



MapReduce-based Similarity Join for Metric Spaces

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Overview

- **Motivation**
- Algorithm
- Implementation
- Performance Evaluation
- Conclusions and Future Work

Introduction

- Similarity Joins used by many companies
- Internet companies have massive amounts of data
- Many non-distributed approaches to Similarity Join problem
- Few cloud based approaches

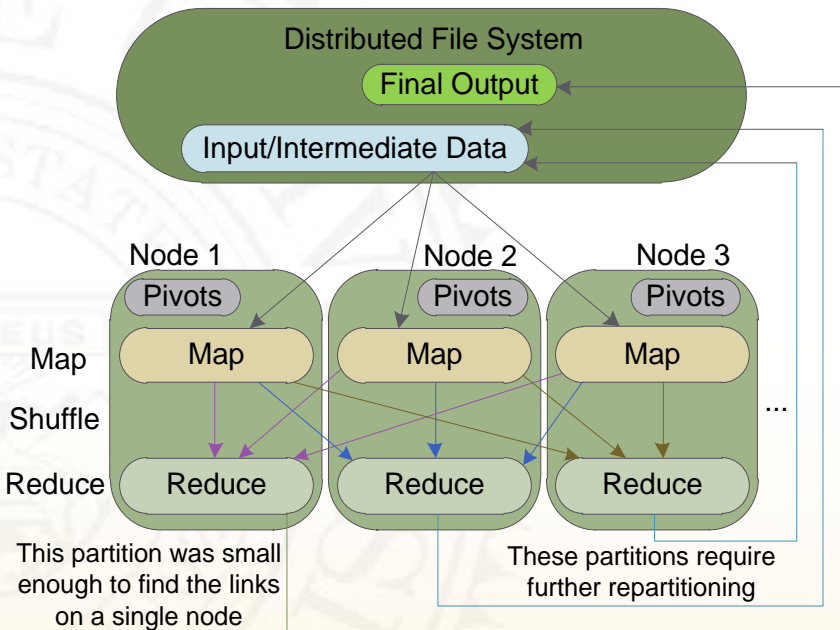
Our Contribution

- MRSimJoin Algorithm
- General enough for any data in metric space
- Guidelines to implement in Hadoop
- Evaluation of performance and scalability
- Evaluation of pivot numbers, means of choosing a good number of pivots

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MRSimJoin Round



- MRSimJoin iteratively partitions the data
 - If partition is small enough, solve in single node SJ routine
- The process is divided into a sequence of rounds
- The initial round partitions the input data
- Any subsequent round repartitions a previously generated partition

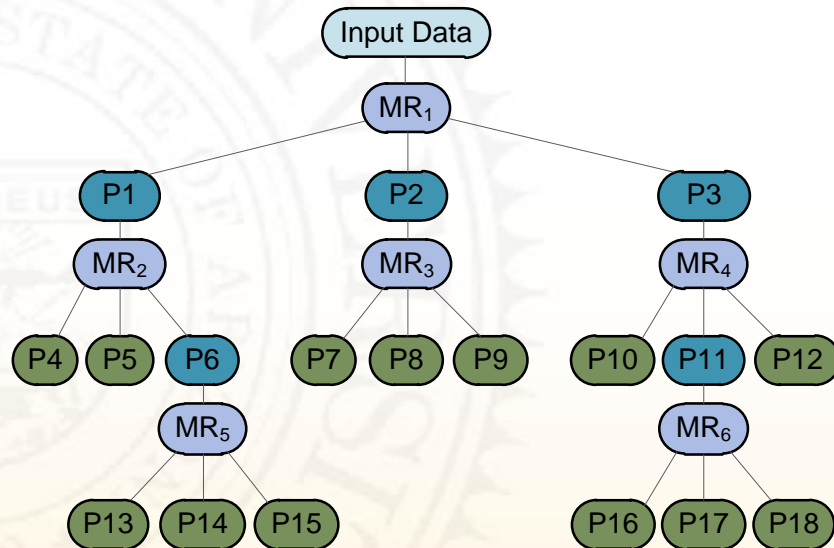
Multiple Rounds

Single-node

The partition is small enough to be solved in a single node. Results written to final output in DFS.

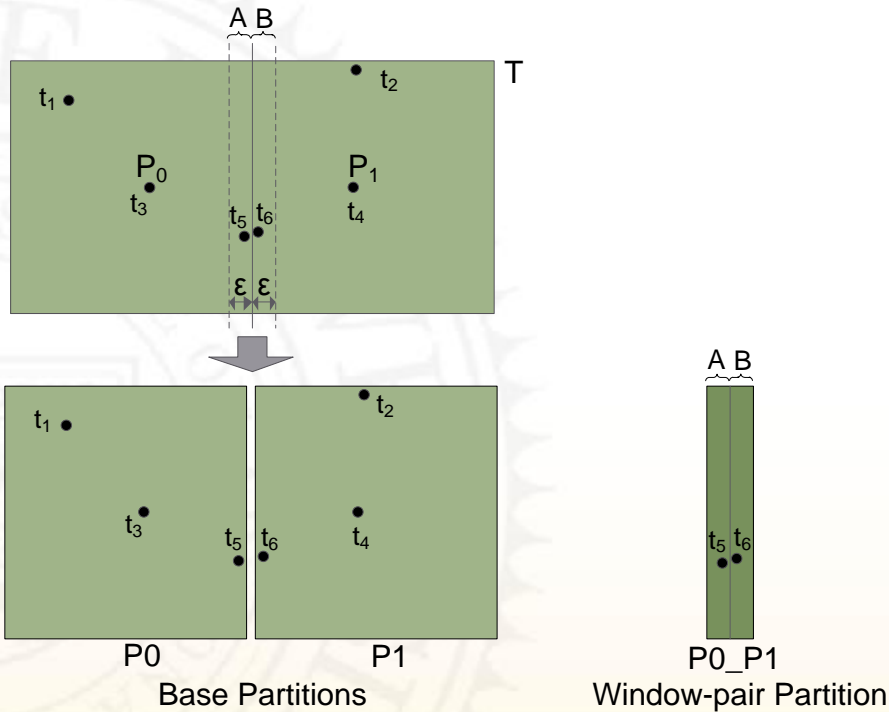
Distributed

The partition will need to be further re-partitioned in additional MapReduce rounds. Intermediate data is written to DFS.

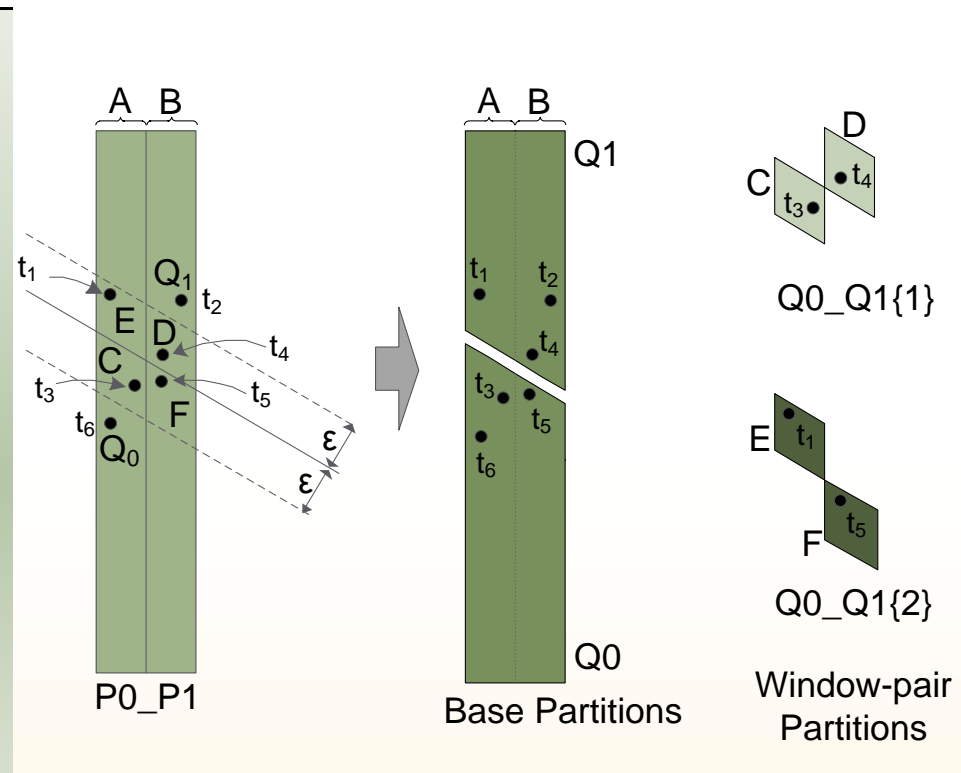


- Each round corresponds to a MapReduce job
- The output of a round includes:
 1. Result links for the small partitions that were processed in a single-node
 2. Intermediate data for partitions that require further partitioning

Partitioning Data

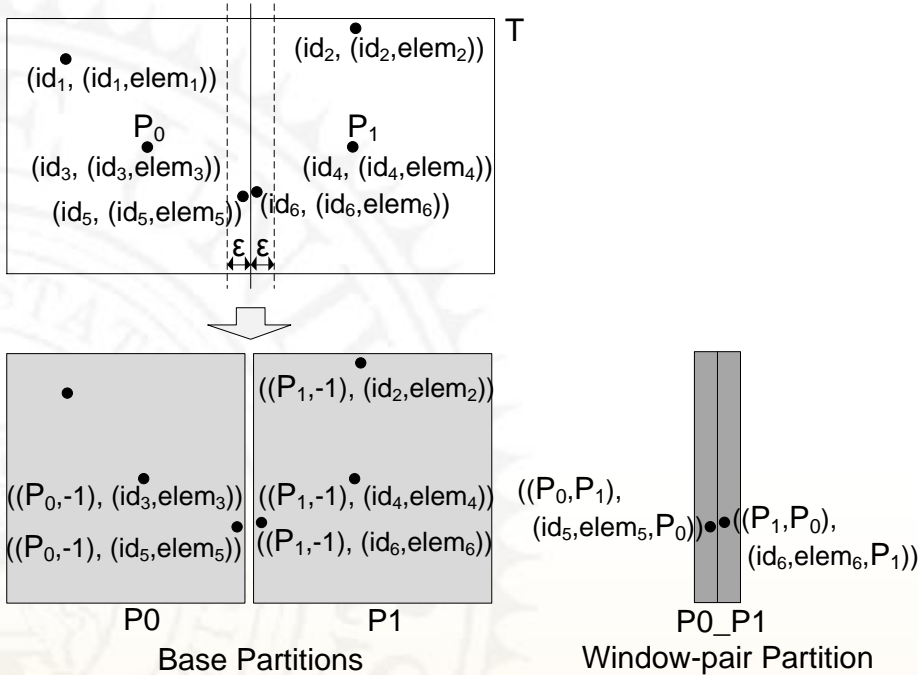


Partitioning a Base Partition



Partitioning a Window-Pair Partition

Partition a Base Set



High order

Window-pair partitions. Ordered by (min pivot index, max pivot index)

Base partitions. Ordered by pivot index

Low order

(a) General order of partitions

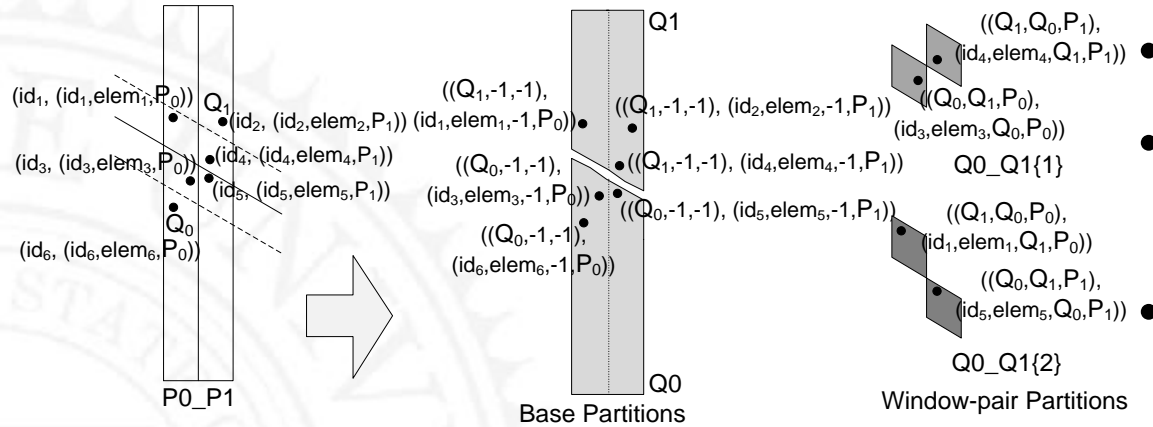
P0_P1	$((P_0, P_1), (id_5, elem_5, P_0))$ $((P_1, P_0), (id_6, elem_6, P_1))$
P1	$((P_1, -1), (id_2, elem_2))$ $((P_1, -1), (id_4, elem_4))$ $((P_1, -1), (id_6, elem_6))$
P0	$((P_0, -1), (id_1, elem_1))$ $((P_0, -1), (id_3, elem_3))$ $((P_0, -1), (id_5, elem_5))$

(b) Order of partitions with 2 pivots

- Choose pivots (randomly chosen subset of input data)
- Create base partitions around closest pivots

- Create window-pair partitions between partitions
- Each partition is sent to a reduce group

Partition a Window-Pair Set



- Choose pivots
- Partition data around pivots
- Create windows space between base partitions

– The window of a window is aware of previous partitioning

High order					
Window-pair partitions. Ordered by (min pivot index, max pivot index, sequence)	<table border="1"> <tr> <td>Q0_Q1{2}</td> <td> $((Q_1, Q_0, P_0), (id_1, elem_1, Q_1, P_0))$ $((Q_0, Q_1, P_1), (id_5, elem_5, Q_0, P_1))$ </td> </tr> <tr> <td>Q0_Q1{1}</td> <td> $((Q_1, Q_0, P_1), (id_4, elem_4, Q_1, P_1))$ $((Q_0, Q_1, P_0), (id_3, elem_3, Q_0, P_0))$ </td> </tr> </table>	Q0_Q1{2}	$((Q_1, Q_0, P_0), (id_1, elem_1, Q_1, P_0))$ $((Q_0, Q_1, P_1), (id_5, elem_5, Q_0, P_1))$	Q0_Q1{1}	$((Q_1, Q_0, P_1), (id_4, elem_4, Q_1, P_1))$ $((Q_0, Q_1, P_0), (id_3, elem_3, Q_0, P_0))$
Q0_Q1{2}	$((Q_1, Q_0, P_0), (id_1, elem_1, Q_1, P_0))$ $((Q_0, Q_1, P_1), (id_5, elem_5, Q_0, P_1))$				
Q0_Q1{1}	$((Q_1, Q_0, P_1), (id_4, elem_4, Q_1, P_1))$ $((Q_0, Q_1, P_0), (id_3, elem_3, Q_0, P_0))$				
Base partitions. Ordered by pivot index	<table border="1"> <tr> <td>Q1</td> <td> $((Q_1, -1, -1), (id_1, elem_1, -1, P_0))$ $((Q_1, -1, -1), (id_2, elem_2, -1, P_1))$ $((Q_1, -1, -1), (id_4, elem_4, -1, P_1))$ </td> </tr> <tr> <td>Q0</td> <td> $((Q_0, -1, -1), (id_3, elem_3, -1, P_0))$ $((Q_0, -1, -1), (id_6, elem_6, -1, P_0))$ $((Q_0, -1, -1), (id_5, elem_5, -1, P_1))$ </td> </tr> </table>	Q1	$((Q_1, -1, -1), (id_1, elem_1, -1, P_0))$ $((Q_1, -1, -1), (id_2, elem_2, -1, P_1))$ $((Q_1, -1, -1), (id_4, elem_4, -1, P_1))$	Q0	$((Q_0, -1, -1), (id_3, elem_3, -1, P_0))$ $((Q_0, -1, -1), (id_6, elem_6, -1, P_0))$ $((Q_0, -1, -1), (id_5, elem_5, -1, P_1))$
Q1	$((Q_1, -1, -1), (id_1, elem_1, -1, P_0))$ $((Q_1, -1, -1), (id_2, elem_2, -1, P_1))$ $((Q_1, -1, -1), (id_4, elem_4, -1, P_1))$				
Q0	$((Q_0, -1, -1), (id_3, elem_3, -1, P_0))$ $((Q_0, -1, -1), (id_6, elem_6, -1, P_0))$ $((Q_0, -1, -1), (id_5, elem_5, -1, P_1))$				

Low order
(a) General order of partitions

(b) Order of partitions with 2 pivots

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- **Implementation**
- Performance Evaluation
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Implementation

- Generic enough to implement in any MR framework

- Hadoop implementation:



- Distribution of Atomic parameters
 - Uses jobConf
- Distribution of pivots
 - Uses Distributed Cache
- Renaming Directories
 - Renaming directories does not move data

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Testing Platform

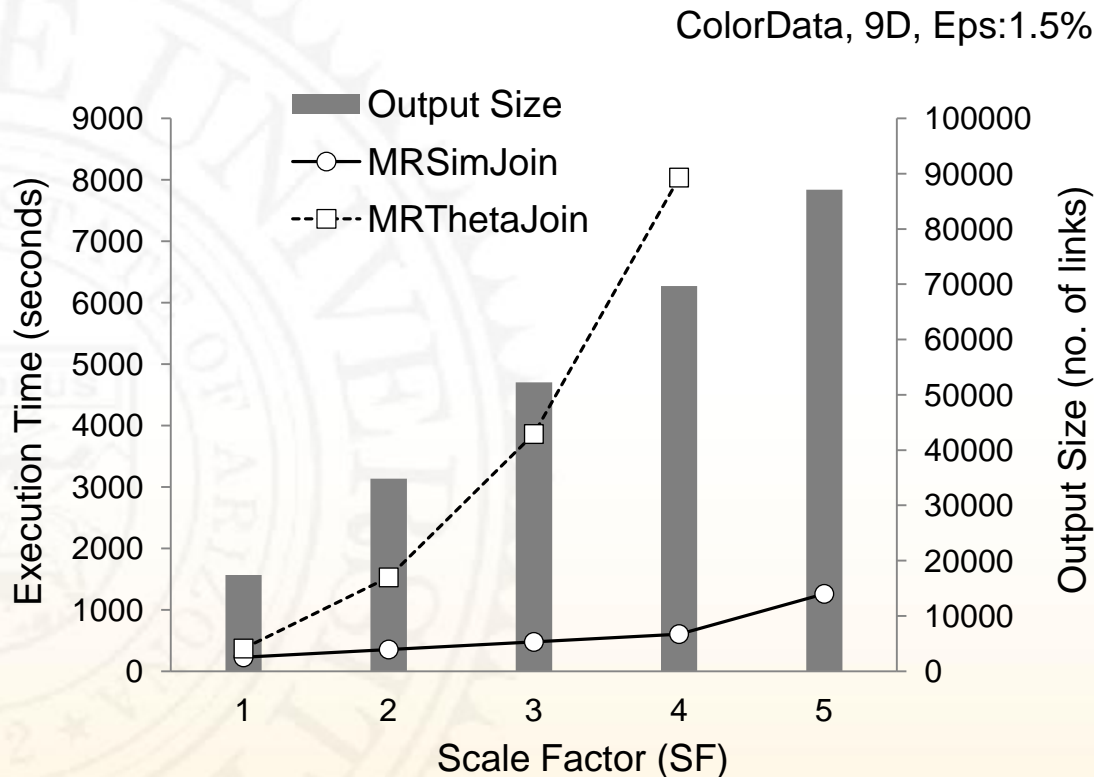
- Amazon EC2 Cloud
 - 4 virtual cores (2 EC2 Compute Units each)
 - 15 GB memory
 - 1,690 GB local storage
 - 64 bit platform
- Hadoop 0.20.2
 - 64 MB block size
 - 10 nodes (1 master, 9 worker nodes)
- Memory Threshold
 - 32 MB

Test Data Information



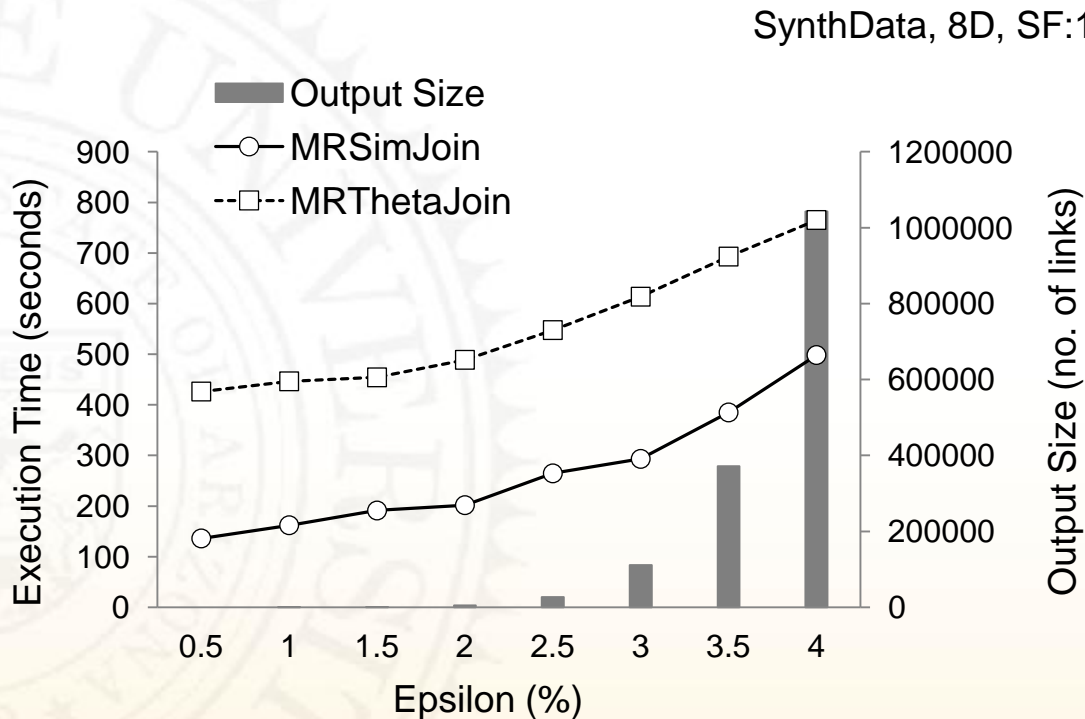
- SynthData
 - Synthetic Data set
 - 16D Data
 - Vector components values are [0-1000]
 - Scale Factor 1 = 5 million records
- ColorData
 - Corel Color Moments Dataset
 - 9D Data
 - Vector components values are [-4.8 – 4.4]
 - Scale Factor 1 = 5 million records

Increasing Scale Factor



- ColorData
 - SF1-SF5
 - 9D Color Vectors
 - Epsilon 1.5%
 - 1.6x (SF1) – 13.3x (SF4)
- SynthData
 - SF1-SF5
 - 8D Vectors
 - Epsilon 1.5%
 - 2.4x (SF1) – 11.4x (SF3)

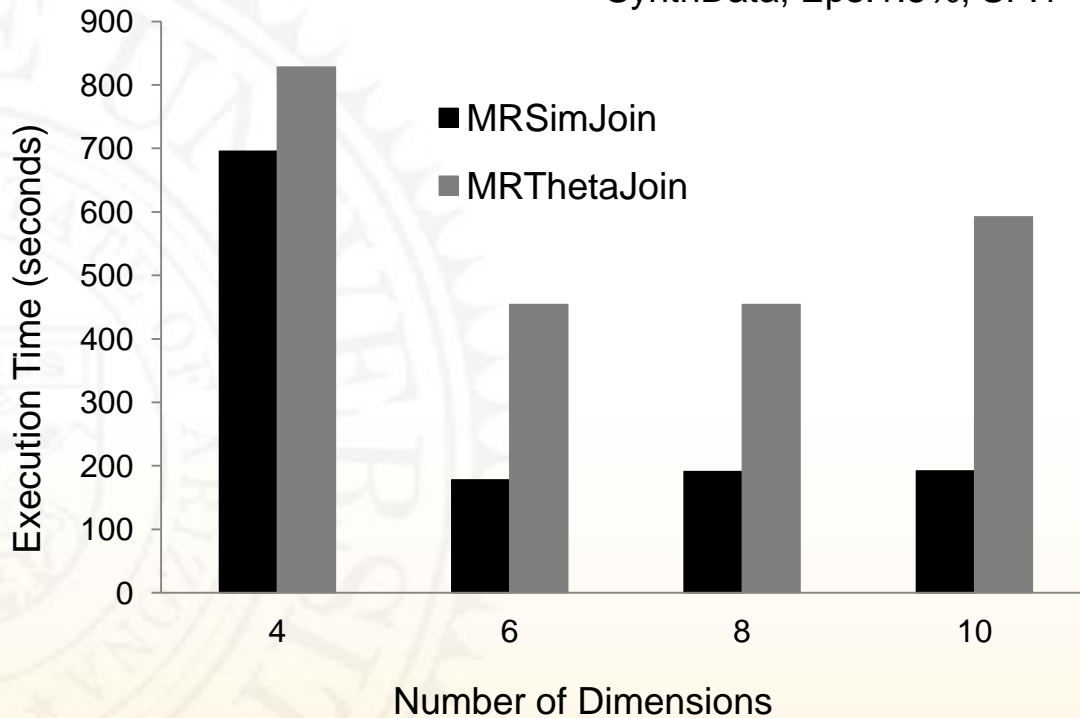
Increasing Epsilon



- SynthData
 - 0.5% - 4.0% epsilon
 - 8D Vectors
 - SF1
 - 1.4x – 3x
- ColorData
 - 0.5% - 2.5% Epsilon
 - 9D Color Vectors
 - SF1
 - ~60% of MRThetaJoin

Increasing Dimension

SynthData, Eps:1.5%, SF:1



- SynthData

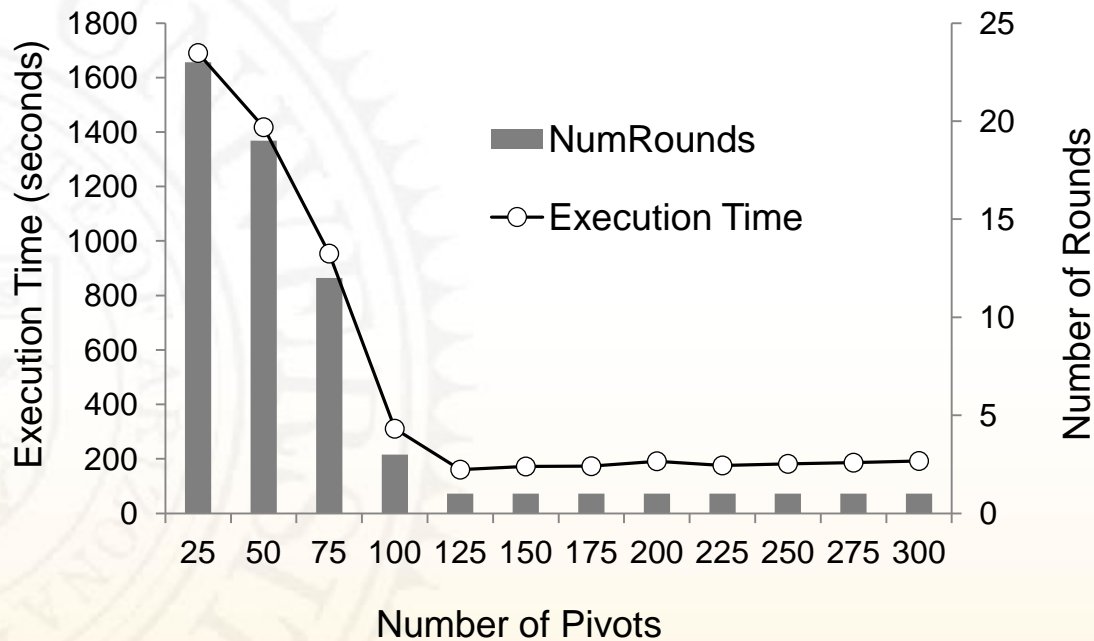
- 4D-10D
- Epsilon 1.5%
- SF1
- MRThetaJoin is 20 - 200% higher

Increasing Pivot Number

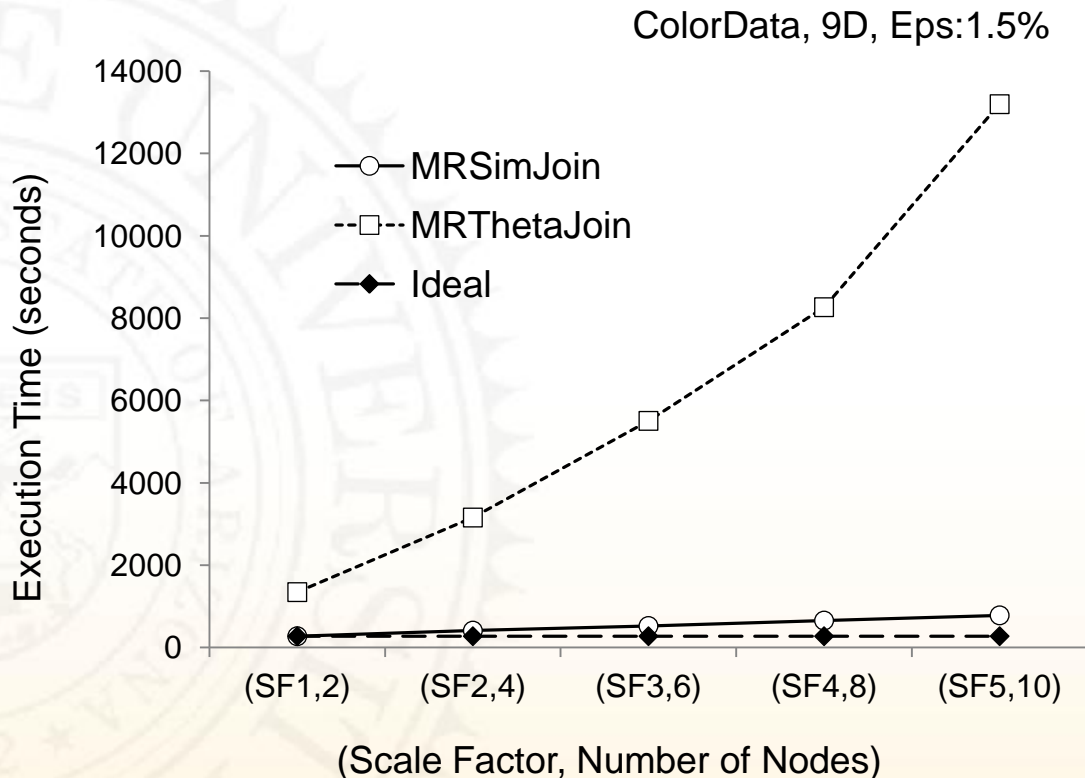


- SynthData
 - 25 -300 pivots
 - 8D vector
 - Epsilon 1.5%

SynthData, 8D, SF:1, Eps:1.5%



Increasing Node Number & SF



- ColorData

- (SF1, 2 nodes) – (SF5, 10 nodes)
- 9D Color Vector
- Epsilon 1.5%
- MRThetaJoin
 - 9.8x between (SF1, 2) & (SF5, 10)
- MRSimJoin
 - 2.8x between (SF1, 2) & (SF5, 10)

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Conclusions

- MRSimJoin efficiently solves the distributed Similarity Join problem
- Significantly better than state-of-the-art MapReduce arbitrary join algorithm
- Partitions data till data can be joined in single node
- Any data set that lies in a metric space
- Scalable
- Highly parallel

Future Work

- Other similarity-aware operators
 - kNN Join, kDistance Join, etc
- Indexing techniques for implementing Similarity Join operations
- Cloud queries with multiple similarity-based operators

Questions?

MR SimJoin ASU ARIZONA STATE UNIVERSITY

Core: Co-occurrences | Core: Color Moments Data | DBLP | Hadoop Configuration

Query Parameters

Epsilon	Input Directory	Number of Pivots	Memory threshold
0.9	/core/colorMomentsData/	200	32MB
	Output Directory	Number of Reducers	
	/dataOut/core/colorMoments/	25	

Query Output

Figure 1	Figure 2	Distance
IMG0010692	IMG0045893	0.06996983
IMG0013483	IMG0045838	0.06997345
IMG0013538	IMG0045838	0.07212310
IMG0015994	IMG0045887	0.07322370
IMG0017033	IMG0045850	0.07508767
IMG0017044	IMG0045851	0.08664375
IMG0018757	IMG0045844	0.08763093
IMG0019481	IMG0045844	0.08873102
IMG0019481	IMG0045889	0.08909231

Job Statistics

Matches Found: 14,832	Total Mappers: 6	Total Reducer Groups: 459
Total Run Time: 00:01:33 (HH:MM:SS)	Average Mappers/Round: 6	Average Reducer/Round: 459
Total Number of Rounds: 1		