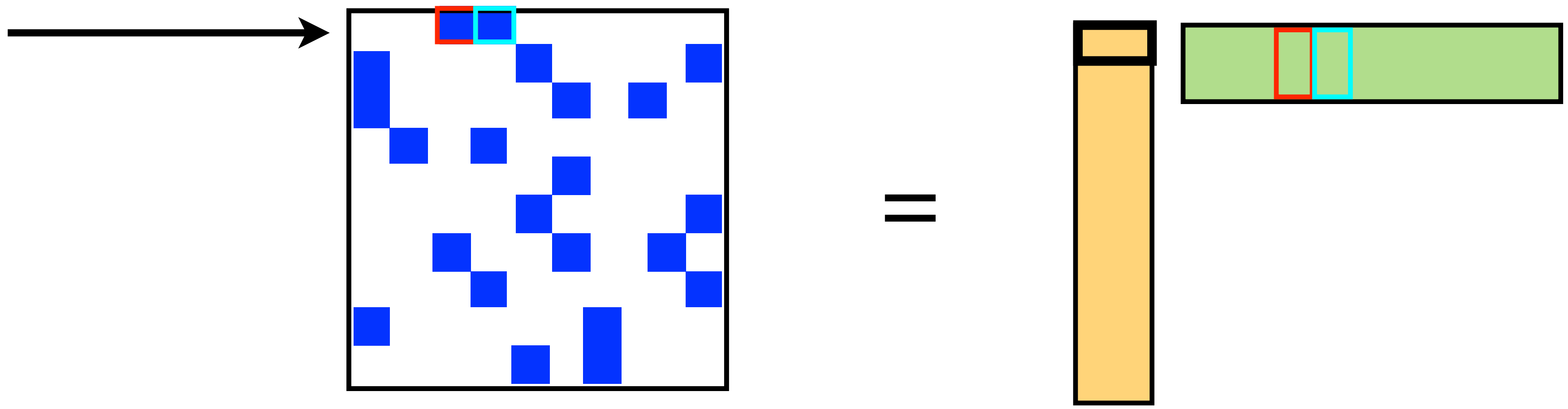
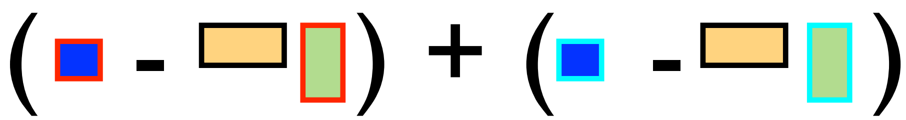


training error for first user = 

ALS: alternate between updating user and movie factors

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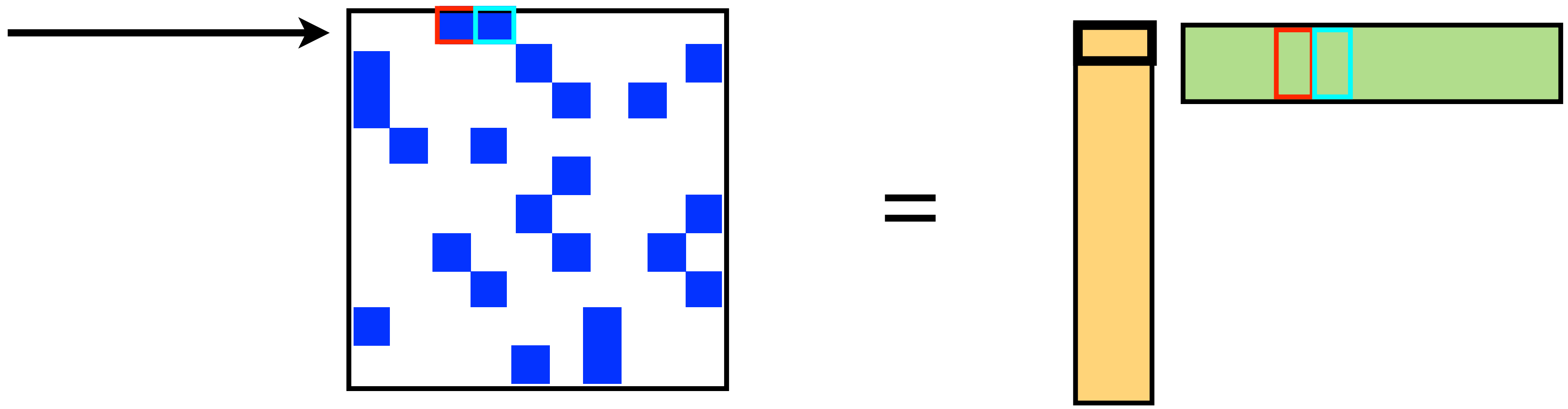

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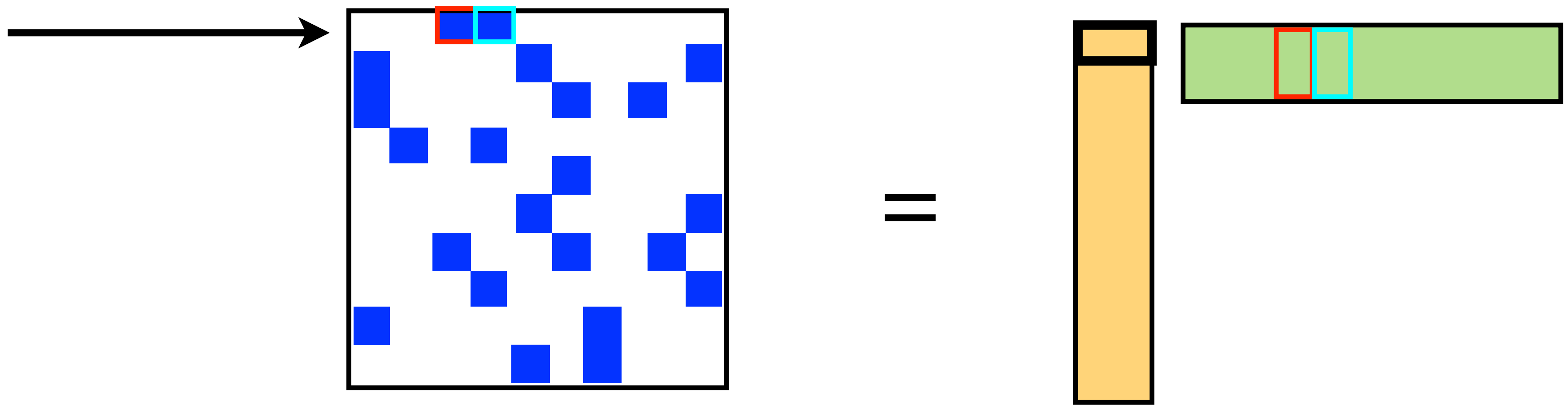
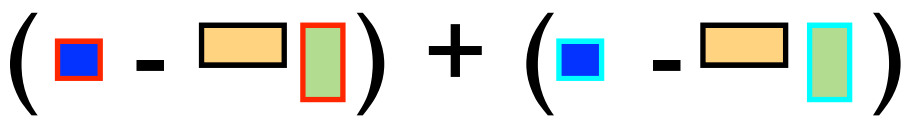


training error for first user = 

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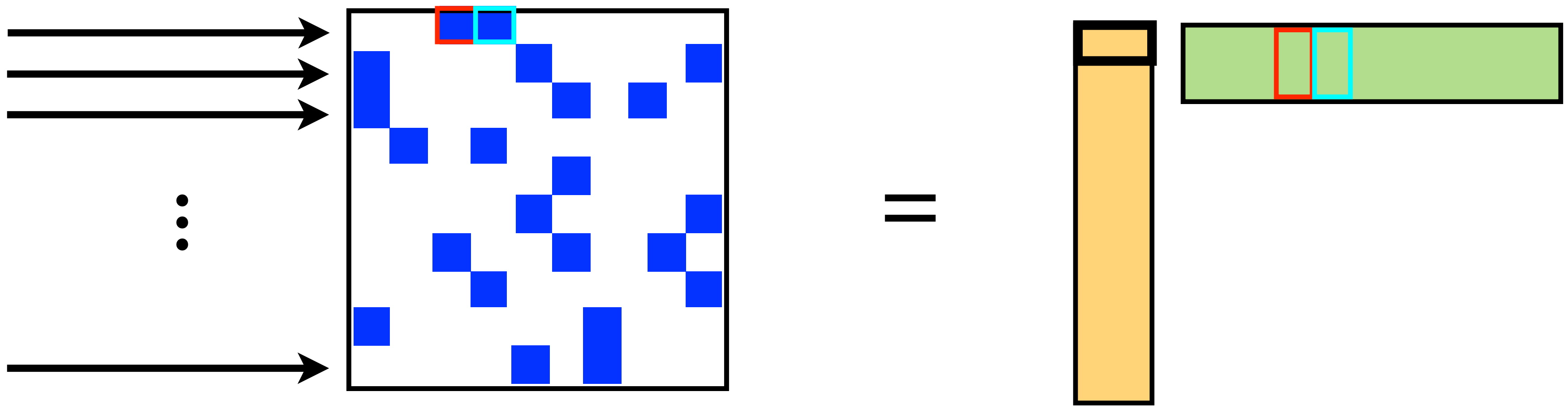
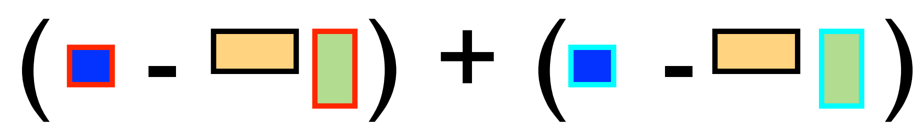


training error for first user = 

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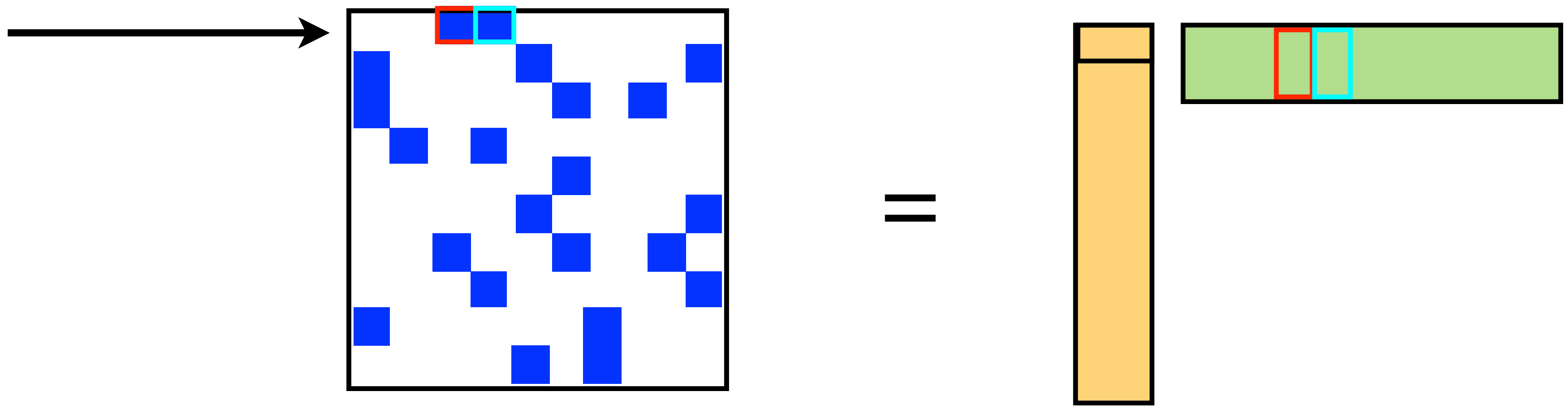
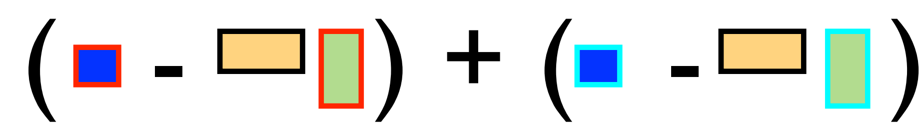
can update all users in parallel!

Alternating Least Squares



training error for first user = 

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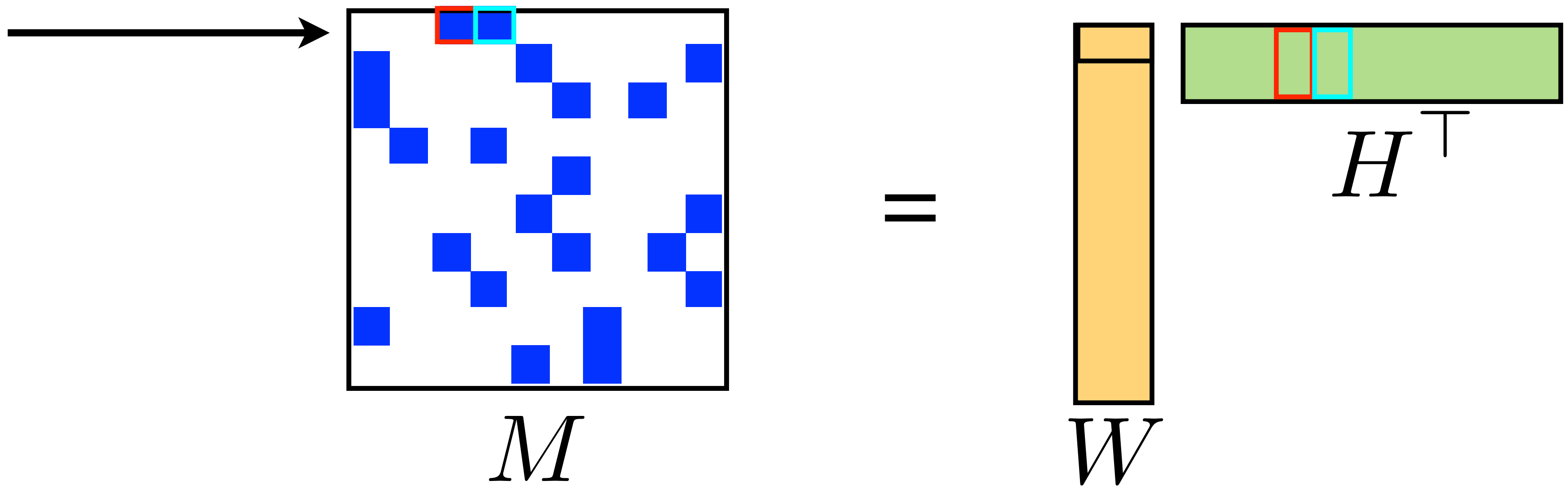
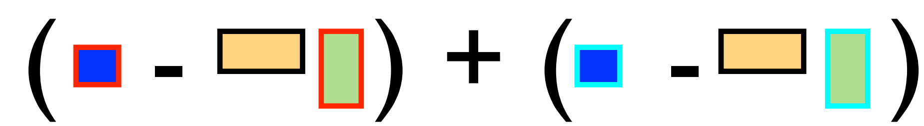


training error for first user = 

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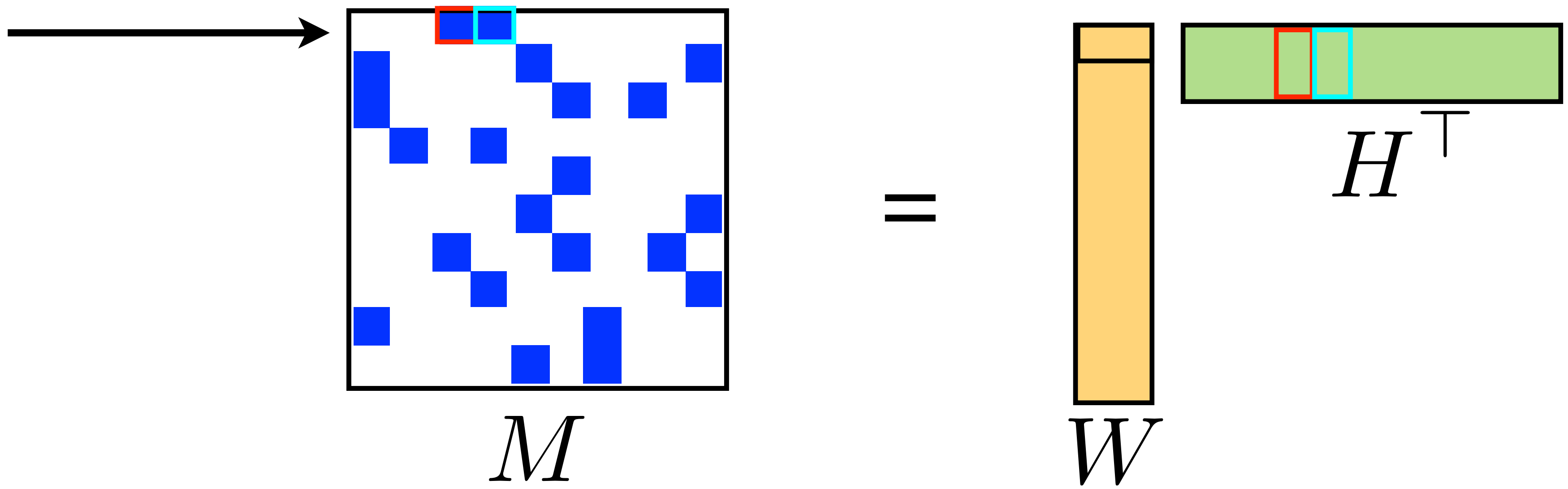

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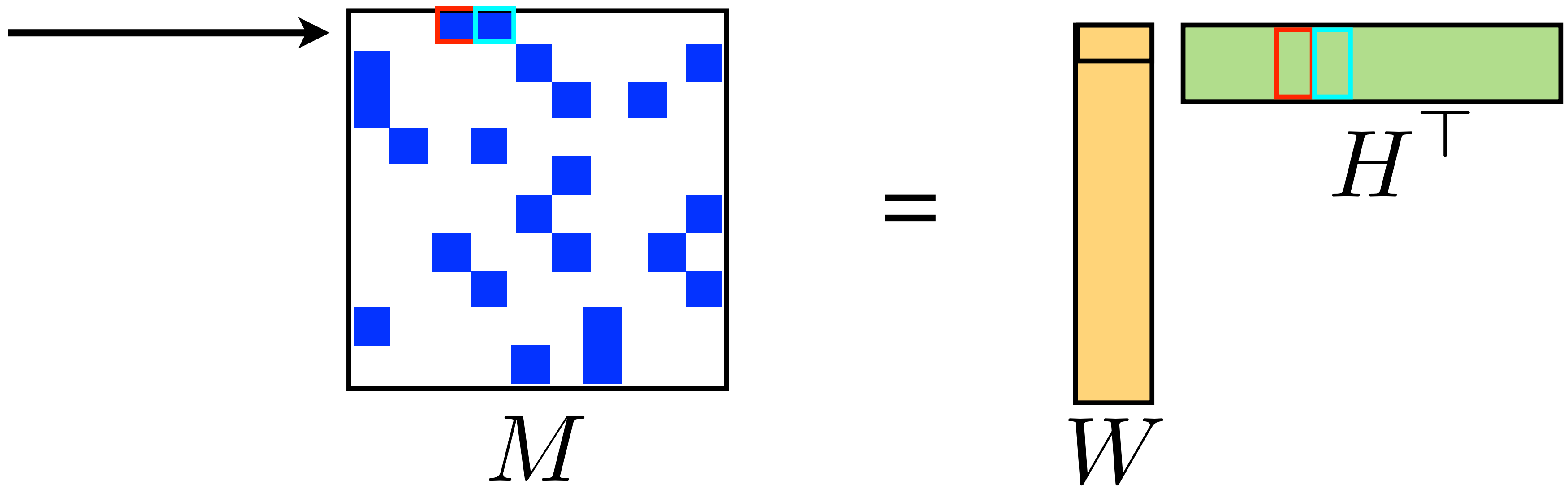

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$$W_1^* = (H_{\Omega_1}^\top H_{\Omega_1})^{-1} H_{\Omega_1}^\top M_{1\Omega_1}^\top$$

Exercise Today

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- Load 1,000,000 ratings from MovieLens.

Exercise Today

- Load 1,000,000 ratings from MovieLens.
- Get **YOUR** ratings.

Exercise Today

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- Great example of a Spark application!

Vision

MLlib

Collaborative Filtering

ALS Details

Three Kinds of ALS

- Broadcast Everything
- Data Parallel
- Fully Parallel

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Broadcast Everything

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- Master loads (small) data file and initializes models.
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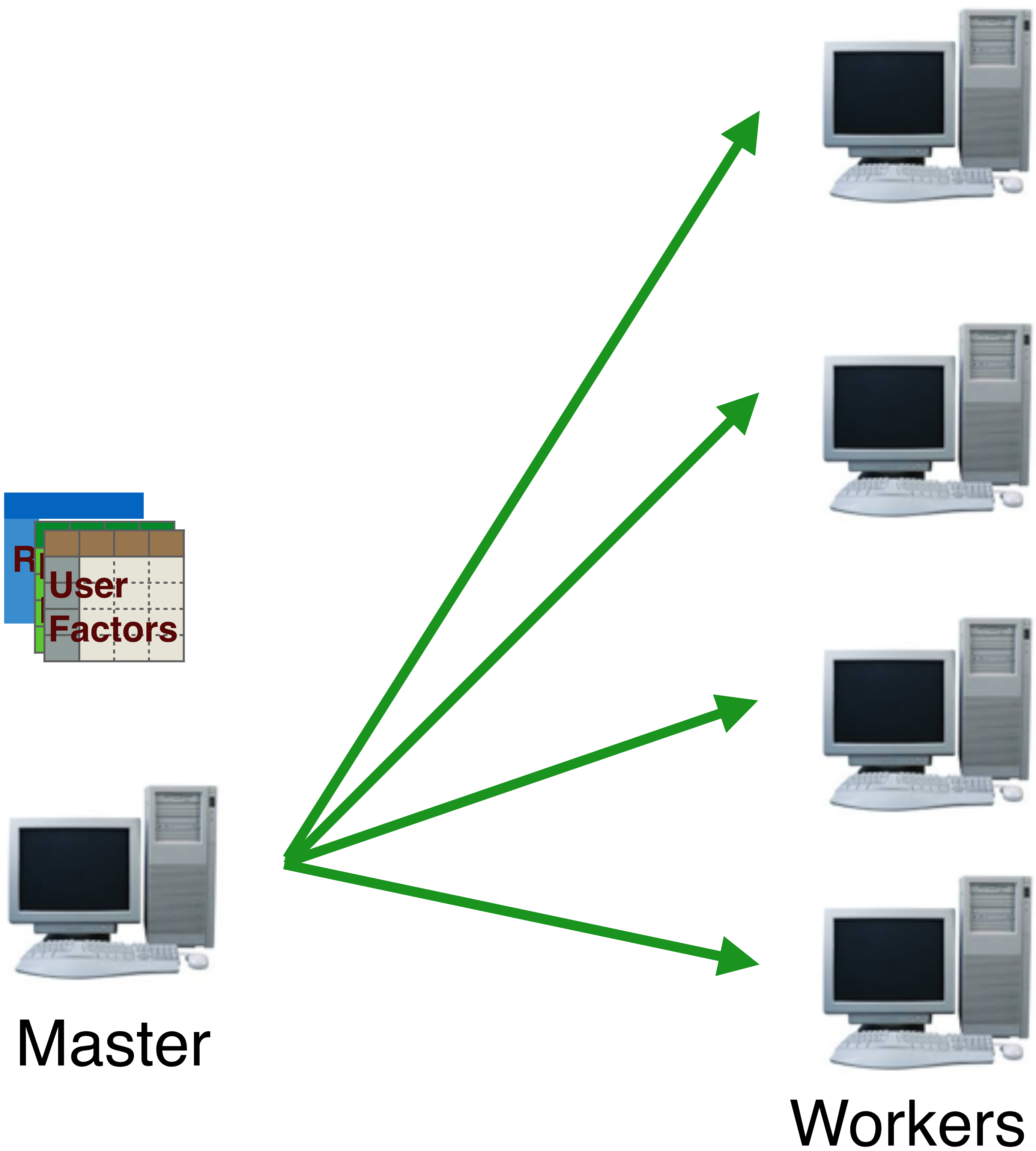

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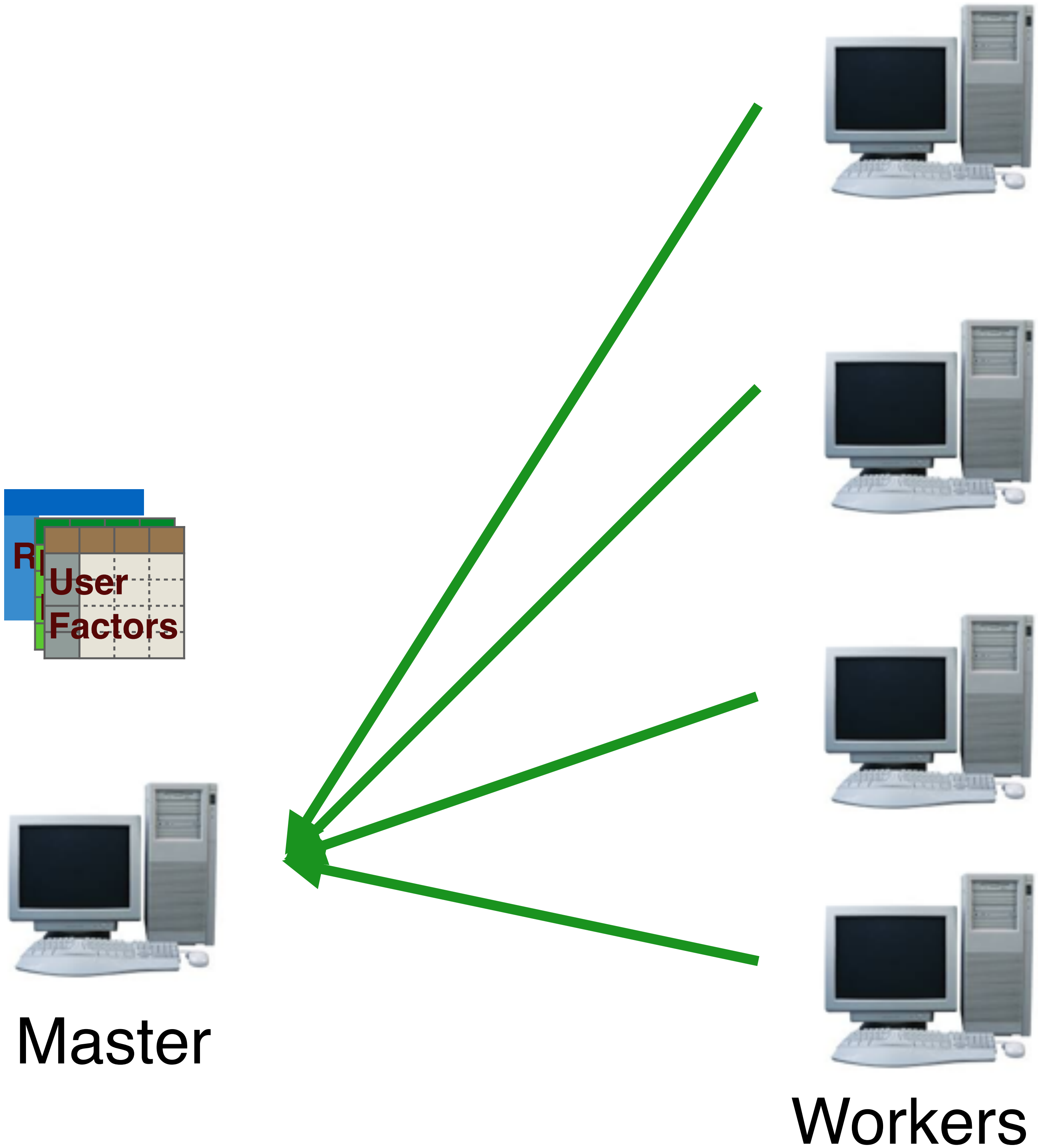

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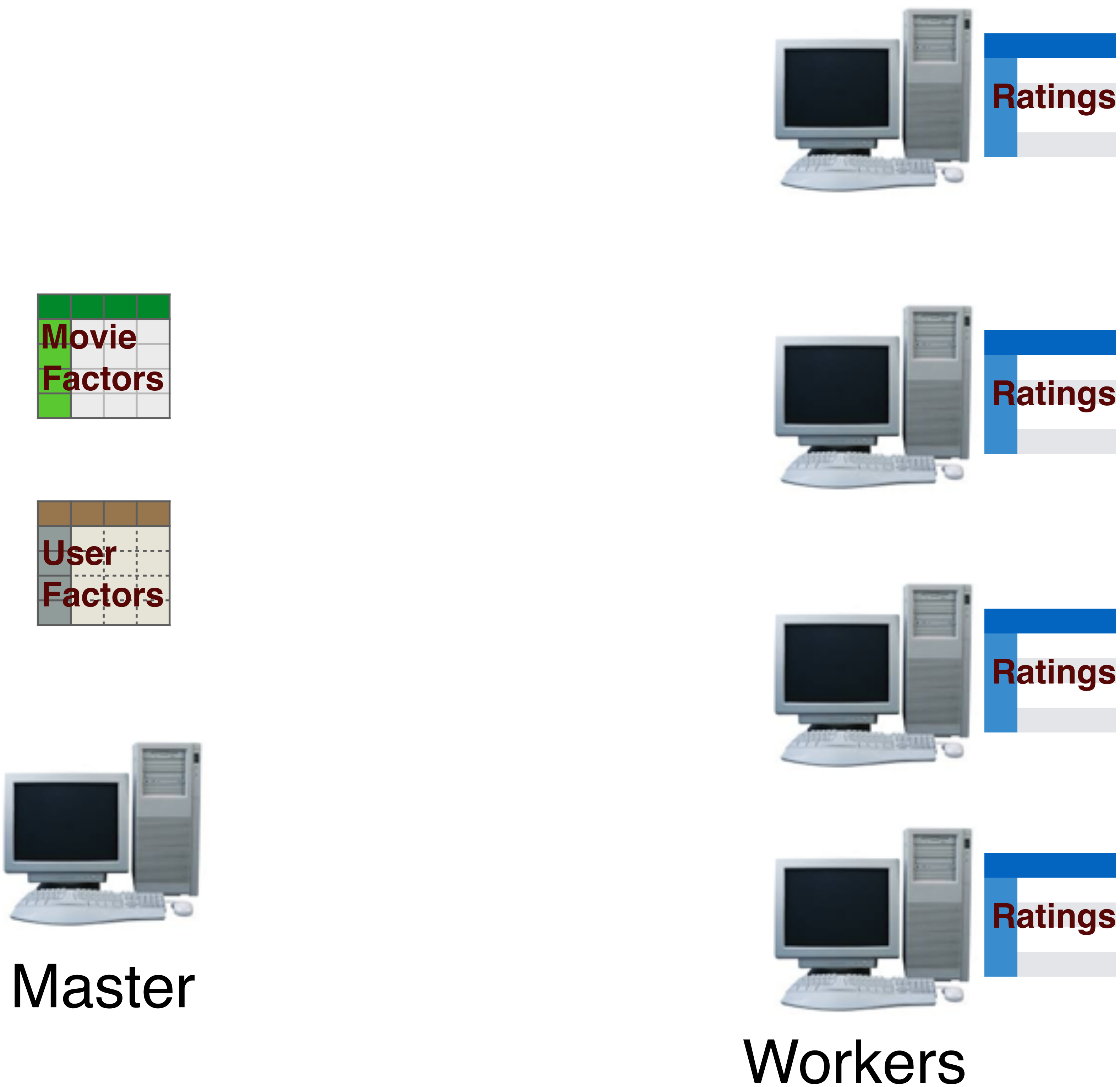

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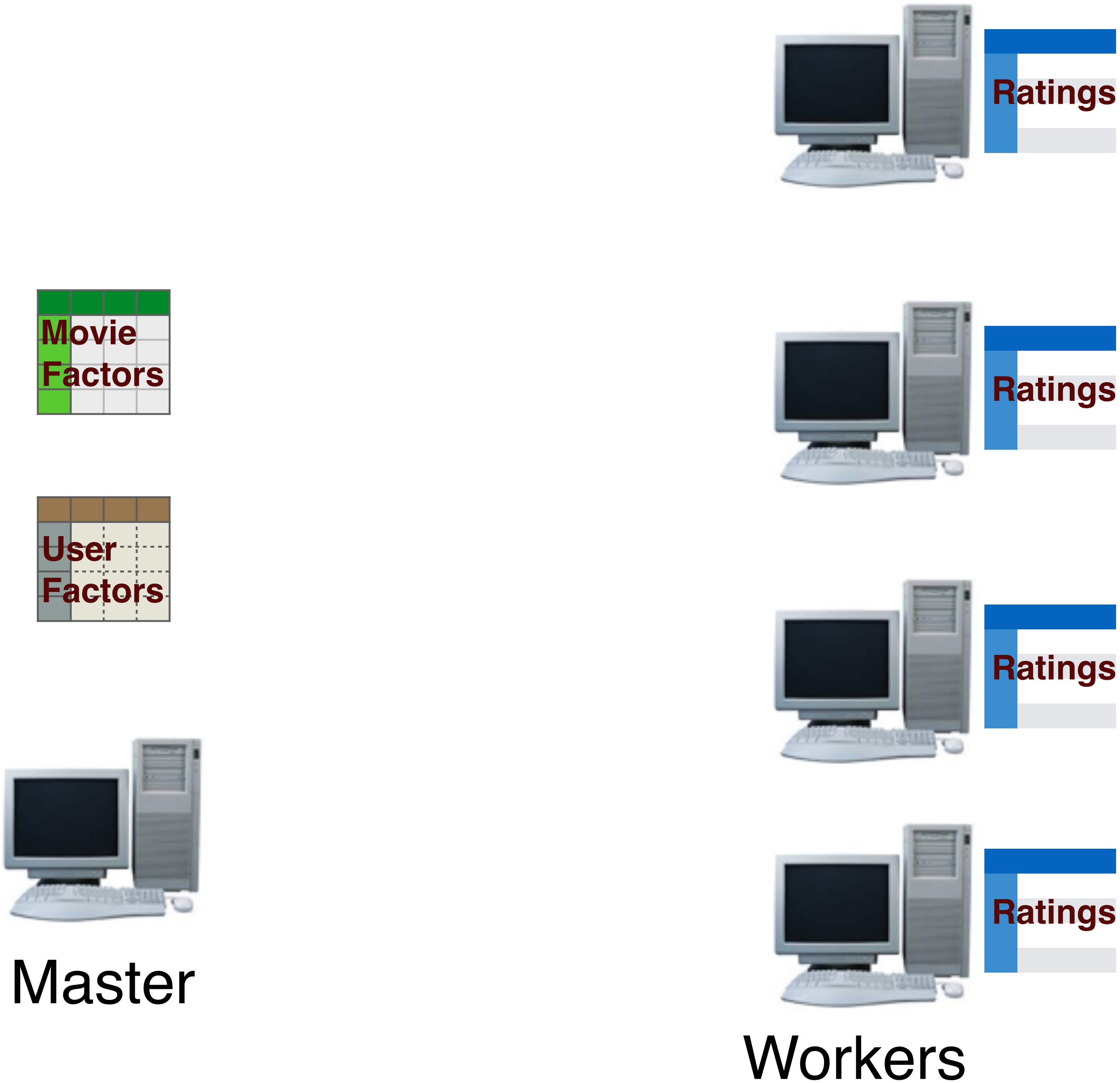

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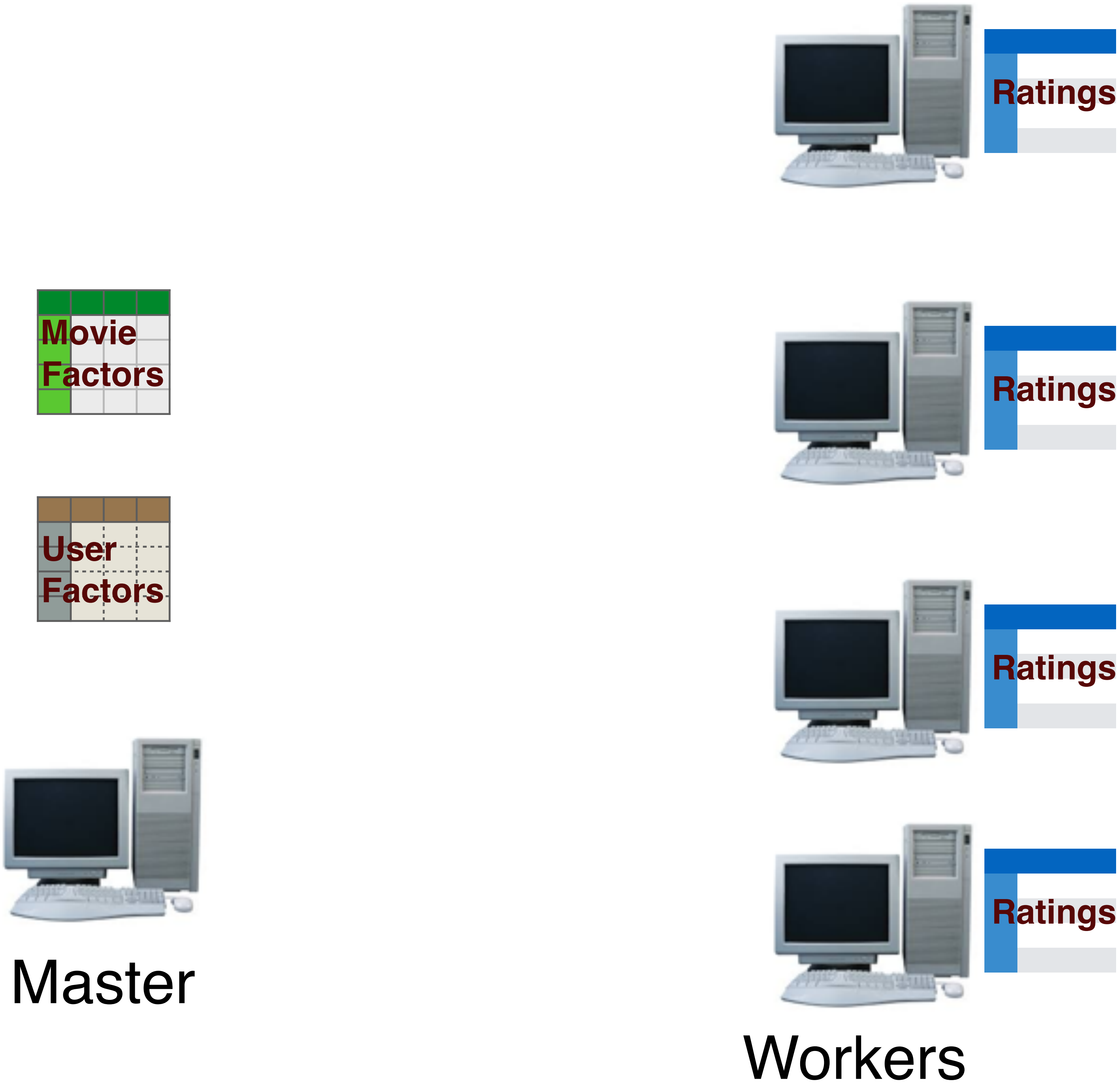

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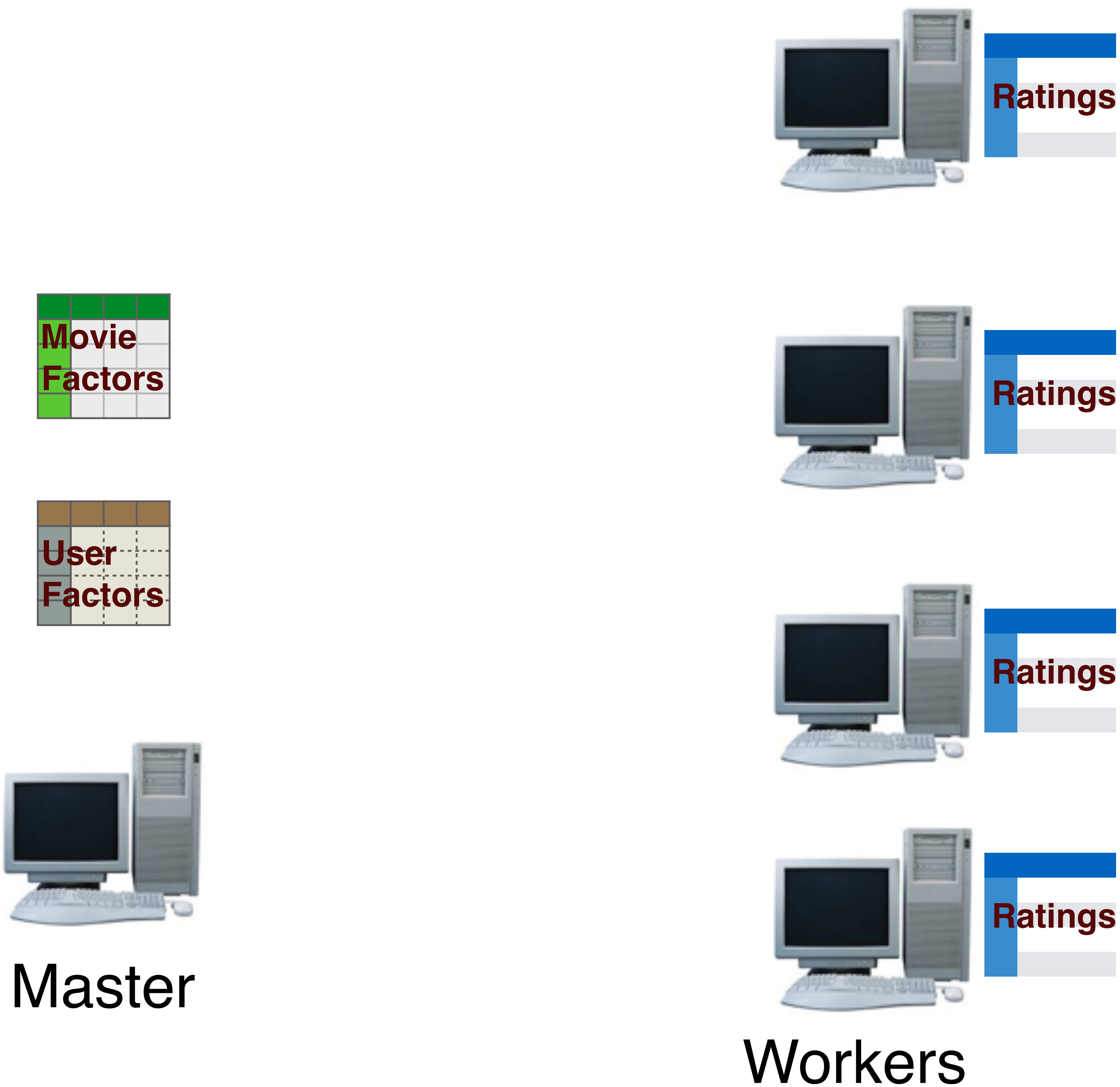

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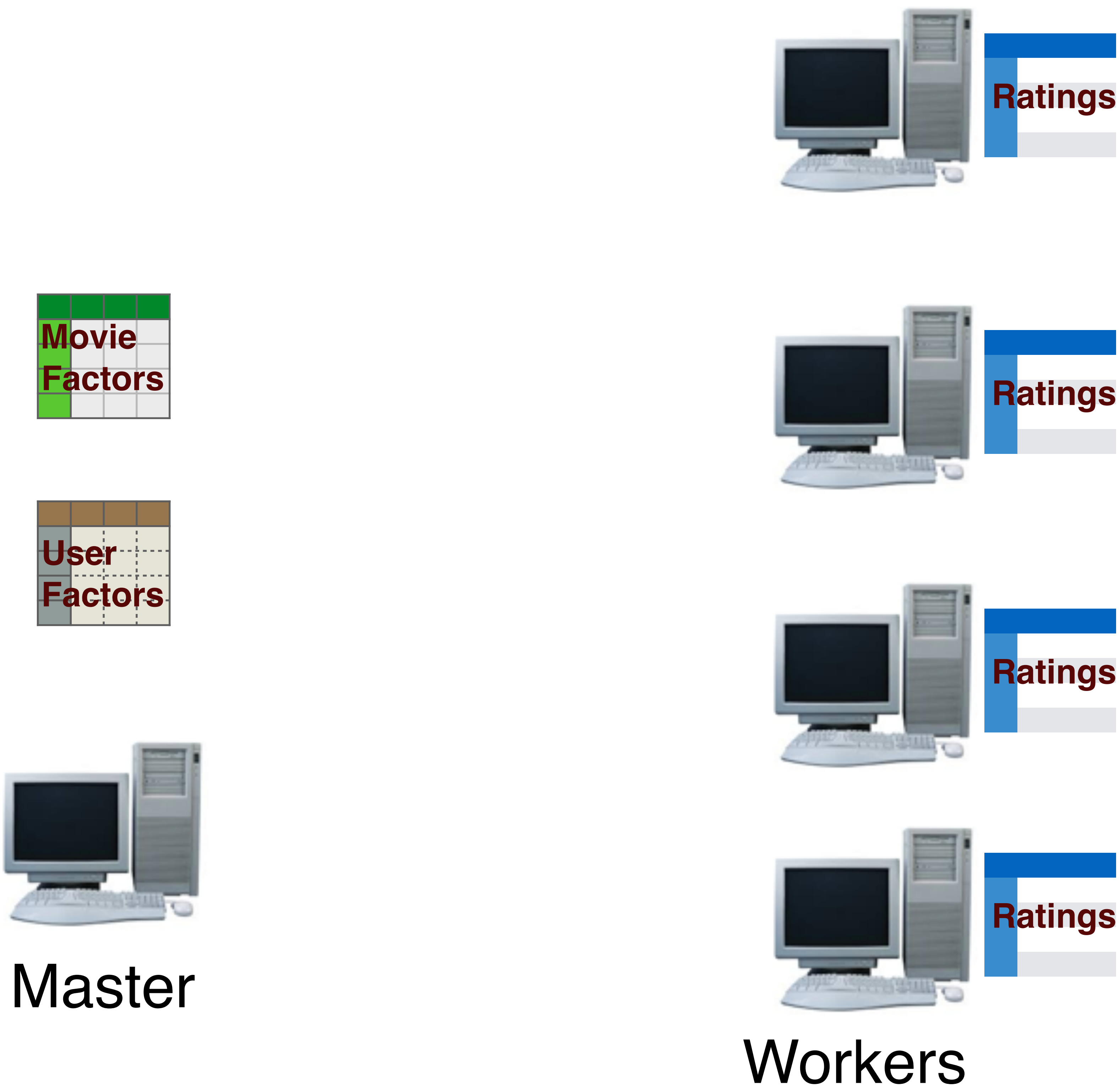

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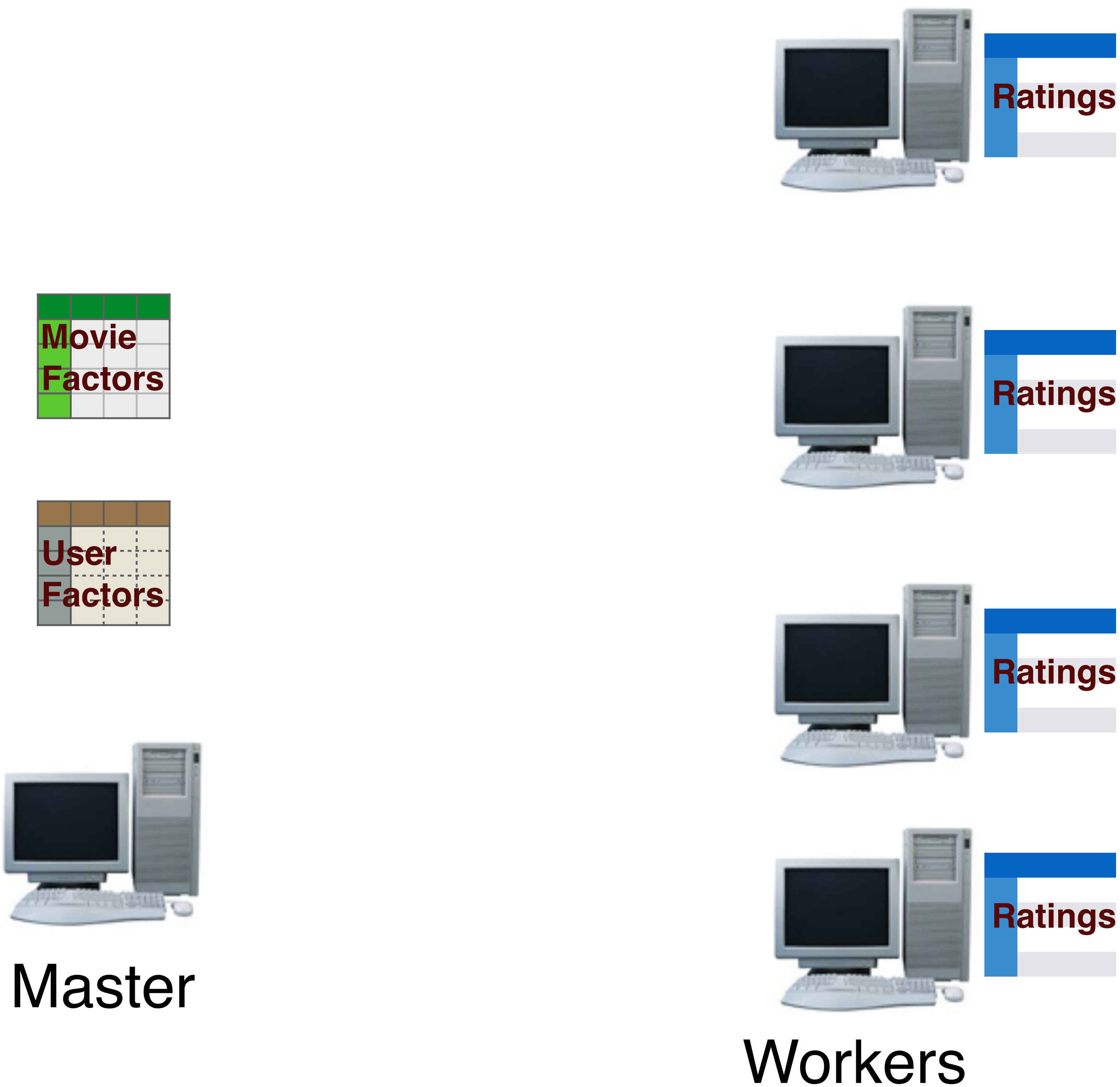

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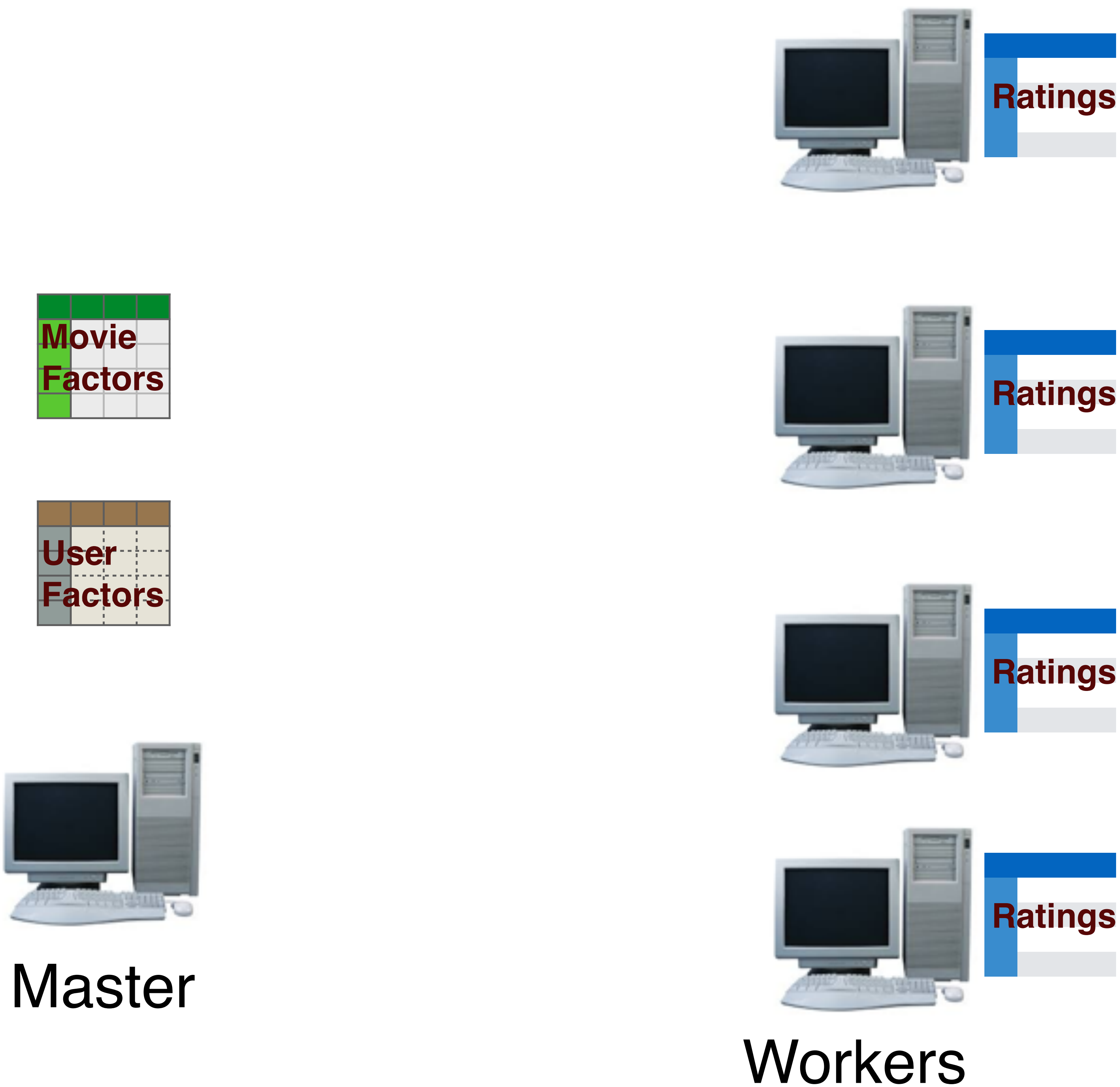

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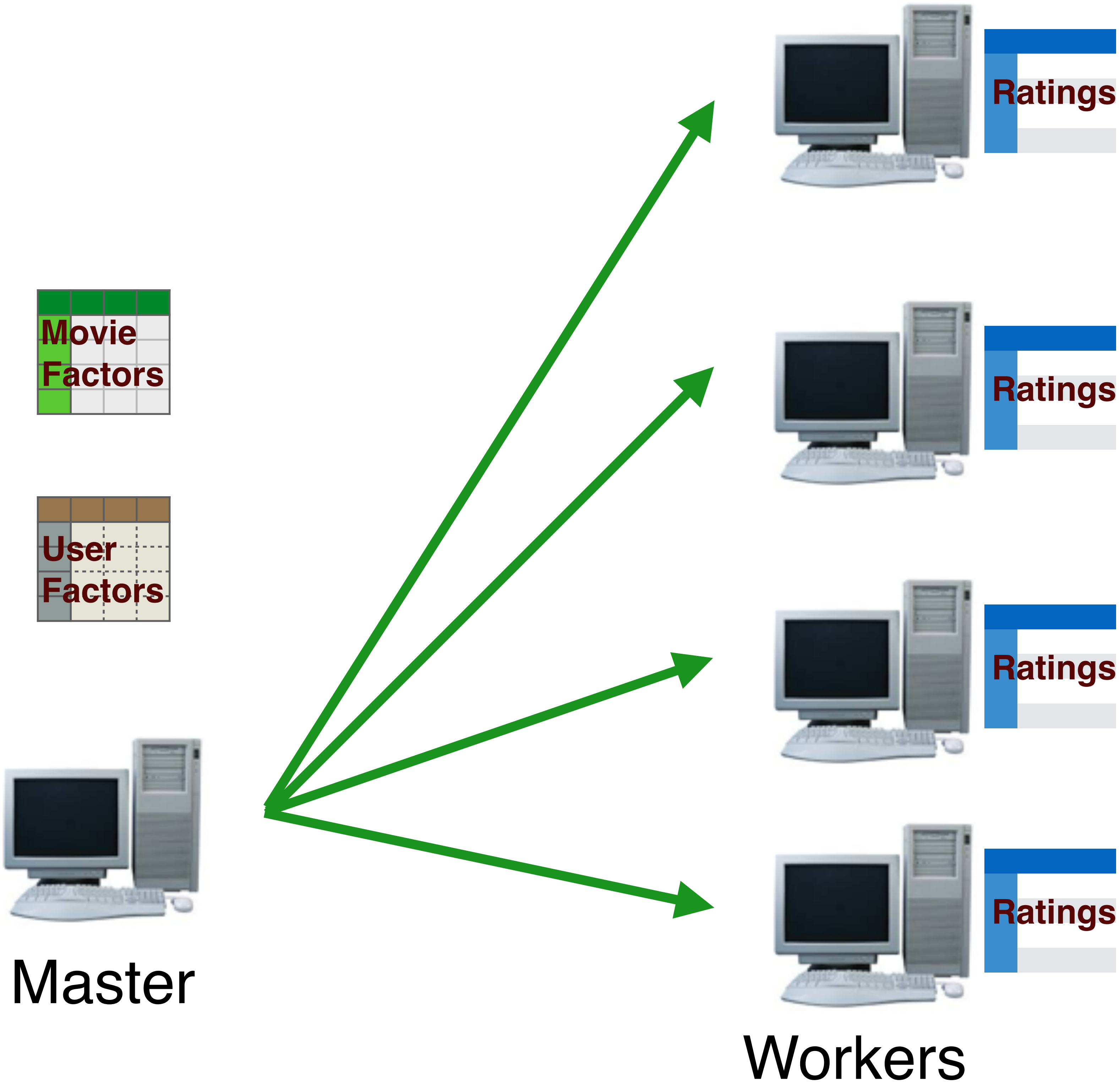

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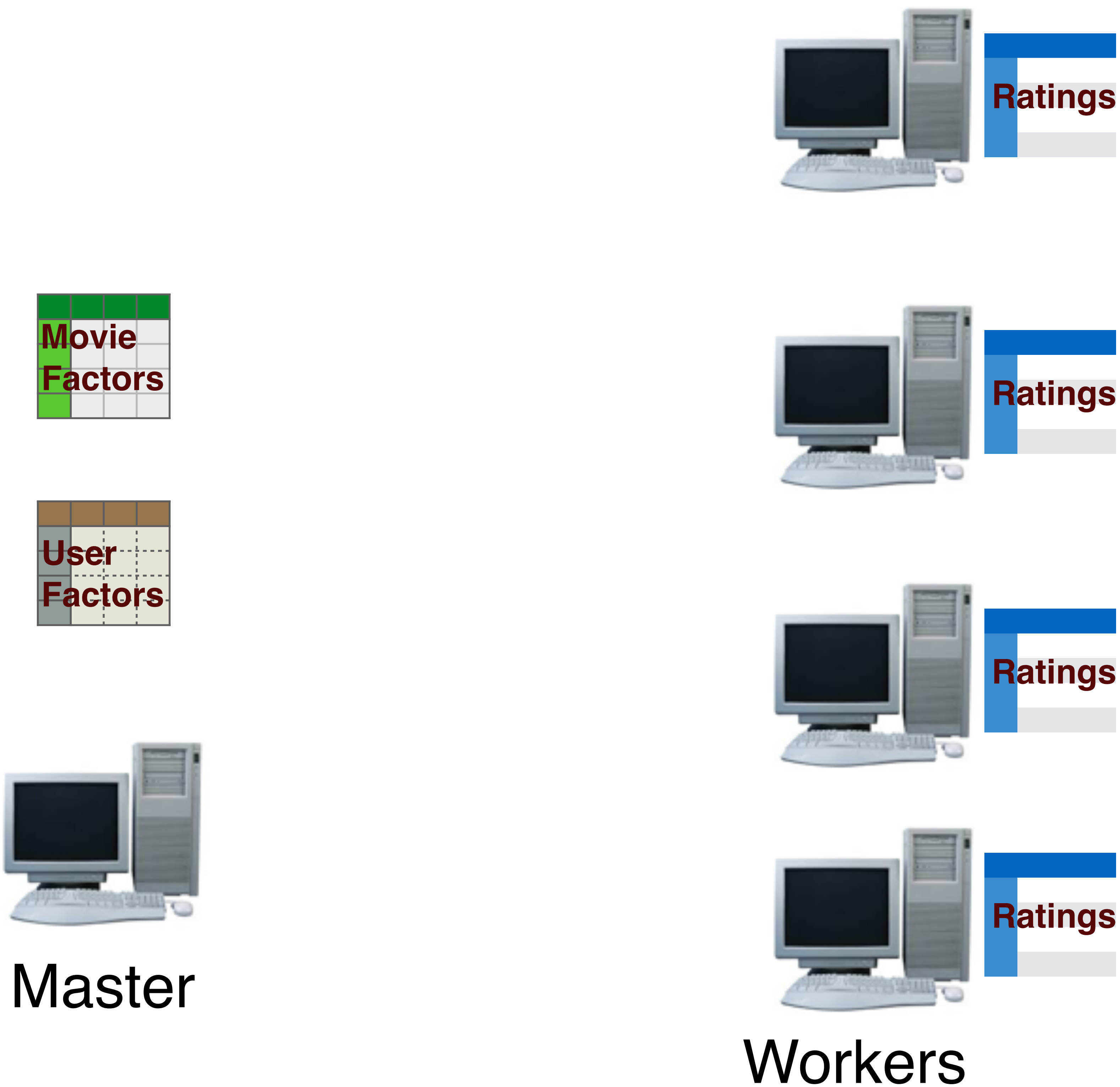

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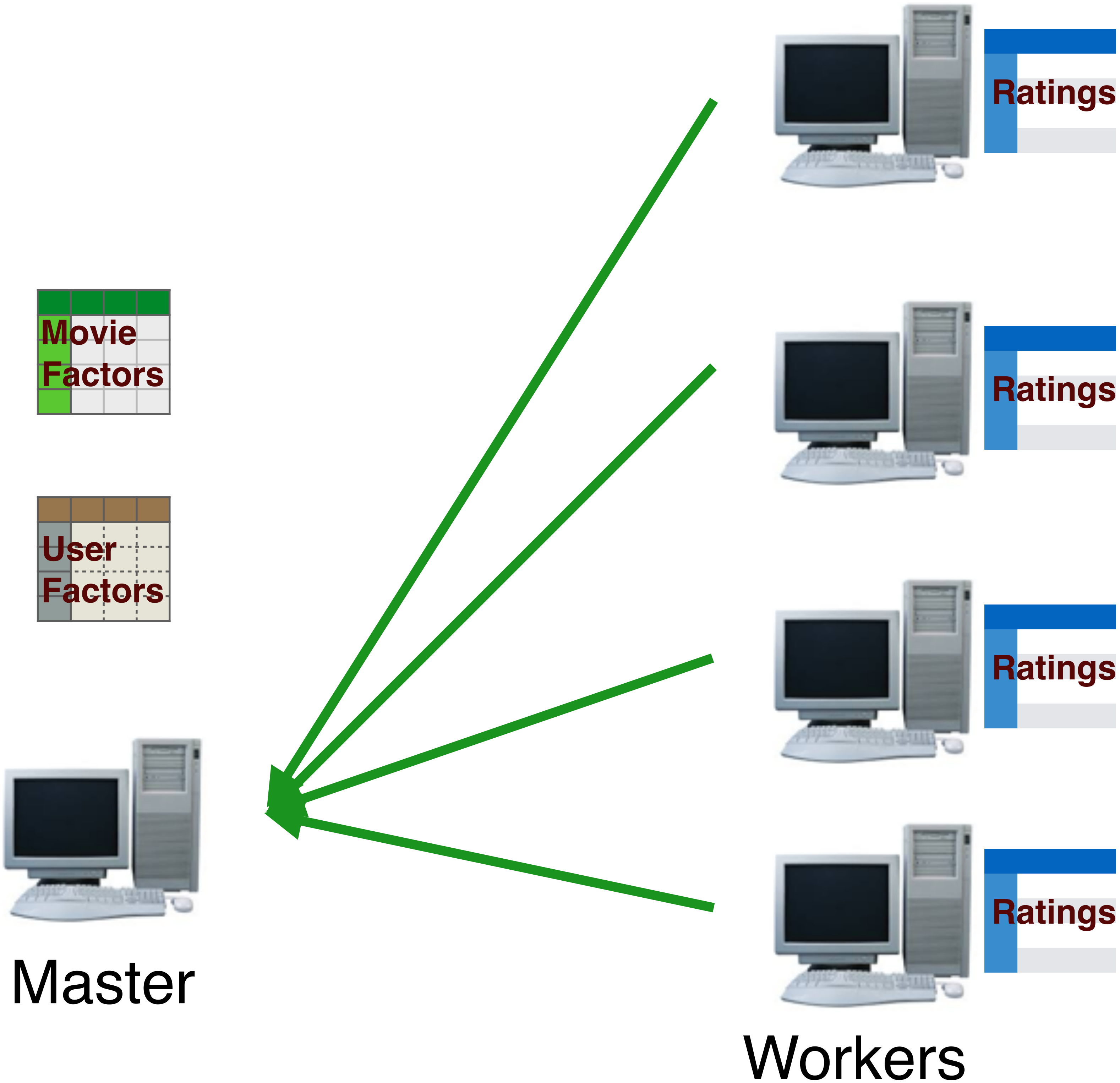

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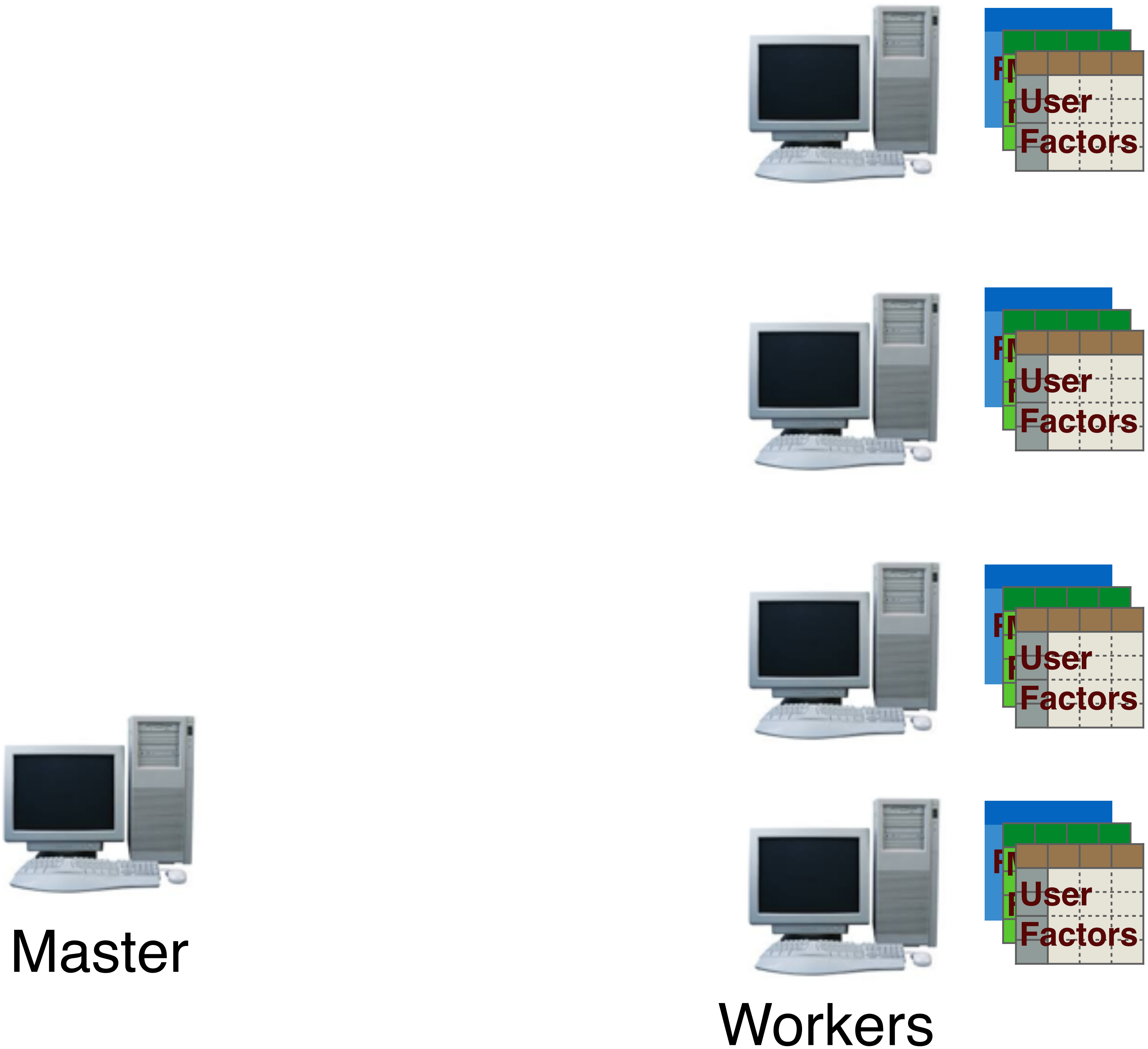

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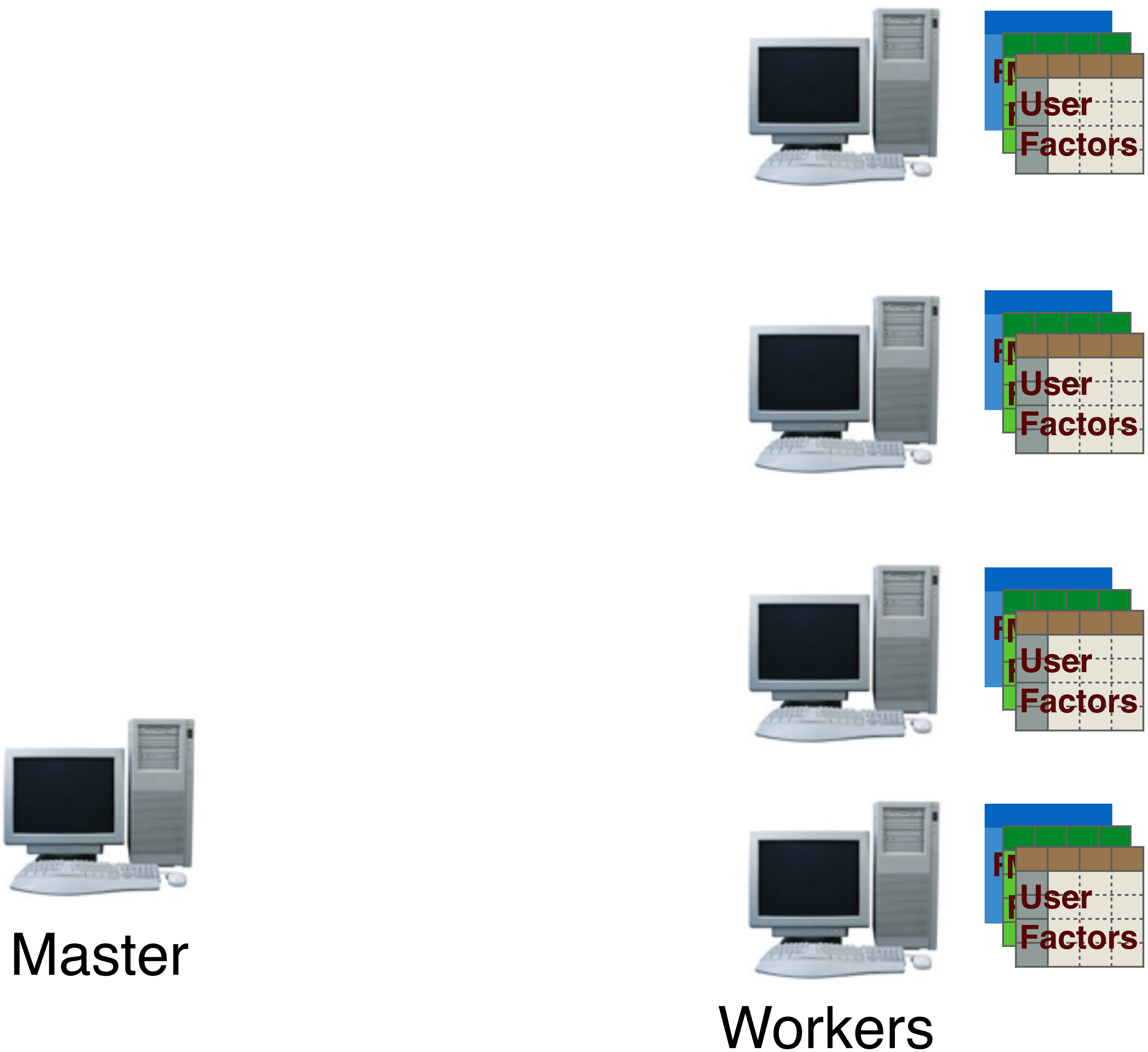

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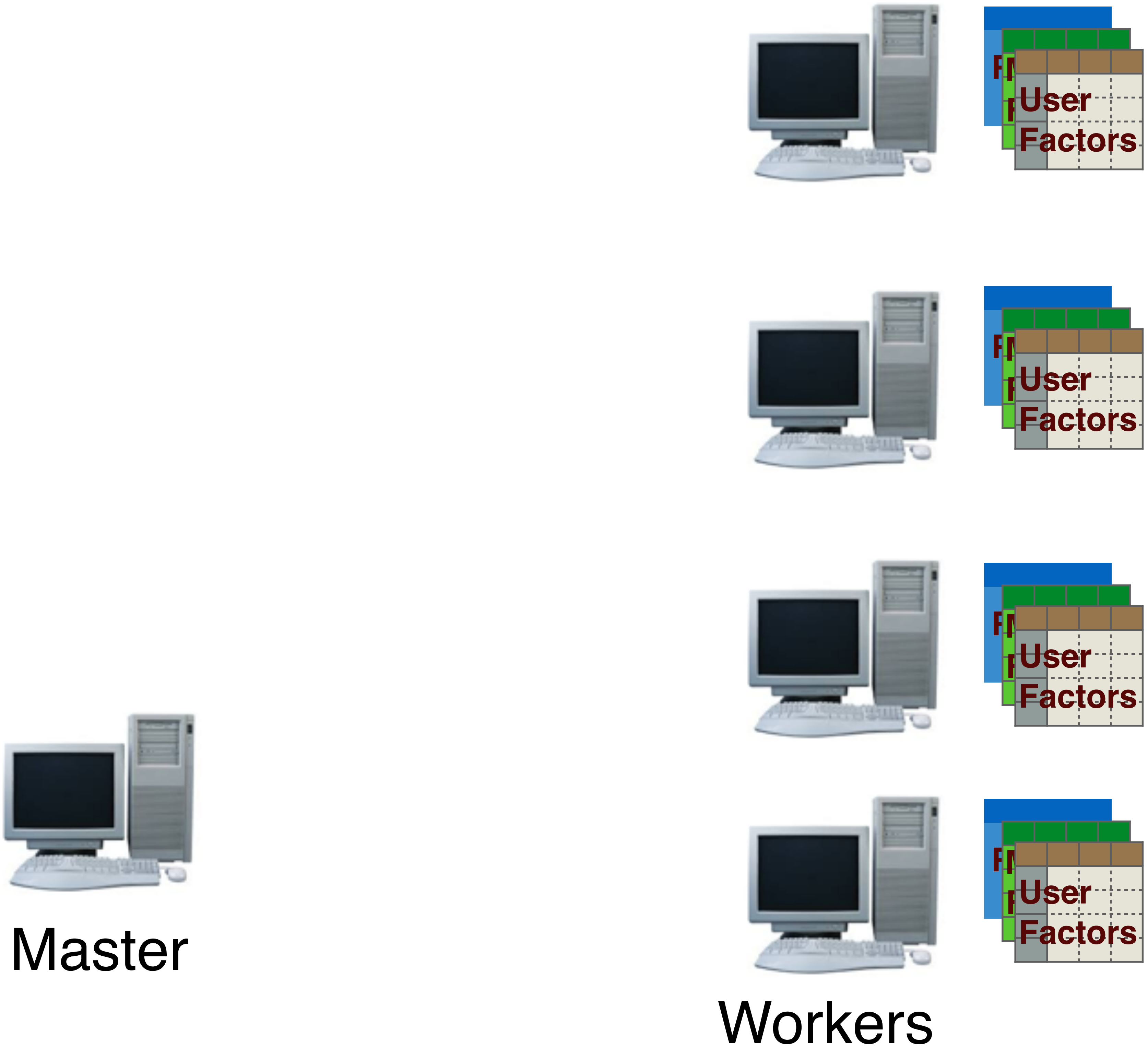

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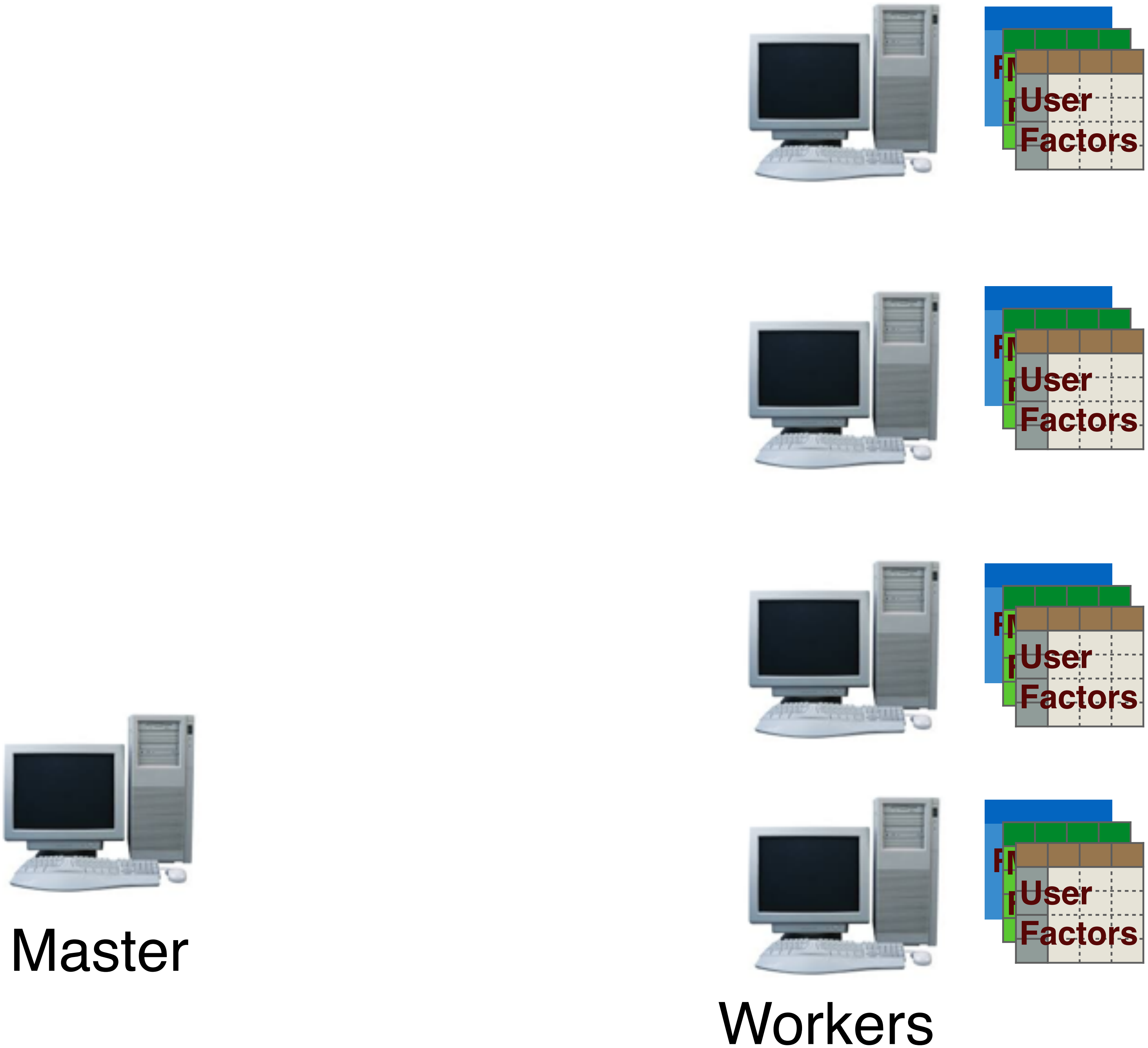

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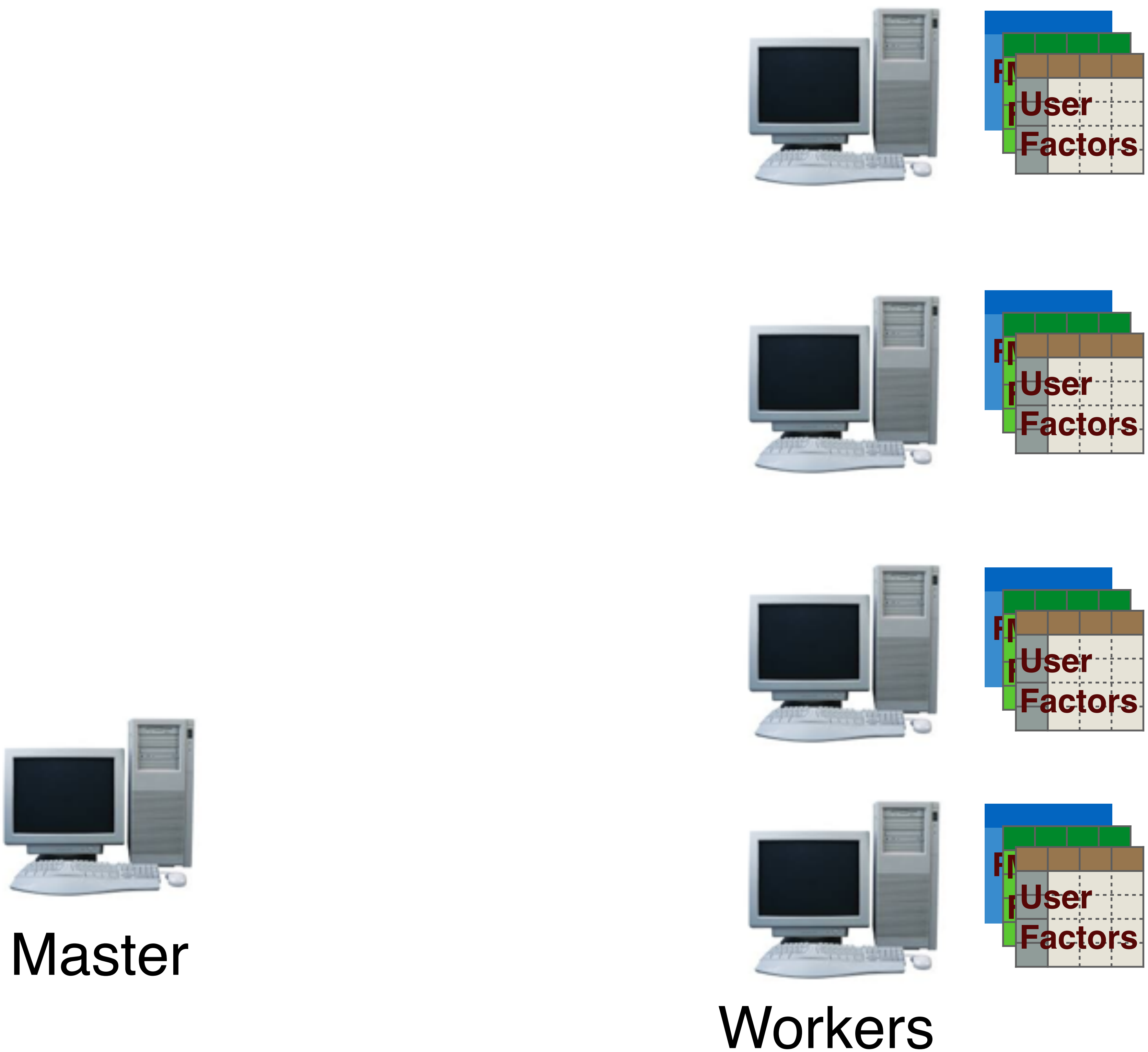

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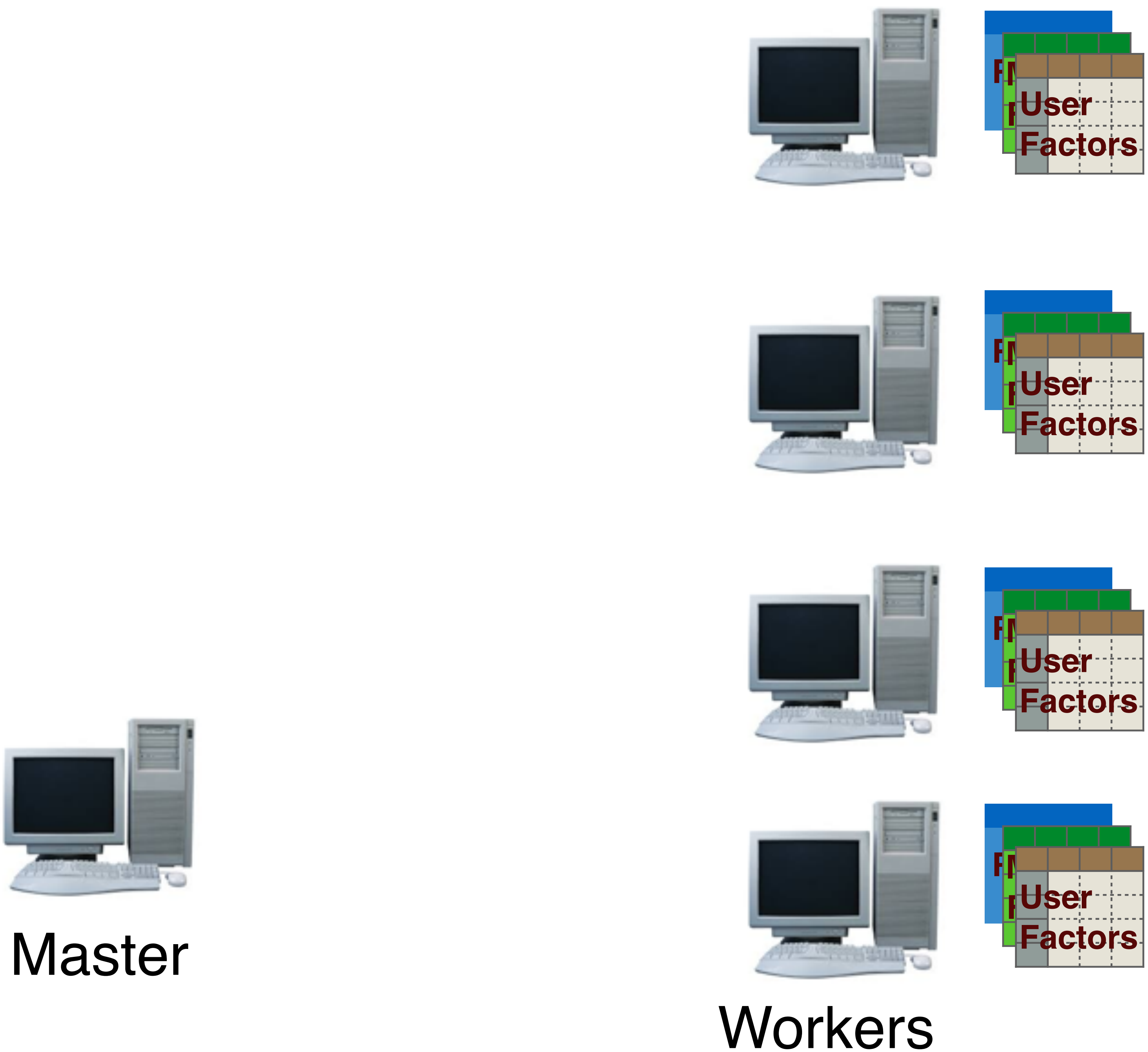

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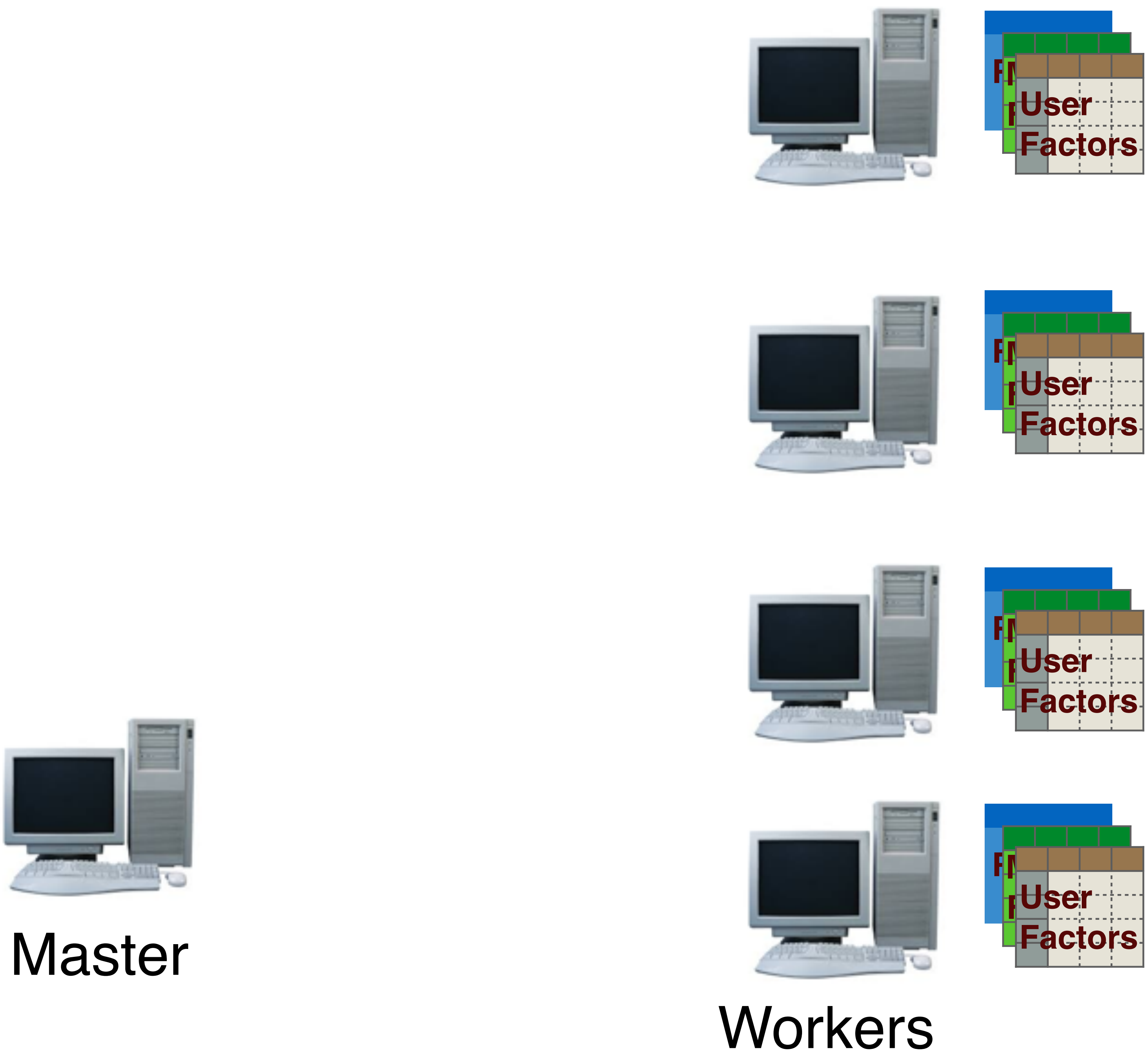

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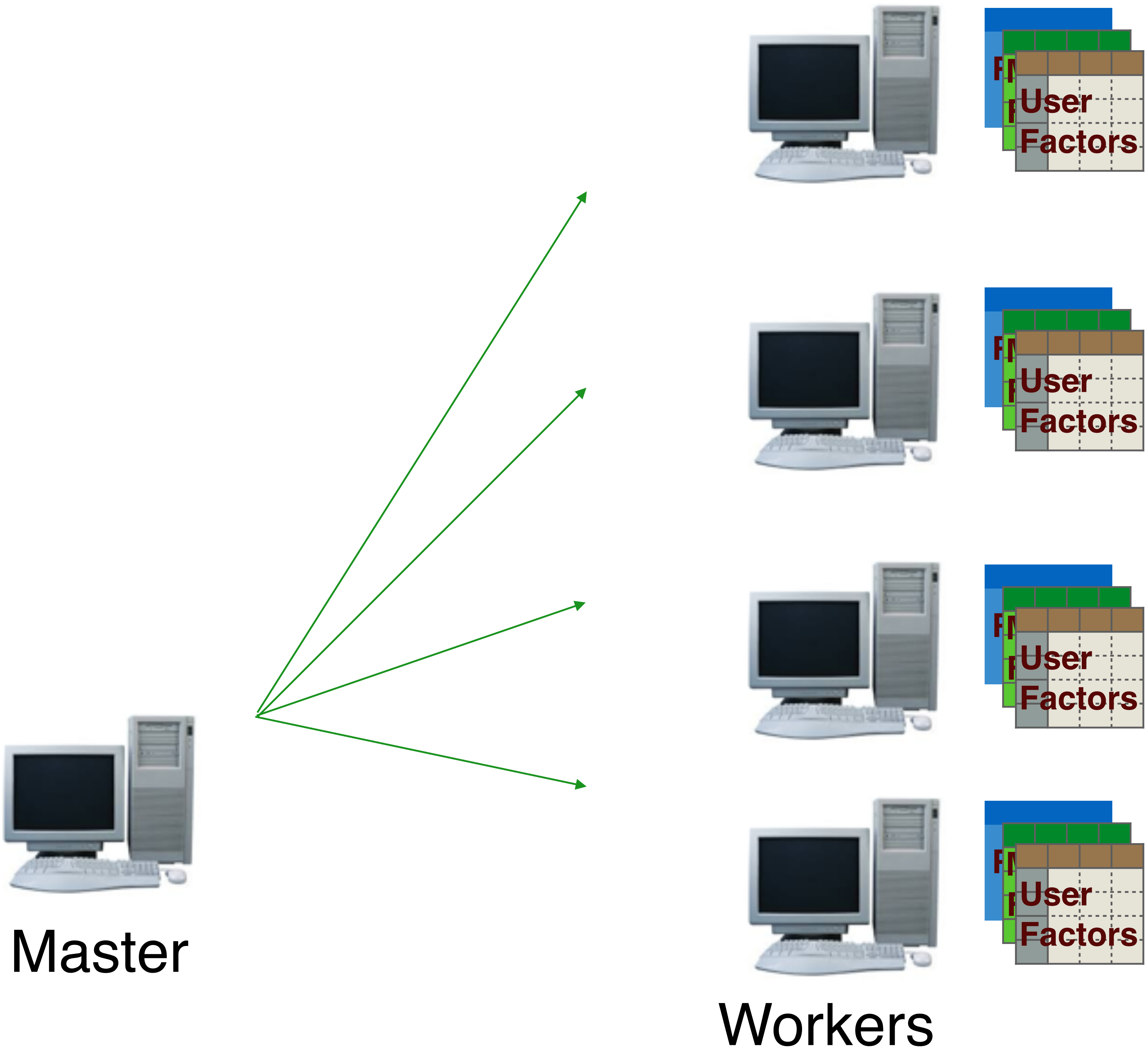

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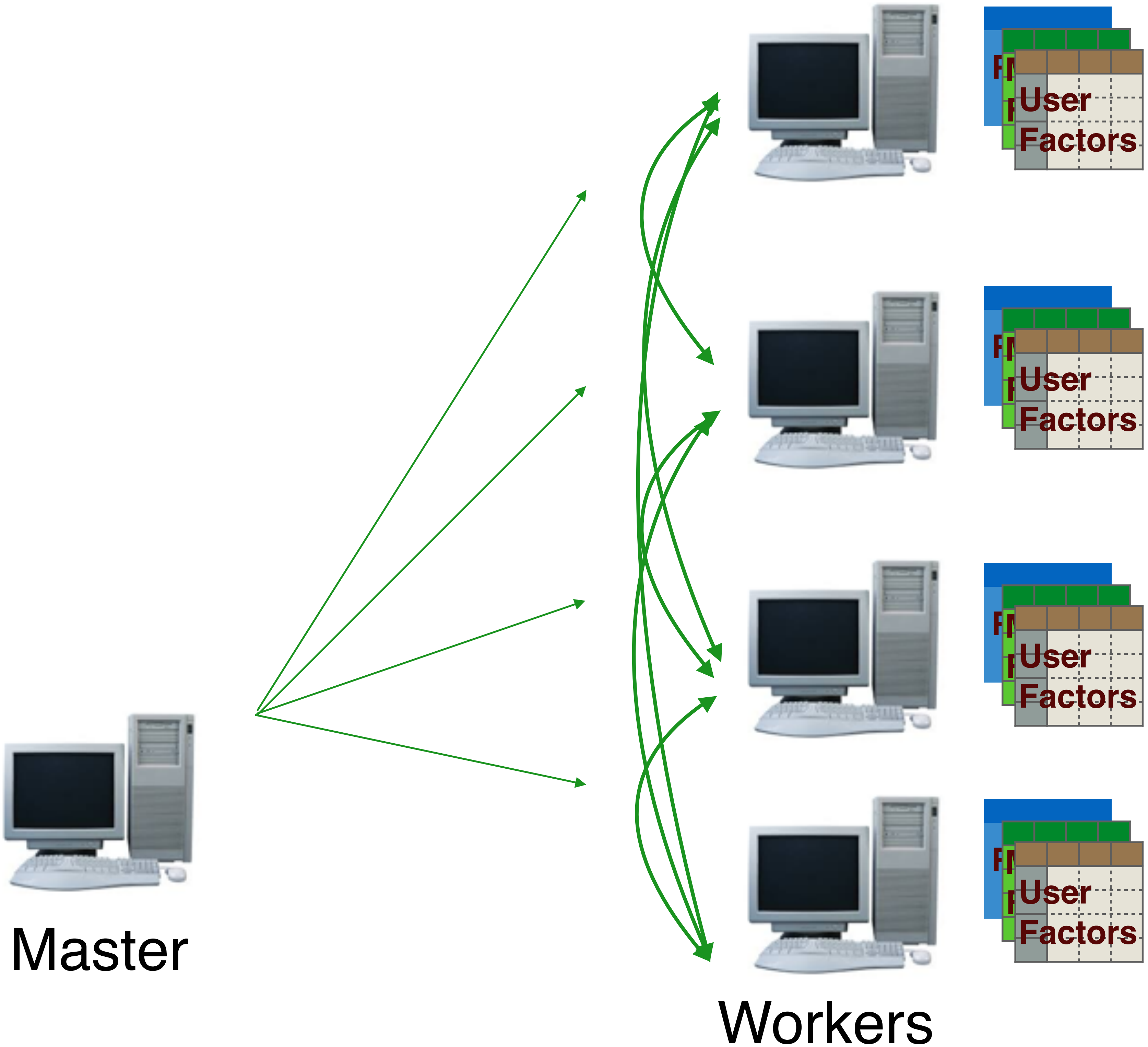

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~~Three~~ Kinds of ALS
Four

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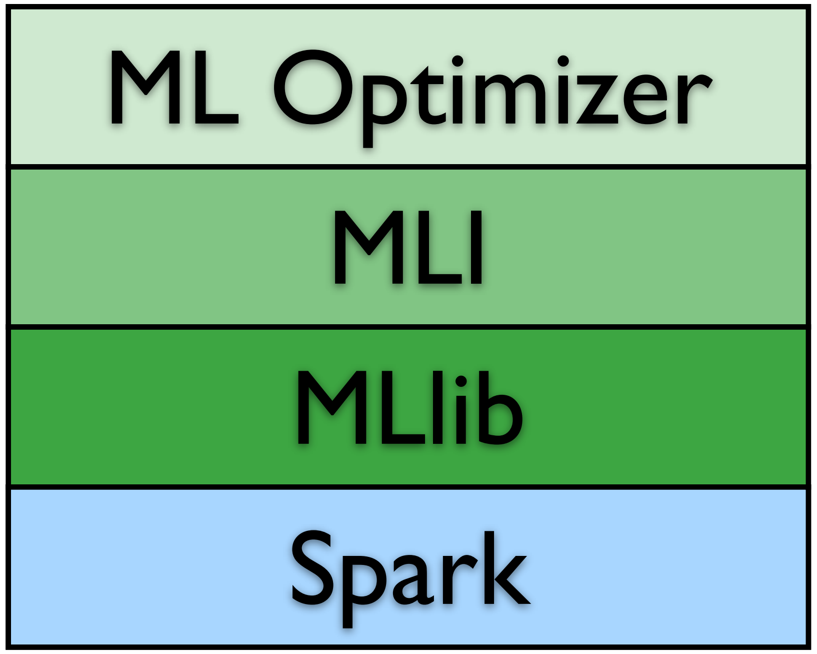
Blocked

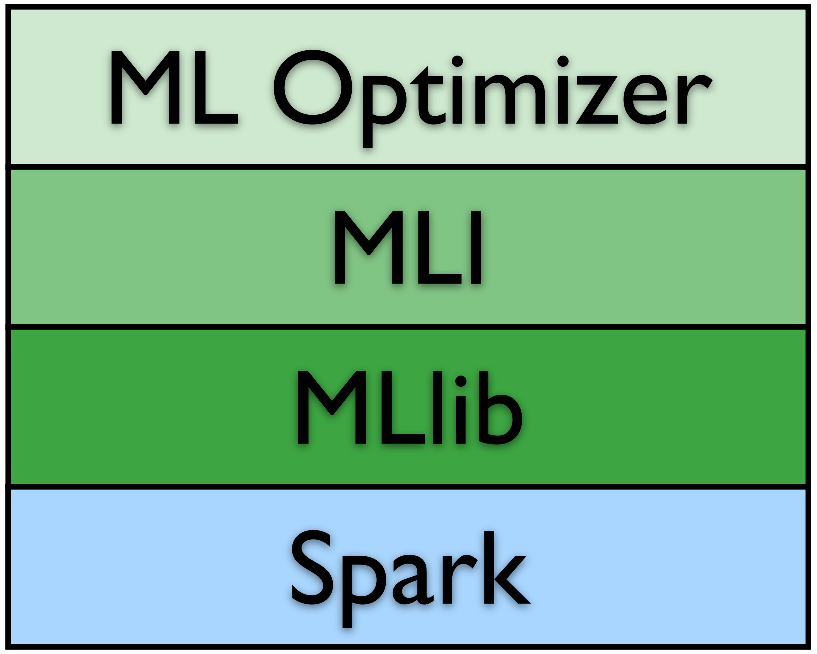


ML Optimizer: a declarative layer to simplify access to large-scale ML

MLI: experimental API for simplified feature extraction and algorithm development

MLlib: production-quality ML library in Spark

Spark: cluster computing system designed for iterative computation



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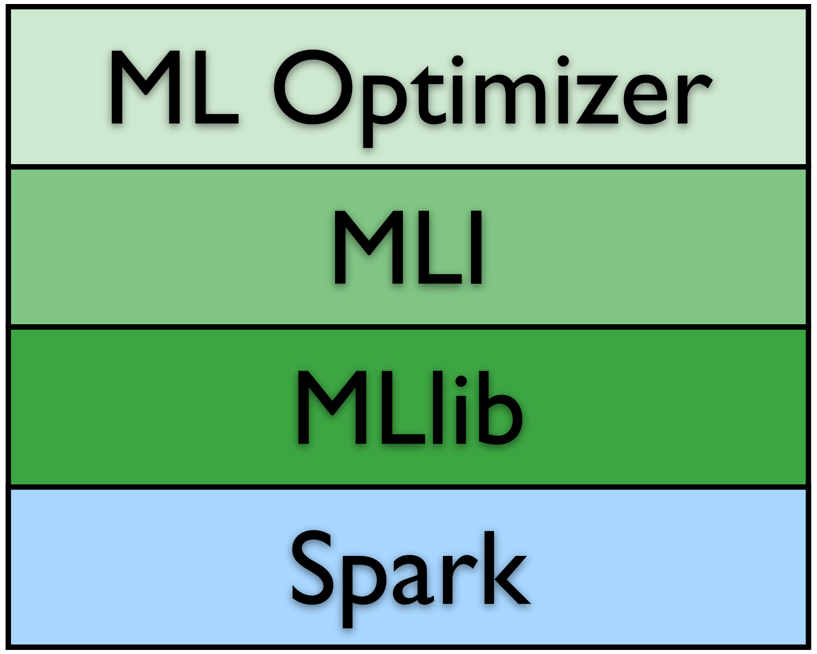
www.mlbase.org



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THANKS!
QUESTIONS?

MLbase

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