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An Experimental Survey of MapReduce-based Similarity Joins

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Motivation

The Problem

- Big-Data systems have been introduced to efficiently process and analyze massive amounts of data.
- One of the key data processing and analysis operations is the Similarity Join (SJ), which finds similar pairs of objects of two datasets.
- Several SJ techniques for Big-Data (MapReduce) have been proposed [1-7] but many of these techniques were not compared against alternative approaches.
  - Some techniques were developed in parallel.
  - Others were not implemented as part of their original publications.
- Consequently, there is not a clear understanding of how these techniques compare to each other and which technique to use in specific scenarios.

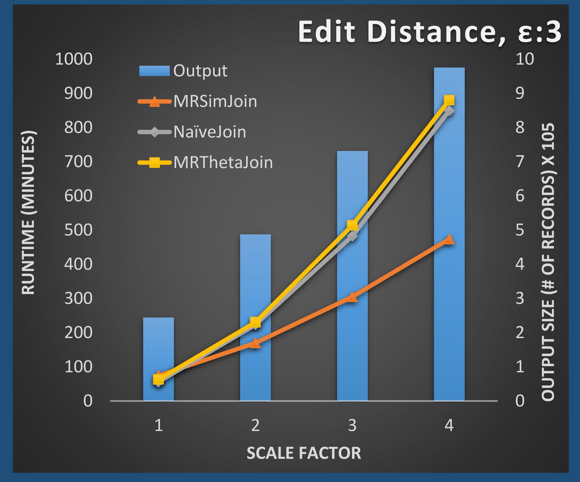
Our Contribution

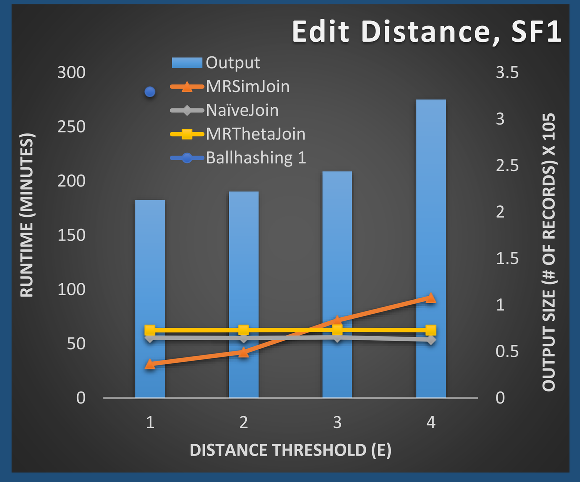
- The classification of Similarity Join techniques based on the supported data types and distance functions
- An extensive set of experimental results:
  - Compare performance based on supported data type and distance function
  - Evaluate performance under various dataset sizes and distance thresholds
- The availability of the authors' open-source implementation of various Similarity Join algorithms [9].

Hadoop Cluster Configuration

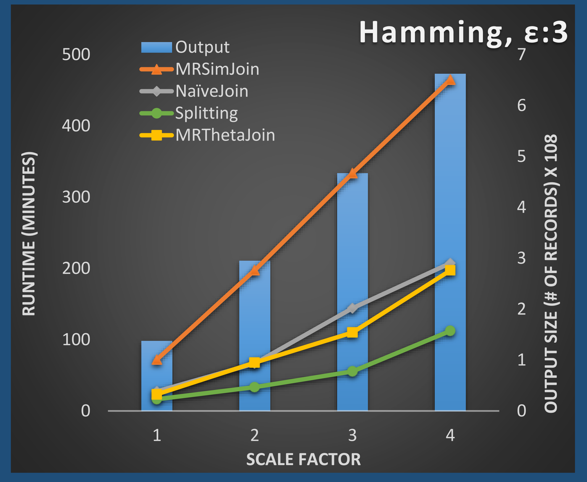
- The experiments were performed using a Hadoop cluster running on the Amazon EC2.
- We used a cluster of 10 nodes.
  - 15 GB of memory.
  - 4 virtual cores with 2 EC2 Compute Units each.
  - 1,690 GB of local in-stance storage.
  - 64-bit platform.
- The number of reducers was computed as: 0.95×⟨no. worker nodes⟩×⟨max reduce tasks per node⟩ = 25.

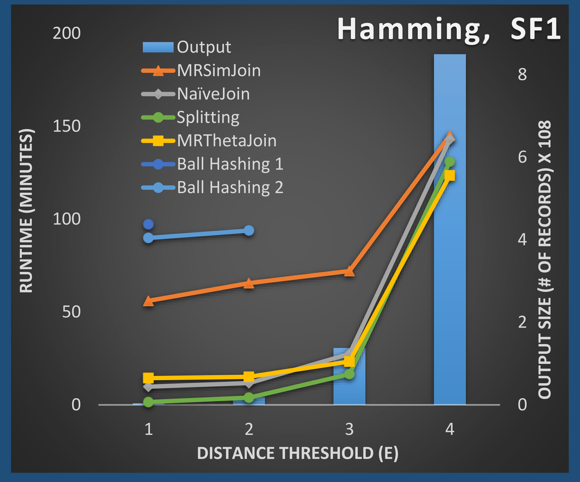
Variable-length Strings – Edit Distance



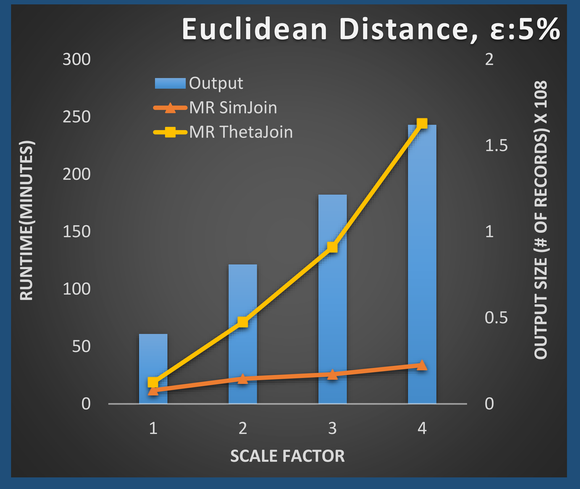


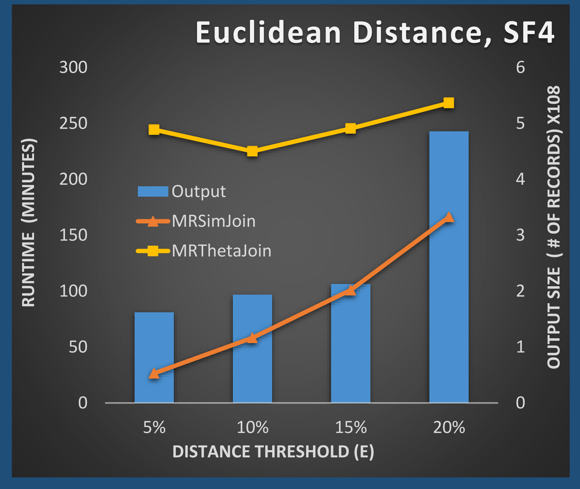
Fixed-length Strings – Hamming Distance



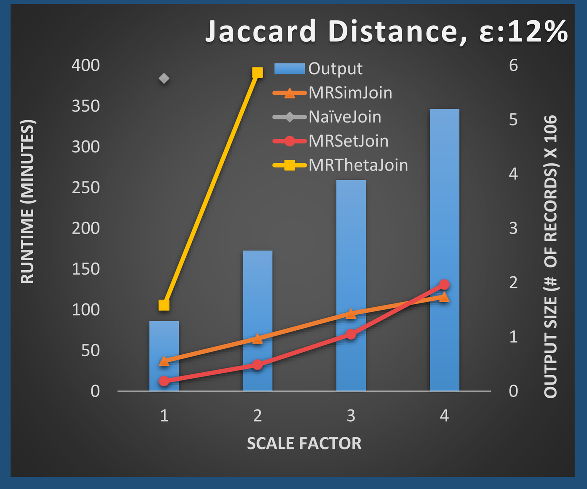


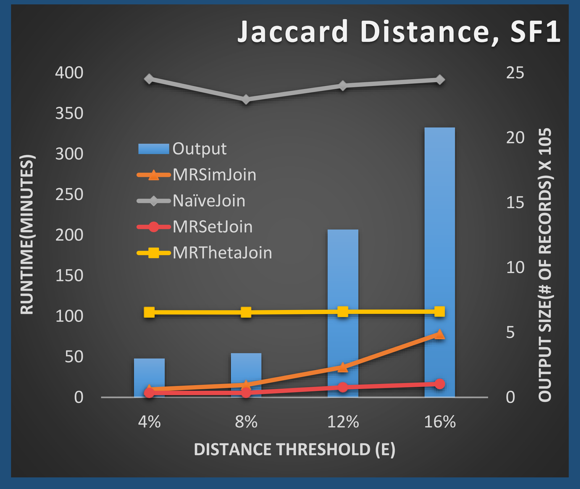
Vector Data (10D) – Euclidean Distance





Set Data – Jaccard Distance





Classification of the Algorithms

Algorithm	Supported Distance/ Similarity Functions	Supported Data Types: Text/String	Numeric	Vector	Set
Naïve Join	Any DF	●	●	*	●
Ball Hashing 1	Hamming Distance Edit Distance	●			
Ball Hashing 2	Hamming Distance Edit Distance	●			
Subsequence	Edit Distance	●			
Splitting	Hamming Distance Edit Distance	●			
Hamming Code	Hamming Distance	●			
Anchor Points	Hamming Distance Edit Distance	●	*	*	
MRThetaJoin	Any DF	●	●	●	●
MRSimJoin	Any metric DF	●	●	●	●
MRSetJoin	JS, TC, CC, Edit Distance*	*			●
Online Aggregation	JS, RS, DS, SC, VC				●
Lookup	JS, RS, DS, SC, VC				●
Sharding	JS, RS, DS, SC, VC				●

● Natively Supported

* Can be extended to support this data type or distance function

JS=Jaccard Similarity, TC=Tanimoto Coefficient, CC=Cosine Coefficient, RS=Ruzicka Similarity, DS=Dice Similarity, SC=Set Cosine Sim., VC=Vector Cosine Sim.

Dataset

- We used a slightly modified version of the Harvard bibliographic dataset [8].
- Attributes: unique ID, title, date issued, record change date, record creation date, Harvard record-ID, first author, all author names, and 10D vector (augmented).
- Minimum and maximum length of attributes:

Unique ID	Title	Date issued	Record change date	Record creation date	Harvard record-ID	First author	All author names
(9, 9)	(6, 996)	(4, 4)	(15, 15)	(6, 6)	(10, 10)	(6, 94)	(6, 2462)

- Scale Factor 1 (SF1) dataset contains 200K records.
- Larger datasets were generated in such a way that the number of matches of any SJ in SF*N* is *N* times the number of matches in SF1.
- The records of each dataset are equally divided between tables *R* and *S*.

Key Findings

- The algorithms vary significantly in terms of Supported distance functions.
  - MRSimJoin and MRThetaJoin support multiple metrics.
  - Subsequence and Hamming Code support only one.
- No single algorithm outperforms all the others for all the evaluated data types and distance functions.
  - In some cases, an algorithm performs consistently better than the others for a given data type and metric.
  - In others, the identification of the best algorithm depends on the dataset size and distance threshold.

References

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