

Object oriented software engineering: Spatial Algorithms

Lecture and Workshop 5

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Feedback

- You all have feedback now for each learning diary entry
- Use the feedback already recieved to help with the assignment 2
- Moderation of learning diaries is this week
- Final marks/grades delivered Friday or early next week.

Assignment 2

- Testing Coding Ability
- Testing problem solving and spatial analytical skills
- I cannot answer specific questions about what should be done as it is for you to decide what should be done
- If you are confused or stuck:
 - Sketch out the problem on paper
 - Test the existing code to see what it is doing (later tasks build on previous tasks)
 - Pseudo-code and english descriptions of the problem and data may help
 - If you are still stuck take a break!

Week by week guide

~~1. Handling spatial data:~~

~~a) Simple geometric calculations, distance and bearing, range searching and data sorting.~~

~~2. Divide and Conquer~~

~~a) Binary searching, recursion and line generalisation~~

~~3. Grid data and arrays~~

~~a) Handling, traversing and searching raster data. Point and focal functions.~~

~~4. Raster Analysis and Problem Solving~~

~~a) DEM and Flow, integrating vector and raster data and concepts~~

5. Spatial analysis packages

1. Nearest neighbour, KdTree, Gdal

2. Coursework Help session

Any problems

- Office hours:
 - Wednesday 09:00 – 11:00
- Help Session
 - Monday April 2nd 9:00 – 11:00 in here??????
- Outside these hours: contact me by email gary.watmough@ed.ac.uk

Nearest Neighbour Searching in point field

- There are lots of situations we need to search for nearest point neighbours. E.g.
 - Generating TINs
 - Point filtering
 - A 'travelling salesman' algorithm
- Brute force methods are okay for small datasets but can be a major limitation once datasets get larger
- Are there better ways of doing this?

How to code distance?

```
def distance(self, other_point):  
    xd=  $x_i - x_t$   
    yd=  $y_i - y_t$   
    return math.sqrt((xd*xd)+(yd*yd))
```

Where;

- x_d/y_d are the differences in the x/y coordinates of two points
- x_i/y_i the x/y coordinate of the *ith* point in a list and x_t/y_t is another point location we are interested in.

Example: distance

PointField

x	Y
4	3
10	3
3	6
5	7
8	6
1	7
4	10

Other Point

x	y
4	7

Differences

xd	Yd
0	-4
6	-4
-1	-1
1	0
4	-1
-3	0
0	3

$$\sqrt{(0 * 0) + (-4 * -4)}$$

$$\sqrt{(6 * 6) + (-4 * -4)}$$

$$\sqrt{(0 * 0) + (3 * 3)}$$

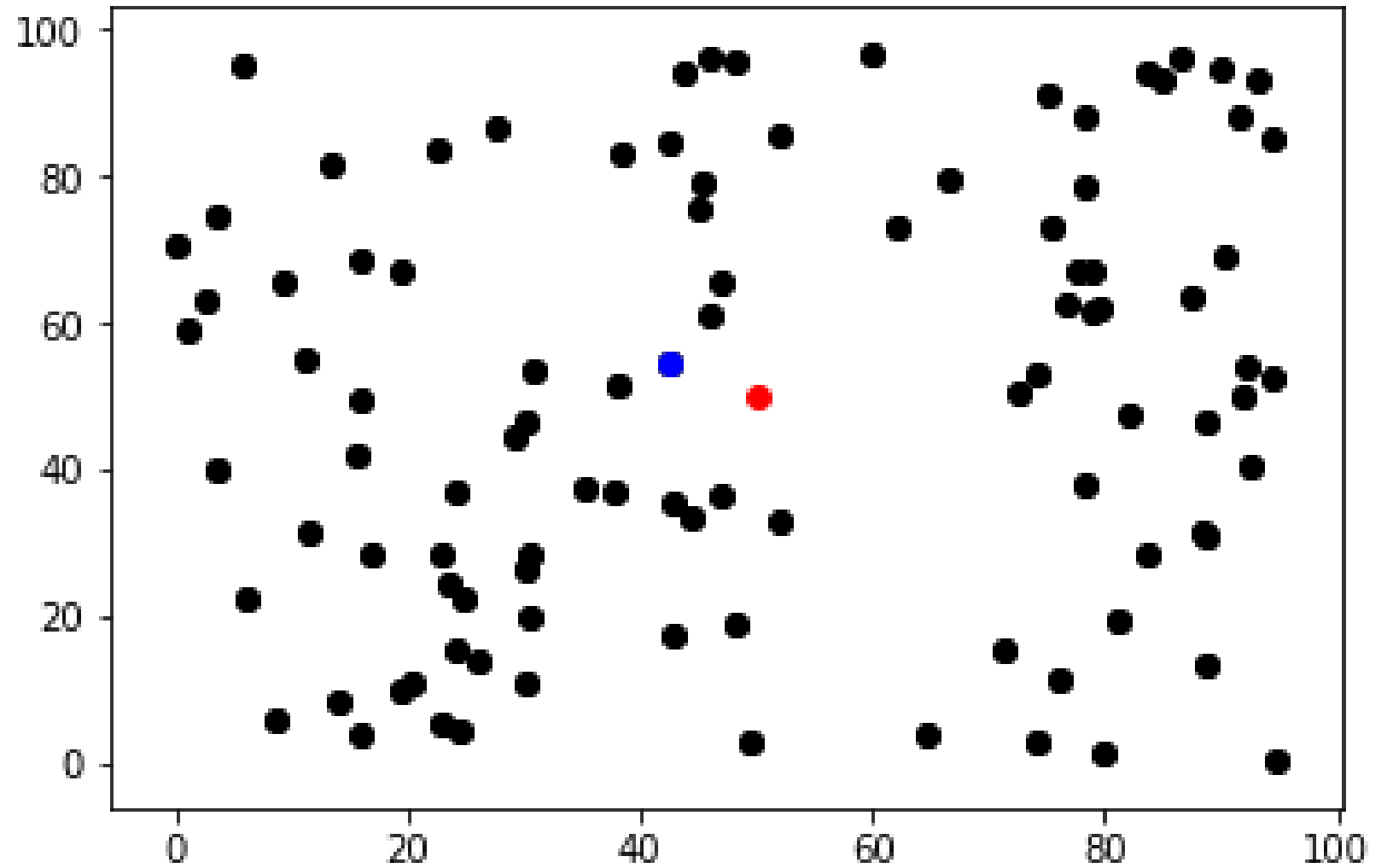
Distance

4
7.2
1.4
1
4.1
3
3

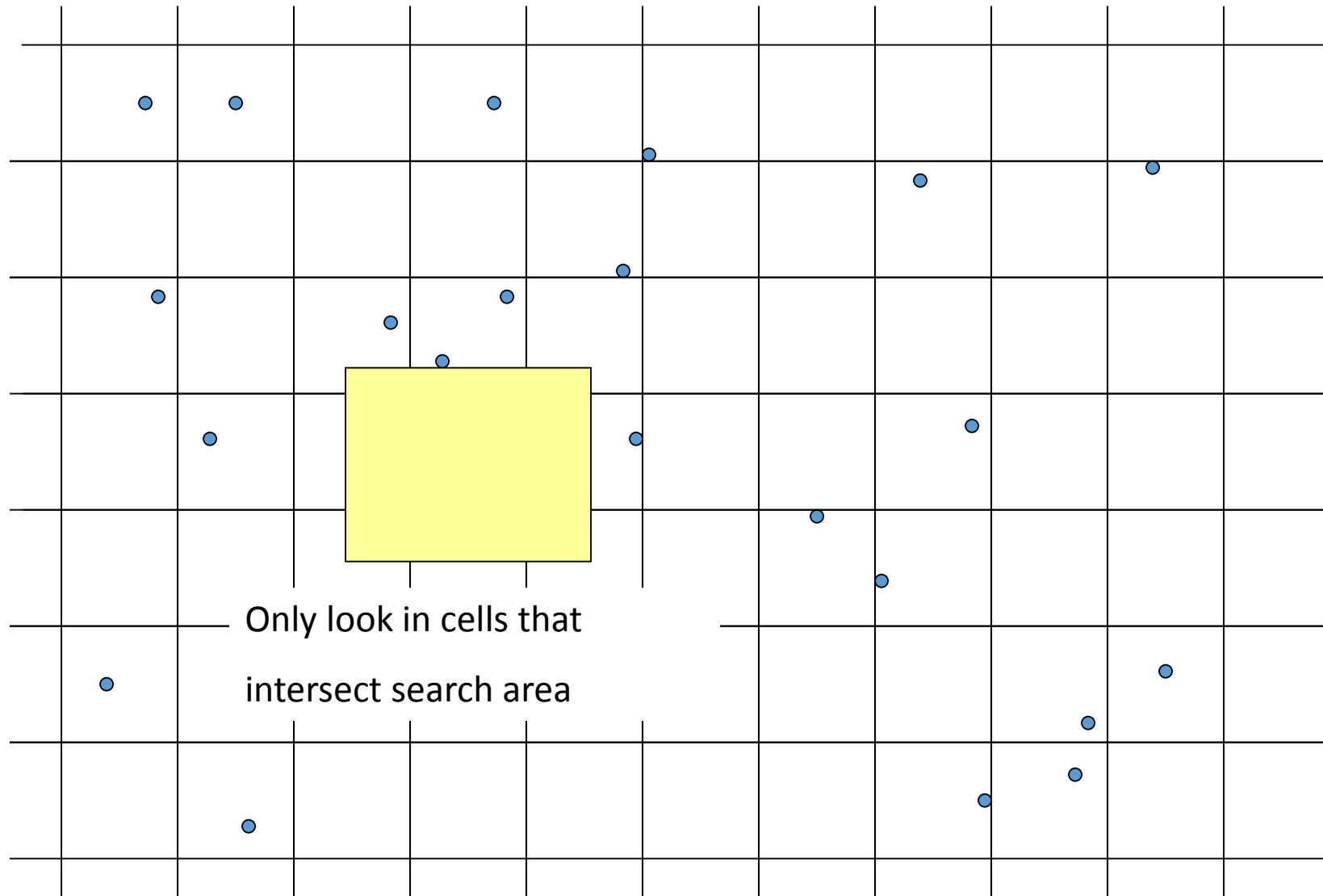
Task: How to code nearest neighbour?

- Need to hold onto the *ith* point with the lowest distance to the target in x and y.
- Open `points.py`
 - The `nearestPoint` method requires the distance to be calculated
 - The `distance` method name is provided in line 47
 - Currently we `pass` on the method.
 - Can you write a method that calculates a simple distance between a target point in X and Y and the pointfield – exactly as we just did in the previous slide.
 - Once written, open the driver `NN Driver final` and run the analysis

Example
output

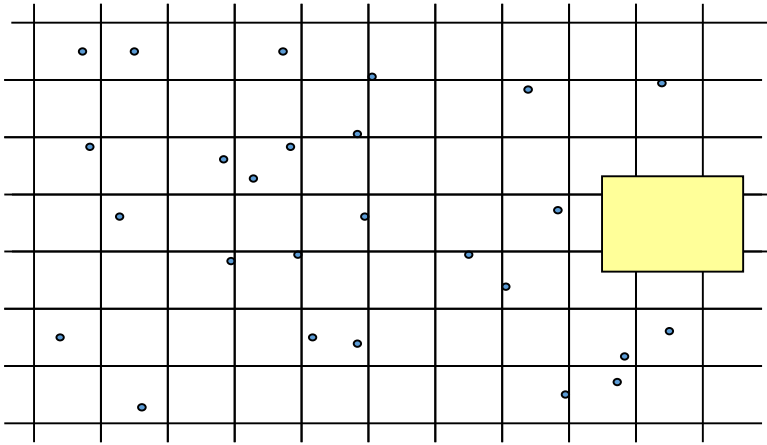


Grid Methods

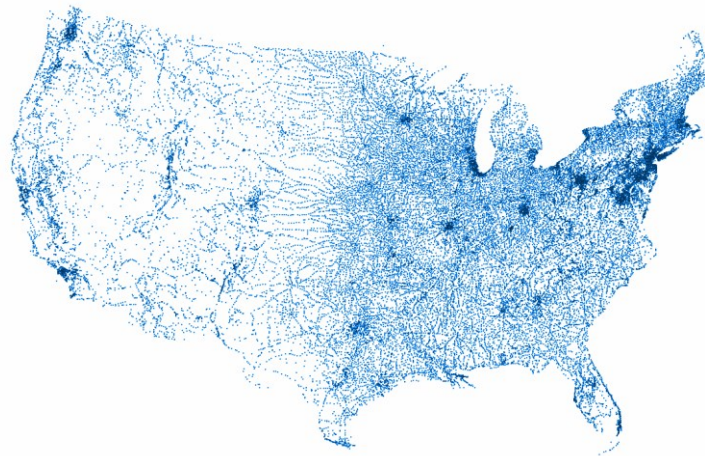
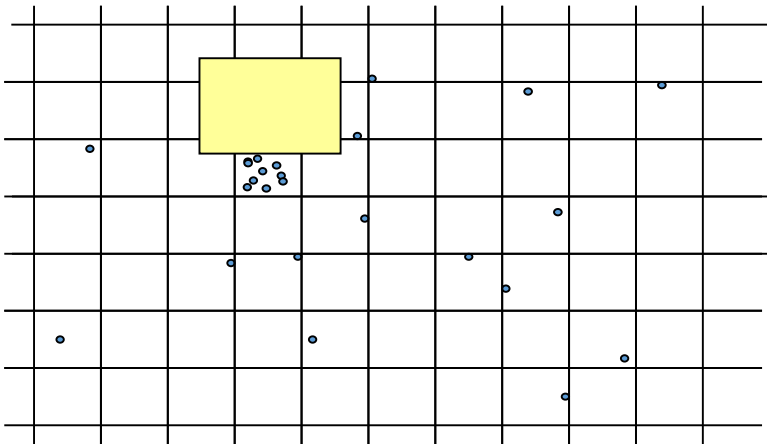


- Identify all points in each grid cell, hold in a list
- Only work on points within the cells that intersect our range.
- Grid cell size is important, too big and it includes lots of points and doesn't speed things up
- Too small – lots of objects created

Grid Method



- Works on evenly distributed points
- Not so good on uneven distributions
- If all points lie in one cell, you are not improving much
- Real data is more likely clustered



Source: <https://simplemaps.com/data/us-cities>

If place 1000 grid cells over the 13000 cities

Half of the cells would be empty

Half of the cities are in 10% of the cells.

Other options?

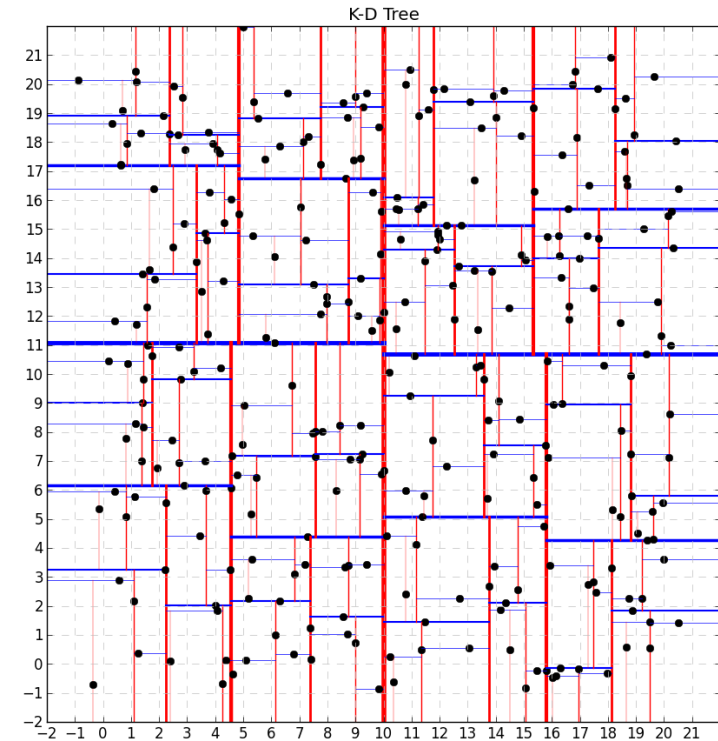
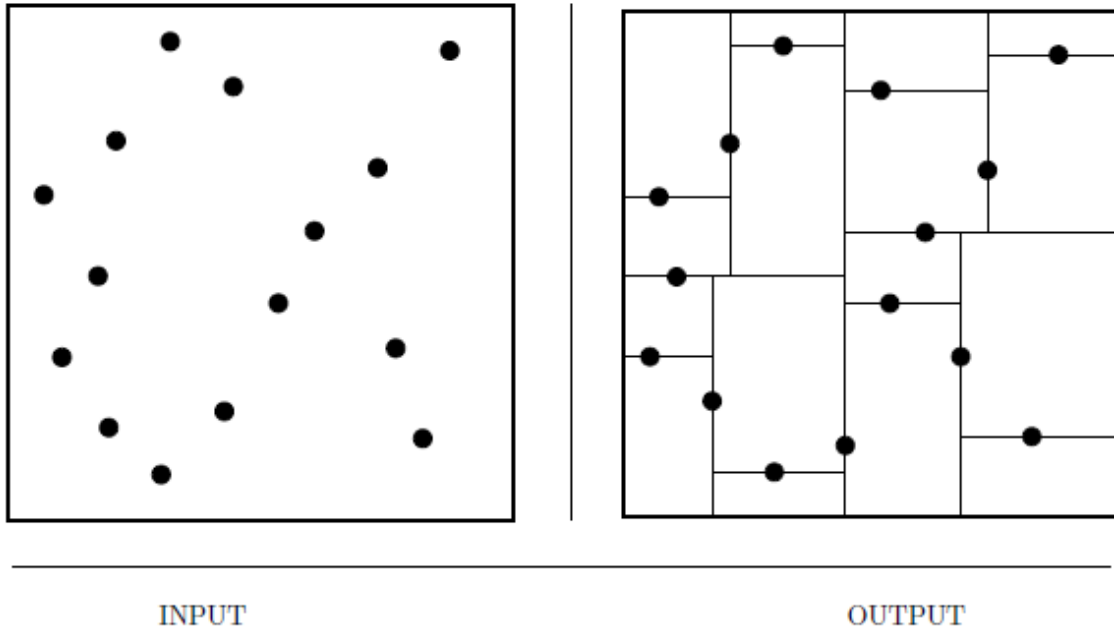
- So we need a data structure that can adapt to unevenly distributed data points
 - kd tree – recursively divides space into two half planes
 - Quadtree – recursively divides space into four quadrants
 - Many others...
-
- 2d-Tree

K(2)-dimensional trees (Kd-Tree)

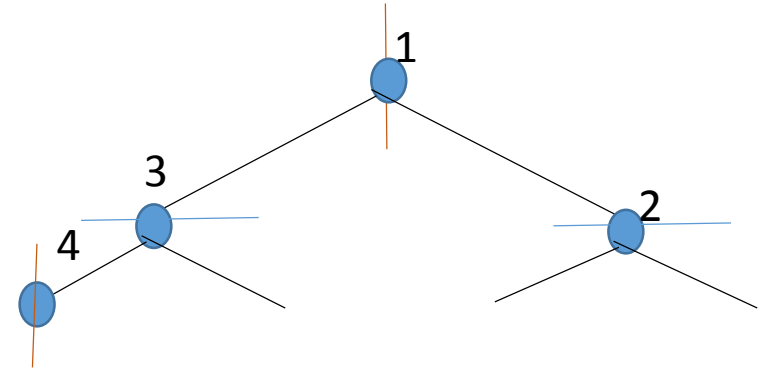
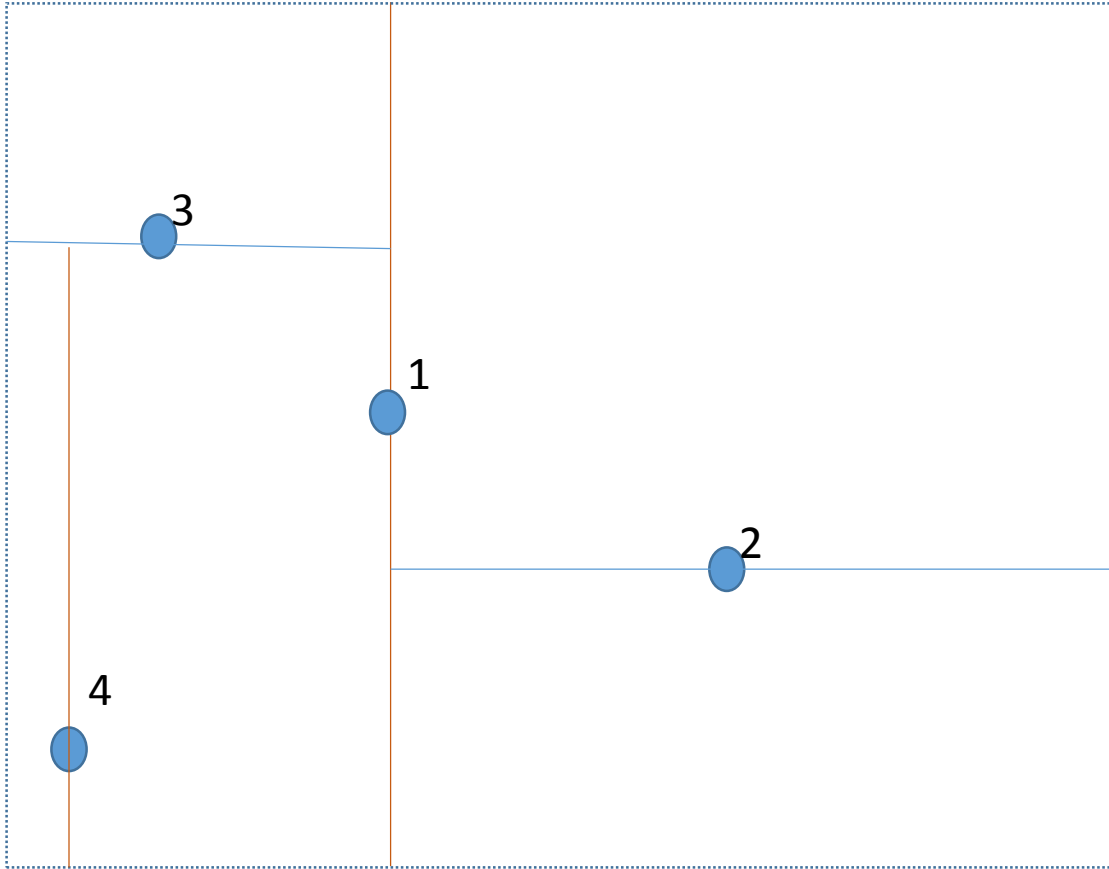
- Generalisation of a binary search tree
- Useful for range and NN searches
- Common operation in:
 - Computer vision
 - Computational geometry
 - Data mining
 - Machine learning
- Good for queries such as:
 - What is close by
 - Which is the nearest point

Kd-tree

- Partition space by half-planes such that each object is contained in its own region
- Hierarchically decompose space into small number of cells each containing a few points
- Provides a fast way to access objects by position



Construction



- Switch the key (x/y coordinate) each time
- On a vertical split all points on the left of the line appear to the left of the tree node
- On horizontal split the left sub-trees are below the line and right subtrees are above.

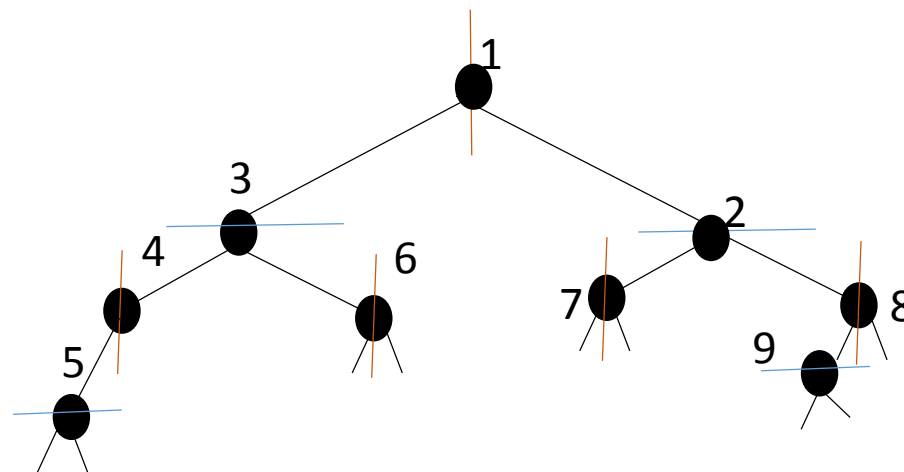
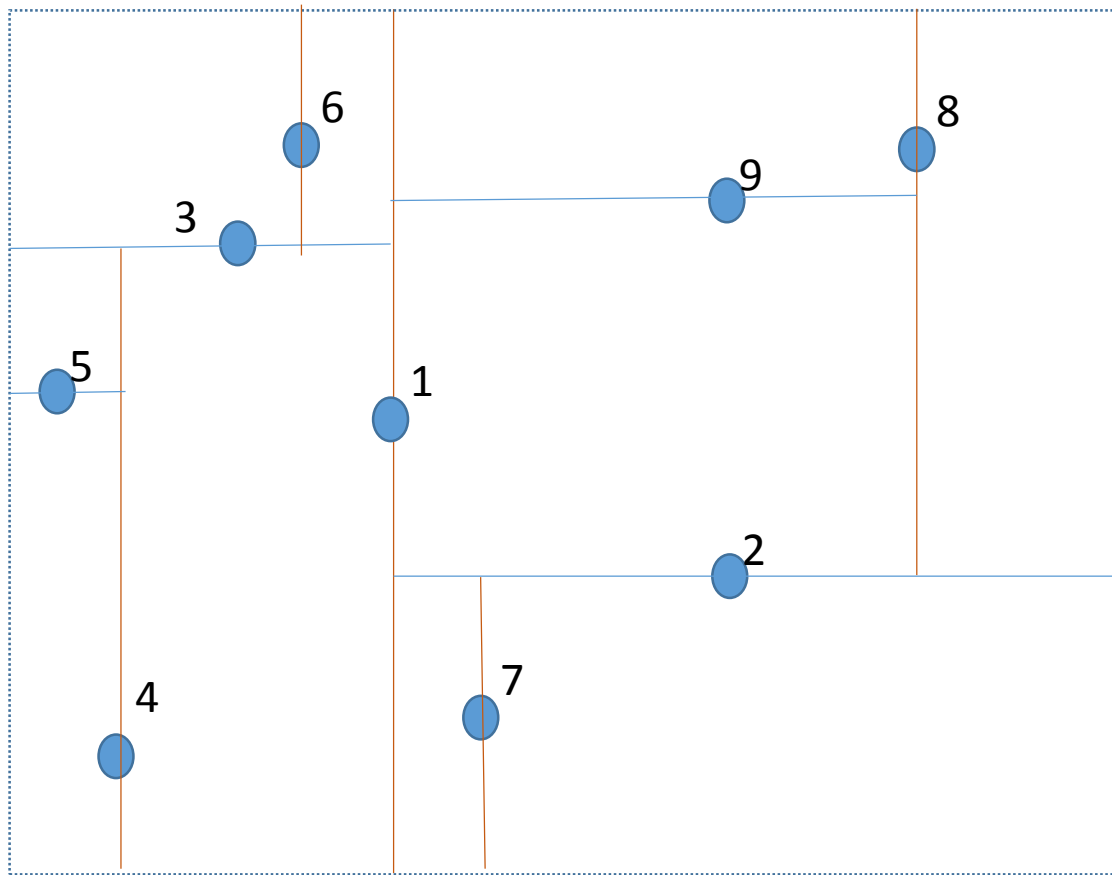
2-dimensional tree example

- At root of tree all data points are split based on 1st dimension
- Split by hyperplane perpendicular to the corresponding axis
- If the 1st dimension coordinate (say x) is $<$ root it is in the left subtree
- If coordinate is $>$ root it is in the right subtree
- At each level the tree divides on the next dimension
- Returns to the first dimension once all dimensions considered

How to build the tree (partitioning data)

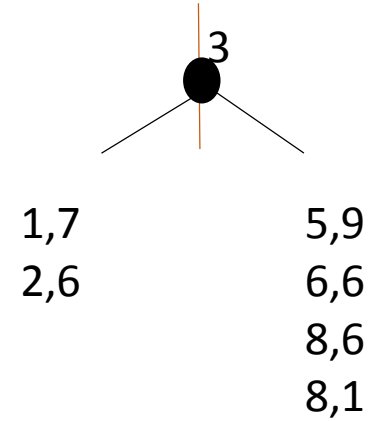
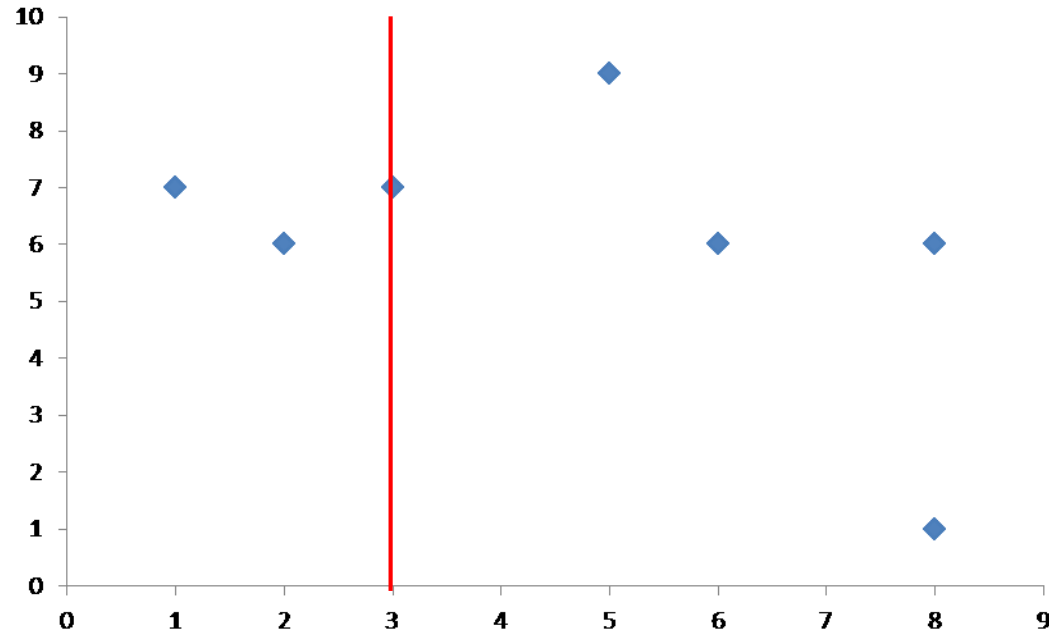
- Use a partitioning method such as QuickSort
 - This places the median point at the root
 - Everything smaller to left
 - Everything larger to right
 - Repeat on left and right subtrees
 - Continue until last to be partitioned are composed of only 1 element (leafs).
- But there are other ways of constructing the tree (Skiena 2011).

Tree construction



Construction: Consider a 2-d array of x,y points

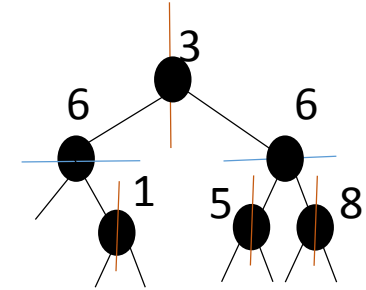
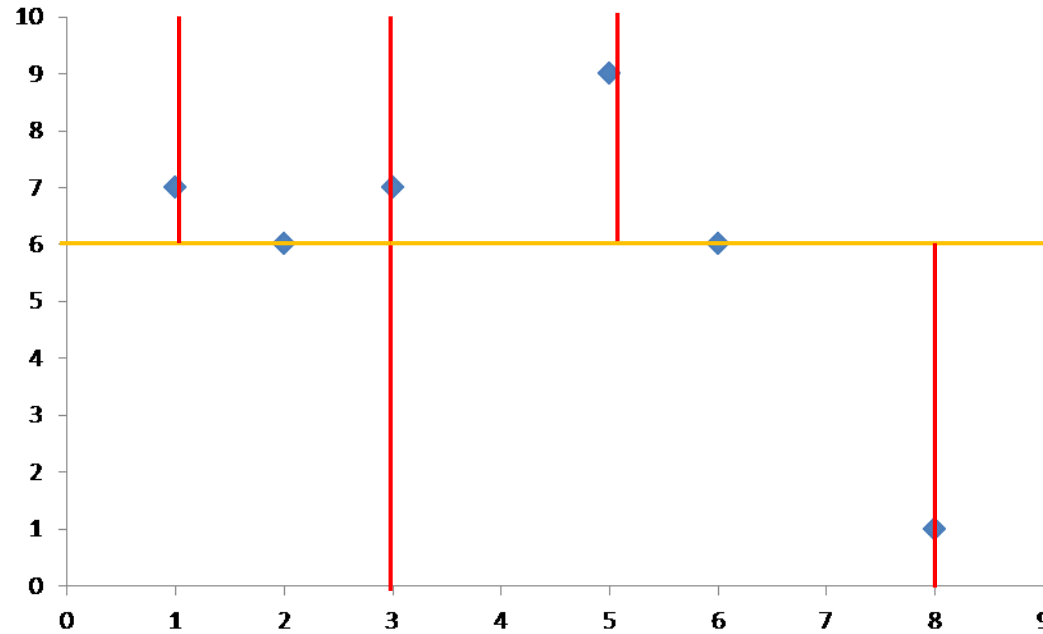
X	Y
3	7
8	1
6	6
2	6
1	7
8	6
5	9



1. Root median (x): median = 3 (3,4,6,2,1,8,5))
2. Left subtree (y): median = 6 (6, 7) – floor division arbitrarily select either
3. Right subtree (y): median = 6 (9,6,6,1)
4. X coordinate = 1 (complete)
5. X coordinate = 8 (complete)
6. X coordinate = 5 (complete)

Construction: Consider a 2-d array of x,y points

X	Y
3	7
8	1
2	6
1	7
6	6
5	9



1. Root median (x): median = 3 (3,4,6,2,1,8,5))
2. Left subtree (y): median = 6 (6, 7) – floor division arbitrarily select either
3. Right subtree (y): median = 6 (9,6,6,1)
4. X coordinate: median = 1 (1,7)
5. X coordinate: median = 8 (8,1)
6. X coordinate: median = 5 (5,9)

Using the tree: traversing

- Traverse down the tree until we find the smallest cell containing our object
- Then scan through the objects in this cell to identify the right one

Nearest neighbour search

- Find point in S closest to query point q
- Perform point location to find cell c containing q (as above)
- Since c is bordered by some point p we can compute the distance $d(p, q)$ from p to q
- Point p is likely close to q
- But it might not be the single closest neighbour (if q is close to a boundary of a cell q 's nearest neighbour might lie in another cell)
- Therefore, we must traverse all cells that lie within a distance of $d(p, q)$ of cell c and check none contain closer points

Example: Nearest Neighbour

X	Y
3	7
8	1
2	6
1	7
6	6
5	9

$$\text{distance} = \sqrt{(x_i - x_t)^2 + (y_i - y_t)^2}$$

Target (q) = 5,7

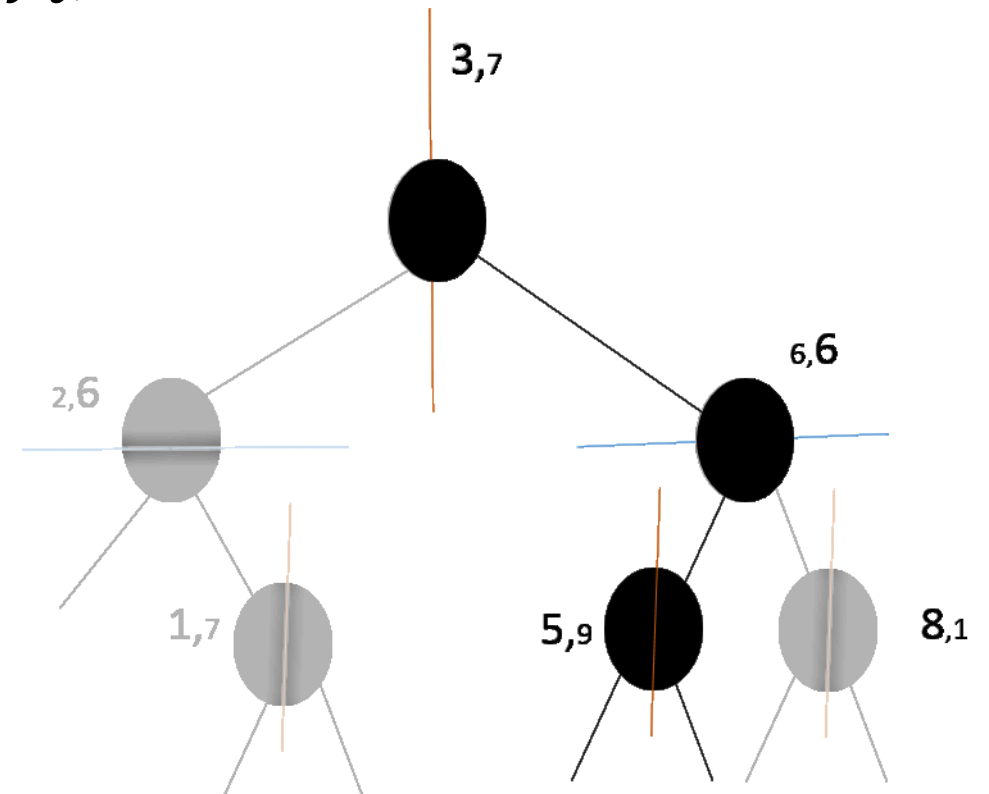
$S = [3,7; 8,1; 2,6; 1,7; 6,6; 5,9]$

X domain: $5 > 3$ – move to right

Y domain: $7 > 6$ – move to left

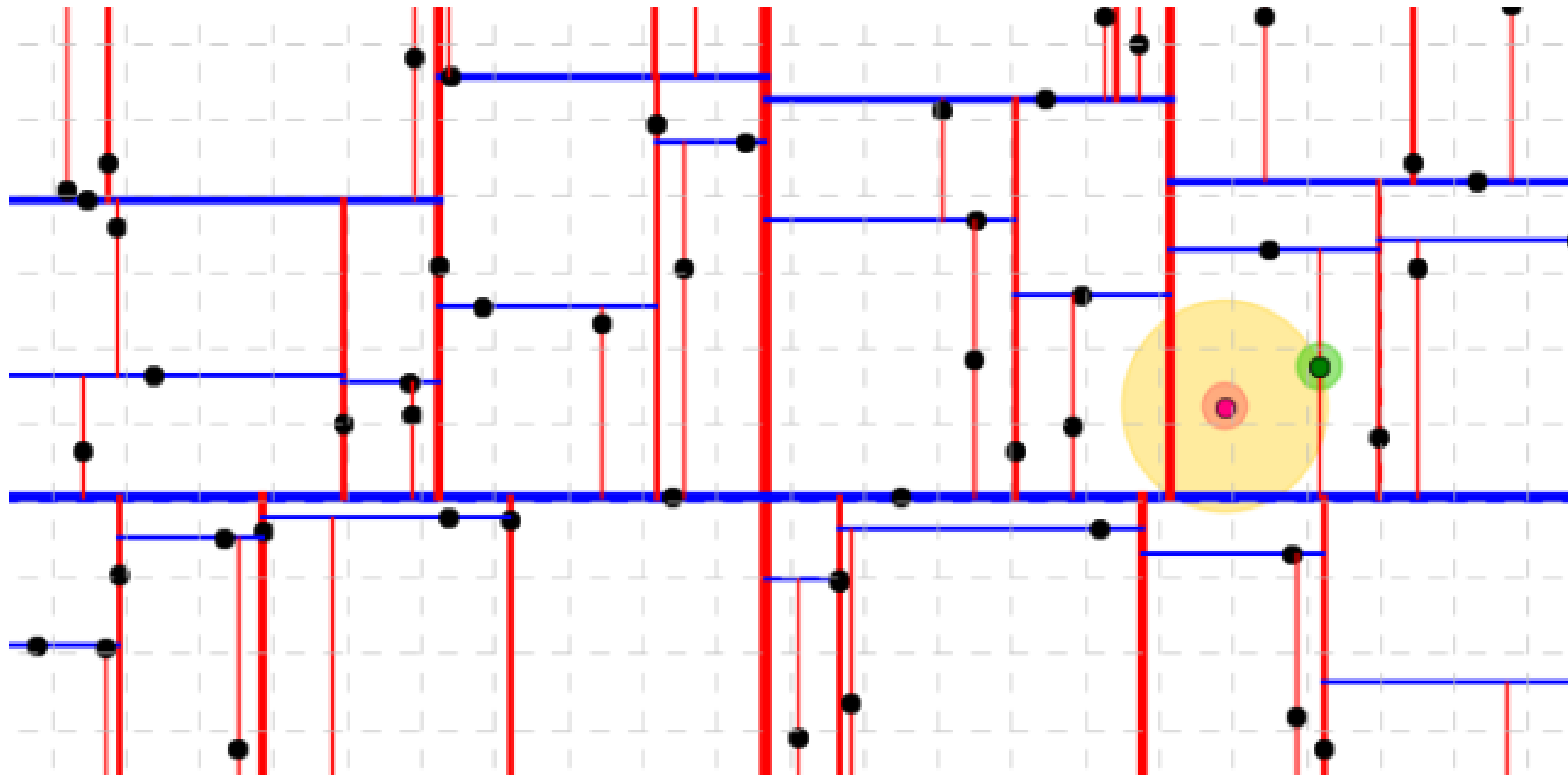
Left with: 5,9; 6,6

Trace back and test the distance's of these points





In Python

- Traversing the tree the algorithm saves the node with the shortest distance to our target as the current best
- Once the algorithm reaches the leaf node (end) it unwinds the recursion using the following steps:
 - If the current node is closer than the current best it becomes current best
 - Algorithm checks if there could be any points on the other side of the splitting plane that are closer than the current best
 - Does this by intersecting the splitting hyperplane with a hypersphere around the target point
 - This sphere has a radius equal to the current nearest distance
 - If the sphere crosses a plane there could be a point on the other side that is nearer
 - So the algorithm must also move down the other branch of the tree from the current node to check



Fortunately.... This is already part of SciPy....

 SciPy.org 

SciPy.org Docs SciPy v0.14.0 Reference Guide Spatial algorithms and data structures (`scipy.spatial`)

index modules next previous

scipy.spatial.KDTree

`class scipy.spatial.KDTree(data, leafsize=10)` [\[source\]](#)

kd-tree for quick nearest-neighbor lookup

This class provides an index into a set of k-dimensional points which can be used to rapidly look up the nearest neighbors of any point.

Parameters:

- data** : *(N,K) array_like*
The data points to be indexed. This array is not copied, and so modifying this data will result in bogus results.
- leafsize** : *int, optional*
The number of points at which the algorithm switches over to brute-force. Has to be positive.

Raises:

- RuntimeError**
The maximum recursion limit can be exceeded for large data sets. If this happens, either increase the value for the *leafsize* parameter or increase the recursion limit by:

Previous topic
[scipy.spatial.distance.yule](#)
Next topic
[scipy.spatial.KDTree.count_neig](#)

<https://docs.scipy.org/doc/scipy-0.15.1/reference/generated/scipy.spatial.KDTree.query.html>

This has a number of methods that exploit the tree structure....

Methods

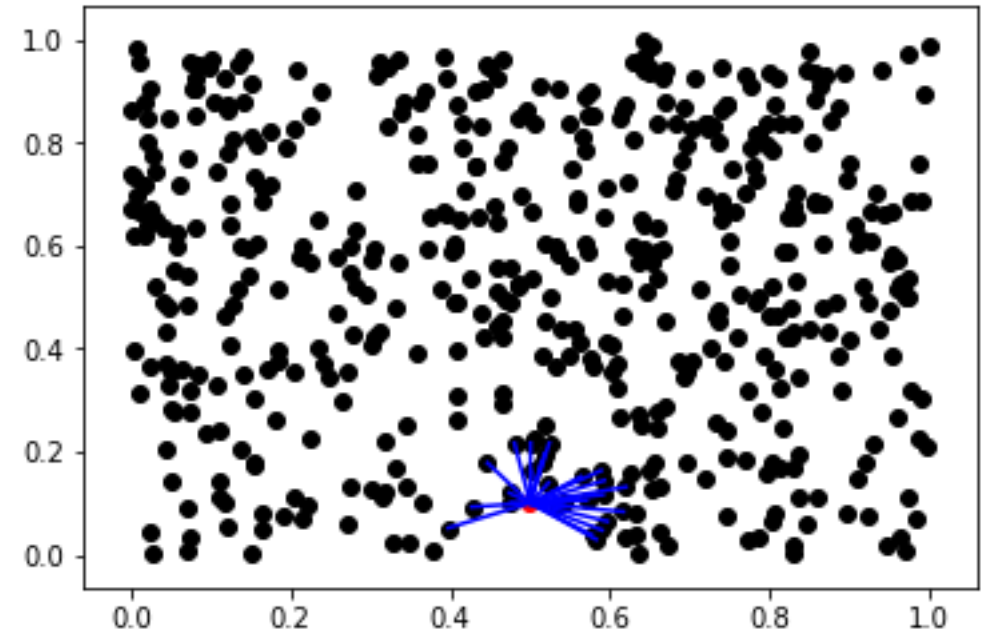
<code>count_neighbors(other, r[, p])</code>	Count how many nearby pairs can be formed.
<code>innernode</code>	
<code>leafnode</code>	
<code>node</code>	
<code>query(x[, k, eps, p, distance_upper_bound])</code>	Query the kd-tree for nearest neighbors
<code>query_ball_point(x, r[, p, eps])</code>	Find all points within distance r of point(s) x.
<code>query_ball_tree(other, r[, p, eps])</code>	Find all pairs of points whose distance is at most r
<code>query_pairs(r[, p, eps])</code>	Find all pairs of points within a distance.
<code>sparse_distance_matrix(other, max_distance)</code>	Compute a sparse distance matrix

The main issue is getting the data in the right format to make a tree: It's expecting a list (or array) of tuples:
 $[(x_1, y_1), (x_2, y_2), (x_2, y_3), (x_4, y_4), \dots, (x_n, y_n)]$

One way is to use the zip function (see the Kdtree driver.py)

Identify nearest neighbours: `tree.query`

```
1 import matplotlib.pyplot as mp
2 import scipy.spatial as spatial
3 import random
4
5 x=[]
6 y=[]
7 for i in range(500):
8     x.append(random.uniform(0,1))
9     y.append(random.uniform(0,1))
10
11 points=zip(x,y) #converts two lists in to a tuple
12 print(type(points))
13
14 pointsList=list(points)
15 print(pointsList)
16
17 for x, y in pointsList:
18     print ("x={}, y={}".format(x, y))
19     mp.scatter(x,y,color="black")
20
21 myTree=spatial.KDTree(pointsList)
22
23
24 pointsToCheck = (0.5, 0.1)
25
26 # query for one nearest neighbour
27 #res = myTree.query(pointsToCheck)
28 #print ("Nearest point is index {}, distance {}, coordinate {}".format(res[1], res[0], pointsList[res[1]]))
29
30 # query for multiple nearest neighbour
31 dist, ind = myTree.query(pointsToCheck, 25)
32
```



Kdtree

- Useful for small to moderate number of dimensions
- Can lose effectiveness as the dimensionality increases
- Try to reduce number of dimensions to more manageable size before proceeding (dimension reduction techniques)
- More information:
 - [Nice worked example on this blog: https://salzis.wordpress.com/2014/06/28/kd-tree-and-nearest-neighbor-nn-search-2d-case/](https://salzis.wordpress.com/2014/06/28/kd-tree-and-nearest-neighbor-nn-search-2d-case/)
 - Skiena (2011) Algorithm design manual

Break Time

Next: Spatial analysis packages

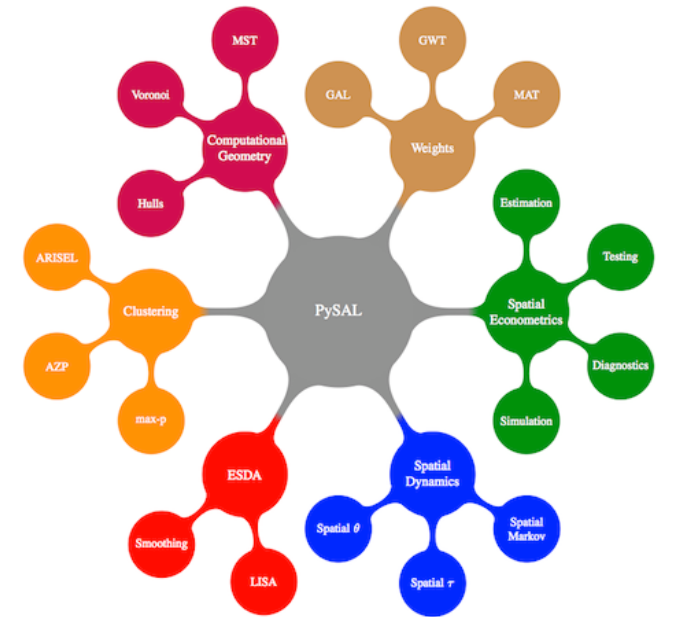
Other spatial packages

- Numpy
 - Scipy
 - PySal – [Python Spatial Analysis Library](#)
 - Pandas – [Python data analysis library](#)
 - Shapely – [Computational Geometry package](#)
 - Fiona – [Reading and writing geospatial data files](#)
 - Six – [Python 2 and 3 compatibility library](#)
 - Gdal – [Geospatial Data Abstraction Library](#)
- Some packages are not included in different installs (anaconda)

Data handling	Analysis	Plotting data
Shapely	Shapely	Matplotlib
GDAL	Numpy , scipy	Prettyplotlib – improvements to matplotlib – no longer supported.
pyQGIS – python plugin to QGIS	Pandas , geopandas - extends datatypes in pandas to allow spatial operations	Decartes -
Pyshp – reading ESRI shapefiles	PySal	cartopy
Pyproj – converting between projections	Rasterio – read in GeoTif and other formats and store as gridded raster	
Fiona : reading and writing GIS formats	Rtree : NN search and others	
	Statsmodels : statistical modelling can it be as good as R?	

PySal: Vector data

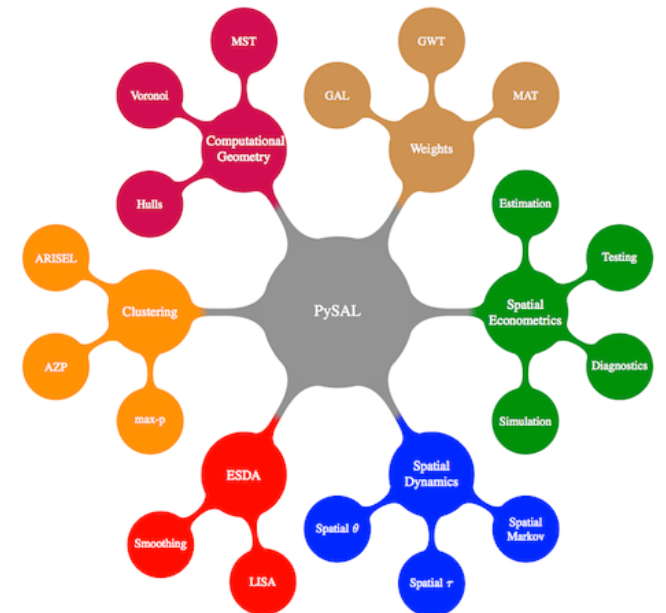
- Not deterministic – overlays etc
- Focus on spatial statistical analysis
- Spatial Weights – express spatial relationships
 - Geographical relationships
- Computational geometry
 - Need this to format data for other analytical processes
- Clustering –
 - Finding neighbourhoods that are homogeneous and contiguous
- ESDA – exploratory spatial data analysis (autocorrelation)
 - *Is the spatial distribution of the attribute random?*



http://darribas.org/gds_scipy16/

PySAL

- Spatial Dynamics
 - Adding in time components as well to clustering problems for example
- Spatial econometrics
 - Spatial regression techniques



Rasterio: raster geoprocessing and data analysis

- Raster Manipulation
 - Stacking and merging bands
 - Calculations across bands
 - Vegetation indices
 - Conversions from different types of raster file types
- It does require several other libraries/packages including gdal.

GeoPandas

- Vector geoprocessing
 - Buffer,
 - Intersect
 - Union
 - Difference
- Requires other python packages
 - Numpy, pandas, shapely, Fiona, six
- Can be difficult to install with some versions or setups.

Packages and Libraries

- Often find others have already had similar questions/problems
- Worth searching online for pre-existing algorithms or approaches before you begin coding something new

Coursework help session

We cannot answer all of the questions