SS-ZG548: ADVANCED DATA MINING

Lecture-05: Incremental Clustering

Dr. Kamlesh Tiwari
Assistant Professor
Department of Computer Science and Information Systems Engineering,
BITS Pilani, Rajasthan-333031 INDIA

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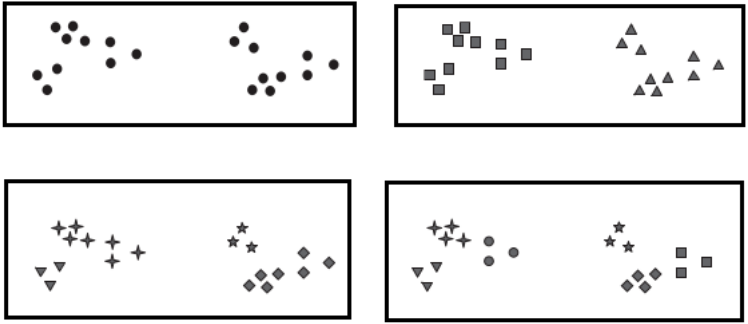
Clustering

Grouping data based on their homogeneity (similarity or closeness).



Objects within a group are similar (or related) and are different from the objects in other groups. When it is better?

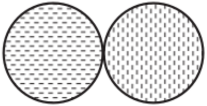
Clustering

- **Unsupervised** in nature (i.e. right answers are not known)
- Clustering is useful to 1) Summarization, 2) Compression, and 3) Efficiently Finding Nearest Neighbors
- **Type:**
  - Hierarchical (nested) versus Partitional
  - Exclusive versus Overlapping versus Fuzzy
  - Complete versus Partial
- **K-means:** This is a prototype-based[1], partitional clustering technique that attempts to find a user-specified number of clusters (K), which are represented by their centroids.

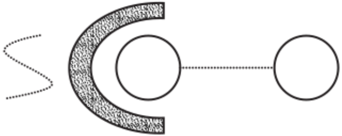
[1] object is closer (more similar) to a prototype

Clustering

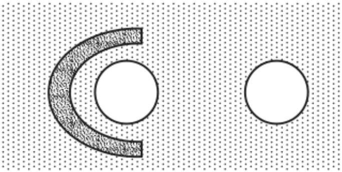
Well-separated clusters.



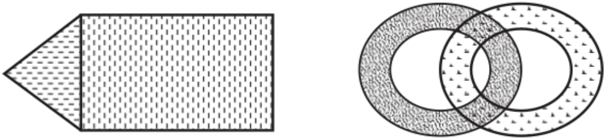
Center-based clusters.



Contiguity-based clusters.



Density-based clusters.



Conceptual clusters.

K-means Algorithm

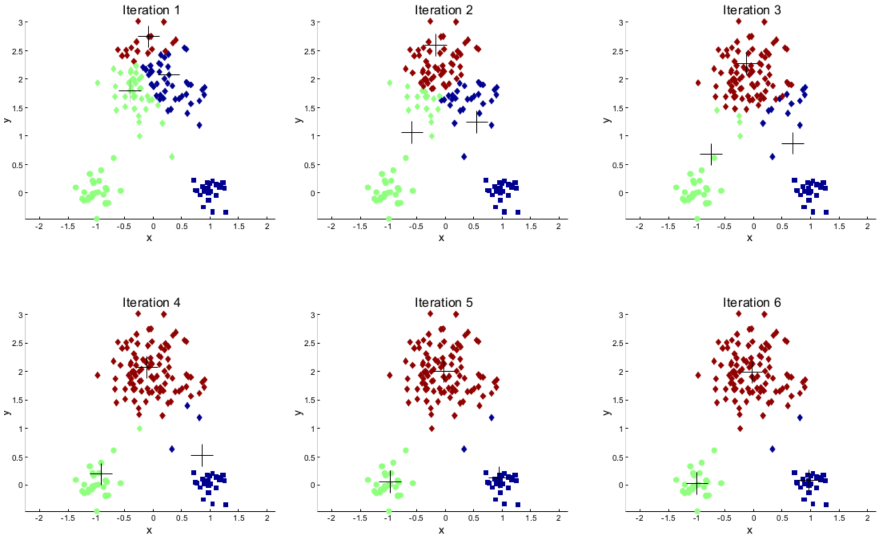
Number of clusters *i.e.* the value of K is provided by the user

Algorithm 0.1: K-means

```
1  Randomly select K points as centroids
2  repeat
3      foreach datum point d_i do
4          Assign d_i to one of the closest centroids
           (thereby forming K clusters)
5      Recompute centroid (mean) for each cluster
6  until The centroids converge;
```

Closeness is measured by **Euclidean distance**, cosine similarity, correlation, Bregman divergence *etc*

K-means in Action



Evaluation of K-means

For a given data set $\{x_a, x_2, ..., x_n\}$, let K-means partitions it in $\{S_1, S_2, ..., s_K\}$ then the objective is

$$\underset{S}{\text{argmin}} \sum_{i=1}^{K} \sum_{x \in S_i} dist^2(x, \mu_i)$$

- Where μ_i corresponds to i^{th} centroid. $\mu_i = \frac{1}{m_i} \sum_{x \in S_i} x$
- Typical choice for *dist* function is Euclidean Distance

How to proceed?

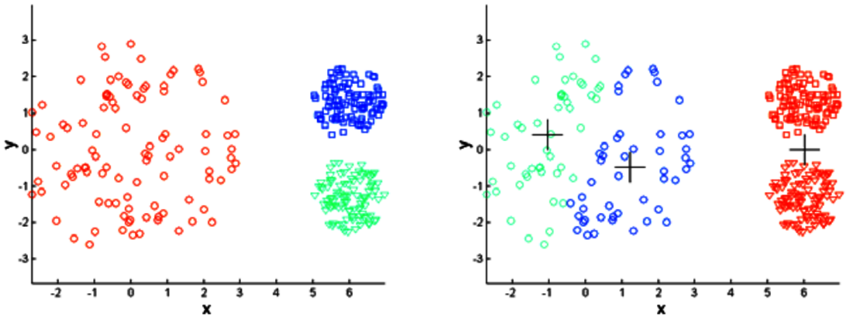
- Choose a K (How? [2])
  - Run K-means algorithm multiple times
  - Choose clusters corresponding to the one that minimized sum of squared error (SSE)
- If $K == n$, no error.
- Good clustering has smaller K

[2] Hamerly, Greg and Elkan, Charles, "Learning the k in k-means", pp 281–288, NIPS-2003

Evaluation of K-means

- **Choosing K:** 1) Domain Knowledge, 2) Preprocessing with another algorithm, 3) Iteration on K
- **Initialization of Centers:** 1) Random point in space, 2) Random point of data, 3) look for dense region, 4) Space uniformly in feature space
- **Cluster Quality:** 1) Diameter of cluster verses Inter-cluster distance, 2) Distance between members of a cluster and the cluster center, 3) Diameter of smallest sphere, 4) Ability to discover hidden patterns

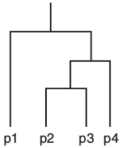
Limitations of K-means

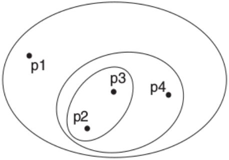


- Has problem when data has
  - Different size clusters
  - Different densities
  - Non-globular shape
- Handling Empty Clusters
- When there are outliers
- Updating Centroids Incrementally

Other Approaches

- **K-Medoids:** chooses data-points as centers and minimizes a sum of pairwise dissimilarities. Resistance to noise and/or outliers
- **Agglomerative Hierarchical Clustering:** repeatedly merging the two closest clusters until a single (Single Link)





- **DBSCAN:** density-based clustering algorithm that produces a partitional clustering, in which the number of clusters is automatically determined by the algorithm.

Important Note:

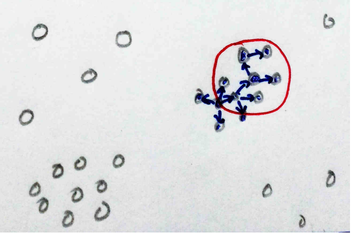
- K-Means and K-NN are different (K nearest neighbors)

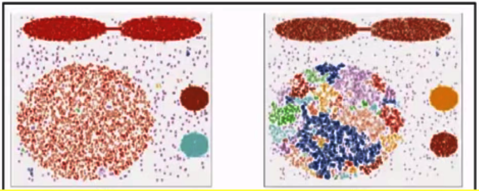
K-NN is a **supervised** approach for **classification**

DBSCAN

DBSCAN (Density-Based Spatial Clustering of Applications with Noise) is a spatial clustering algorithm of KDD96

- Parameters (Eps/MinPts) and points (core/border/noise)
- Uses DFS

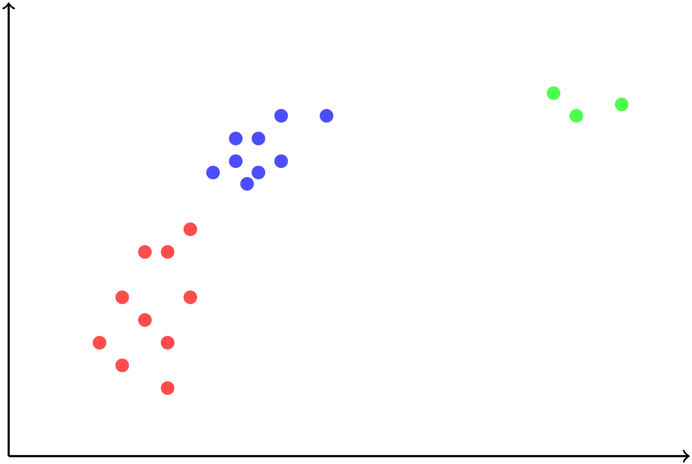




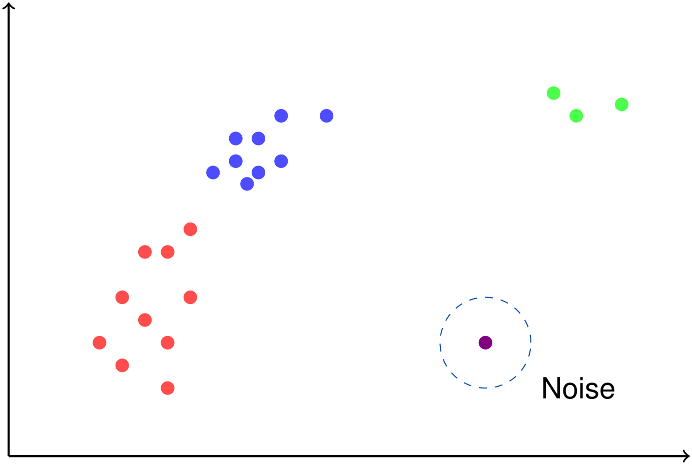
Figures from G. Karypis, E.-H. Han, and V. Kumar, *COMPUTER*, 32(8), 1999

- Advantage: clusters of arbitrary shape
- Disadvantage: Sensitive to parameters

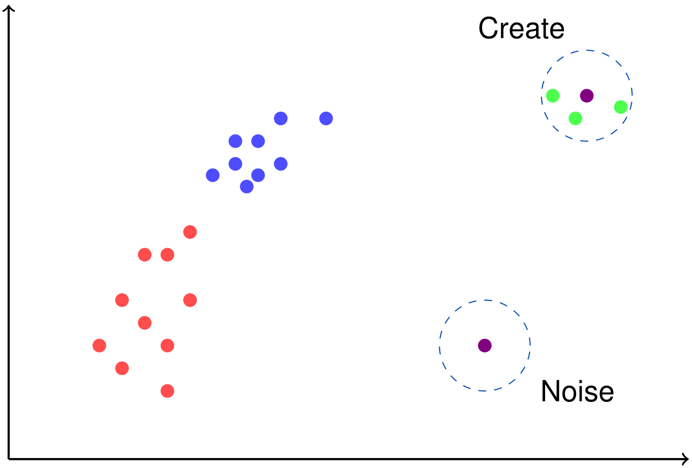
Incremental DBSCAN (Addition)



Incremental DBSCAN (Addition)



Incremental DBSCAN (Addition)



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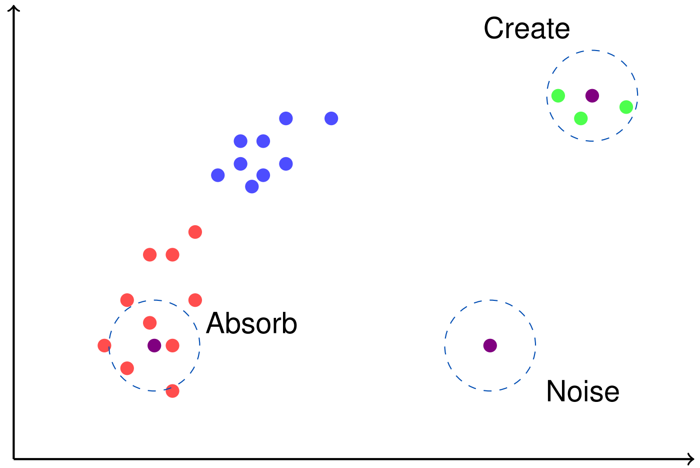

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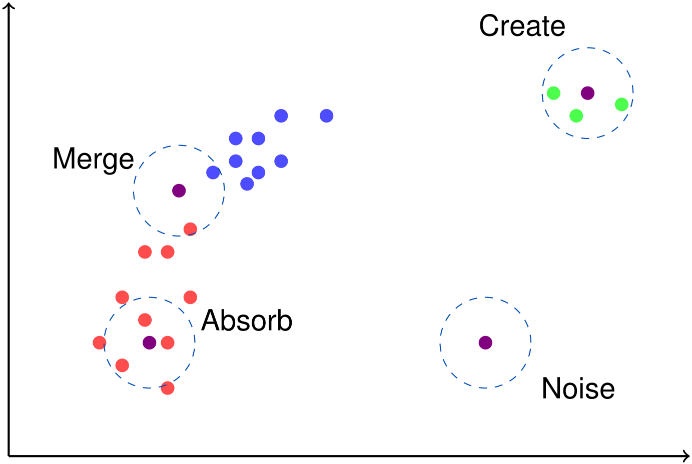
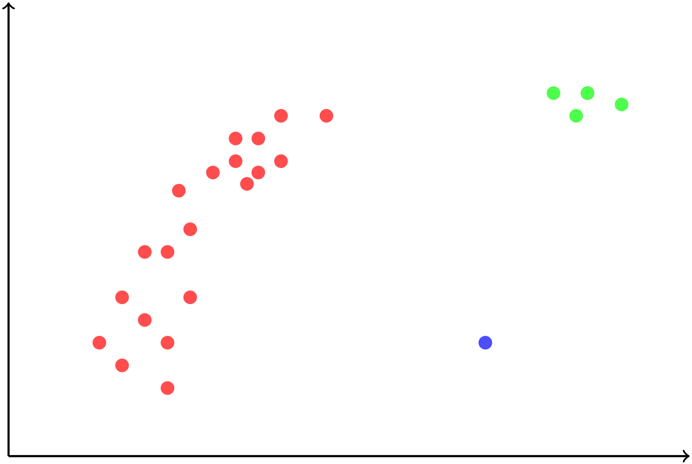


Incremental DBSCAN (Deletion)



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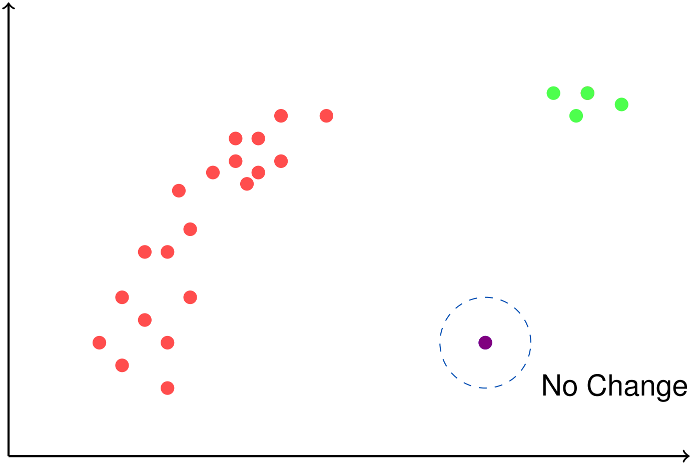
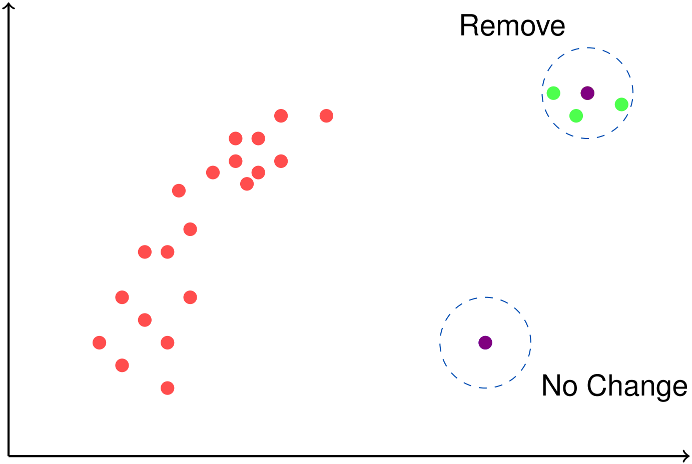
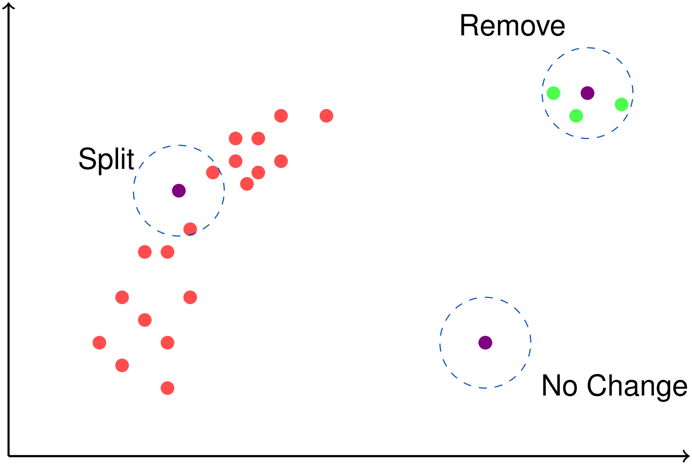


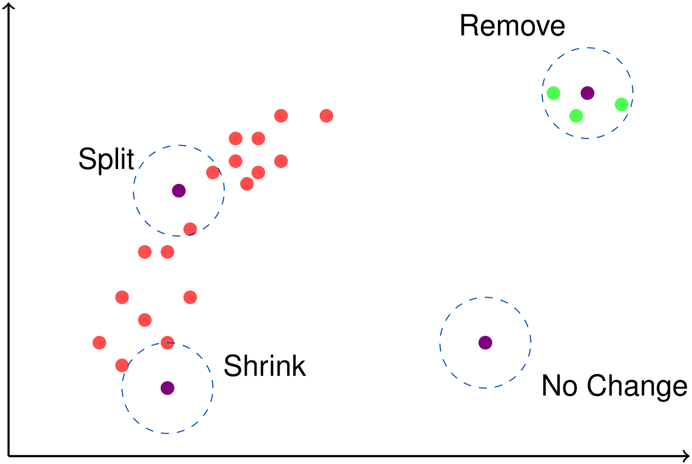
Incremental DBSCAN (Deletion)



Incremental DBSCAN (Deletion)



Incremental DBSCAN (Deletion)



Incremental DBSCAN

- Insertion and deletion are treated separately
- Based on change in density in affected region, clusters are updated.
- Update cost is proportional to number of points in affected region that is high
- You may be doing redundant operations

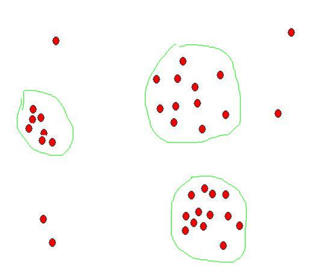
Differ update for some time

Assume periodic arrival of updates.

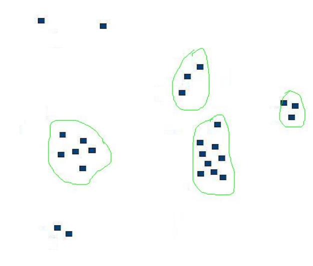
- Cluster new data
- Merge it with previous clusters (it is easy to see the density change)

Incremental DBSCAN

Initial Database

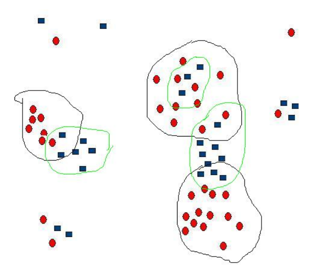


New Date

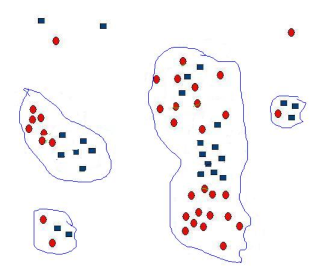


- Region based merging is applied

Incremental DBSCAN



Overlapping of clusters made from original and the new data points looks as



- Point p is in set of intersection I' if $\exists p' \in D$ such that p and p' are neighbor
- It is necessary an sufficient to process all $p \in I'$
- Efficiently compute I'. How?

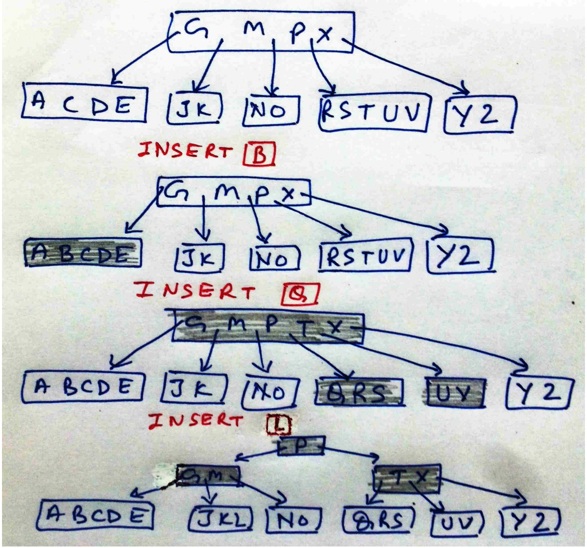
R-tree an efficient date structure

- R-tree provides an approach to index multidimensional spatial data
- Locating a nearest object to a current location is easy by using R-tree
- Or finding all objects in vicinity
- Uses a minimum bounding rectangle (MBR)
- It is a smallest rectangle that always contains the specified object
- Each node in the index contains its children
- Leaves of the tree points the actual objects
- Tree is height-balanced so height is $O(\log n)$
- R-Tree node usually corresponds to database points
- Similar to B-Tree

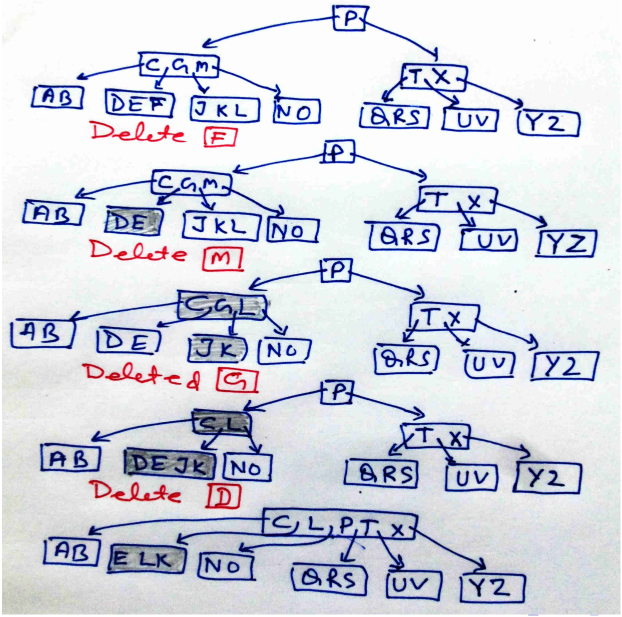
Remember B-tree

- B-Tree is a rooted tree. Every node x has $n(x)$ number of keys with $key_1[x] \leq key_2[x] \leq ... \leq key_{n[x]}[x]$ and $leaf[x] = TRUE$ if it is a leaf node
- Internal node also contains $n(x) + 1$ pointers $c_1[x], c_2[x], ..., c_{n[x]+1}[x]$
- For chosen $k > 1$, three exists at least $k - 1$ and at most $2k - 1$ keys at every node except root
- Height of tree $h \leq \log_t \frac{n+1}{2}$

B-tree (insertion)



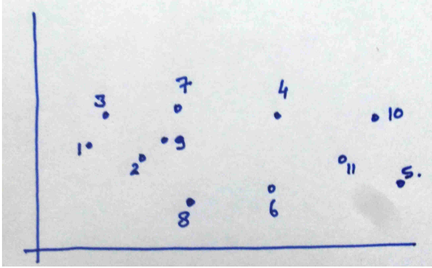
B-tree (deletion)

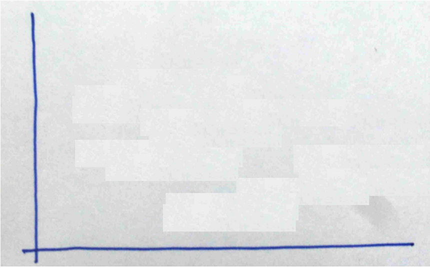


R-tree at Work

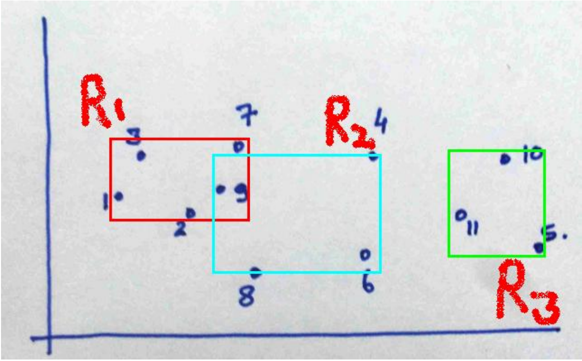
Consider arrival of

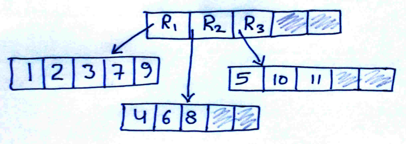
- P_1, P_2, P_3, P_4, P_5
- P_6 (split and region formation)
- P_7 (R1 expands)
- P_8 (R2 expands)
- P_9, P_{10}
- P_{11} (Split in R2)





R-tree at Work

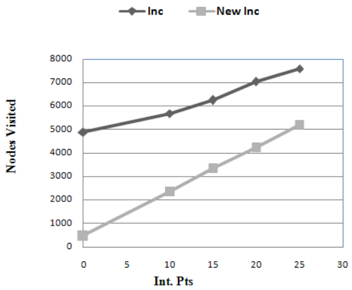


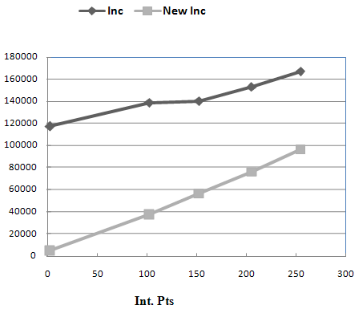


Incremental DBSCAN

- Find overlap region between R and R' with two trees holding objects from D and D'
- This would contains all the points under two nodes which are ϵ distance apart
- Is constructed by taking the intersection of ϵ-expanded MBRs pf the two nodes and the overlap region of the parent nodes
- Relative improvement is high if there is less overlap

http://cs.joensuu.fi/sipu/datasets/





Thank You!

Thank you very much for your attention!

Queries ?