KNN Algorithm

1. To classify document d into class c

2. Define k-neighborhood N as k nearest neighbors (according to a given distance or similarity measure) of d

3. Count number of documents kc in N that belong to c

4. Estimate P(c|d) as kc/k

5. Choose as class argmaxc P(c|d) [= majority class]

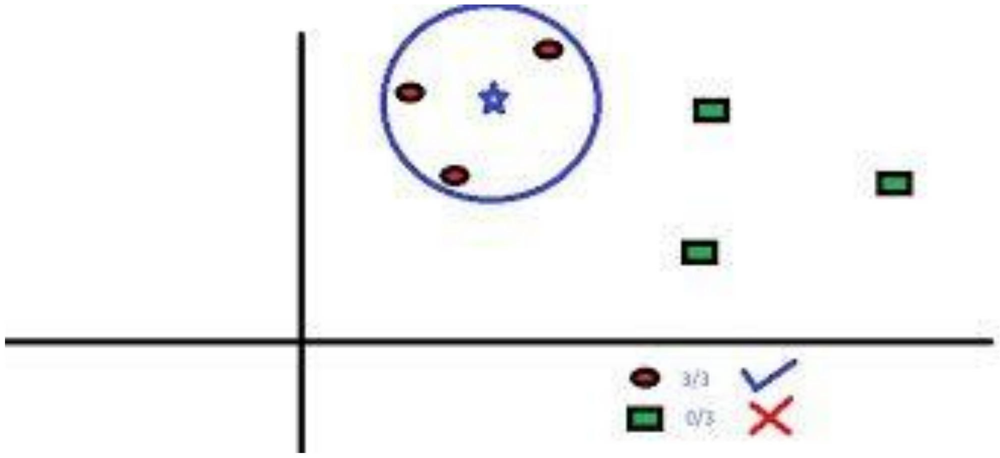
Finding similar rows

Distance functions

Euclidean $$\sqrt{\sum_{i=1}^{k}(x_i - y_i)^2}$$

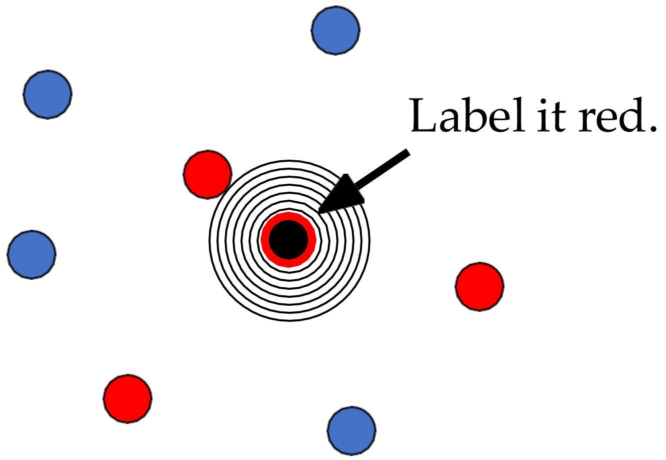
Manhattan $$\sum_{i=1}^{k}|x_i - y_i|$$

Minkowski $$\left(\sum_{i=1}^{k}(|x_i - y_i|)^q\right)^{1/q}$$



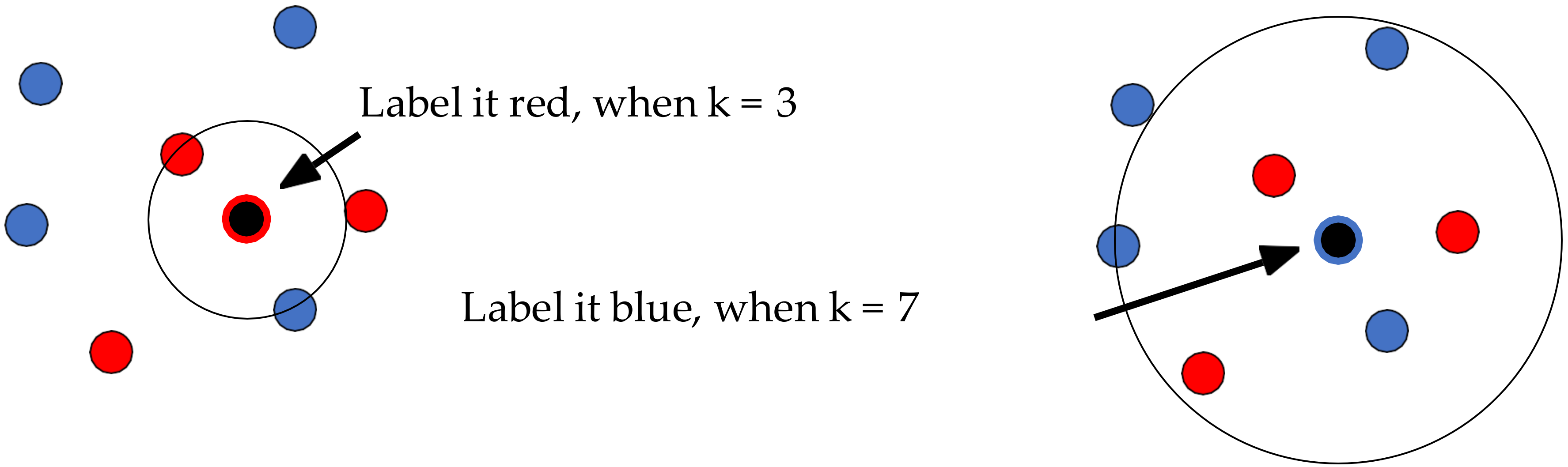
1-Nearest Neighbor

- One of the simplest of all machine learning classifiers
- Simple idea: label a new point the same as the closest known point



k – Nearest Neighbor

- Generalizes 1-NN to smooth away noise in the labels
- A new point is now assigned the most frequent label of its *k* nearest neighbors



KNN Example

	Food (3)	Chat (2)	Fast (2)	Price (3)	Bar (2)	BigTip
1	great	yes	yes	normal	no	yes
2	great	no	yes	normal	no	yes
3	mediocre	yes	no	high	no	no
4	great	yes	yes	normal	yes	yes

Similarity metric: Number of matching attributes (k=2)

- New examples:
  - Example 1 (great, no, no, normal, no) Yes
    - □ most similar: number 2 (1 mismatch, 4 match) □ yes
    - □Second most similar example: number 1 (2 mismatch, 3 match) □ yes
  - Example 2 (mediocre, yes, no, normal, no) Yes/No
    - □ Most similar: number 3 (1 mismatch, 4 match) □ no
    - □Second most similar example: number 1 (2 mismatch, 3 match) □ yes

We have data from survey (to ask people opinion) and objective testing with two attributes(acid durability and strength) to classify whether a special paper tissue is good or not. Here is four training samples

X1(Acid) in seconds	X2(Strength) in kg/square meter	Y = Classification
7	7	Bad
7	4	Bad
3	4	Good
1	4	Good

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Now the factory produces a new paper tissue that pass laboratory test with X1 = 3 and X2 = 7.

Without another expensive survey, can we guess what the classification of this new tissue is?

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X1(Acid) in seconds	X2(Strength) in kg/square meter	Square Distance to query instance(3,7)
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7	4	$(7-3)^2 + (4-7)^2 = 25$
3	4	$(3-3)^2 + (4-7)^2 = 9$
1	4	$(1-3)^2 + (4-7)^2 = 13$

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1	4	(1-3)^2 + (4-7)^2 = 13	2	Yes

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We have 2 good and 1 bad, since 2>1 then we conclude that a new paper tissue that pass laboratory test with X1 = 3 and X2 =7 is included in Good category

KNN – Distance

Age	Loan	Default	Distance
25	$40,000	N	102000
35	$60,000	N	82000
45	$80,000	N	62000
20	$20,000	N	122000
35	$120,000	N	22000
52	$18,000	N	124000
23	$95,000	Y	47000
40	$62,000	Y	80000
60	$100,000	Y	42000
48	$220,000	Y	78000
33	$150,000	Y	8000
48	**$142,000**	**?**	

Euclidean Distance

$$D = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2}$$

KNN – Standardized Distance

Age	Loan	Default	Distance
0.125	0.11	N	0.7652
0.375	0.21	N	0.5200
0.625	0.31	N	0.3160
0	0.01	N	0.9245
0.375	0.50	N	0.3428
0.8	0.00	N	0.6220
0.075	0.38	Y	0.6669
0.5	0.22	Y	0.4437
1	0.41	Y	0.3650
0.7	1.00	Y	0.3861
0.325	0.65	Y	0.3771
0.7	**0.61**	**?**	

Standardized Variable

$$X_s = \frac{X - Min}{Max - Min}$$

Behaviour

Large k : Smoother boundaries (class separating)

Large N : Large storage req. (space complexity)

Large p : lower accuracy (curse of dimensionality)

Step 1

```
import numpy as np
from sklearn.preprocessing import Imputer
from sklearn.cross_validation import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score
```

Step 2 - Import Data

Step 3

```
X_train, X_test, y_train, y_test = train_test_split(
 X, Y, test_size = 0.3, random_state = 100)
y_train = y_train.ravel()
y_test = y_test.ravel()
```

Step 4

```
for K in range(25):
 K_value = K+1
 neigh = KNeighborsClassifier(n_neighbors = K_value, weights='uniform', algorithm='auto')
 neigh.fit(X_train, y_train)
 y_pred = neigh.predict(X_test)
 print "Accuracy is ", accuracy_score(y_test,y_pred)*100,"% for K-Value:",K_value
```

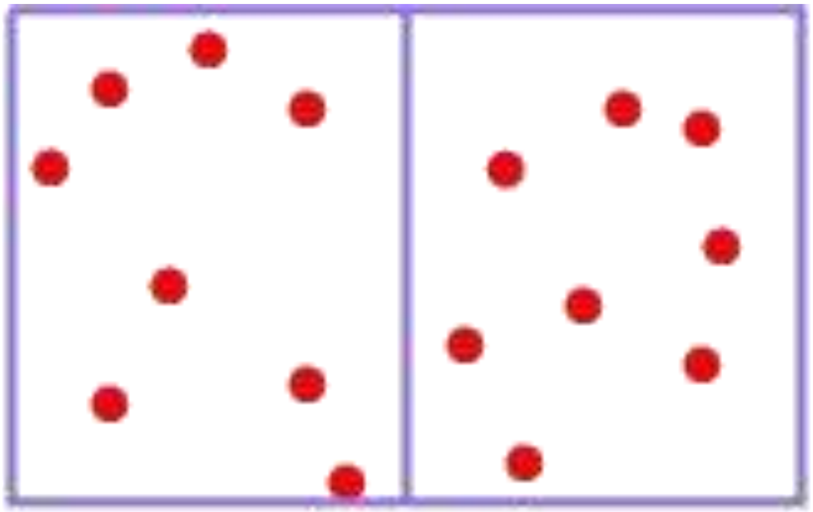
KNN Advantage

- Makes no assumptions about distributions of classes in feature space
- Can work for multi classes simultaneously
- Easy to implement and understand
- Not impacted by outliers

KNN Disadvantage

- Fixing the optimal value of K is a challenge
- Will not be effective when the class distributions overlap
- Does not output any models. Calculates distances for every new point (lazy learner)
- Computationally intensive (O(D(N^2))), can be addressed using KD algorithms which take time to prepare

1.



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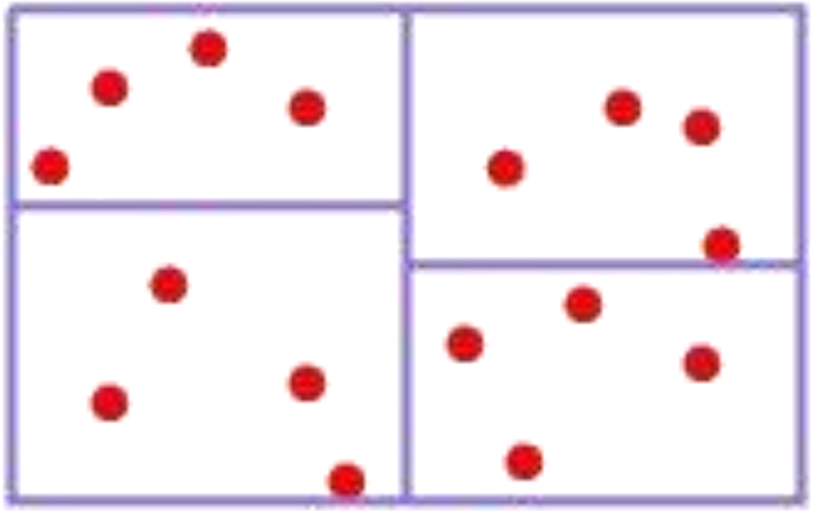

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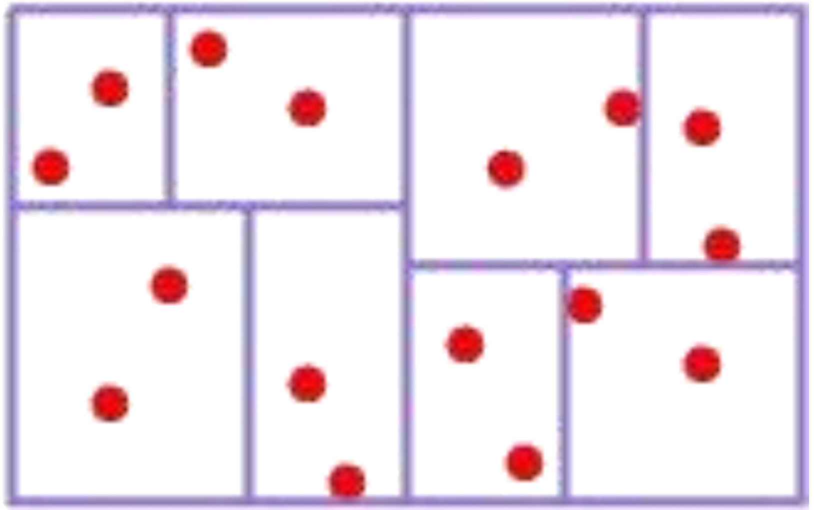

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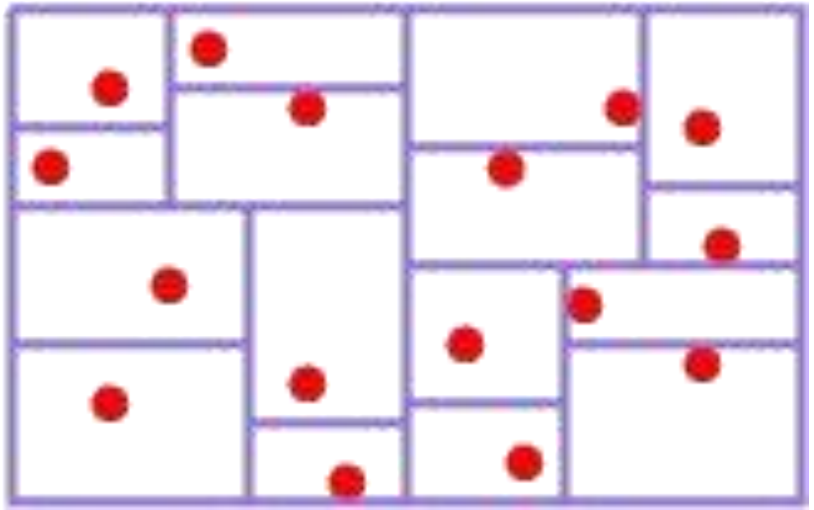

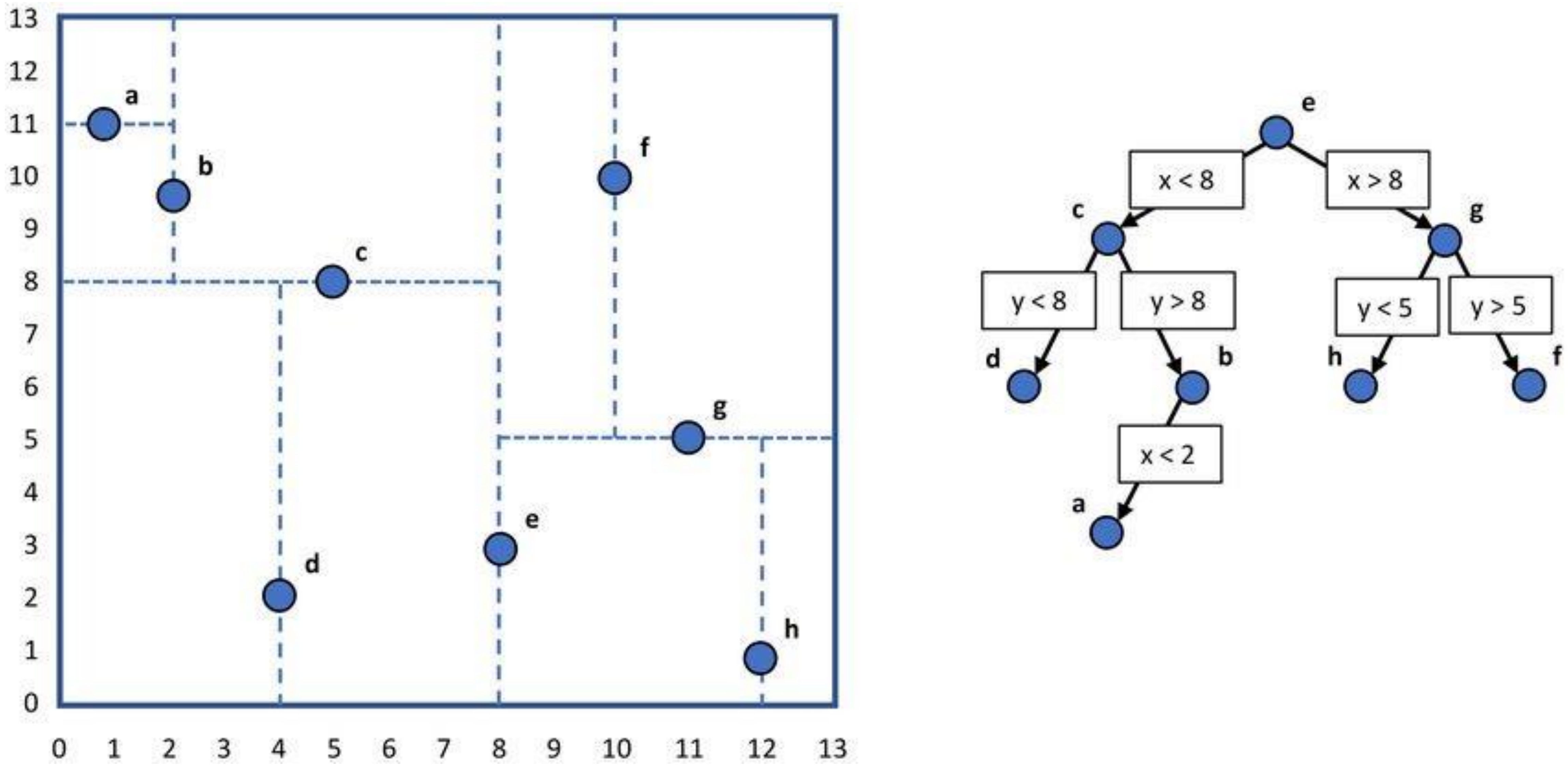

13
12
11
10
9
8
7
6
5
4
3
2
1
0
0 1 2 3 4 5 6 7 8 9 10 11 12 13
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c
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f
g
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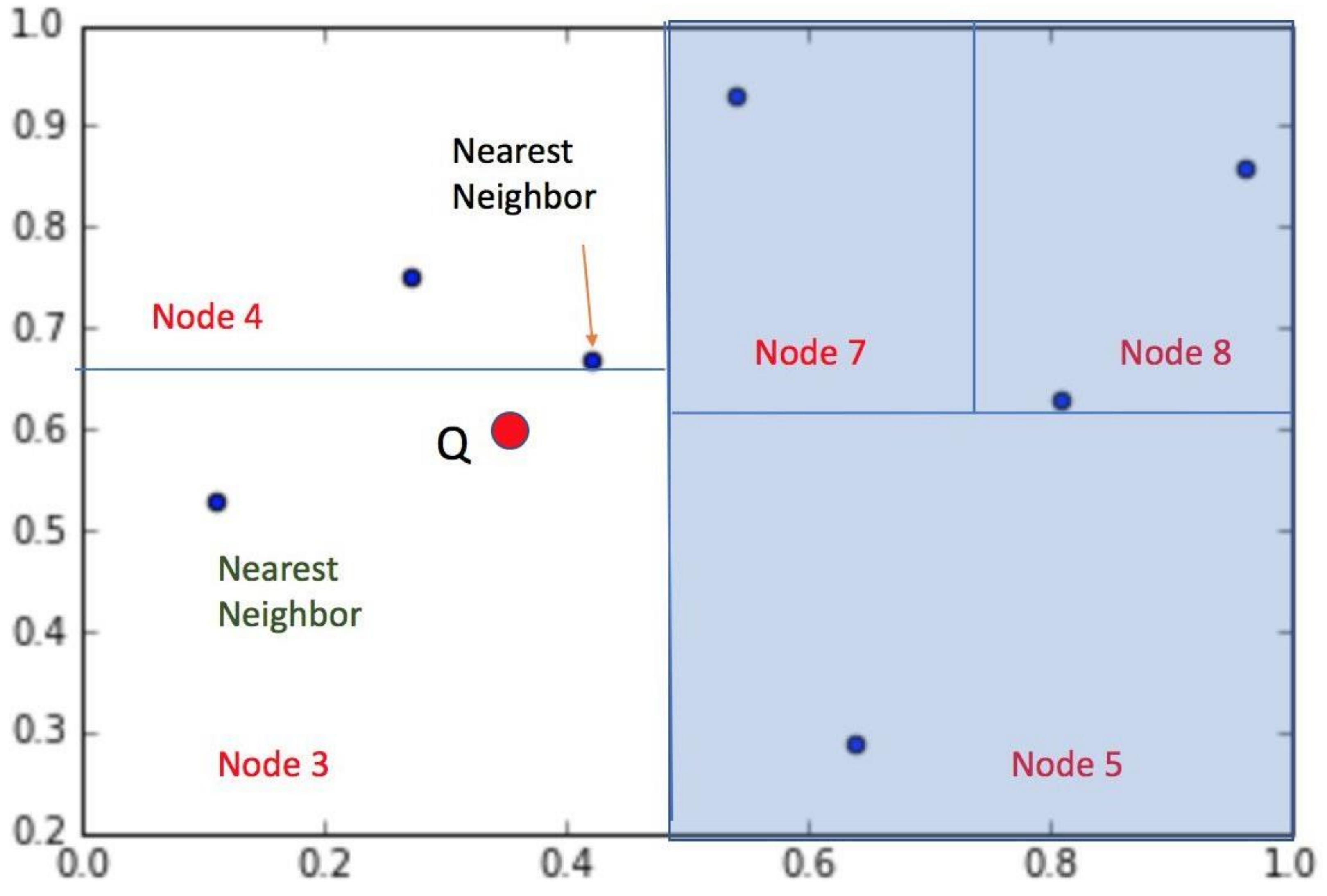
b
h
f
x < 2
a



Nearest Neighbor
Node 4
Q
Node 7
Node 8
Nearest Neighbor
Node 3
Node 5
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.0
0.2
0.4
0.6
0.8
1.0

THANK YOU