Efficient KNN Join Algorithm for spark

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Background

KNN Join

- KNN Join is a classification / regression algorithm
- For every vector in R dataset, [V_{t1}, V_{t2} … V_{tn}], we find K nearest vectors based on distance in S dataset [v_1, v_2 … v_k] and classify V_{tx} based on neighbour vectors' class.
- Complexity = $O(|R|*|S|)$

Spark

- Spark is large scale data processing framework with in memory primitives
- Designed for high scalability and performance
- About 100 times faster than Hadoop Mapreduce when the data can fit into memory

Problem

- High Complexity => Unusable for Large Dataset
- How to improve the overall running time of the algorithm ?

Previous Works

- Focused only on reducing comutational complexity
- Designed only for single node system
- Algorithms were focusing on creating a spatial index for the data. This means there is a huge initial cost and not scalable for a large dataset which cannot fit into memory.
- Only one research work done on creating a distributed algorithm. It uses hadoop Mapreduce as its framework.

  Disadvantage:

  1. High data replication
  2. High disk usage
  3. Does not scale for high dimensions due to number of replications

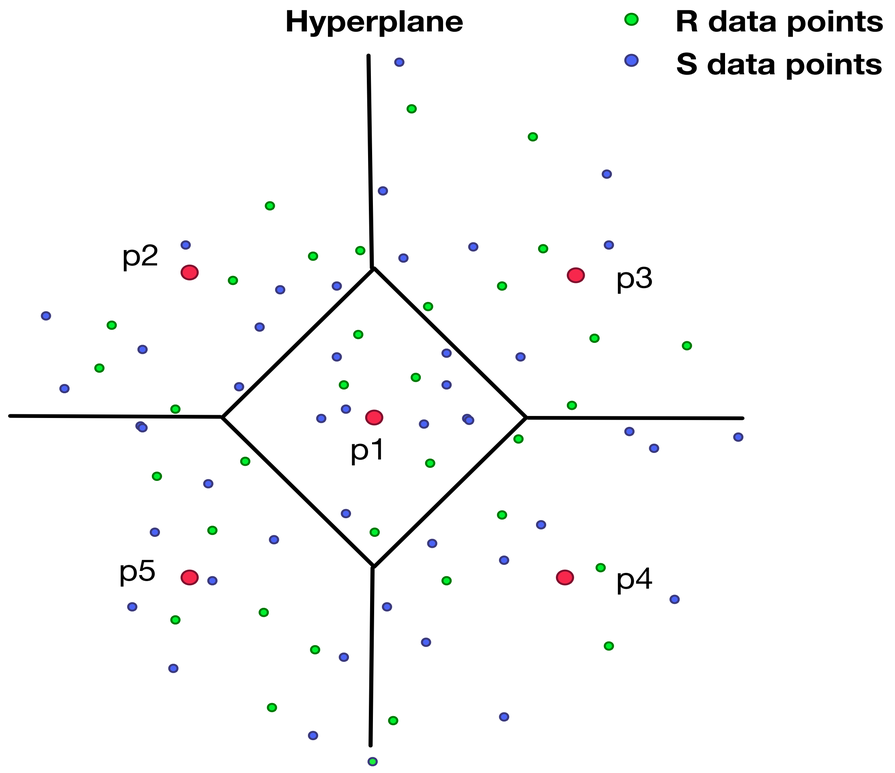
Solution & Contribution

- Designed a Voronoi Partition based distributed algorithm for Spark

Advantages

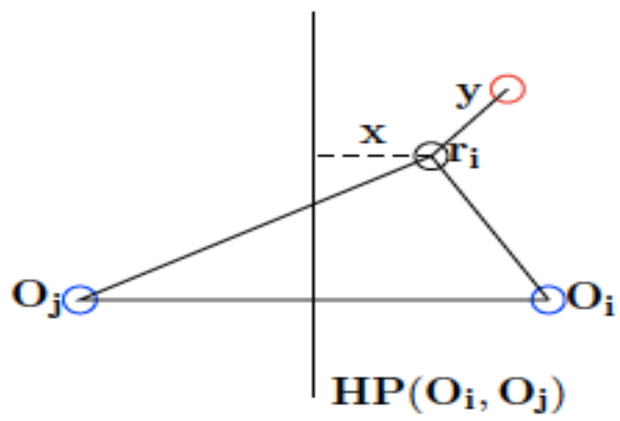
1. Lower computational complexity
2. Distributed algorithm
3. Iterative and Incremental Algorithm
4. Uses Spark framework
5. Scalable for large datasets
6. Minimal data replication and hence minimal usage of disk & memory

Voronoi Partition



$$x = \frac{|p, O_i|^2 - |p, O_j|^2}{2 \times |O_i, O_j|}$$

y = distance of farthest neighbour



Algorithm

1. Select Random Pivots
2. Closest Vector to a pivot form a partition in both R and S.
3. Self Join: For any partition in R, find KNN S in the same partition.
4. If distance to farthest neighbour for a vector *y* is less than the distance to HP*(x)* then K Found Else Nearest partition found. (Refer fig above)
5. Move the vector to first nearest partition and find & update KNN.
6. Check if the new distance *y* is less than the distance to HP(x) and Update the nearest partition list.
7. Repeat Step 5 and 6 until KNN found for all Vectors
8. *Additional Optimization*: If the number of replication is less then we can replicate to all the partition and then combine the results after wards. This speeds up the process significantly

Experiment Results(On a 10 Node 8core 16G Ram Cluster)

1. About 100 times faster than Brute force for 1M x 1M dataset and Estimated 800-1000 times faster for 11M x 11M
2. 1M x 1M join takes 2 minutes and 11M x 11M Join takes 26 mins
3. For dimensions more than 12 performance drops, this is because of curse of dimensionality

Future Work

Improve performance of the algorithm at higher dimensions

References

Index-driven similarity search in metric spaces http://dl.acm.org/citation.cfm?id=958948

When is "nearest neighbor" meaningful? http://link.springer.com/chapter/10.1007/3-540-49257-7_15

Efficient parallel kNN joins for large data in MapReduce http://dl.acm.org/citation.cfm?id=2247602