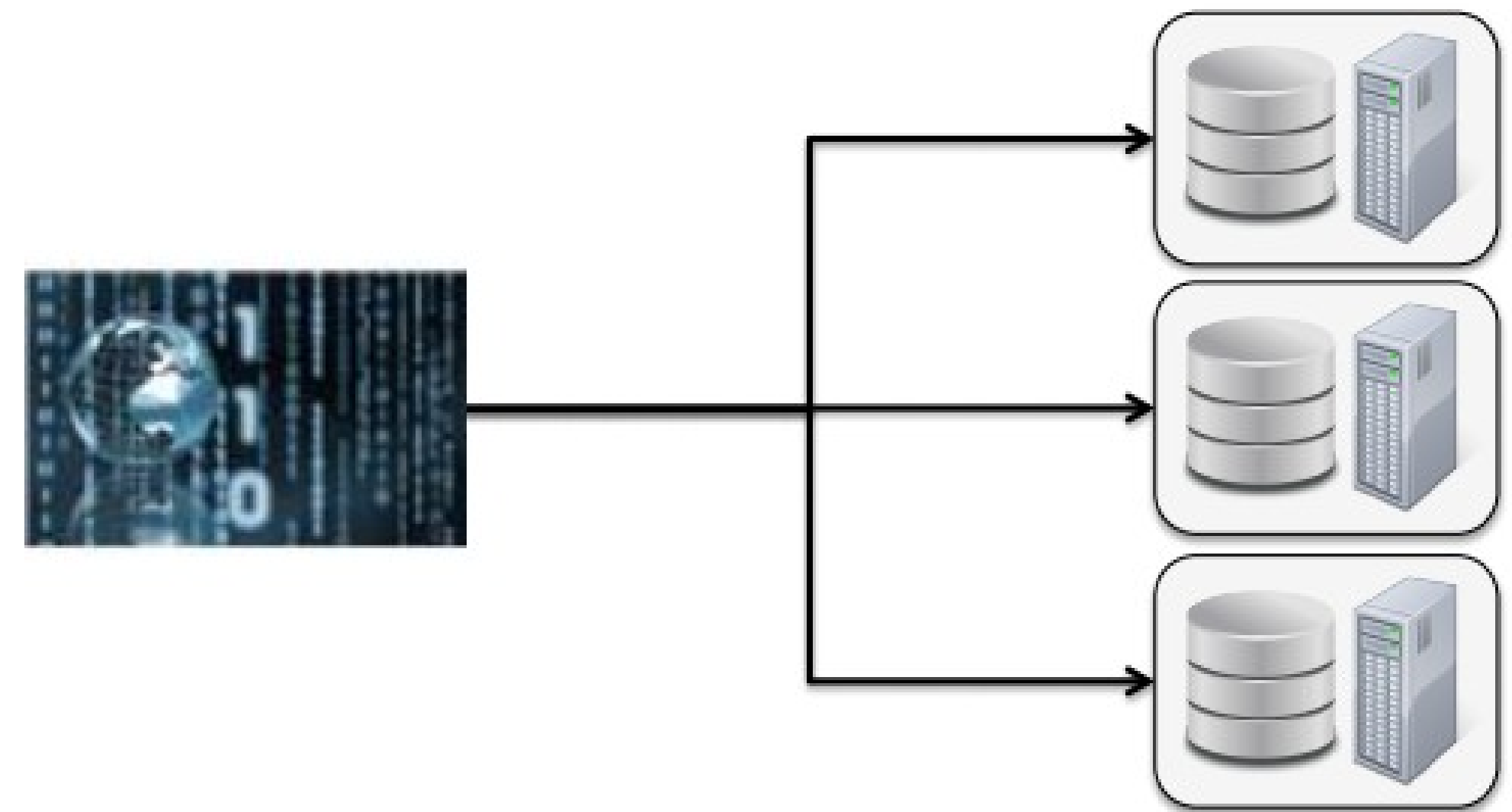


Apache Spark for machine learning

Quick recap

What's big data, again?

- as data increase becomes the bottleneck
- the solution, more machines
- the data is distributed in several machines
- in this way each machine only process a share of the data



Quick recap

What's spark, again?

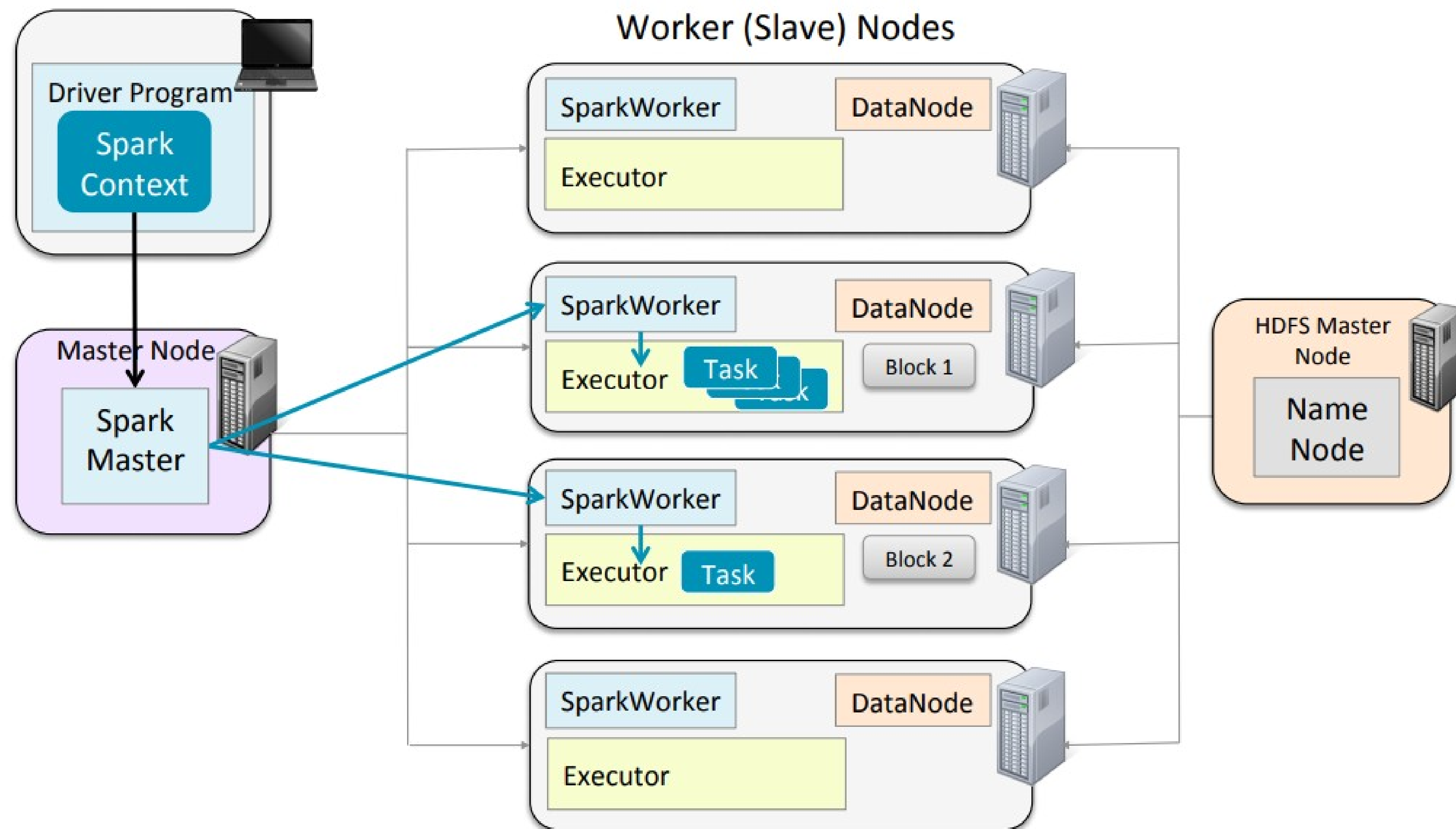
Apache Spark is a fast, general engine for large-scale data processing on a cluster

- High level programming framework
- Cluster computing
- Distributed storage
- Data in memory
- Provides fault tolerance
- Adding nodes adds capacity proportionally



Quick recap

What's the spark architecture, again?



Quick recap

What's rdd, dataframe, etc, again?

- RDD Is building block of spark. No matter which abstraction Dataframe or Dataset we use, internally final computation is done on RDDs
 - Distributed: Processed across the cluster
 - Resilient: If data in memory is lost, it can be recreated
 - No schema defining columns and rows
- DataFrame offers huge performance improvement over RDDs
 - Custom Memory management
 - Optimized Execution Plans
 - but Lack of Type Safety
- DataSet is an extension to Dataframe API
 - comes with OOPs style and developer friendly compile time safety



Spark and ML

MLlib is first Spark scalable machine learning library

MLlib provides main ML Algorithms like:

- classification
- regression
- clustering
- collaborative filtering



Machine learning problems

- developers use to think that machine learning is basically learning algorithms
- Libraries like MLLIB and Mahout implements this way of thinking
- but productions is different
- in the real world we have end to end applications with several steps
 - data exploration
 - data preparation
 - model training
 - model evaluation
 - model tuning
 - and most important, repeat the process several times



Problems with Spark MLlib

- build on top of RDD
- only focus on model learning
- no way implement a pipeline
- no way combine steps
- no uniform across algorithms

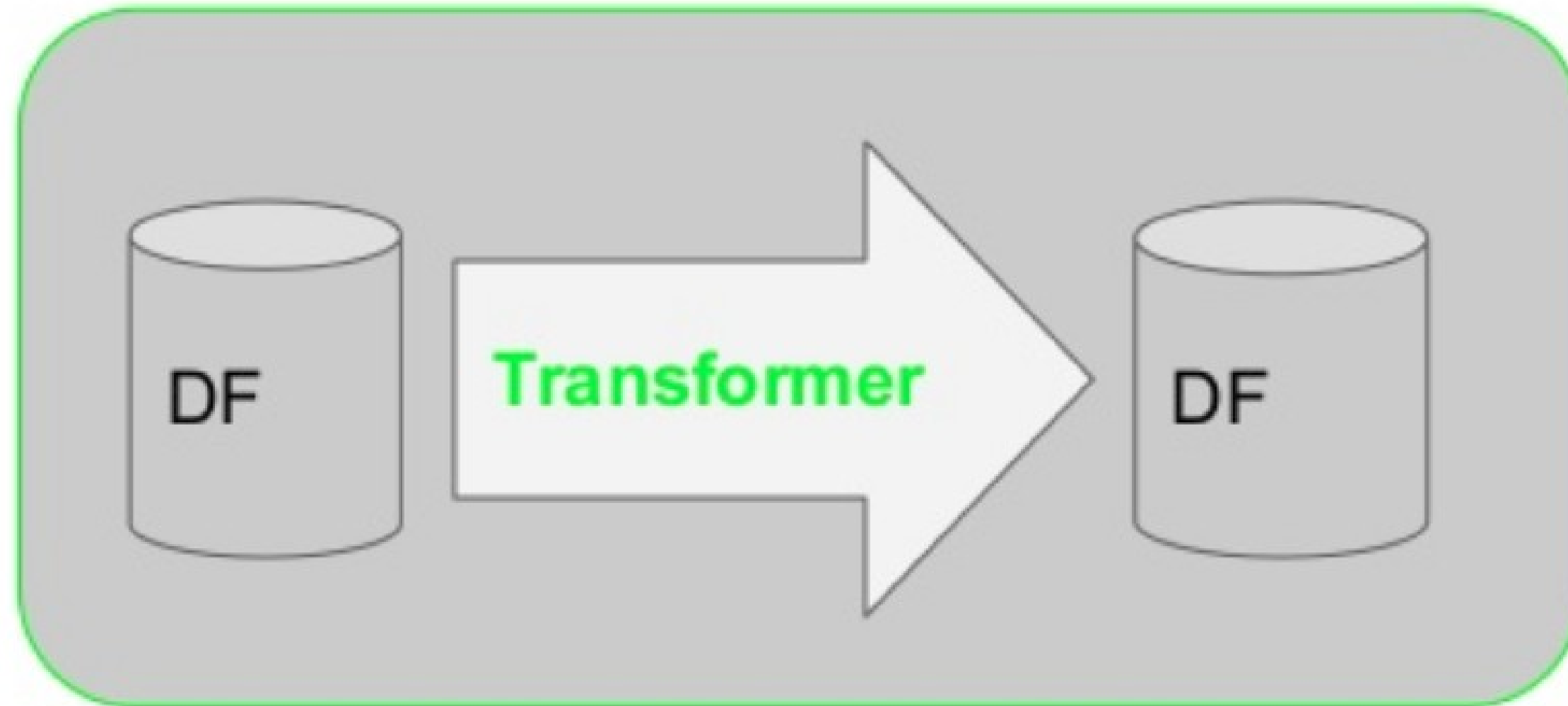
Solution: Spark ML

- provide API for create workflows
- uniform across algorithms
- build on top of dataframes
- MLlib will be deprecated



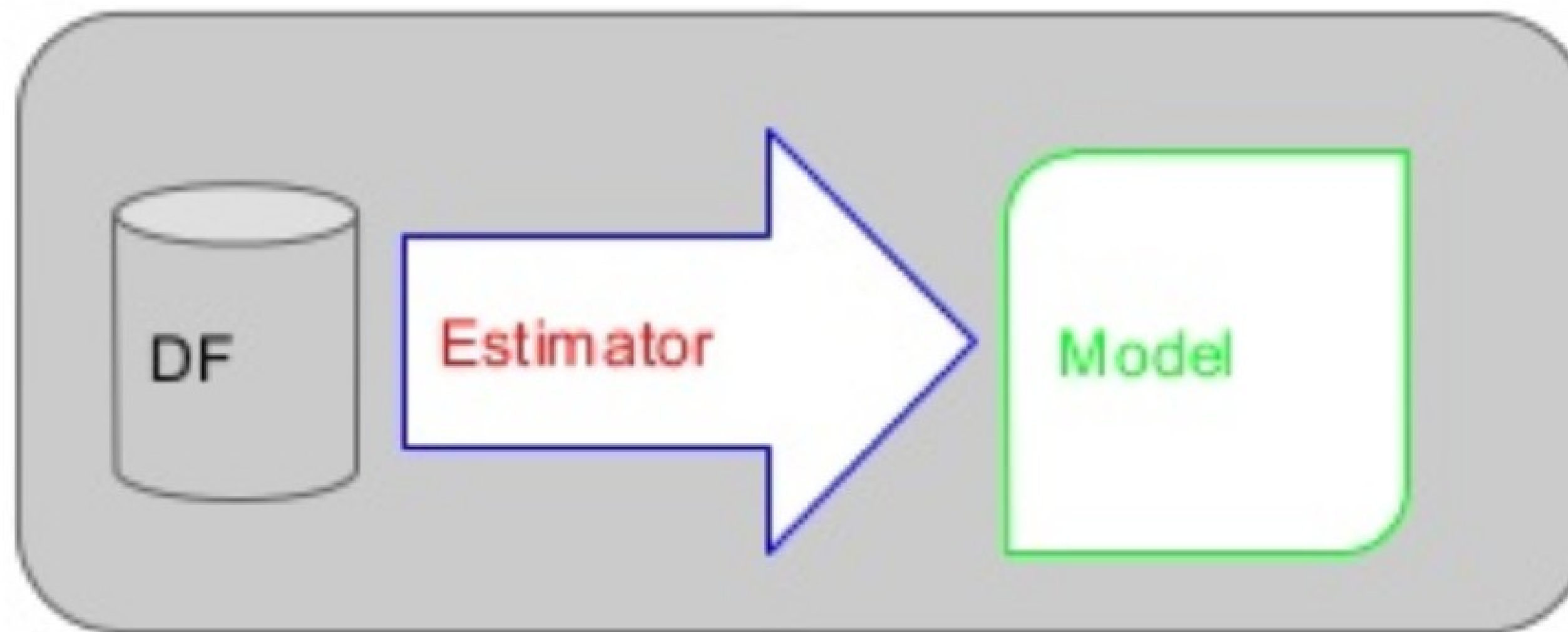
Elements: Transformer

- convert a DataFrame into another DataFrame
- implement the method *transform()*



Elements: Estimator

- take a DataFrame and produces a Model
- implements the method *fit()*

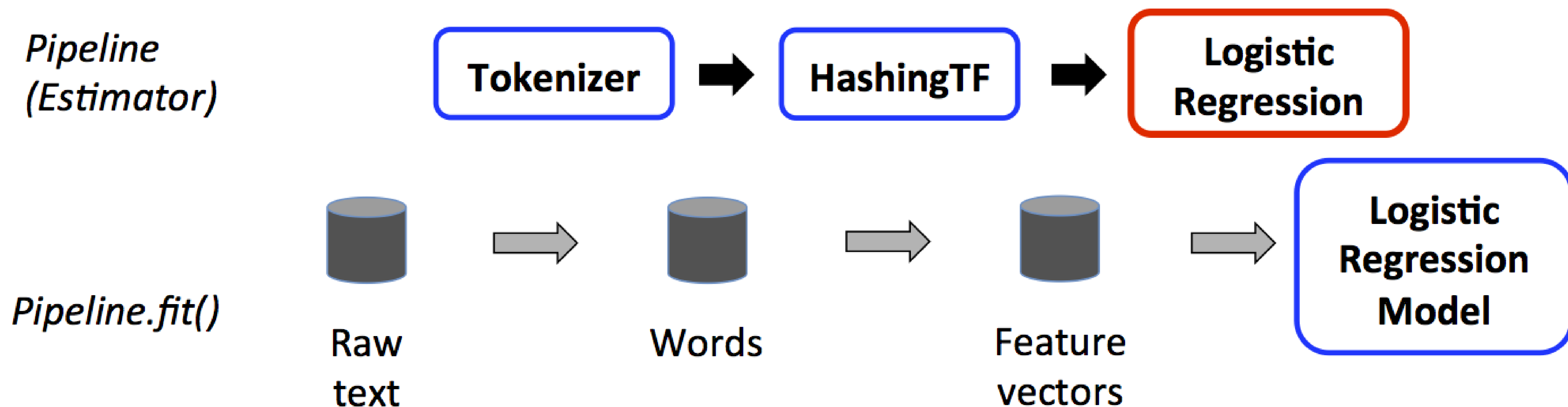


Elements: Pipelines(1)

- sequence of stages
- concat Transformers or Estimators
- Pipeline itself is an Estimator
 - fitted on a DataFrame turning into a model
- We can define a pipeline make different data sets go through the same steps



Elements: Pipelines(2)



How is an algorithm implemented? (1)

Logistic regression definition

FEATURE VECTOR $\longrightarrow x = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_d \end{bmatrix}$

$w = \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_d \end{bmatrix}$ \longleftarrow WEIGHTS

$\hat{y} = \frac{1}{1 + e^{-(w_1 \cdot x_1 + w_2 \cdot x_2 + \dots + w_d \cdot x_d)}}$ \longleftarrow PREDICTION

LOSS $\longrightarrow J = -\frac{1}{N} \sum_{i=1}^N y^{(i)} \log \hat{y}^{(i)} + (1 - y^{(i)}) \log(1 - \hat{y}^{(i)})$

WEIGHT UPDATE $\begin{cases} w_k = w_k - \alpha \frac{\partial J}{\partial w_k} \longleftarrow \text{DERIVATIVE OF LOSS} \\ w = w - \alpha \nabla J \longleftarrow \text{GRADIENT} \end{cases}$



How is an algorithm implemented? (2)

Logistic regression vectorized

EXAMPLES

FEATURES

WEIGHTS

PREDICTIONS

$$\begin{bmatrix} x_1^{(1)} & x_2^{(1)} & \dots & x_d^{(1)} \\ x_1^{(2)} & x_2^{(2)} & \dots & x_d^{(2)} \\ \vdots & \vdots & \ddots & \vdots \\ x_1^{(N)} & x_2^{(N)} & \dots & x_d^{(N)} \end{bmatrix} \cdot \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_d \end{bmatrix} = \begin{bmatrix} z^{(1)} \\ z^{(2)} \\ \vdots \\ z^{(N)} \end{bmatrix}, \quad \hat{y} = \begin{bmatrix} \sigma(z^{(1)}) \\ \sigma(z^{(2)}) \\ \vdots \\ \sigma(z^{(N)}) \end{bmatrix}$$

$w = w - \alpha \nabla J$

DOT PRODUCTS

How to compute the gradient vector

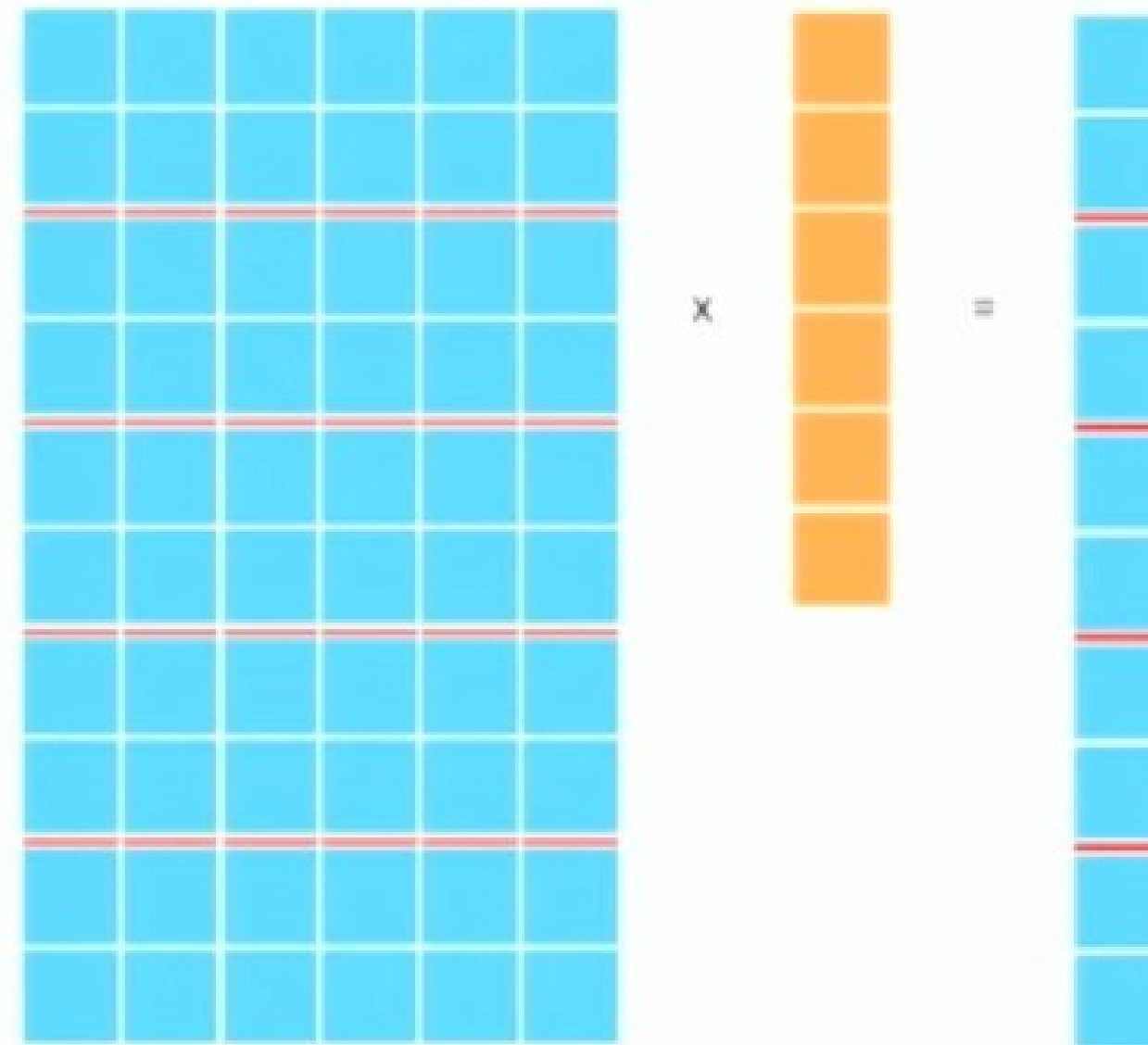
$$\nabla J = \frac{1}{N} X^T (\hat{y} - y)$$
$$\nabla J = \frac{1}{N} \cdot \begin{bmatrix} x_1^{(1)} & x_1^{(2)} & \dots & x_1^{(N)} \\ x_2^{(1)} & x_2^{(2)} & \dots & x_2^{(N)} \\ \vdots & \vdots & \ddots & \vdots \\ x_d^{(1)} & x_d^{(2)} & \dots & x_d^{(N)} \end{bmatrix} \cdot \begin{bmatrix} \hat{y}^{(1)} - y^{(1)} \\ \hat{y}^{(2)} - y^{(2)} \\ \vdots \\ \hat{y}^{(N)} - y^{(N)} \end{bmatrix}$$



How is an algorithm implemented? (3)

Computing dot products and predictions

$$\begin{bmatrix} x_1^{(1)} & x_2^{(1)} & \dots & x_d^{(1)} \\ x_1^{(2)} & x_2^{(2)} & \dots & x_d^{(2)} \\ \vdots & \vdots & \ddots & \vdots \\ x_1^{(N)} & x_2^{(N)} & \dots & x_d^{(N)} \end{bmatrix} \cdot \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_d \end{bmatrix} = \begin{bmatrix} z^{(1)} \\ z^{(2)} \\ \vdots \\ z^{(N)} \end{bmatrix}$$



How is an algorithm implemented? (4)

