

# 1 Implementation of Quad nearest neighbors

## 1.1 Quad Tree

### 1. The Quad tree data structure[1]

- It's a tree data structure have four children
- Partition two dimension space recursively by dividing it into four quadrant
- **Space subdivision rule**
  - Divide in the middle - can cause the points distribution unevenly(the rule used in this Implementation)
  - Divide by the median of the points within the current Quad tree
- **Recursion stopping criteria**

When the number of points within the current quadrant  $< c$ .  $C$  decided by the user(In this implementation, I used  $c = 5/10/20$ ).

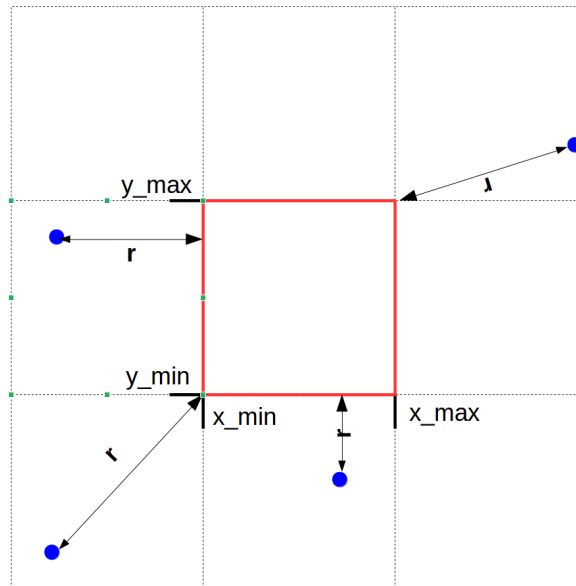
Turned out different  $c$ s can cause the algorithm speed different by 10% ,i.e. from .5 s to .4 or so. In the final demo, I used 10 neither too small or too big comparing to the  $k$ (number of nearest neighbors).

### 2. Data structure implementation

Class built for the quad tree/point/rectangular and their attributes

- **Points:** the points in the training set
  - x: x-axis
  - y: y-axis
  - cls\_: the category of this point

```
class Point:
    def __init__(self,x,y,_cls):
        self.x = x
        self.y = y
        self.cls_ = _cls
```
- **Rect:** Rectangular store the shape and other attribute of the quadtree
  - x: rectangular center point x-axis
  - y: rectangular center point y-axis
  - width: the 1/2 width of the rectangular
  - height: the 1/2 height of the rectangular
  - **method** contain: to validate whether a point is inside of the rectangular



- **method** within: to validate whether the rectangular is with in the circle of center(point\_x,point\_y) and the radius r Note: this is calculated follow the figure below.[2]

```
class Rect:
    def __init__(self,x,y,width,height):
        self.x = x
        self.y = y
        self.width = width
        self.height = height
    def contain(self,point):
        return (point.x>=(self.x - self.width)) and \
            (point.x <= (self.x +self.width)) and \
            (point.y>=(self.y-self.height)) and \
            (point.y<=(self.y + self.height))
    def within(self,point,d):
        def dist(x1,y1,x2,y2):
            return math.sqrt((x1-x2)**2+(y1-y2)**2)
        l_x = self.x - self.width
        b_y = self.y - self.height
        h_x = self.x + self.width
        t_y = self.y + self.height
        if point.x>=h_x and point.y>=t_y:
            return dist(h_x,t_y,point.x,point.y)<=d
        elif point.x>=h_x and point.y<=b_y:
            return dist(h_x,b_y,point.x,point.y)<d
        elif point.x>=h_x and point.y<t_y and point.y >b_y:
```

```

        return dist(h_x,0,point.x,0)<=d
    elif point.x<=l_x and point.y<=b_y:
        return dist(l_x,b_y,point.x,point.y)<d
    elif point.x<=l_x and point.y>=t_y:
        return dist(l_x,t_y,point.x,point.y)<d
    elif point.x<=l_x and point.y>=b_y:
        return dist(l_x,0,point.x,0)<d
    elif point.x>=l_x and point.x<=h_x and point.y>=t_y:
        return dist(0,t_y,0,point.y)<d
    elif point.x>=l_x and point.x<=h_x and point.y<=b_y:
        return dist(0,b_y,0,point.y)<d
    elif self.contain(point):
        return True

```

### • Quad Tree:

Attributes:

- boundary: the rectangular that store the shape and center
- capacity: the maximum number of points can be stored in this quadtree.
- isleaf: denote whether the quadtree is subdivided or not.
- points: the points that are stored in the quadtree, only is not empty when isleaf is True
- northwest/southwest/northeast/southeast: the sub quadtree node stored by the relative direction
- color the style of coloring for quadtree visualization(optional)

Methods:

- subdivide: subdivide the big quad tree into 4 sub quadtree and distribute the points into the corresponding sub quadtree

```

def subdivide(self):
    x = self.boudary.x
    y = self.boudary.y
    width = self.boudary.width
    height = self.boudary.height
    ne = Rect(x + width/2,y+height/2, width/2, height/2)
    nw = Rect(x - width/2,y+height/2, width/2, height/2)
    sw = Rect(x - width/2,y-height/2, width/2, height/2)
    se = Rect(x + width/2,y-height/2, width/2, height/2)
    self.northwest = quadTree(nw,\
[p for p in self.points if p.x<=x and p.y>=y],self.capacity)
    self.southwest = quadTree(sw,\
[p for p in self.points if p.x<=x and p.y<y],self.capacity)
    self.northeast = quadTree(ne,\
[p for p in self.points if p.x>x and p.y>=y],self.capacity)
    self.southeast = quadTree(se,\
[p for p in self.points if p.x>x and p.y<y],self.capacity)

```

- construct: construct the quadtree if not reaching the stopping criteria then keep subdividing.
- showfig: quadtree visualization

## 1.2 k Nearest Neighbor algorithm

### 1. Steps

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#### Algorithm 1 Quad nearest neighbor

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```

1: for  $p \in points$  do
2:   Initialize  $r = \infty$ ,  $stack = [quad\_tree\_root]$ ,  $pnt = []$ 
3:   while  $stack$  is not null do
4:      $cur := pop\ stack$ 
5:     if  $cur$  is a leaf quad tree then
6:       for  $i \in points$  in the  $cur$  do
7:         if  $length\ pnt < k$  then append to  $pnt$ , update  $r$ 
8:         else
9:           if if the distance between point  $i$  and the center  $p$  then
10:            pop up the point in  $pnt$  that has the largest  $r_p$ 
11:            update  $r$ 
12:          end if
13:        end if
14:      end for
15:    end if
16:    if  $cur$  is not a leaf quad and the  $distance(p, cur.boundary) < r$  then
17:      append the children of  $cur$  to the  $stack$ 
18:    end if
19:  end while
20: end for result is the mode of the  $pnt$  list

```

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Note:  $pnt$  is list for  $k$  nearest neighbors of each point, it's maintained as a heap, thus it can pop out the item with the max  $r$  and insert new point, with a time complexity of  $O(\log n)$

### 2. Implementation in python

```

def knn(quad, pnt, k):
    res = []
    for p in tqdm(pnt):
        stack = [quad]
        r = (float('-inf'), "")
        pnt_ = []
        while len(stack):
            cur = stack.pop(-1)
            if cur.isleaf and cur.boudary.within(p, -r[0]):

```

```

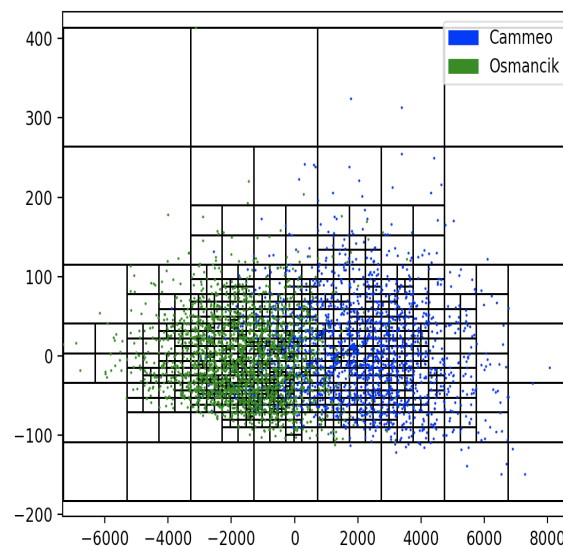
for i in cur.points:
    if len(pnt_)<k:
        heapq.heappush(pnt_,\
            (-math.sqrt((i.x - p.x)**2+(i.y - p.y)**2),i.cls_))
        r = heapq.nsmallest(1,pnt_)[0]
    elif math.sqrt((i.x - p.x)**2+(i.y - p.y)**2)<-r[0]:
        heapq.heappop(pnt_)
        heapq.heappush(pnt_,\
            (-math.sqrt((i.x - p.x)**2+(i.y - p.y)**2),i.cls_))
        r = heapq.nsmallest(1,pnt_)[0]
elif not cur.isleaf:
    if cur.boudary.within(p,-r[0]):
        if cur.northwest:
            stack.append(cur.northwest)
        if cur.southeast:
            stack.append(cur.southeast)
        if cur.northeast:
            stack.append(cur.northeast)
        if cur.southwest:
            stack.append(cur.southwest)
res.append(mode([itr[1] for itr in pnt_]))
return res

```

### 1.3 Results

Some outputs

1. scatter plot



2. The model time and the fitting(compared with naive knn)

### 3. Interpretation

Overall when  $k = 5$ , the accuracy is higher, this might be because in case  $k = 1$ , the model is overfitted.

## References

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