Using R for Iterative and Incremental Processing

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UC Berkeley and HP Labs





Big Data, Complex Algorithms









PageRank (Dominant eigenvector)

Recommendations (Matrix factorization)

Anomaly detection (Top-K eigenvalues)

User Importance (Vertex Centrality)

Big Data, Complex Algorithms



PageRank

(Dominant eigenvector)

Machine learning + Graph algorithms

Iterative Linear Algebra Operations



Allomaly detection

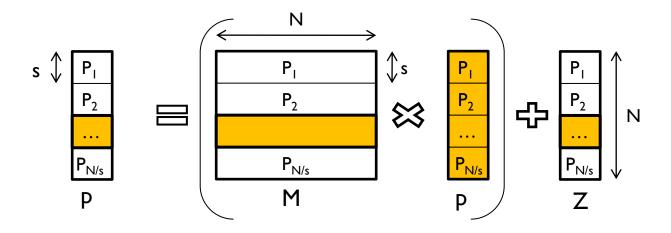
(Top-K eigenvalues)



User Importance

(Vertex Centrality)

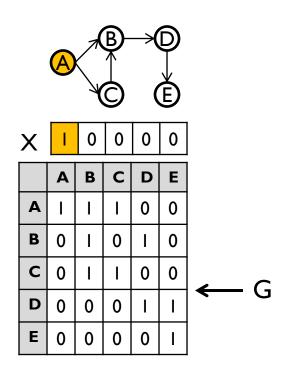
PageRank Using Matrices



Dominant eigenvector

M = modified web graph matrix
p = PageRank vector

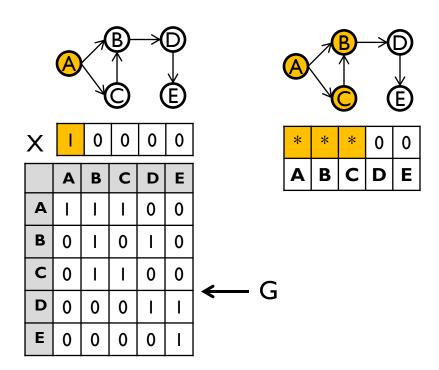
repeat {
$$p = M*p + Z$$
}



G = adjacency matrix

X = BFS vector

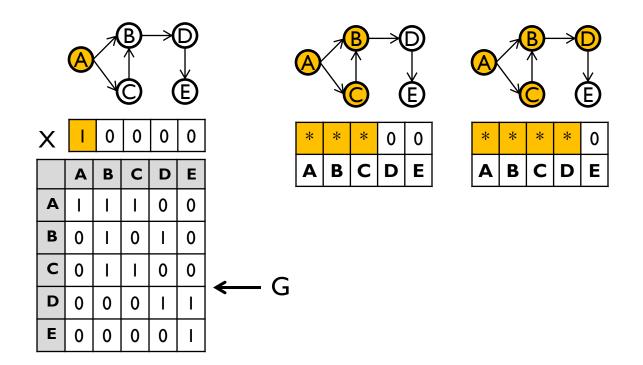
repeat
$$\{ X = G^*X \}$$



G = adjacency matrix

X = BFS vector

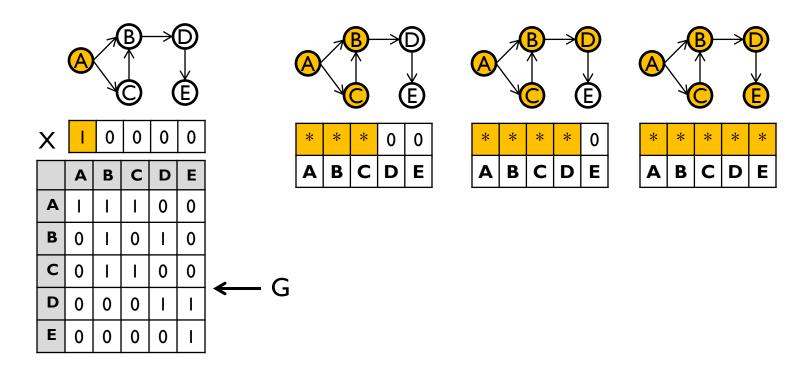
repeat
$$\{X = G^*X\}$$



G = adjacency matrix

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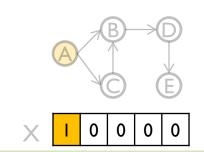
repeat {
$$X = G*X$$
 }

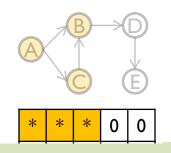


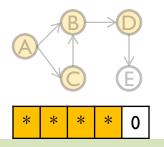
G = adjacency matrix

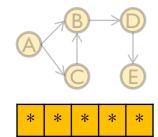
X = BFS vector

repeat
$$\{ X = G^*X \}$$









Matrix operations

Easy to express Efficient to implement

G = adjacency matrix

X = BFS vector

Simplified algorithm:

repeat $\{X = G^*X\}$

Linear Algebra on Existing Frameworks

Matrix Operations: Structured, coarse grained Need global state

Linear Algebra on Existing Frameworks

Matrix Operations: Structured, coarse grained Need global state

Data-parallel frameworks - MapReduce/Dryad

- Process each record in parallel
- Use case: Computing sufficient statistics

Linear Algebra on Existing Frameworks

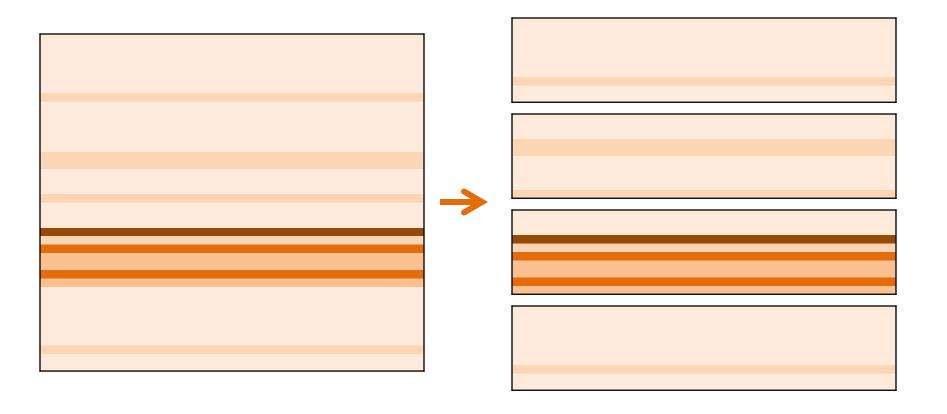
Matrix Operations: Structured, coarse grained Need global state

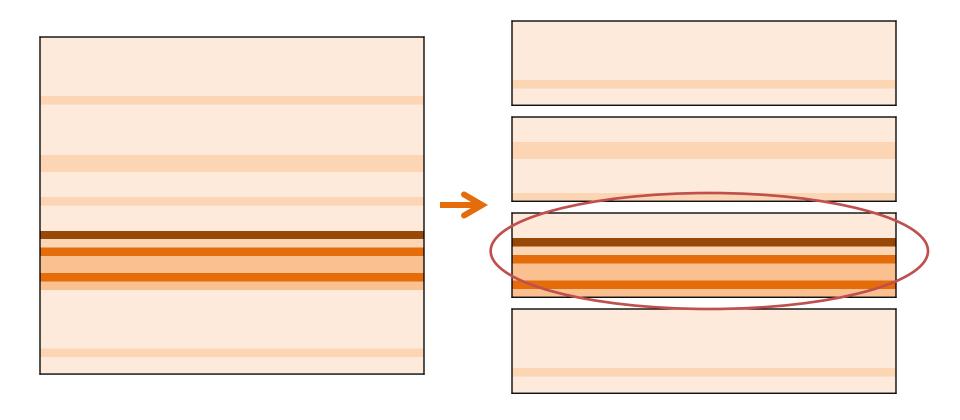
Data-parallel frameworks - MapReduce/Dryad

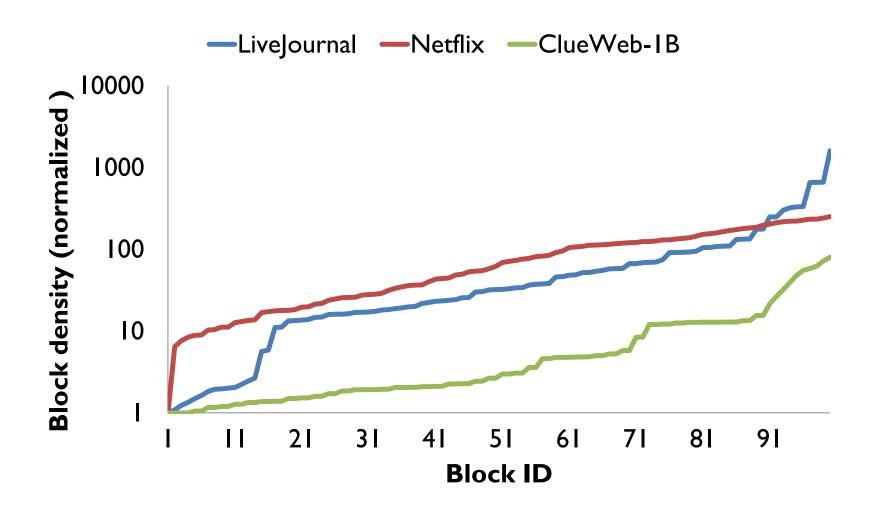
- Process each record in parallel
- Use case: Computing sufficient statistics

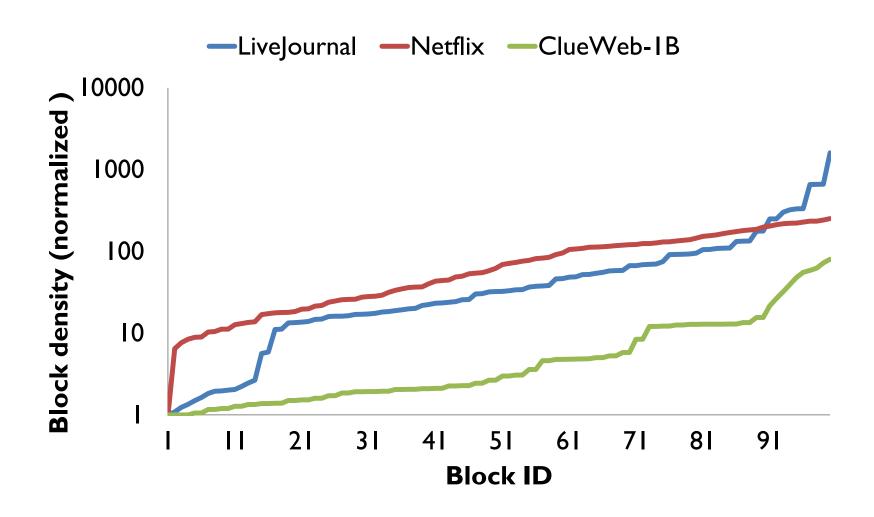
Graph-centric frameworks - Pregel/GraphLab

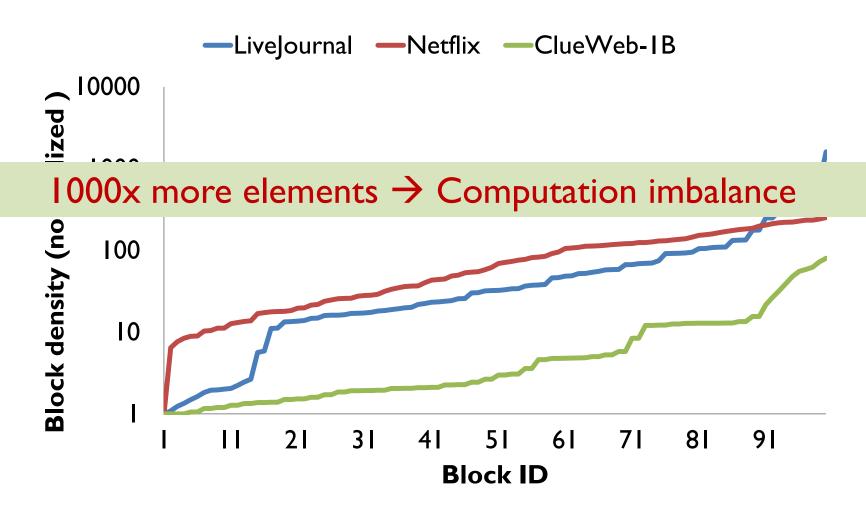
- Process each vertex in parallel
- Use case: Graph models



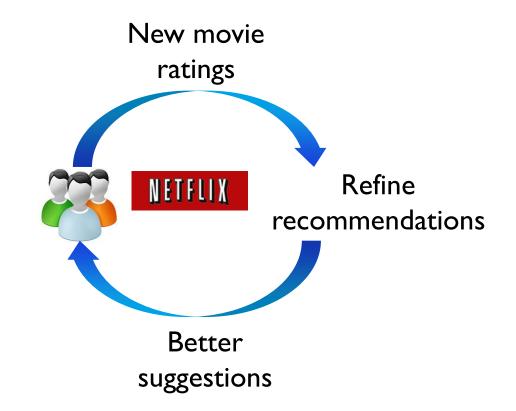








Challenge 2 – Incremental Updates



Incremental computation on consistent view of data

Presto

Framework for large-scale iterative linear algebra

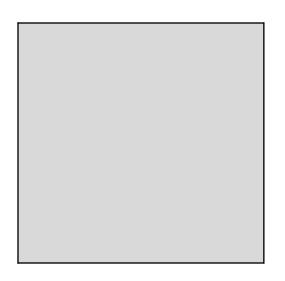
Extend R for scalability and incremental updates

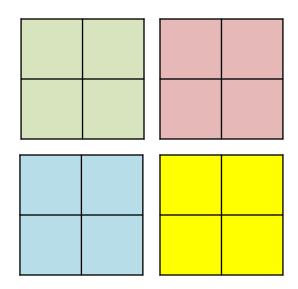
Outline

- Motivation
- Programming model
- Design
- Applications and Results

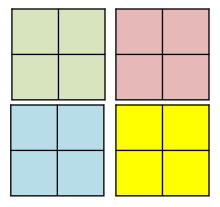
One data structure: Distributed Array

 $A \leftarrow darray(...)$

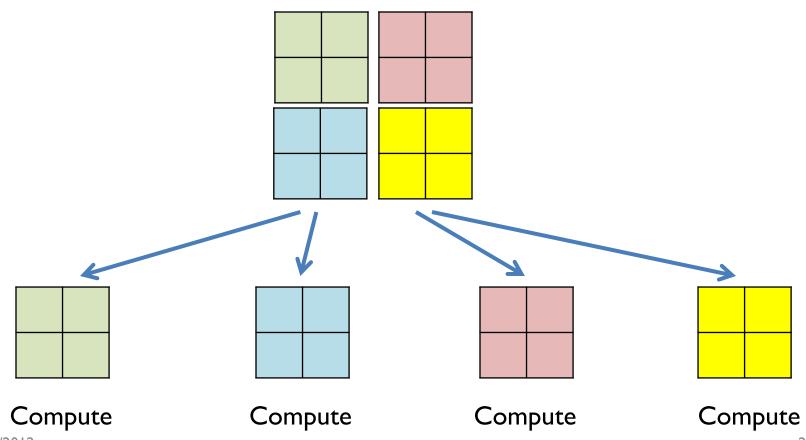




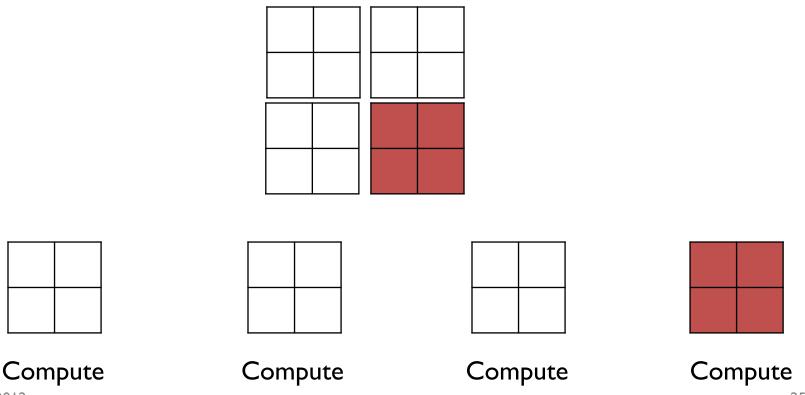
Iteration: foreach



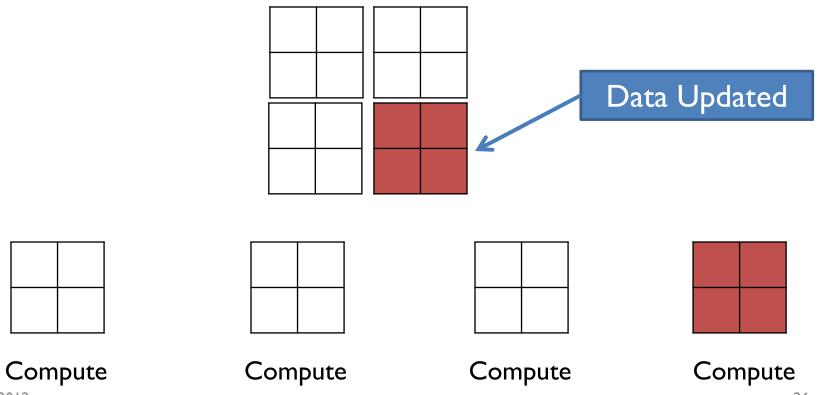
Iteration: foreach



Incremental updates: onchange, update



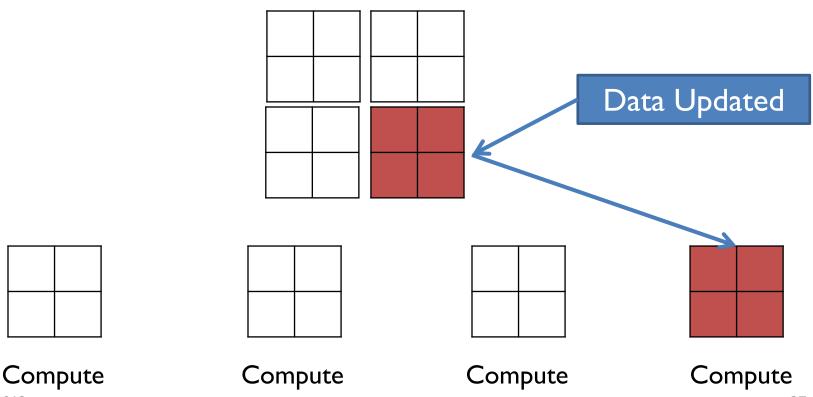
Incremental updates: onchange, update

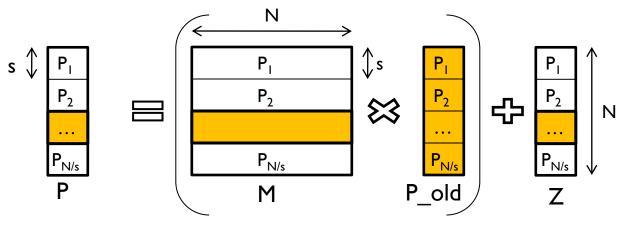


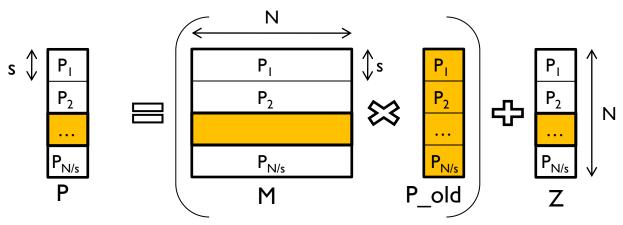
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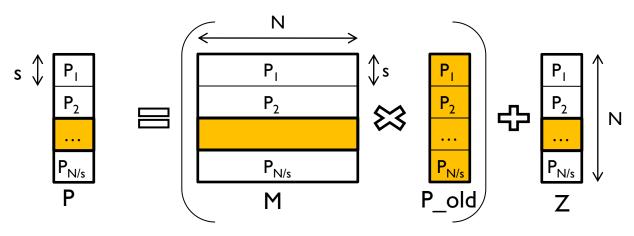
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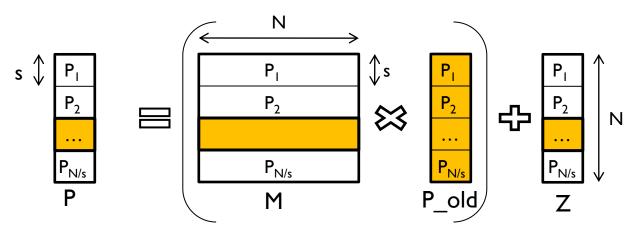
Incremental updates: onchange, update

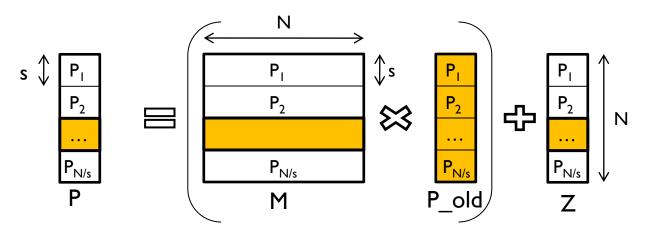






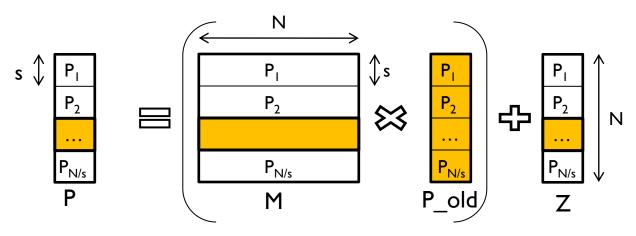




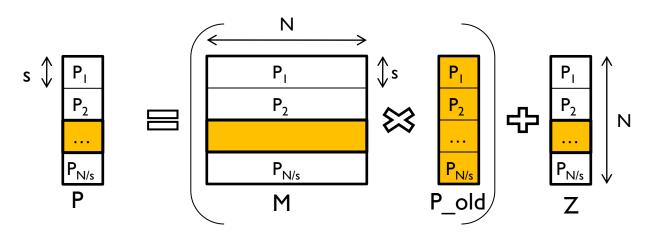


P old \leftarrow P

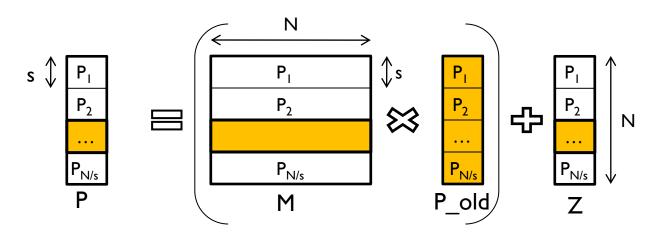
Incremental PageRank



Incremental PageRank



Incremental PageRank



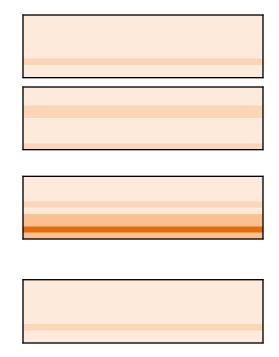
```
M \leftarrow darray(dim=c(N,N),blocks=(s,N))
                                                      Execute when data changes
P \leftarrow darray(dim=c(N,1),blocks=(s1))
onchange(M) { <</pre>
  while(..){
    foreach(i,1:len,
        calculate(p=splits(P,i), m=splits(M,i),
                   x=splits(P_old), z=splits(Z,i)) {
            p \leftarrow (m*x)+z
            update(p)
        })
```

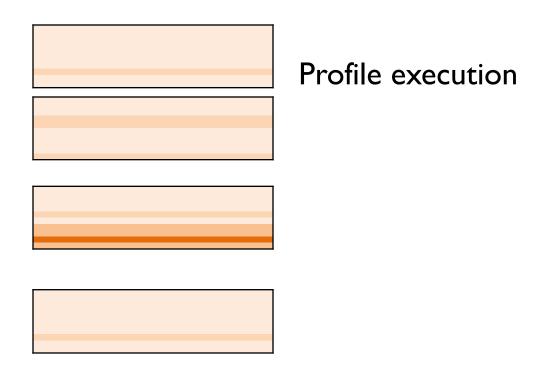
old \leftarrow P

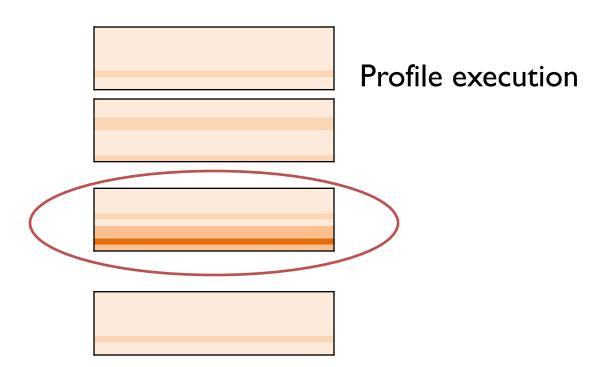
Update page rank vector

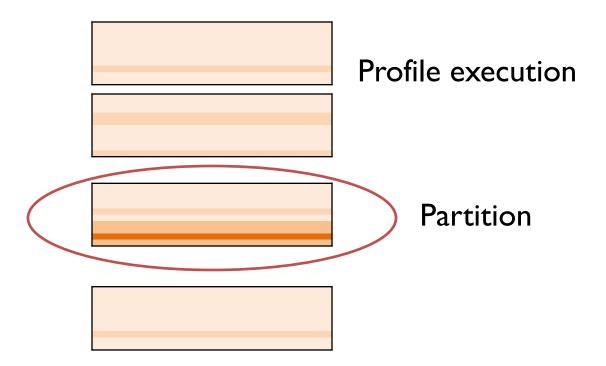
Outline

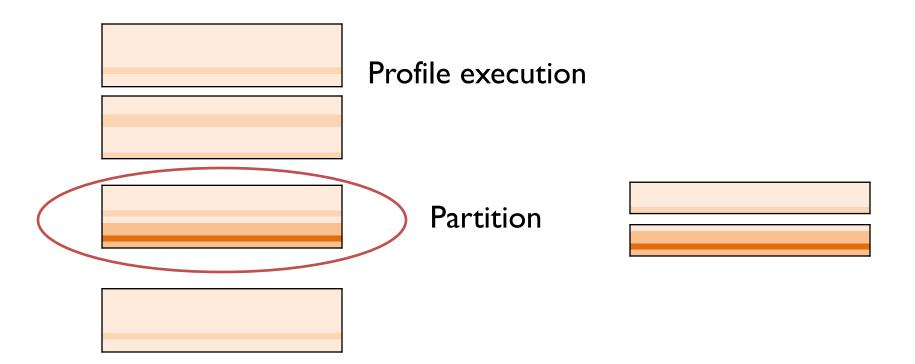
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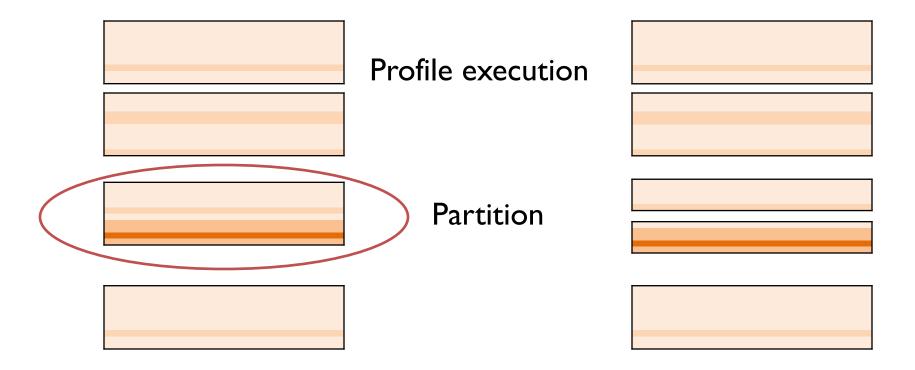


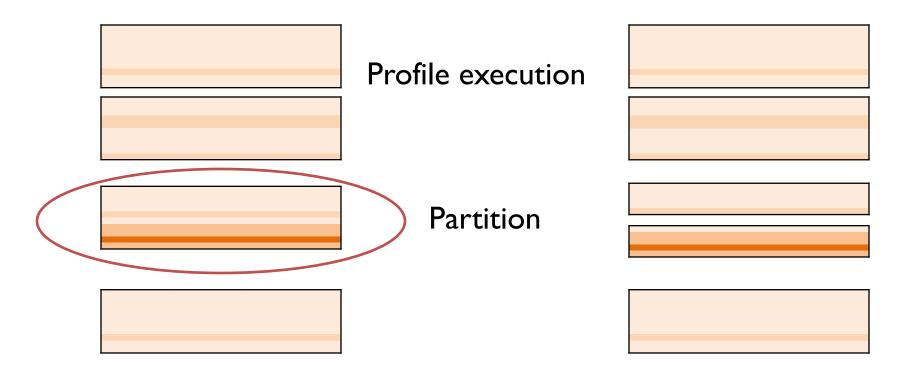




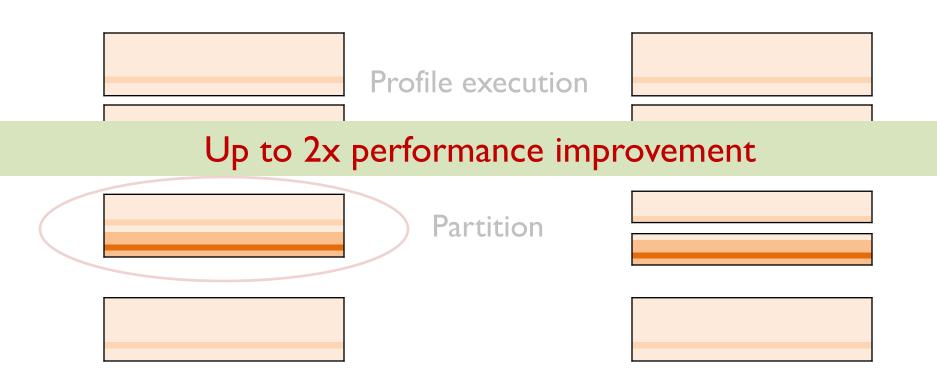




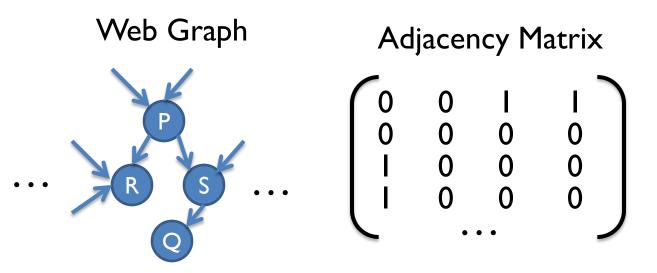


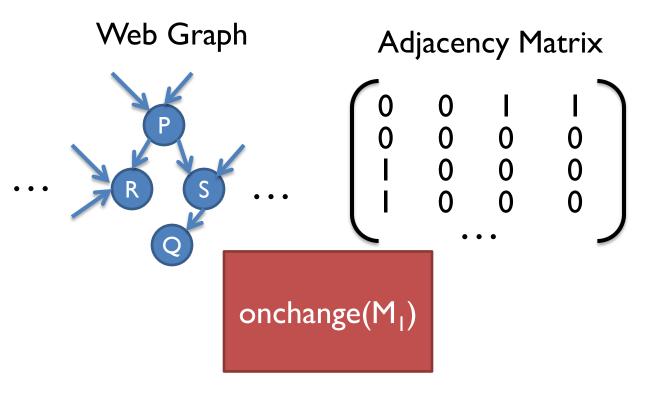


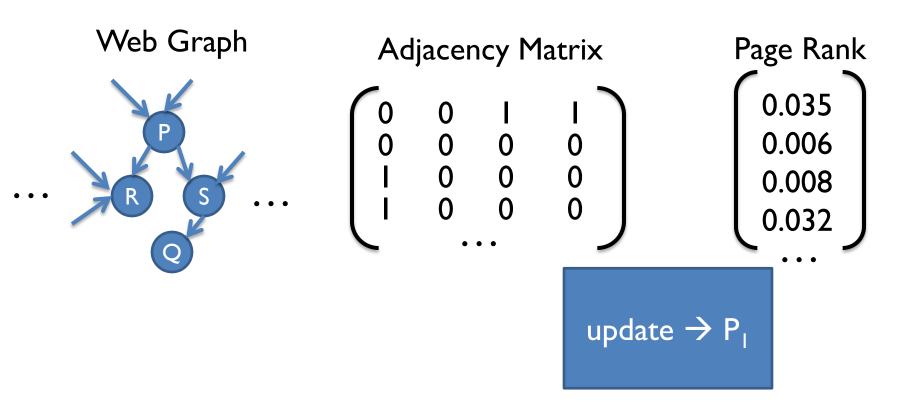
Programmers specify size invariants.



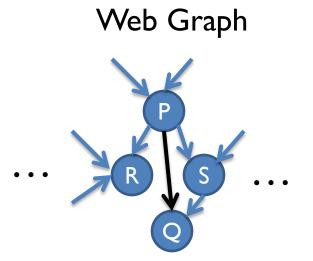
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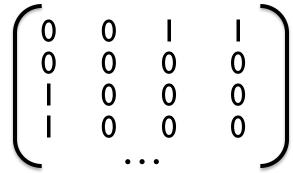




6/29/2012 47

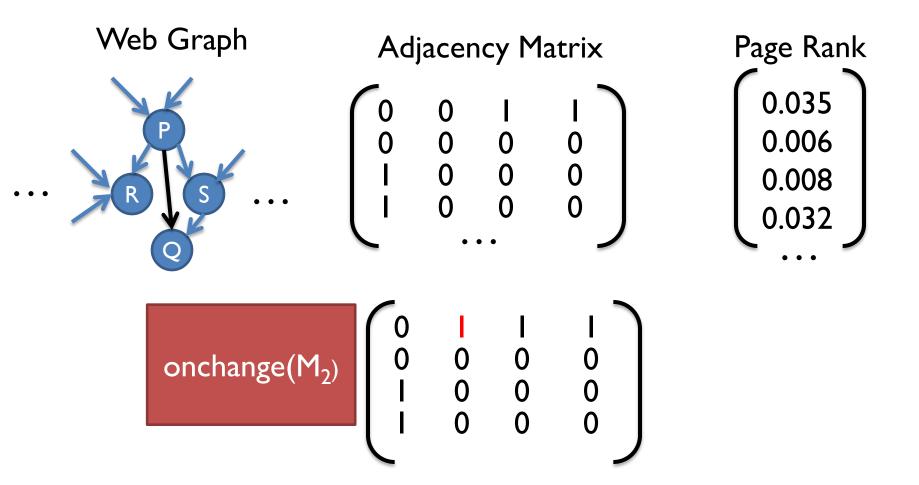


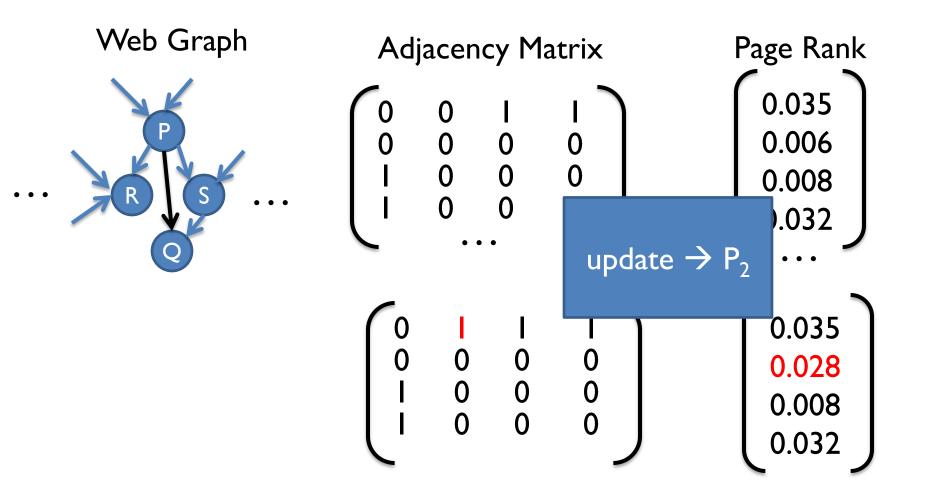




Page Rank

0.035 0.006 0.008 0.032





Versioned Distributed Arrays

Mechanics of versioning

- update: Increment version number
- onchange: Bind a version number for the array before executing the handler

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Applications Implemented in Presto

| Application | Algorithm | Presto LOC |
|------------------------|-------------------------|------------|
| PageRank | Eigenvector calculation | 41 |
| Triangle counting | Top-K eigenvalues | 121 |
| Netflix recommendation | Matrix factorization | 130 |
| Centrality measure | Graph algorithm | 132 |
| k-path connectivity | Graph algorithm | 30 |
| k-means | Clustering | 71 |
| Sequence alignment | Smith-Waterman | 64 |

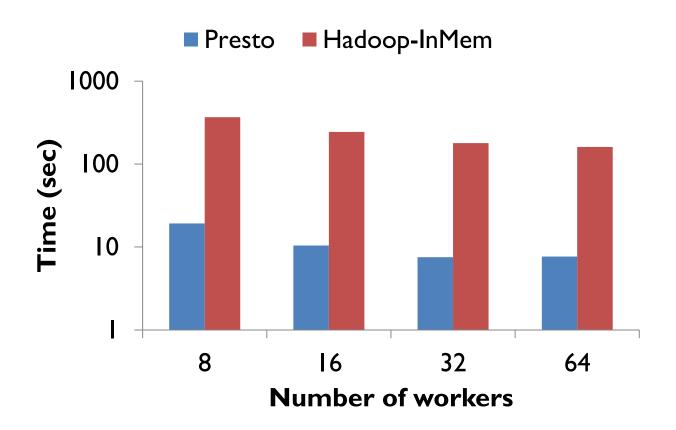
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| Fewer than 140 lines of code | | | |
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54

Presto is Fast!

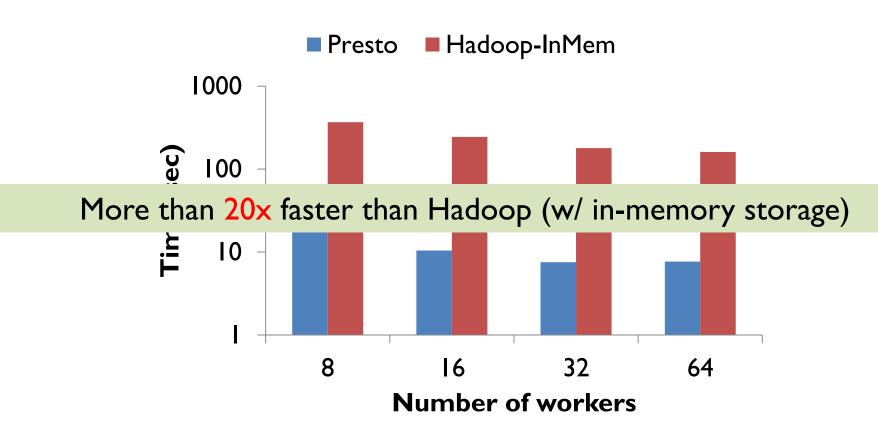
PageRank per-iteration execution time



Data: 100M nodes, 1.2B edges. Setup: 10G network. 12 cores, 96GB RAM.

Presto is Fast!

PageRank per-iteration execution time



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More in the Paper

- Memory management, caching of partitions
- Scheduling operations
- Storage driver interface to HBase
- Fault tolerance

Conclusion

Linear Algebra is a powerful abstraction Easily express machine learning, graph algorithms

Challenges: Sparse matrices, Incremental data Presto – prototype extends R

Open source version soon!