Apache MADlib (Incubating)

Distributed In-Database Machine Learning for Fun and Profit

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Jan 31, 2016

FOSDEM'16

Machine learning and distributed systems are just plain *FUN!!!*

Every large commercial enterprise $$$ uses relational databases

+

=

MADlib

Topics

- Journey to Apache

The Apache Software Foundation
Community-led development since 1999.

- In-database machine learning

MADlib

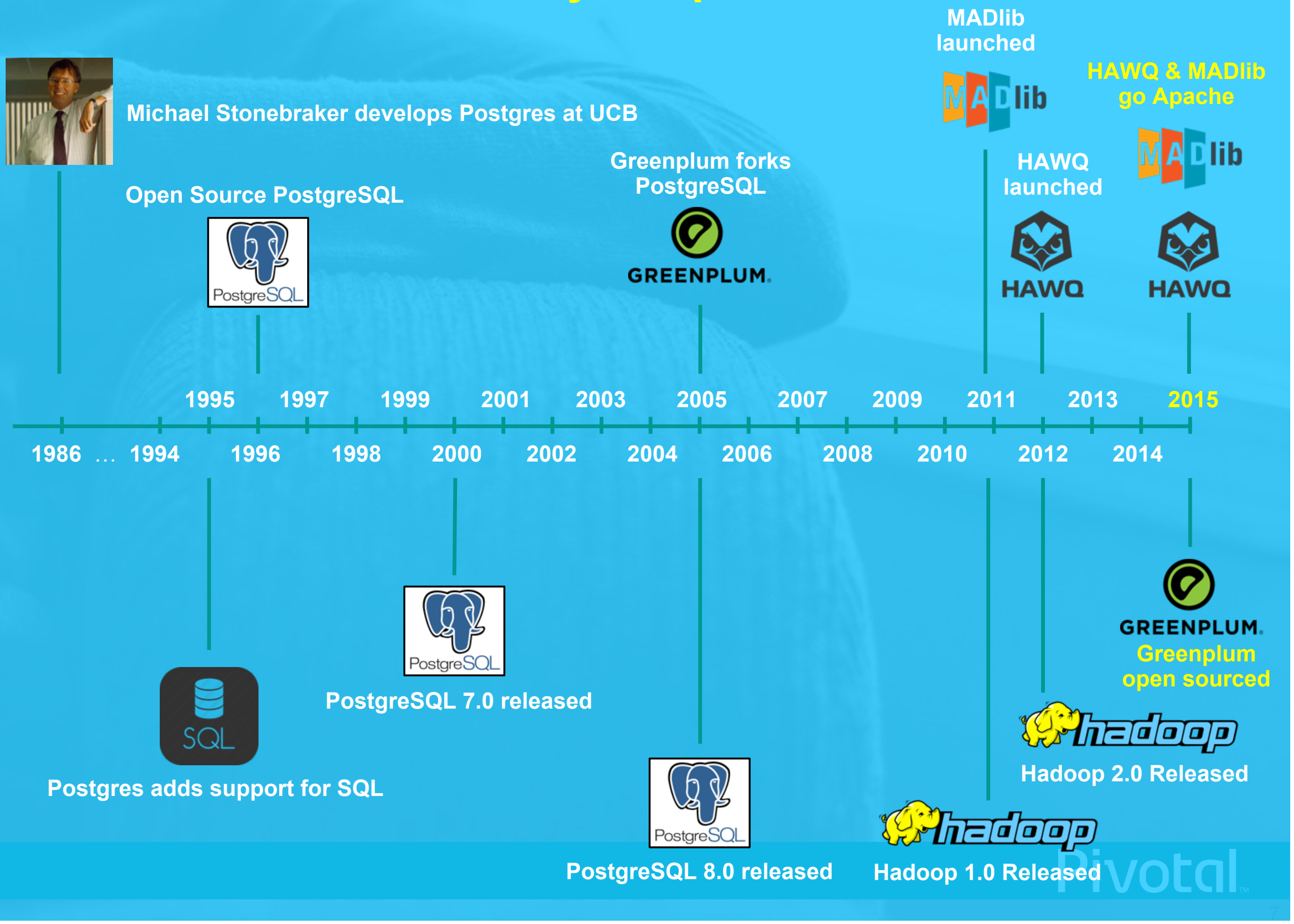
- Making R scalable

PivotalR

Journey to Apache Software Foundation

The Apache Software Foundation
Community-led development since 1999.

Journey to Apache



Michael Stonebraker develops Postgres at UCB

Postgres adds support for SQL

Open Source PostgreSQL

PostgreSQL 7.0 released

PostgreSQL 8.0 released

Greenplum forks PostgreSQL

MADlib launched

Hadoop 1.0 Released

HAWQ launched

Hadoop 2.0 Released

HAWQ & MADlib go Apache

Greenplum open sourced

History

MADlib project was initiated in 2011 by EMC/Greenplum architects and Joe Hellerstein from Univ. of California, Berkeley.

UrbanDictionary.com:
mad *(adj.): an adjective used to enhance a noun.*

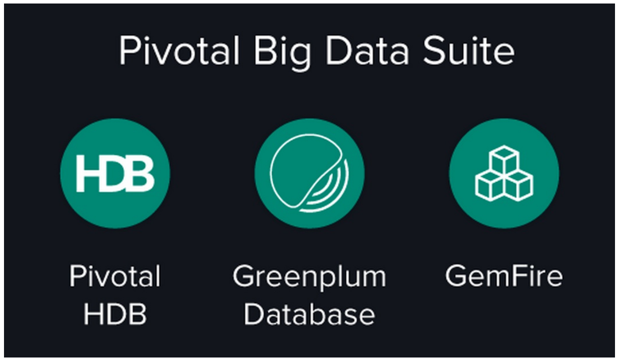
> *1- dude, you got skills.*
> *2- dude, you got* ***mad*** *skills.*

Why Apache?

The Apache Software Foundation
Community-led development since 1999.

- Because the ASF is a great place to be!
- Collaborate on software in open and productive ways
- Need strong community for innovation

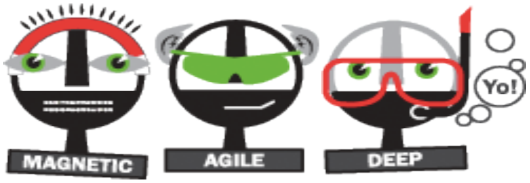
Pivotal is Committed to Open Source

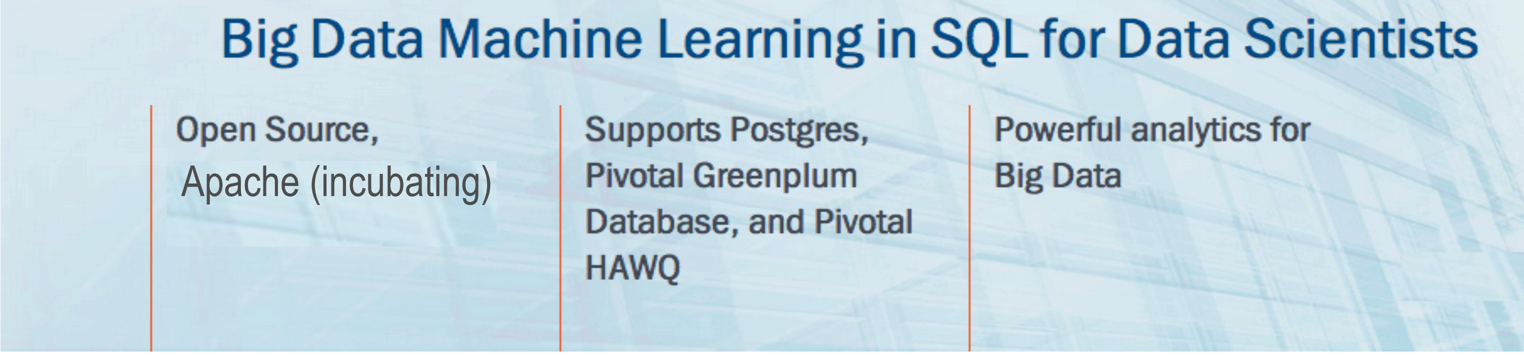

Pivotal Big Data Suite

✓	Pivotal GemFire	→	Apache Geode (April 2015)
✓	Pivotal HDB	→	Apache HAWQ (Sept 2015)
✓	MADlib OSS (BSD License)	→	Apache MADlib (Sept 2015)
✓	Pivotal Greenplum	→	Greenplum Database (Oct 2015) (Apache 2 License)
✓	Pivotal Query Optimizer	→	gporca, part of Greenplum Database (Jan 2016) (Apache 2 License)

Apache MADlib Overview

Scalable, In-Database Machine Learning





Big Data Machine Learning in SQL for Data Scientists

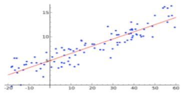
Open Source, Apache (incubating)

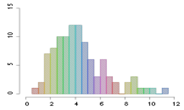
Supports Postgres, Pivotal Greenplum Database, and Pivotal HAWQ

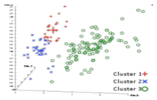
Powerful analytics for Big Data

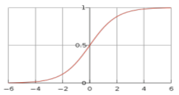
- Open Source https://github.com/apache/incubator-madlib
- Supports Greenplum DB, Apache HAWQ/HDB and PostgreSQL
- Downloads and Docs: http://madlib.incubator.apache.org/

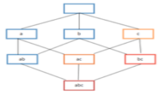
MADlib Functions











Predictive Modeling Library

Generalized Linear Models
- Linear Regression
- Logistic Regression
- Multinomial Logistic Regression
- Cox Proportional Hazards Regression
- Elastic Net Regularization
- Robust Variance (Huber-White), Clustered Variance, Marginal Effects

Matrix Factorization
- Singular Value Decomposition (SVD)
- Low Rank

Linear Systems
- Sparse and Dense Solvers
- Linear Algebra

Other Machine Learning Algorithms
- Principal Component Analysis (PCA)
- Association Rules (Apriori)
- Topic Modeling (Parallel LDA)
- Decision Trees
- Random Forest
- Support Vector Machines
- Conditional Random Field (CRF)
- Clustering (K-means)
- Cross Validation
- Naïve Bayes
- Support Vector Machines (SVM)

Time Series
- ARIMA

Descriptive Statistics

Sketch-Based Estimators
- CountMin (Cormode-Muth.)
- FM (Flajolet-Martin)
- MFV (Most Frequent Values)

Correlation and Covariance

Summary

Inferential Statistics

Hypothesis Tests

Support Modules

Array and Matrix Operations

Sparse Vectors

Random Sampling

Probability Functions

Data Preparation

PMML Export

Conjugate Gradient

Path Functions

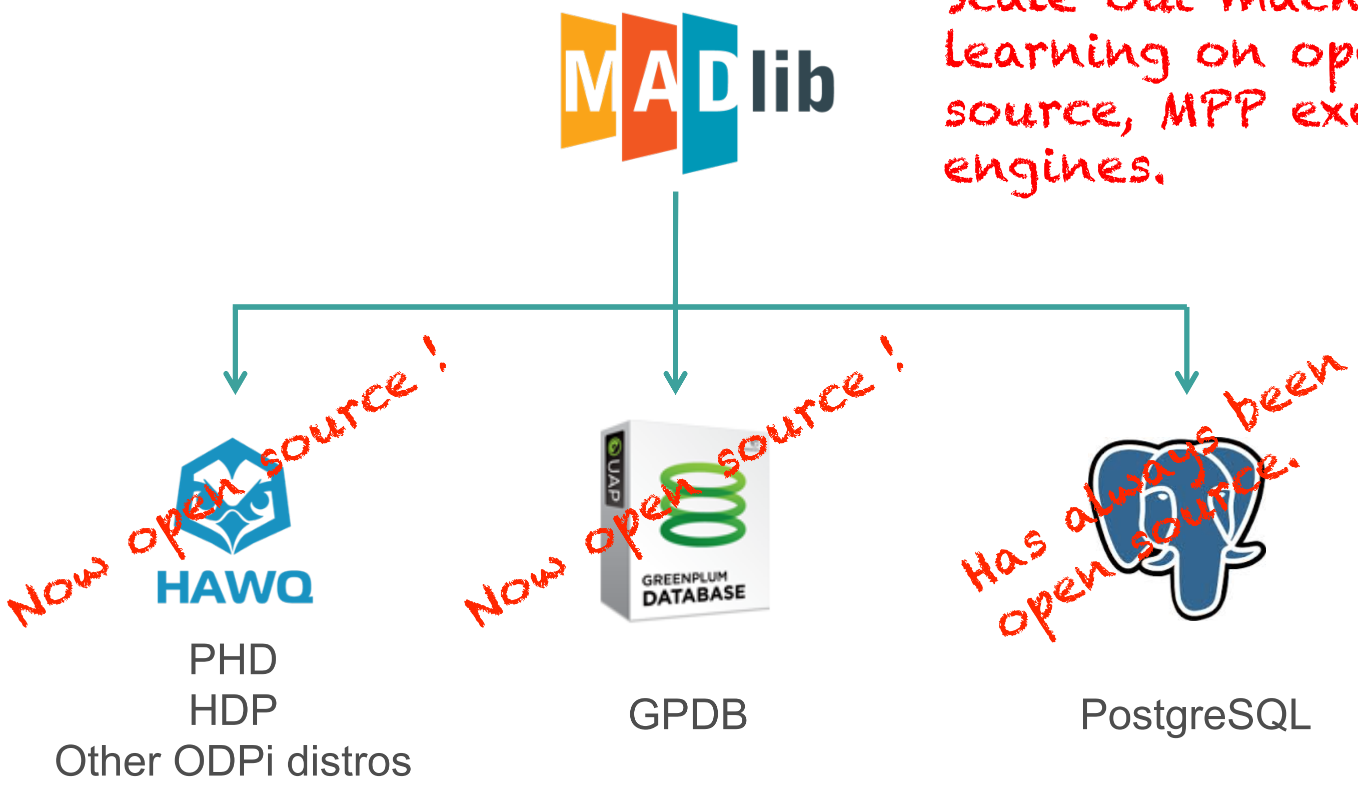
Jan 2016

MADlib Features

- Better parallelism
  - Algorithms designed to leverage MPP and Hadoop architecture
- Better scalability
  - Algorithms scale as your data set scales
- Better predictive accuracy
  - Can use all data, not a sample
- ASF open source (incubating)
  - Available for customization and optimization

Supported Platforms

Scale-out machine learning on open source, MPP execution engines.



PHD
HDP
Other ODPi distros

GPDB

PostgreSQL

Linear Regression on 10 Million Rows in Seconds

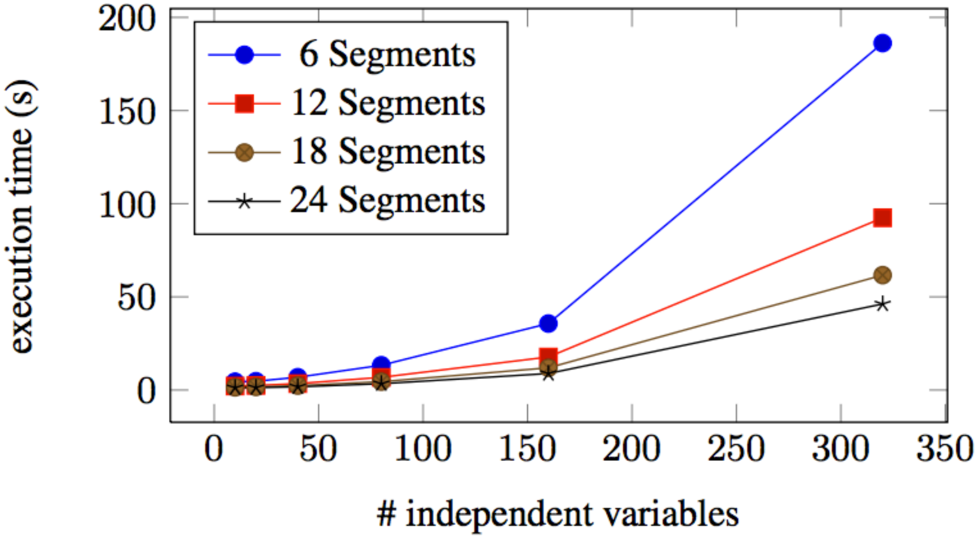
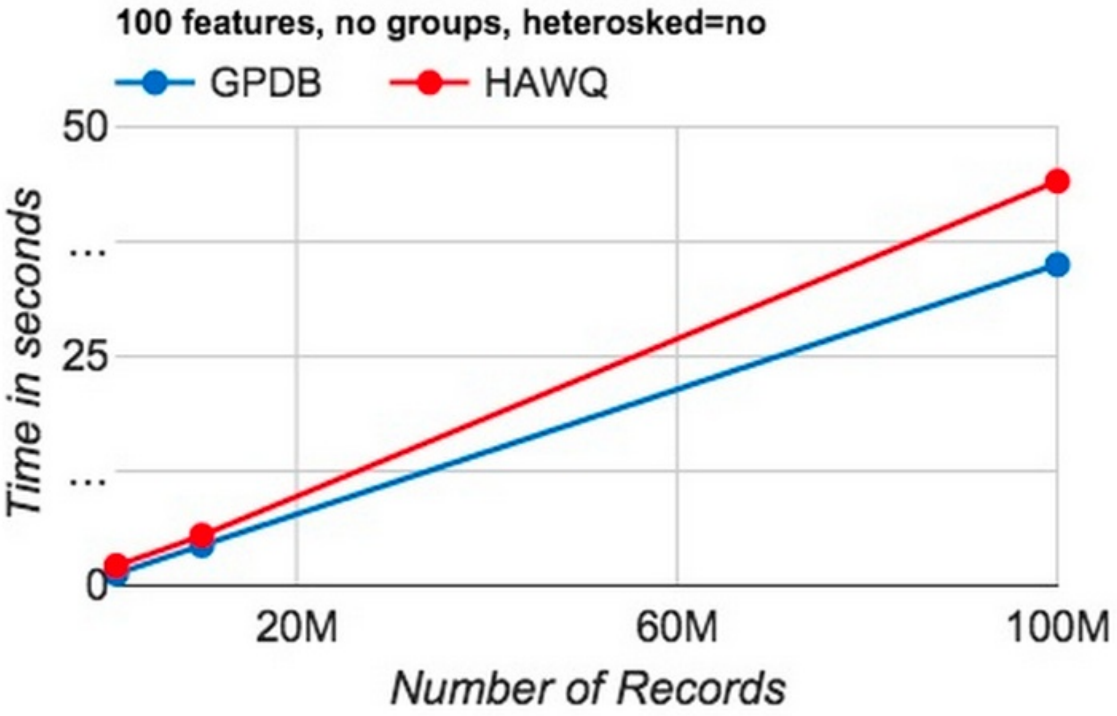


Figure 5: Linear regression execution times using MADlib v0.3 on Greenplum Database 4.2.0, 10 million rows

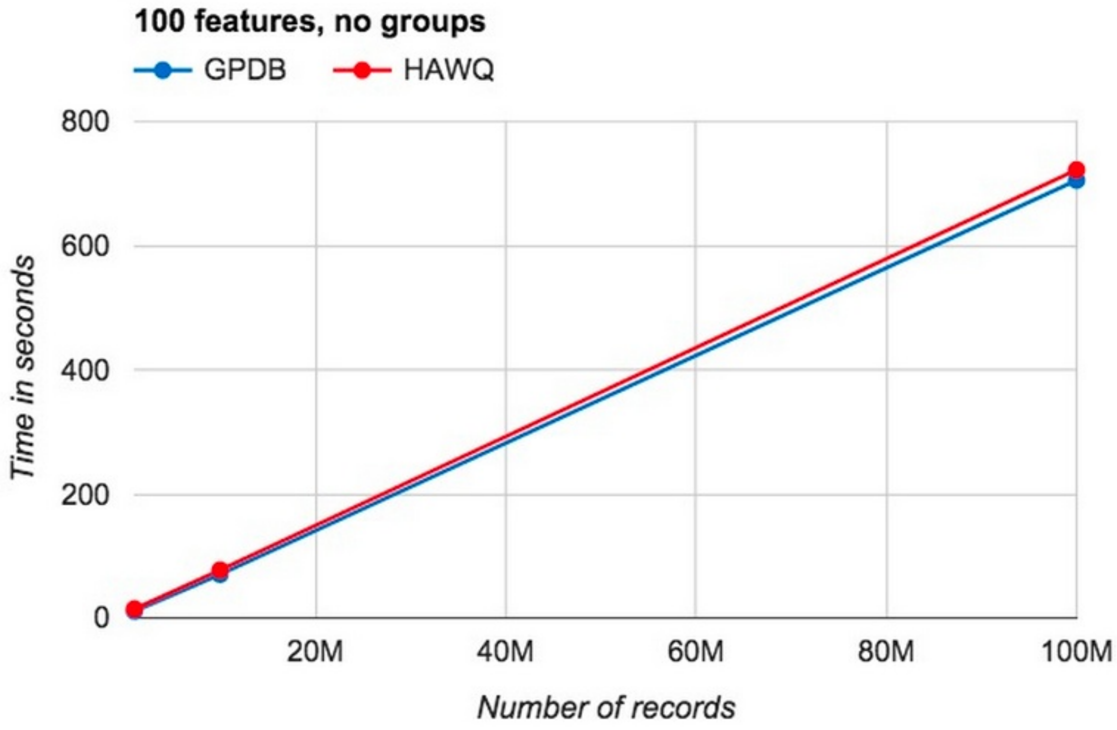
Hellerstein, Joseph M., et al. "The MADlib analytics library: or MAD skills, the SQL." Proceedings of the VLDB Endowment 5.12 (2012): 1700-1711.

Linear Regression Scalability



Performance tests are run on a Pivotal Data Computing Appliance (DCA) half-rack for GPDB 4.2.7.1 and a DCA half-rack for HAWQ 1.2.1.0 with 8 nodes and 6 segments per node.

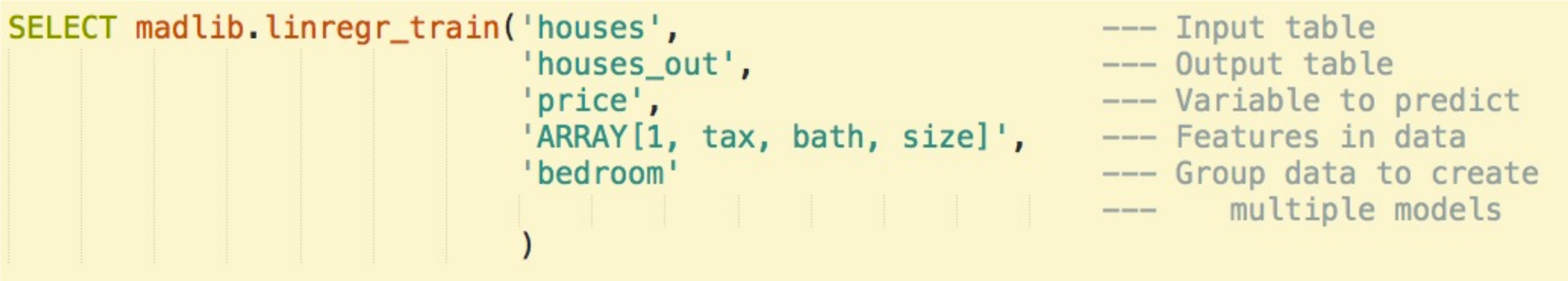
Logistic Regression Scalability



Performance tests are run on a Pivotal Data Computing Appliance (DCA) half-rack for GPDB 4.2.7.1 and a DCA half-rack for HAWQ 1.2.1.0 with 8 nodes and 6 segments per node.

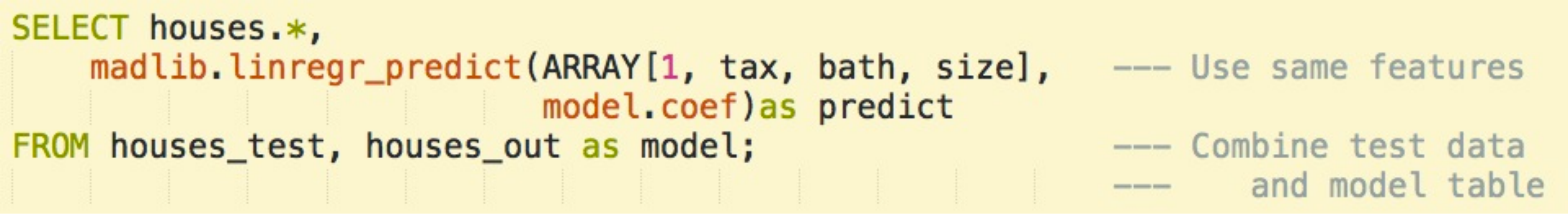
Example Usage

Train a model



```
SELECT madlib.linregr_train('houses',                       --- Input table
                            'houses_out',                   --- Output table
                            'price',                        --- Variable to predict
                            'ARRAY[1, tax, bath, size]',    --- Features in data
                            'bedroom'                       --- Group data to create
                                                            ---    multiple models
                            )
```

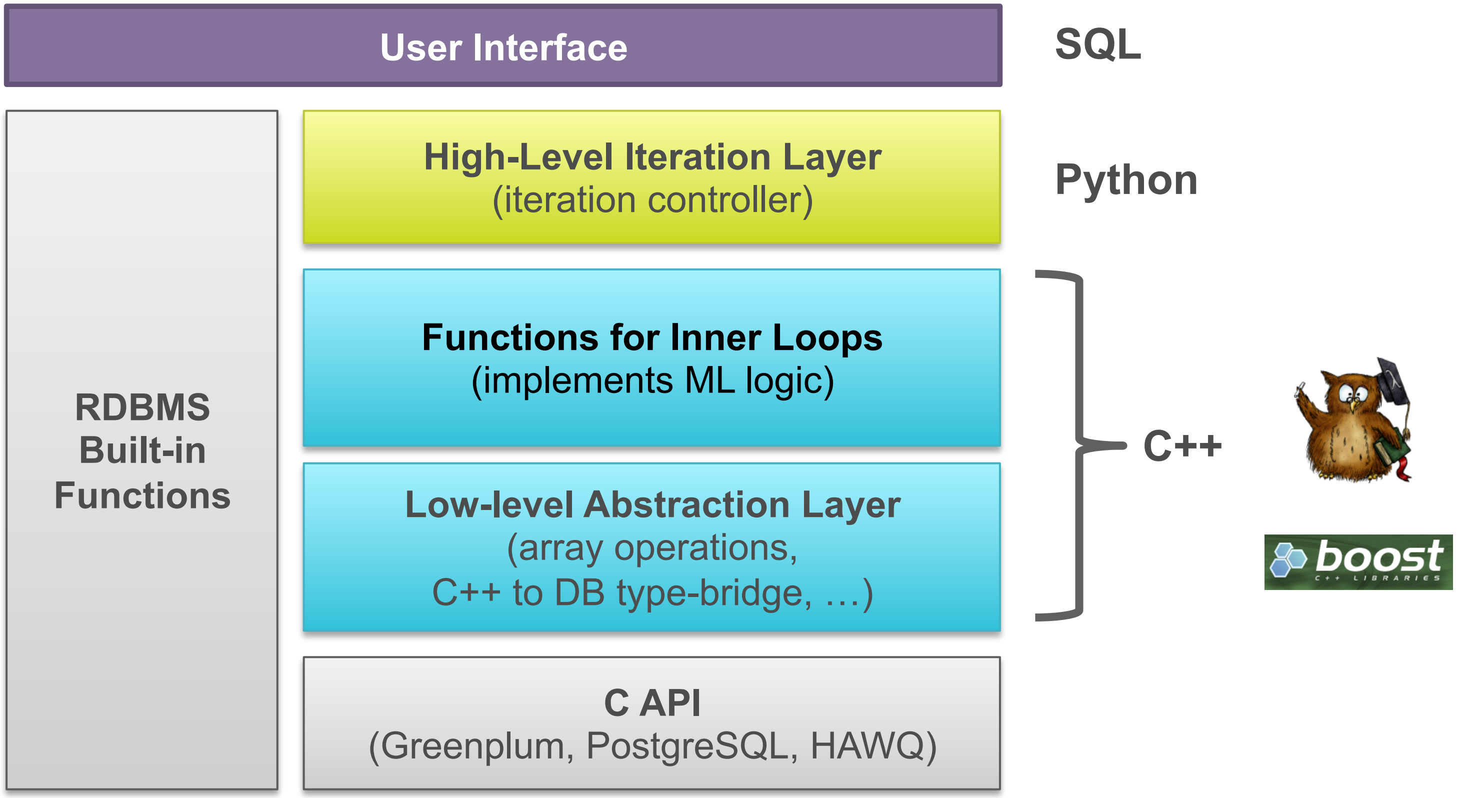
Predict for new data



```
SELECT houses.*,
    madlib.linregr_predict(ARRAY[1, tax, bath, size],       --- Use same features
                           model.coef)as predict
FROM houses_test, houses_out as model;                      --- Combine test data
                                                            ---    and model table
```

Architecture

Architecture



User Interface

SQL

RDBMS Built-in Functions

High-Level Iteration Layer
(iteration controller)

Python

Functions for Inner Loops
(implements ML logic)

Low-level Abstraction Layer
(array operations,
C++ to DB type-bridge, …)

C++

boost C++ LIBRARIES

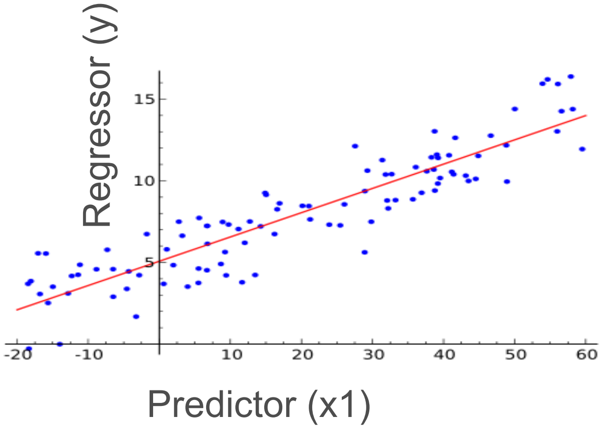
C API
(Greenplum, PostgreSQL, HAWQ)

How to Implement Scalability

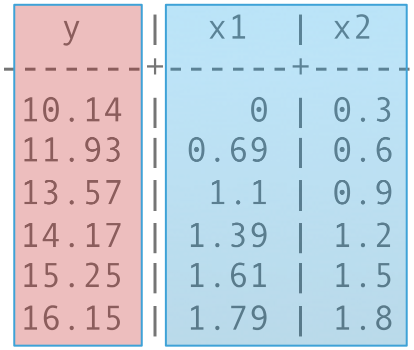
Example: Linear Regression

- Finding linear dependencies between variables

$y \approx c_0 + c_1 \cdot x_1 + c_2 \cdot x_2$ *i.e., want to find c_1, c_2*



Vector of dependent variables y



```
   y    |   x1   | x2
--------+--------+-----
10.14   |      0 | 0.3
11.93   |   0.69 | 0.6
13.57   |    1.1 | 0.9
14.17   |   1.39 | 1.2
15.25   |   1.61 | 1.5
16.15   |   1.79 | 1.8
```

Feature matrix X

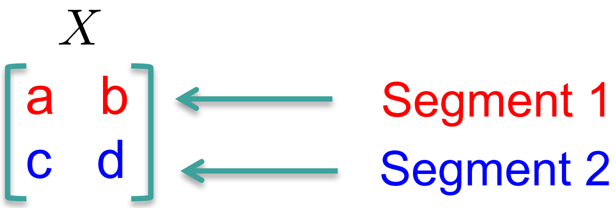
Solve Using Ordinary Least Squares

$$\widehat{\boldsymbol{c}} = (X^T X)^{-1} X^T \boldsymbol{y}$$

OLS for Parallel Computation

$$\widehat{\boldsymbol{c}} = \underline{(X^T X)}^{-1} X^T \boldsymbol{y}$$

1



X

a b

c d

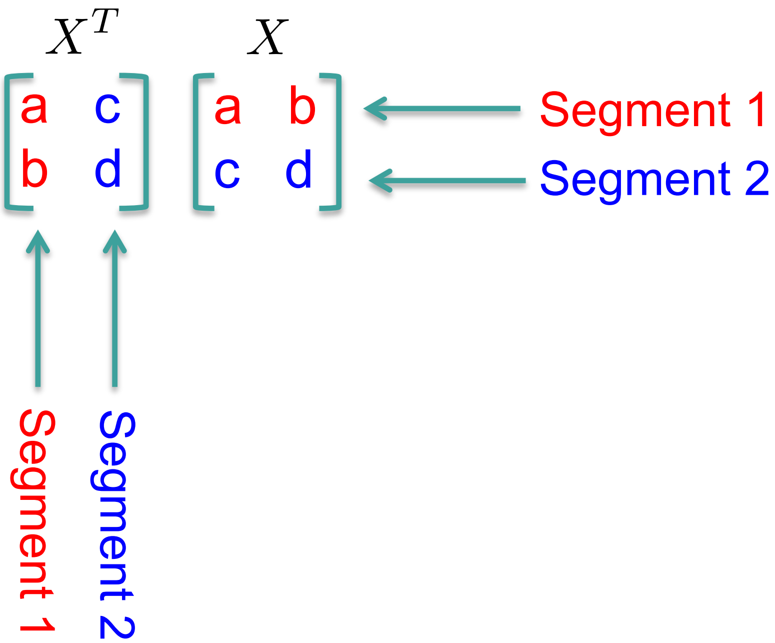
Segment 1

Segment 2

OLS for Parallel Computation

$$\widehat{\boldsymbol{c}} = \underline{(X^TX)}^{-1}X^T\boldsymbol{y}$$

1



$$X^T \begin{bmatrix} a & c \\ b & d \end{bmatrix} \quad X \begin{bmatrix} a & b \\ c & d \end{bmatrix}$$

Segment 1

Segment 2

Segment 1

Segment 2

OLS for Parallel Computation

$$\hat{\boldsymbol{c}} = \underline{(X^TX)}^{-1}X^T\boldsymbol{y}$$

1

$$\begin{array}{cc} X^T & X \\ \begin{bmatrix} a & c \\ b & d \end{bmatrix} & \begin{bmatrix} a & b \\ c & d \end{bmatrix} \end{array}$$

$$= \begin{bmatrix} a^2 + c^2 & \\ & \end{bmatrix}$$

Operating across segments increases network traffic

OLS for Parallel Computation

$$\widehat{\boldsymbol{c}} = \underline{(X^T X)}^{-1} X^T \boldsymbol{y}$$

1

$$\begin{array}{cc} X^T & X \\ \begin{bmatrix} a & c \\ b & d \end{bmatrix} & \begin{bmatrix} a & b \\ c & d \end{bmatrix} \end{array}$$

$$= \begin{bmatrix} a^2 + c^2 & ab + cd \\ ba + dc & b^2 + d^2 \end{bmatrix}$$

Looking at algebra, this is decomposable

OLS for Parallel Computation

$$\widehat{\boldsymbol{c}} = \underline{(X^T X)^{-1}} X^T \boldsymbol{y}$$

1

$$\begin{array}{cc} X^T & X \\ \begin{bmatrix} a & c \\ b & d \end{bmatrix} & \begin{bmatrix} a & b \\ c & d \end{bmatrix} \end{array}$$

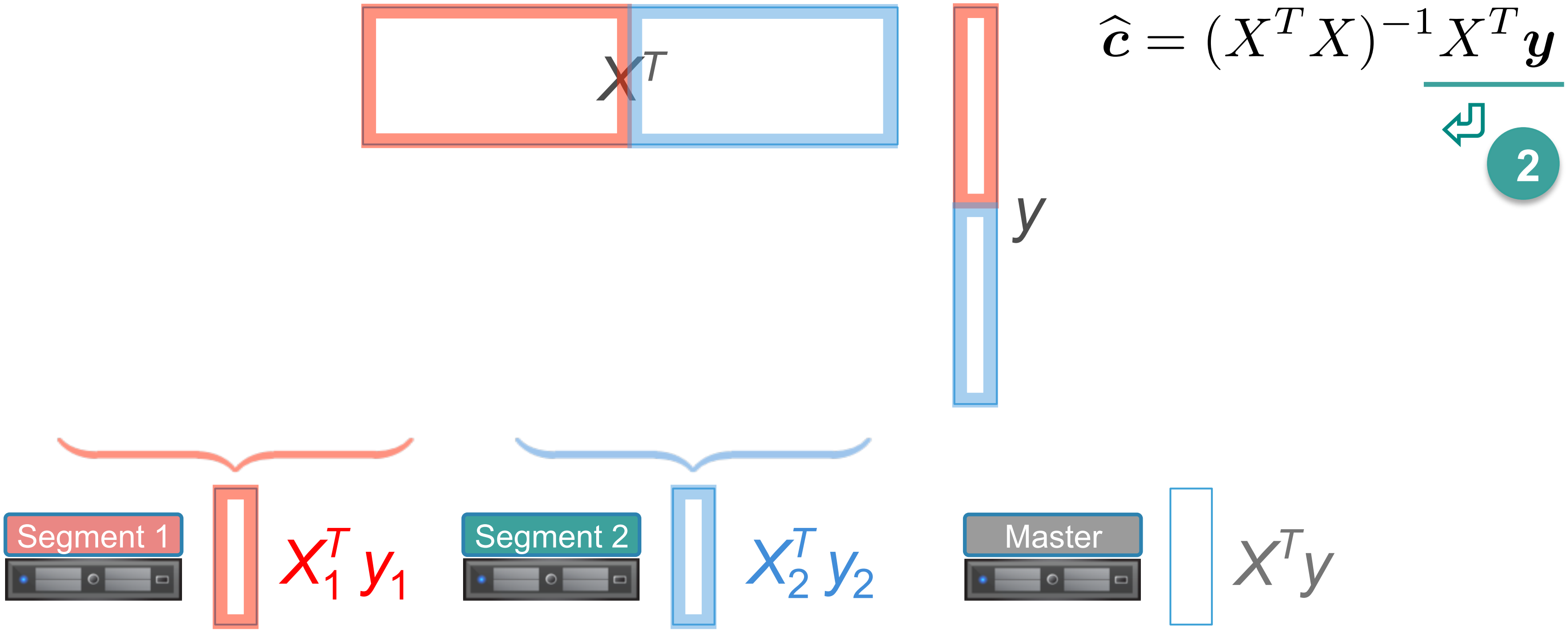
$$= \begin{bmatrix} a \\ b \end{bmatrix} \begin{bmatrix} a & b \end{bmatrix} + \begin{bmatrix} c \\ d \end{bmatrix} \begin{bmatrix} c & d \end{bmatrix}$$

$$= \begin{bmatrix} a^2 + c^2 & ab + cd \\ ba + dc & b^2 + d^2 \end{bmatrix}$$

User outer product for less network traffic

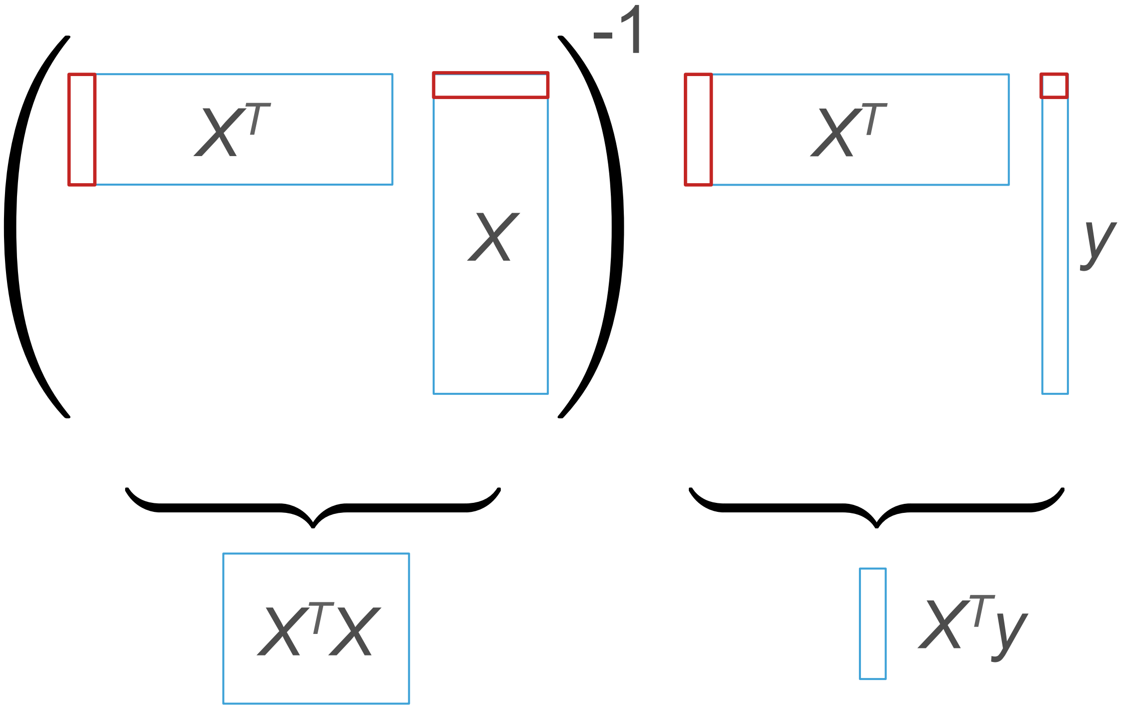
OLS for Parallel Computation

$$\widehat{\boldsymbol{c}} = (X^T X)^{-1} \underline{X^T \boldsymbol{y}}$$



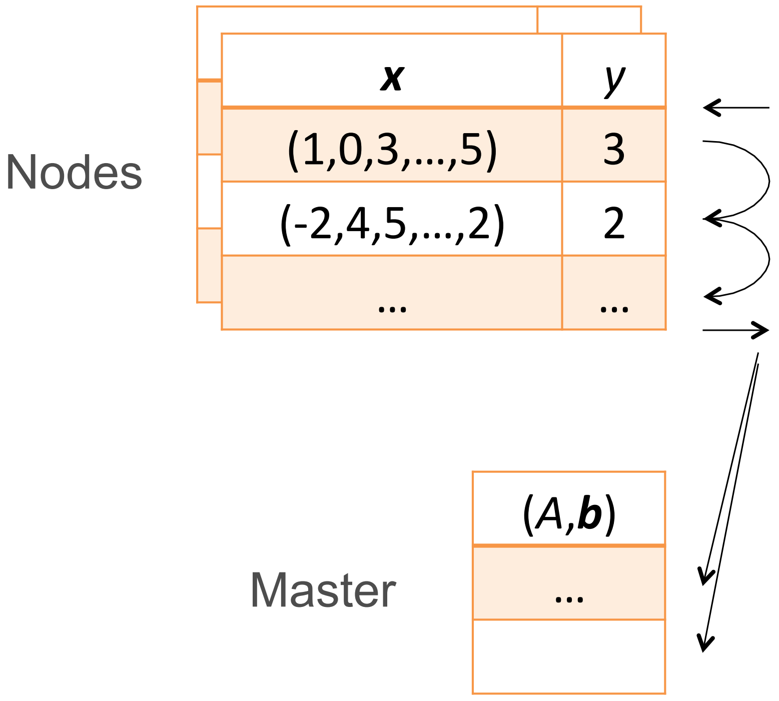
Do in Single Table Scan

$$\widehat{\boldsymbol{c}} = \underline{(X^T X)^{-1} X^T \boldsymbol{y}}$$



1 & 2

Basic Building Block: User-Defined Aggregate



$\boldsymbol{x}$	y
(1,0,3,…,5)	3
(-2,4,5,…,2)	2
…	…

$(A,\boldsymbol{b})$
…

Aggregation phase 1 on each node:

1. Initialize: $(A,\boldsymbol{b}) = (0,0)$
2. Transition for all rows:

   $$(A,\boldsymbol{b}) = (A,\boldsymbol{b}) \underset{\text{reduce}}{+} \underbrace{(\boldsymbol{x}\cdot\boldsymbol{x}^T, \boldsymbol{x}\cdot y)}_{\text{map}}$$
3. Send $(A,\boldsymbol{b})$

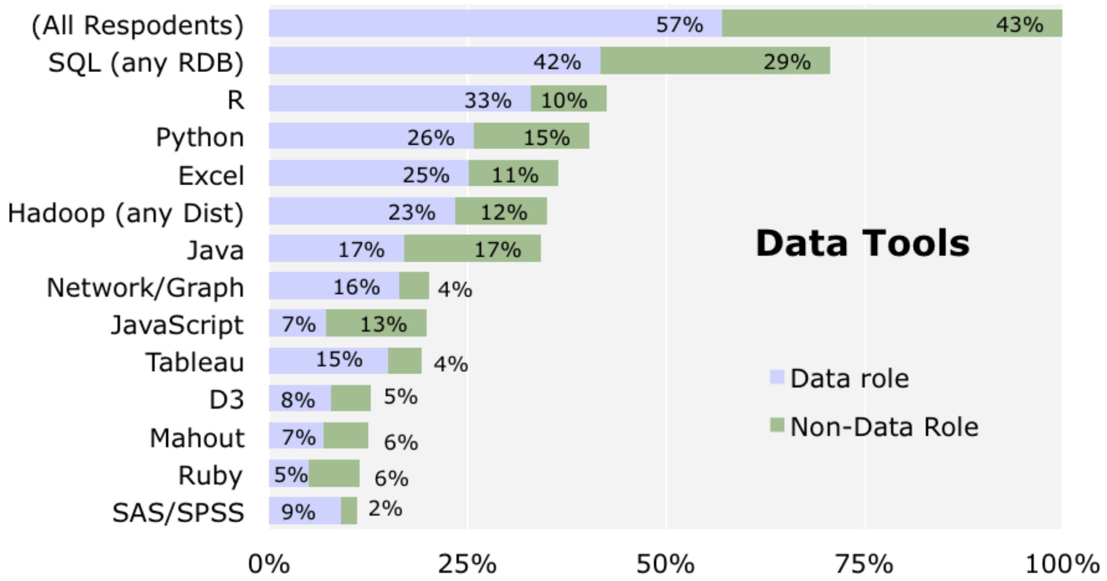
Aggregation phase 2 on master node:

1. Merge: $(\bar{A},\bar{\boldsymbol{b}}) = (\bar{A},\bar{\boldsymbol{b}}) + (A,\boldsymbol{b})$
2. Finalize: $\hat{\beta} = \text{solve}(\bar{A},\bar{\boldsymbol{b}}) = \bar{A}^{-1}\cdot\bar{\boldsymbol{b}}$

But not all data scientists speak SQL …

Making R Scalable

Why R?



“The preponderance of R and Python usage is more surprising …
two most commonly used individual tools, even above Excel. R and Python are likely popular because they are easily accessible and effective open source tools.”

O’Reilly: Strata 2013 Data Science Salary Survey

PivotalR: Bringing MADlib and HAWQ to a Familiar R Interface

- *Harness the familiarity of R’s interface and the performance & scalability benefits of in-DB analytics*

Pivotal R

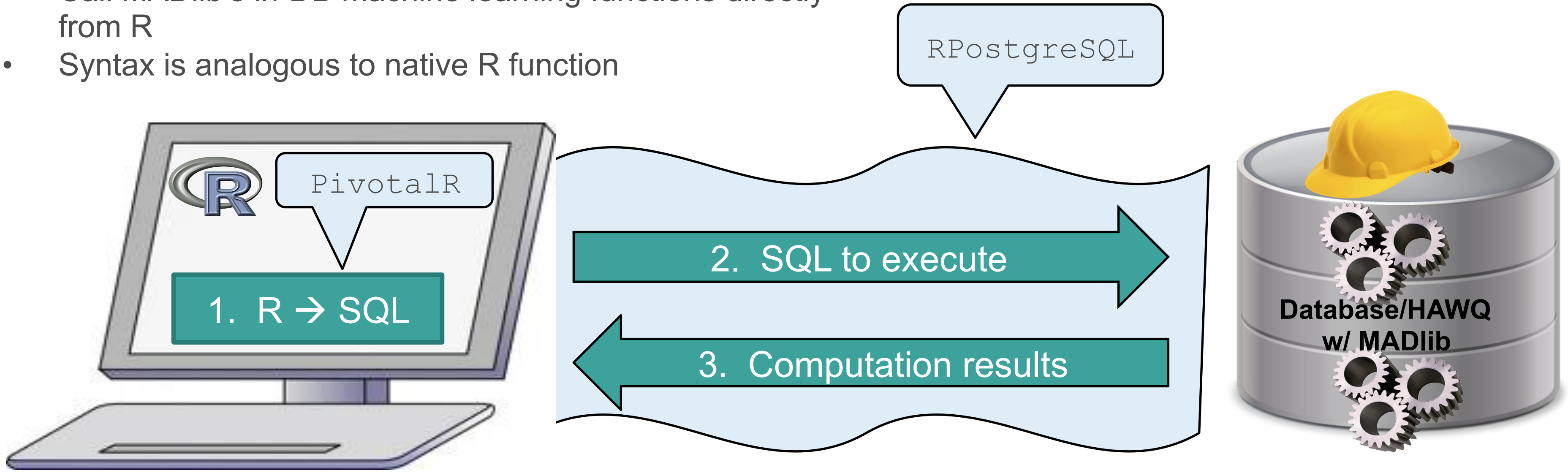
```
d <- db.data.frame(”houses")
houses_linregr <-
     madlib.lm(price ~ tax
                     + bath
                     + size
                , data=d)
```

SQL Code

```
SELECT madlib.linregr_train( 'houses’,
                        'houses_linregr’,
                                 'price’,
          'ARRAY[1, tax, bath, size]’);
```

PivotalR Design Overview

- Call MADlib's in-DB machine learning functions directly from R
- Syntax is analogous to native R function



No data here

- Data doesn't need to leave the database
- All heavy lifting, including model estimation & computation, are done in the database
- Only strings of SQL and model output transferred across DBI

Data lives here

What's Coming Up?

Upcoming Release (1.9)

Predictive Models

- Support vector machines including non-linear kernel (Gaussian, polynomial)

Utilities

- Matrix operations (phase 2)
- Path functions (phase 1)
- Stemming

Descriptive Stats

- Covariance matrix

Potential Future Features*

Predictive Models

- Mixed effects models
- Time series models
- Parameter weights
- Graph models
- Connected components
- Linkage operations

Usability

- Refresh interface for 2.0
- Python API

Utilities

- Path functions (phase 2)
- Pivoting
- Anonymization
- Sessionization
- Prediction metrics
- URI tools
- Stratified sampling

* Subject to community interest

Please Join Us!

- Web sites
  - http://madlib.incubator.apache.org/
  - https://cwiki.apache.org/confluence/display
  - https://cran.r-project.org/web/packages/PivotalR/index.html
- Github
  - https://github.com/apache/incubator-madlib
  - https://github.com/pivotalsoftware/PivotalR
- Mailing lists
  - dev@madlib.incubator.apache.org
  - user@madlib.incubator.apache.org