

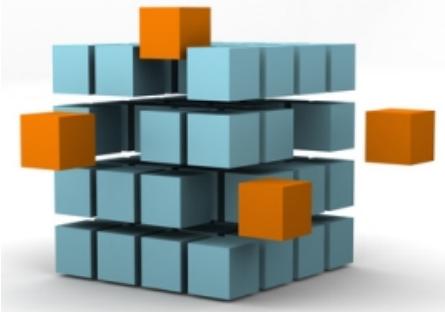
# LINVIEW: Incremental View Maintenance for Complex Analytical Queries

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# Big Data Analytics

## Simple (SQL) Analytics

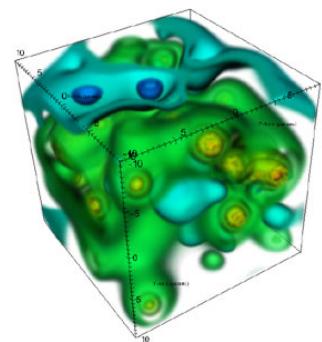


Data Warehouses (OLAP)

## Complex (non-SQL) Analytics



Machine Learning



Scientific Computing

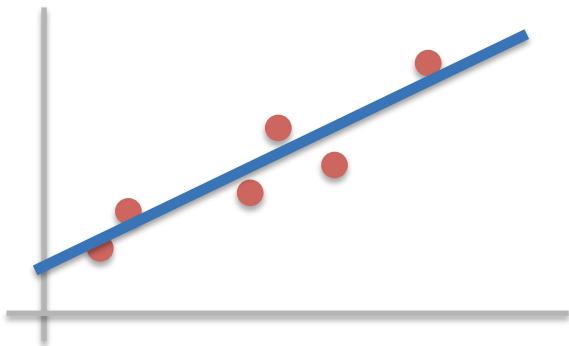


Data Mining

# Complex Analytical Queries

- Often expressed as linear algebra on array data

Example: Ordinary Least Squares



$$Y = X \beta$$

$$\beta^* = (X^T X)^{-1} X^T Y$$

Re-evaluating complex queries on  
every (small) change is inefficient  
=> Do it incrementally!

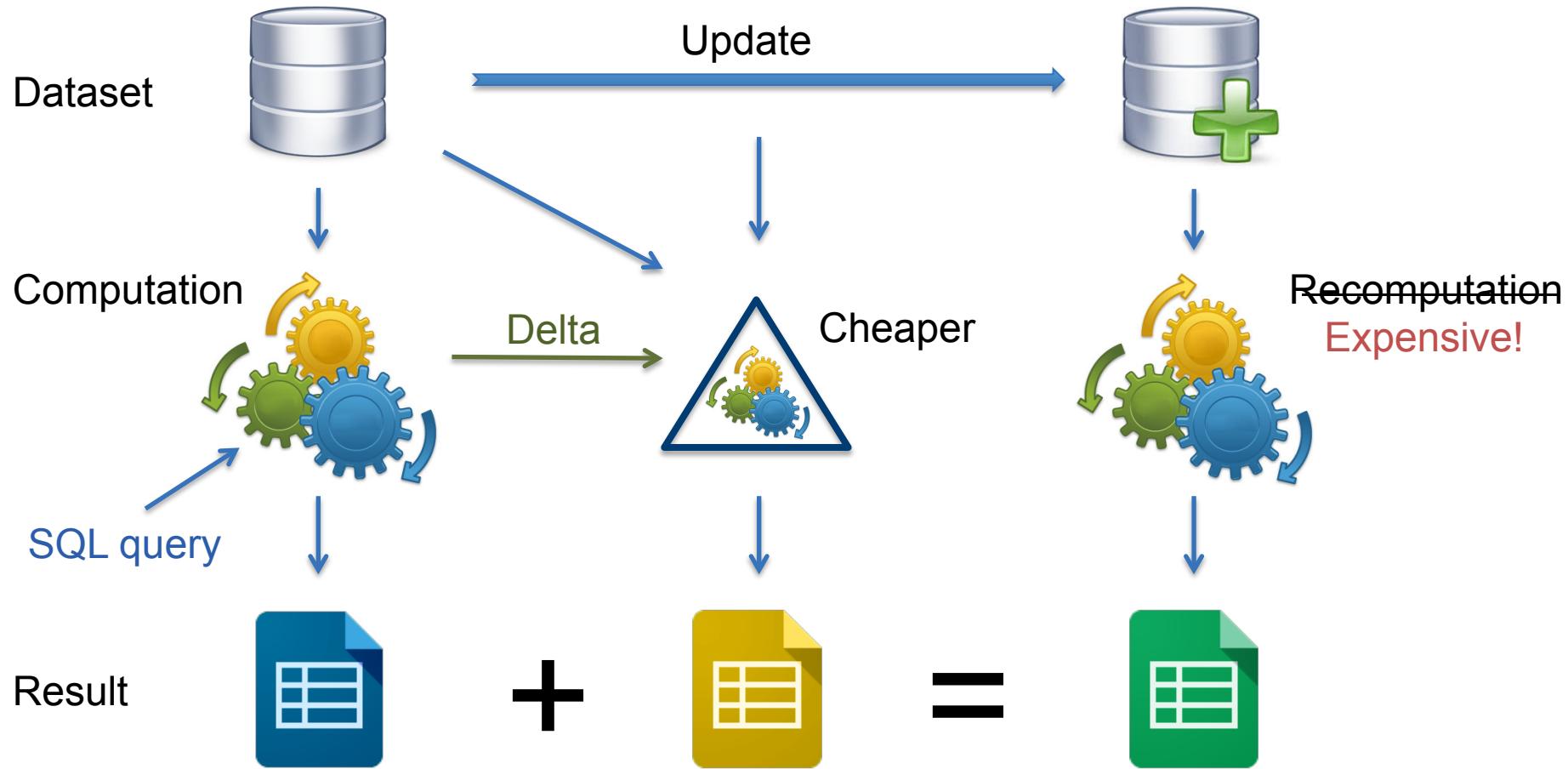
- Multidimensional arrays

HIGH DIMENSIONAL: Data processing is increasingly expensive

DYNAMIC: Continuously changing, evolve through small changes  
(e.g., user's Internet activity)

- Users want frequently fresh views of data

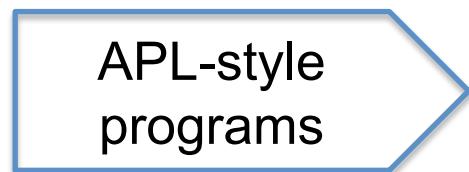
# Incremental Processing



Incremental View Maintenance (IVM) in DBMS (Oracle, DB2, PostgreSQL, ...)

# LINVIEW

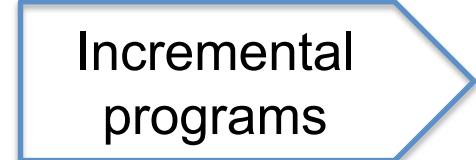
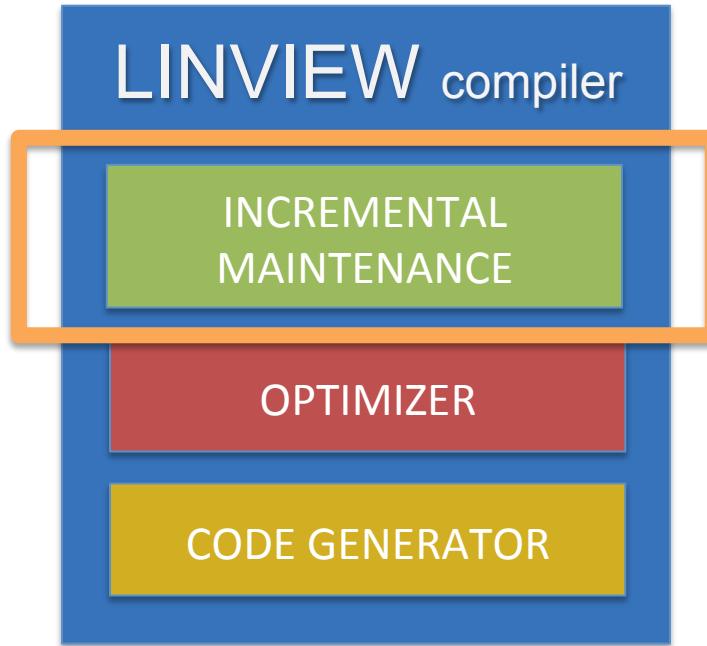
Incremental evaluation of (iterative) linear algebra programs



For instance:  
MATLAB, R, Octave

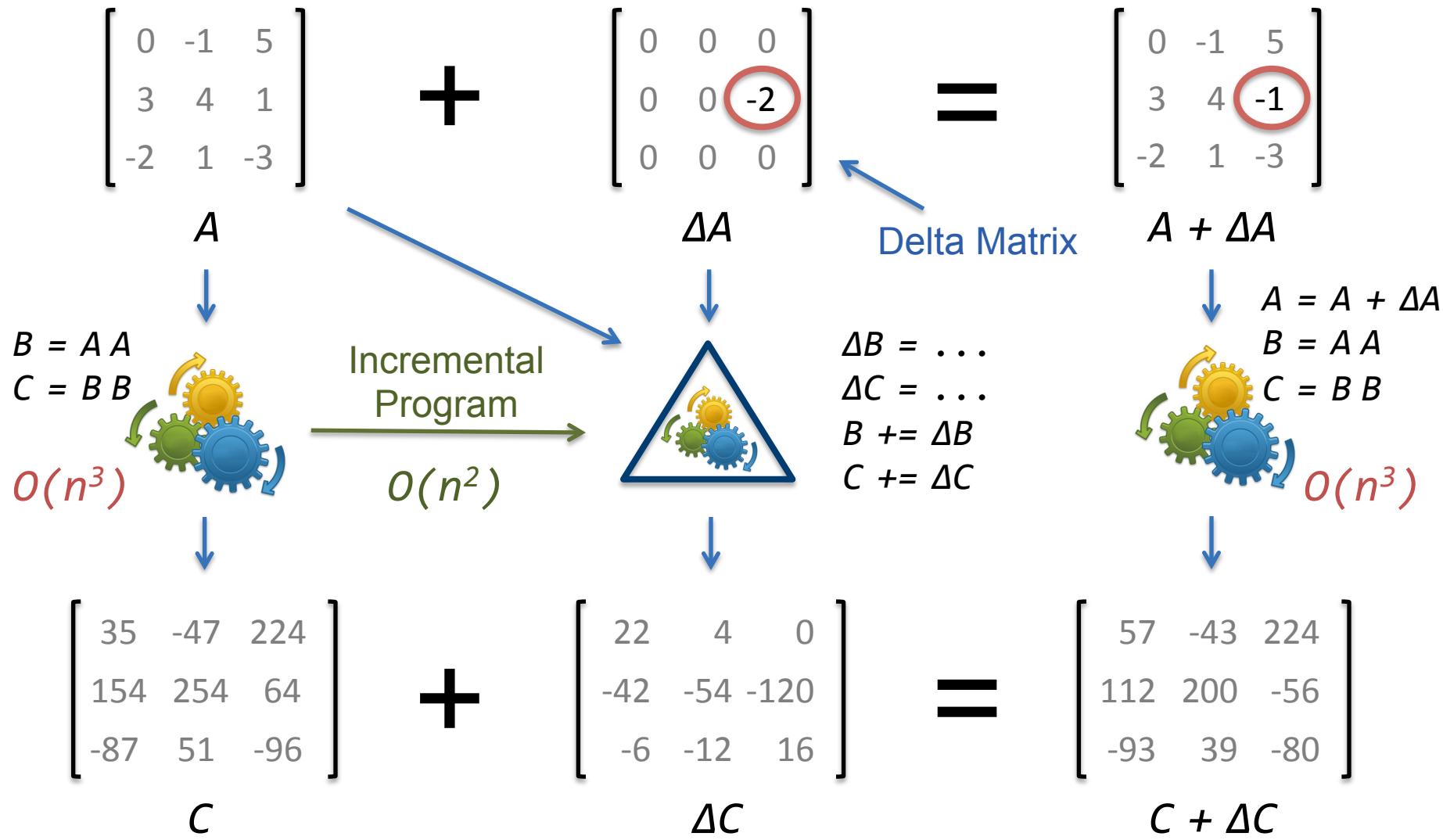
Matrix operations  
 $(+/-, *, A^T, A^{-1})$

Basis of ML algos



Exec over dynamic data  
Different runtimes  
(Spark, Octave)

# Example: Matrix Powers $A^4$



# IVM of Linear Algebra

## Original Program (Expensive)

ON UPDATE A BY  $\Delta A$ :

$$A += \Delta A$$

$$B = A A$$

$$C = B B$$

$O(n^3)$



## Incremental Program (Cheap)

ON UPDATE A BY  $\Delta A$ :

$$\Delta B = A(\Delta A) + (\Delta A)A + (\Delta A)(\Delta A)$$

$$\Delta C = B(\Delta B) + (\Delta B)B + (\Delta B)(\Delta B)$$

$$A += \Delta A$$

$$B += \Delta B$$

$$C += \Delta C$$

$O(n^2)$

... when  $\Delta A$  is “simple”

How to

... derive delta expressions?

... evaluate delta expressions?

... represent delta expressions?



# Delta Derivation

- Exploits properties of matrix operations  
(e.g., distributivity of matrix multiplication over addition)

Example:

$$B[A] = AA \quad (\text{consider } B \text{ as a function of } A)$$

$$\begin{aligned}\Delta B[A, \Delta A] &= B[A + \Delta A] - B[A] \\ &= (A + \Delta A)(A + \Delta A) - AA \\ &= A(\Delta A) + (\Delta A)A + (\Delta A)(\Delta A)\end{aligned}$$

- The Sherman–Morrison formula for maintaining  $(A + \Delta A)^{-1}$

# Delta Evaluation: The Avalanche Effect

$$\begin{bmatrix} 0 & -1 & 5 \\ 3 & 4 & 1 \\ -2 & 1 & -3 \end{bmatrix} \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & -2 \\ 0 & 0 & 0 \end{bmatrix} + \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & -2 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} 0 & -1 & 5 \\ 3 & 4 & -1 \\ -2 & 1 & -3 \end{bmatrix} = \begin{bmatrix} 0 & 0 & 2 \\ 4 & -2 & -2 \\ 0 & 0 & -2 \end{bmatrix}$$

$A$        $\Delta A$        $\Delta A$        $A + \Delta A$        $\Delta B$

$$\begin{bmatrix} -13 & 1 & -16 \\ 10 & 14 & 16 \\ 9 & 3 & 0 \end{bmatrix} \begin{bmatrix} 0 & 0 & 2 \\ 4 & -2 & -2 \\ 0 & 0 & -2 \end{bmatrix} + \begin{bmatrix} 0 & 0 & 2 \\ 4 & -2 & -2 \\ 0 & 0 & -2 \end{bmatrix} \begin{bmatrix} -13 & 1 & -14 \\ 14 & 12 & 14 \\ 9 & 3 & -2 \end{bmatrix} = \begin{bmatrix} 22 & 4 & 0 \\ -42 & -54 & -120 \\ -6 & -12 & 16 \end{bmatrix}$$

$B$        $\Delta B$        $\Delta B$        $B + \Delta B$        $\Delta C$

A single-entry change contaminates the whole output =>  $\Omega(n^2)$

↳ Delta computation involves  $O(n^3)$  matrix multiplication

↳ IVM loses its performance benefit over re-evaluation

How to confine the avalanche effect?



# Delta Representation

- Deltas as single matrices
  - ✗ quickly escalate to full matrices, involve  $O(n^3)$  ops
- Insight: delta matrices have low ranks
  - ✓ represent as **vector outer products**

$$\Delta A = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & -2 \\ 0 & 0 & 0 \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} \begin{bmatrix} 0 & 0 & -2 \end{bmatrix} = u v^T$$

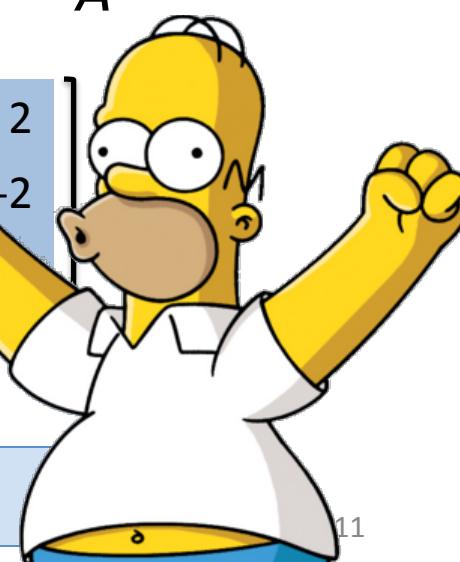
- Factored representation admits efficient evaluation

# Revisited: Matrix Powers $A^4$

$$\Delta A = \begin{bmatrix} \text{blue} \\ \text{white} \\ \text{blue} \end{bmatrix} \begin{bmatrix} \text{red} & \text{white} & \text{red} \end{bmatrix} = u v^T$$

rank-s, efficient when  $s \ll n$   
 $\Delta A$  is a ~~rank-1~~ update  
(e.g., changes of one row/column)

$$\Delta B = \left[ \begin{array}{c|c|c|c} \text{green} & \text{green} & \text{green} & \text{green} \\ \hline \text{green} & \text{white} & \text{white} & \text{green} \\ \hline \text{green} & \text{green} & \text{green} & \text{green} \end{array} \right] \left[ \begin{array}{c} \text{blue} \\ \hline \text{blue} \\ \hline \text{blue} \end{array} \right] \begin{bmatrix} \text{red} & \text{white} & \text{red} \end{bmatrix} + \left[ \begin{array}{c} \text{blue} \\ \hline \text{blue} \\ \hline \text{blue} \end{array} \right] \left[ \begin{array}{c} \text{red} \\ \hline \text{white} \\ \hline \text{red} \end{array} \right] \left[ \begin{array}{c|c|c|c} \text{green} & \text{green} & \text{green} & \text{green} \\ \hline \text{green} & \text{white} & \text{white} & \text{green} \\ \hline \text{green} & \text{green} & \text{green} & \text{green} \end{array} \right] + \dots$$

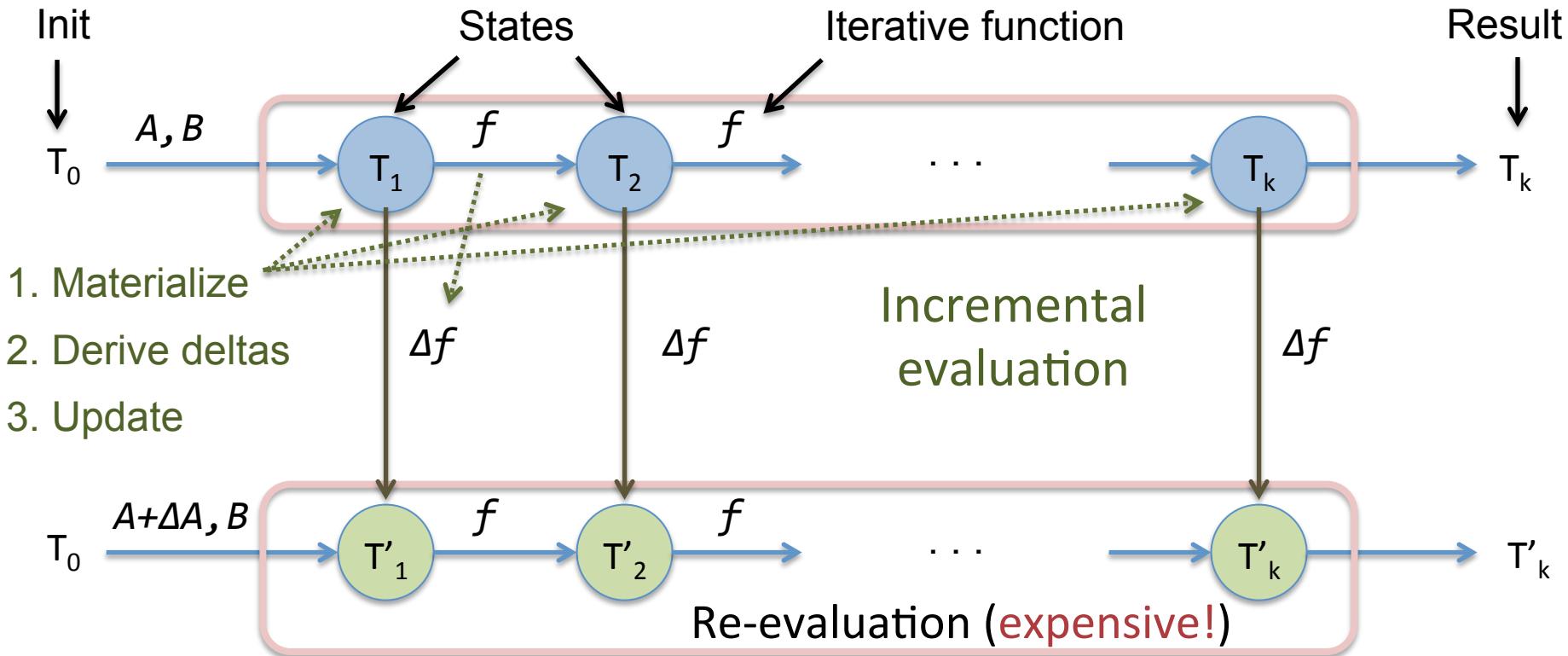
$$= \begin{bmatrix} \text{orange} \\ \hline \text{orange} \\ \hline \text{orange} \end{bmatrix} + \begin{bmatrix} \text{blue} \\ \hline \text{blue} \\ \hline \text{blue} \end{bmatrix} \begin{bmatrix} \text{purple} & \text{purple} & \text{purple} \end{bmatrix} = \begin{bmatrix} 0 & 0 & 2 \\ 4 & -2 & 0 \end{bmatrix}$$


$\Delta C =$  a sum of 4 outer products

Delta computation involves only  $O(n^2)$  operations!

# IVM of Iterative Programs

- Many programs in practice converge within only a few iterations (e.g., 80.7% of pages in PageRank converge in less than 15 iterations<sup>1</sup>)
- Example:  $T_i = f(A, B, T_{i-1}) = A T_{i-1} + B$



[1] S. Kamvar, T. Haveliwala, and G. Golub. Adaptive methods for the computation of PageRank. Technical report, Stanford, 2003

# Time Complexity

(rank-1 updates, big-O notation)

	Re-evaluation	Incremental maintenance
Ordinary Least Squares	$n^3$	$n^2$
Matrix Powers $A^k$	$n^3 \log k$	$n^2 k$
$T_{i+1} = AT_i + B$ where $T = (n \times n)$	$n^3 \log k$	$n^2 k$
$T_{i+1} = AT_i + B$ where $T = (n \times 1)$	$n^2 k$	$n^2 k$

A – dimension ( $n \times n$ )

k – number of iterations

IVM has lower time complexity in most cases!

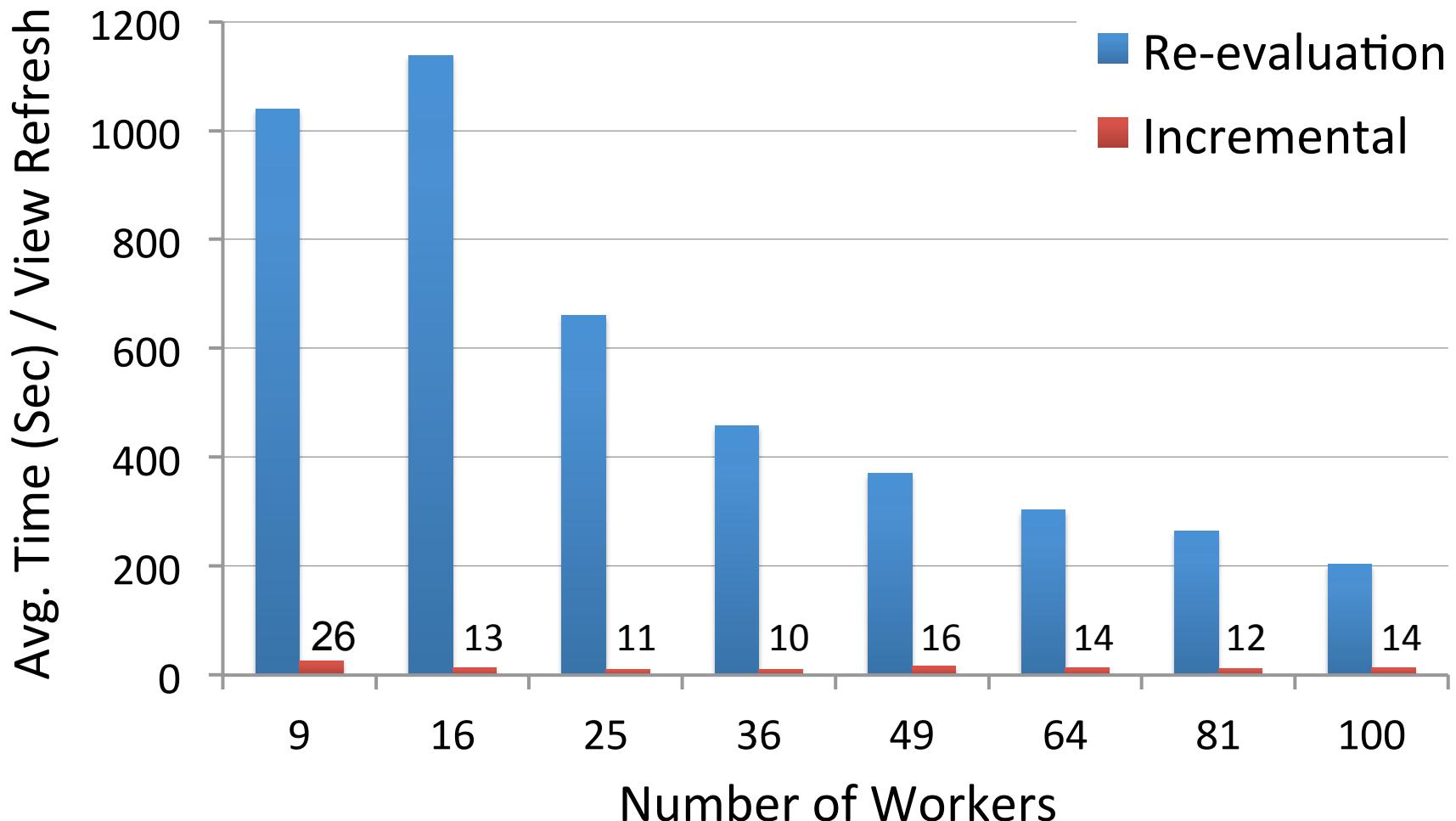
But increases memory consumption ( $\log k$  times, details in paper)

# Experimental Setup

- Analytics: OLS, matrix powers, GD for lin. regression, ...
- Apache Spark
  - EC2 cluster: 100 workers (8 vCPUs, 13.6GB RAM, 10GbE)
- GNU Octave
  - 2 x 2.66GHz 6-Core Intel Xeon, 64GB RAM
- Randomly generated dense matrices
  - Preconditioned for numerical stability
- Stream of rank-1 updates
  - Each update affects one row of the input matrix

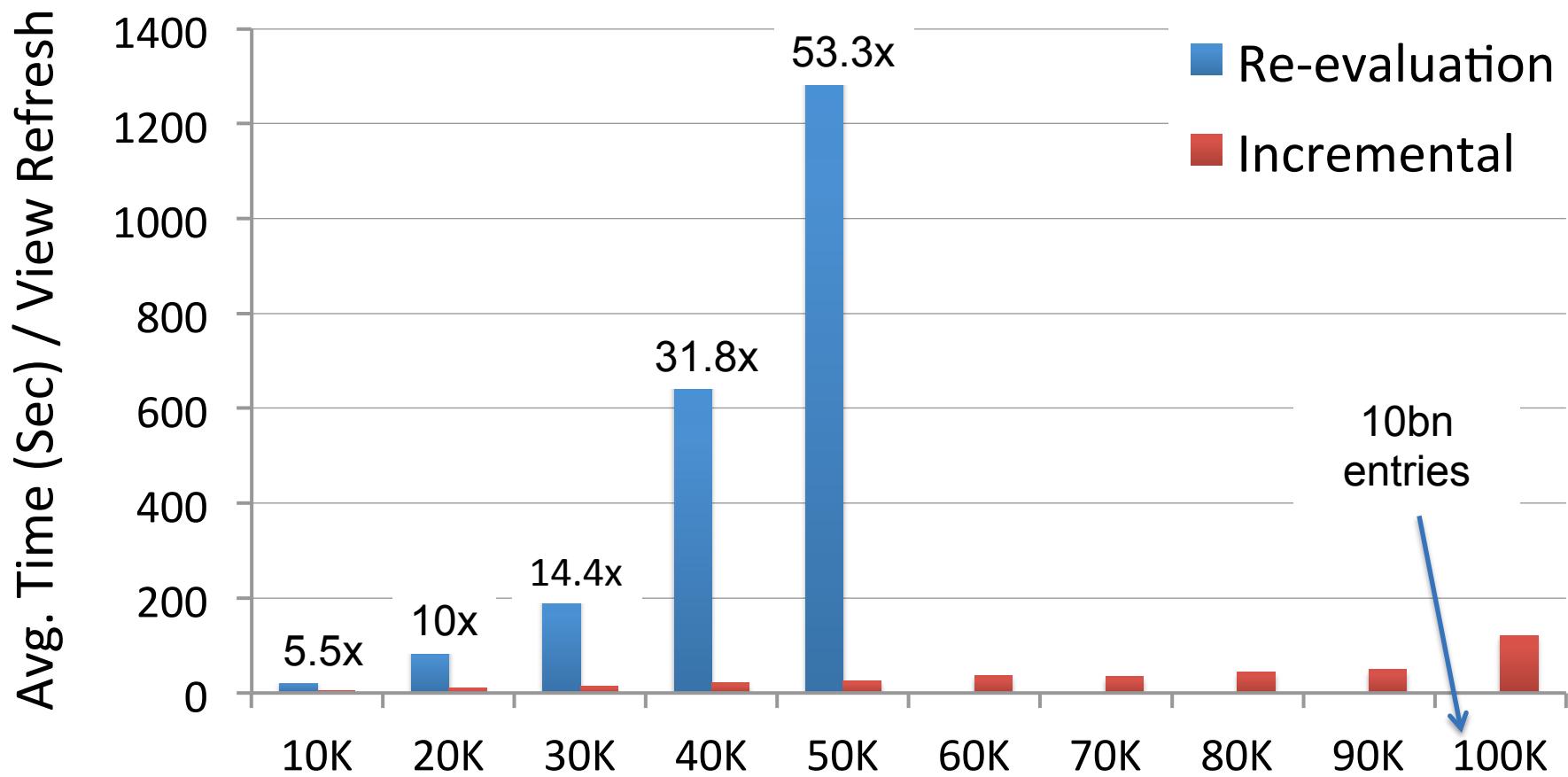
# Matrix Powers – Scalability (nodes)

$A^{16}$  using Spark, updates to  $A = (30K \times 30K)$



# Matrix Powers – Scalability (dimension)

$A^{16}$  using 100 Spark workers, updates to  $A = (n \times n)$

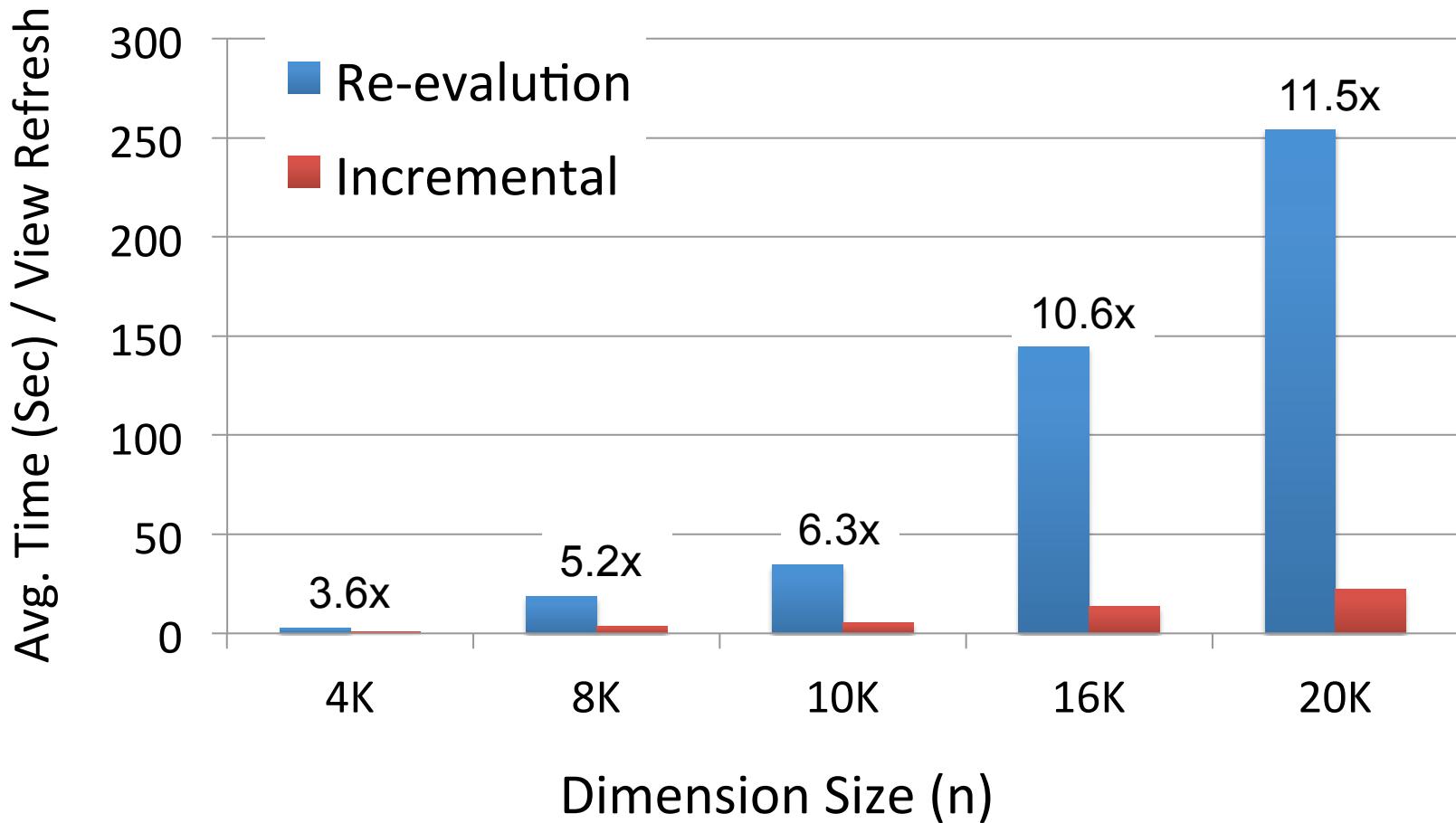


The performance gap increases with higher dimensionality!

# Ordinary Least Squares

$$\beta^* = (X^T X)^{-1} X^T Y$$

GNU Octave, updates to  $X = (n \times n)$ ,  $\beta^*, Y = (n \times 1)$



# LINVIEW: Recap

- Incremental computation of analytical queries expressed as linear algebra programs
- Factored delta representation
  - As (sums of ) vector outer products
  - Confines the avalanche effect
  - Admits efficient evaluation
- IVM has lower time complexity than re-evaluation
  - Can outperform re-evaluation by orders of magnitude

$$\Delta A = \begin{array}{c} \text{blue vertical stack} \\ \Delta A = \\ \text{red horizontal stack} \end{array}$$

<http://data.epfl.ch/linview>