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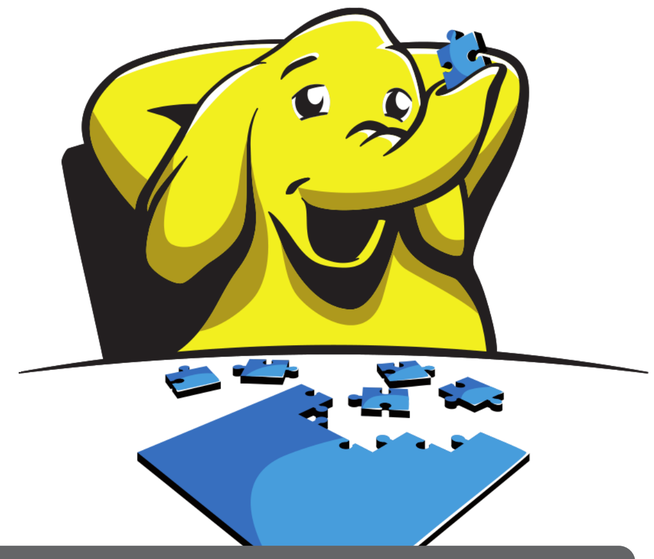
Load Balancing for MapReduce-based Entity Resolution



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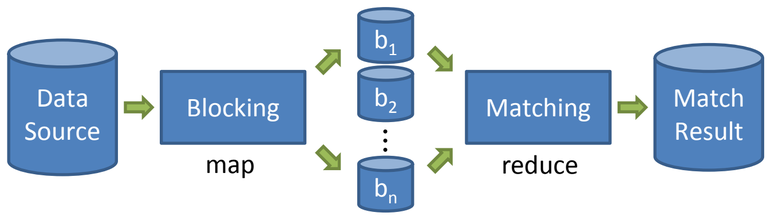
Motivation

Entity Resolution

- Task of identifying entities referring to the same real-world object
- Application of similarity measures on pairs of input entities
  - Evaluation of Cartesian product leads to complexity of $O(n^2)$
  - Based on entity signatures (blocking keys), blocking techniques semantically group similar entities in blocks and restrict matching to entities of the same block



Basic approach

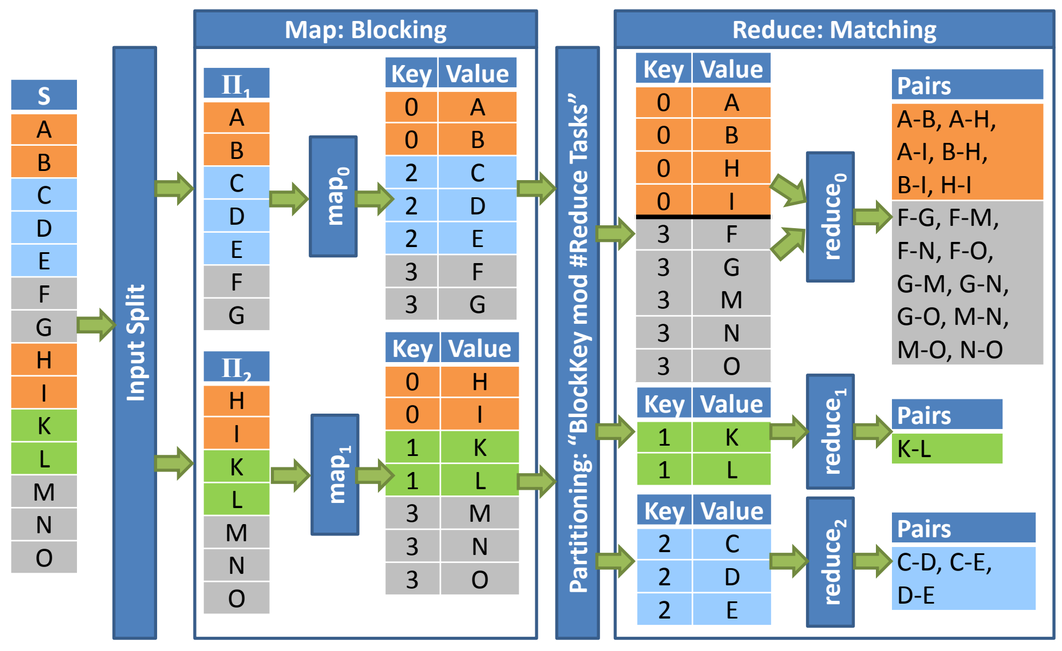
- Map – determine blocking key for every input entity and output (blockkey, entity) pair
- Part – partitioning by blocking key and block-wise redistribution to *r* reduce tasks
- Reduce – matching of entities of the same block

Goals

- Parallelization of time-intensive Blocking-based Entity Resolution with MapReduce
- Load balancing mechanism to evenly utilize available compute capacity ensuring effectiveness and scalability

Example without Load Balancing

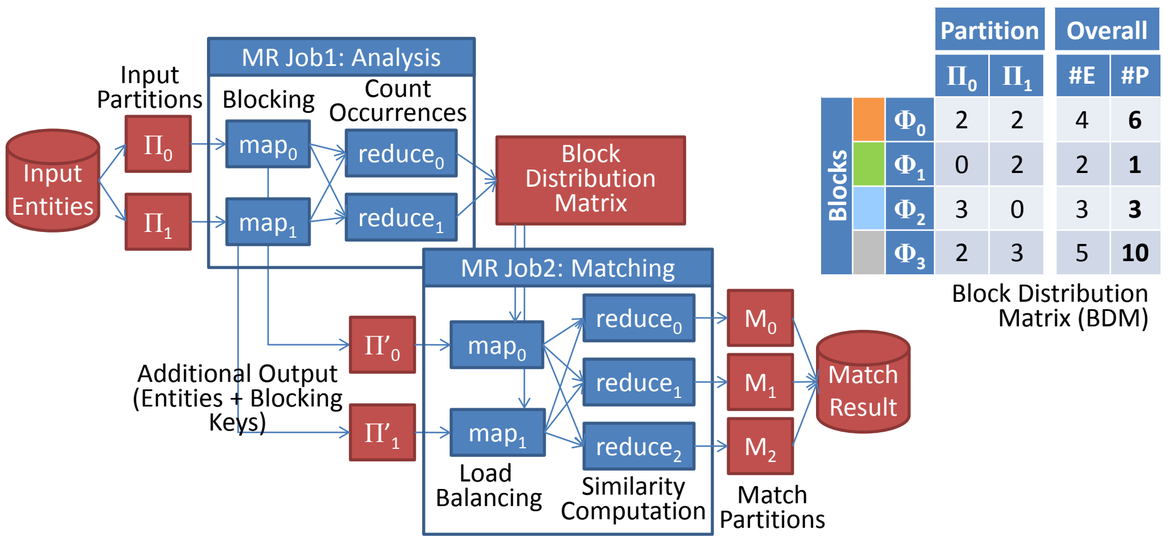
Basic approach (m=2 input partitions/map tasks, r=3 reduce tasks)



Problem

- Susceptible to severe load imbalances due to skewed block sizes
- Execution time dominated by a few tasks that process the largest block
- Large blocks prevent utilization of more than a few nodes

Load Balancing – Overview



Blocks	Partition Π0	Partition Π1	Overall #E	Overall #P
Φ0	2	2	4	6
Φ1	0	2	2	1
Φ2	3	0	3	3
Φ3	2	3	5	10

Block Distribution Matrix (BDM)

Idea

- ER processing in two MR jobs based on the same partitioning of the input data
  1. Analysis job – computation of the BDM that specifies the number of entity pairs per block separated by input partitions
  2. Match job – utilization of the BDM for load balancing strategies (e.g. BlockSplit) during the map phase & matching of entities in reduce phase

BlockSplit

- Generation of match tasks per block & distribution among *r* reduce tasks
- Large block Φ_k is split according to the input partitioning into *m* sub-blocks
  - *m* match tasks *k.i* for matching all entities of i^{th} sub-block
  - $m(m-1)/2$ match tasks *k.i×j* that match Cartesian product of sub-blocks *i* and *j*
- Small block Φ_k is processed within single match task *k.**
- Greedy load balancing – sorting of match tasks in descending order by their size & assignment to fewest loaded reduce task (ignoring empty match tasks)

Example with Load Balancing (BlockSplit)

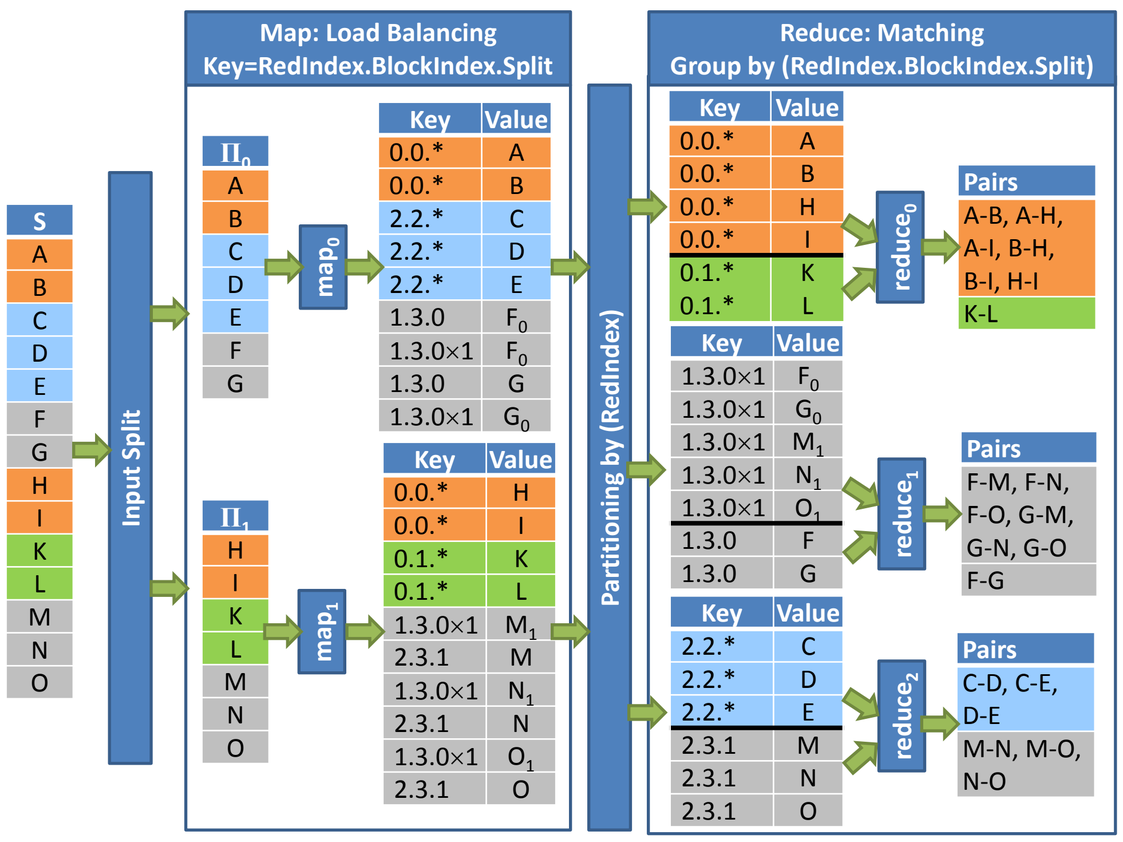
Analysis job

- Average workload per reduce task= 20/3= 6.7
- Large block Φ_3 (#P=10 > 6.7) split in *m*=2 sub-blocks
- $\Phi_{3.0}$, $\Phi_{3.1}$ → match tasks 3.0x1, 3.0, 3.1

	match tasks 0.*	3.0x1	2.*	3.1	1.*	3.0
#Comparisons	6	6	3	3	1	1
Reduce task	0	1	2	2	0	1

Match job

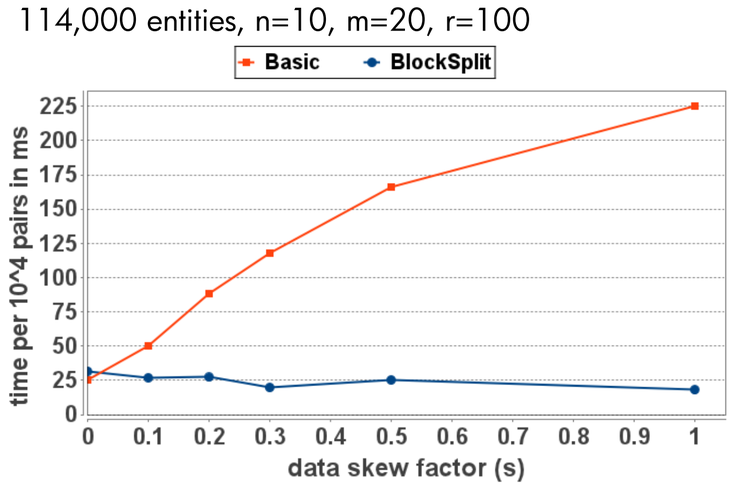
- Composite keys – reduceTask.block.split
- Replication of entities by map
- part(reduceTask.block.split)= reduceTask



Experimental Results (n=#dual core VMs, m=#map tasks, r=#reduce tasks)

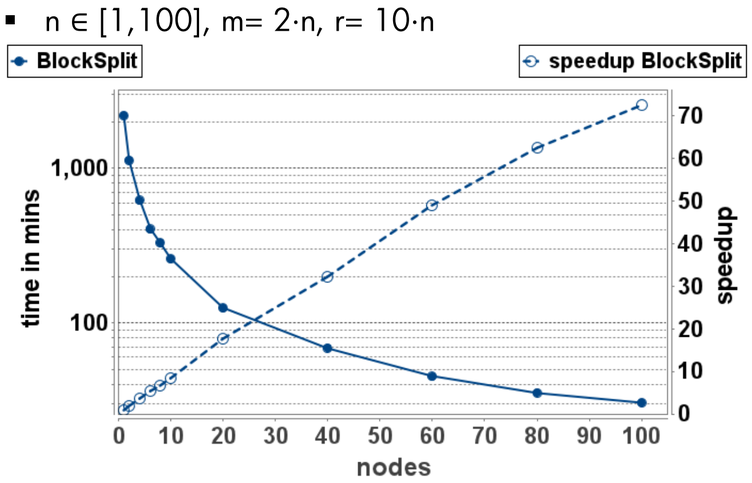
Robustness against data skew

- 100 blocks, size of k^{th} block is proportional to $e^{-s \cdot k}$
- 114,000 entities, n=10, m=20, r=100



Scalability

- 114,000 entities → $3 \cdot 10^8$ comparisons
- n ∈ [1,100], m= 2·n, r= 10·n



Related work

- L. Kolb, A. Thor, and E. Rahm. Parallel Sorted Neighborhood Blocking with MapReduce. BTW, 2011
- L. Kolb, A. Thor, and E. Rahm. Multi-pass Sorted Neighborhood Blocking with MapReduce. CSRD 27(1), 2012
- L. Kolb, H. Köpcke, A. Thor, and E. Rahm. Learning-based Entity Resolution with MapReduce. CloudDB, 2011
- L. Kolb, A. Thor, and E. Rahm. Block-based Load Balancing for Entity Resolution with MapReduce. CIKM, 2011

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