Nearest neighbor search in high dimensional spaces

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Why do we need to optimize KNN?

- Very large datasets
- Very frequent queries
- Duplicates search
- It seems that brute force algorithm doens't use information gained from calculating previous distances: if d(a,b) is big and d(a,c) is small does it mean that d(c,b) is big?

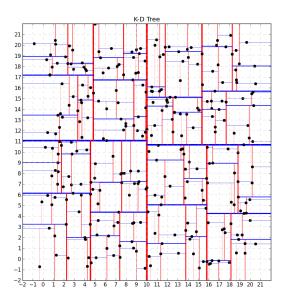
- KD-Tree
- Ball-tree
- Ball*-tree
- R-Tree
- etc...

algorithm: {'auto', 'ball_tree', 'kd_tree', 'brute'}, optional

Algorithm used to compute the nearest neighbors:

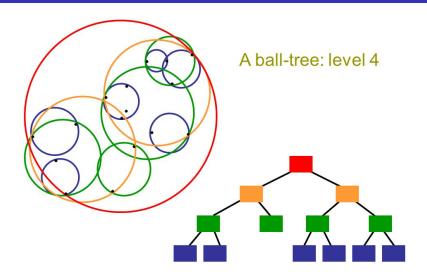
- 'ball_tree' will use BallTree
- 'kd tree' will use KDTree
- · 'brute' will use a brute-force search.
- 'auto' will attempt to decide the most appropriate algorithm based on the values passed to fit method.

Note: fitting on sparse input will override the setting of this parameter, using brute force.



• Tree construction - by $build_node(\{(x_1, y_1), ...(x_N, y_N)\})$:

```
build_node(\Omega): # omega-objects in the node
if |\Omega| < n_{min}:
   node.objects = \Omega
else:
    find feature with maximal spread in \Omega:
       x^{i} = \arg\max_{x^{i}} \sigma(x^{i})
    find median \Omega: \mu = median\{x^i\} # yields balanced tree
   node.feature = i
   node.threshold = \mu
   node.left child =
           build_node(\{x_k \in \Omega : x_k^i < \mu\})
   node.right child =
           build_node(\{x_k \in \Omega : x_k^i > \mu\})
return node
```



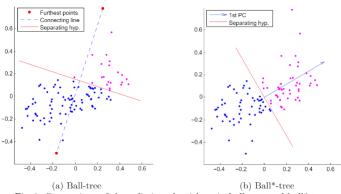
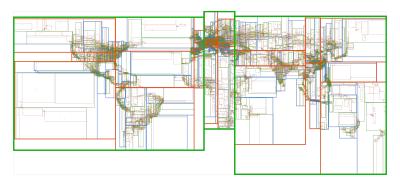


Fig. 2: Comparison of the splitting algorithms in ball-tree and ball*-tree

Dolatshah, Mohamad Hadian, Ali Minaei, Behrouz. (2015). Ball*-tree: Efficient spatial indexing for constrained nearest-neighbor search in metric spaces.

R-tree



Complexity analysis

