

# Classification of points in a euclidean space

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# Our problem

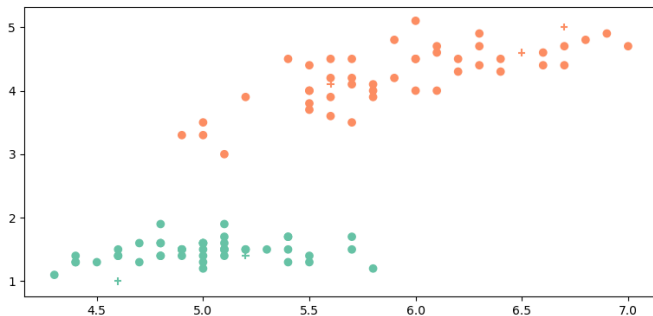


Figure – Classification problem in euclidean space

## Our problem

Let  $S$  be a set of  $I$  points of  $\mathbf{R}^d$ .

Each element of  $S$  has a known label  $y_i$  in  $\{-1, 1\}$ .

Let  $U$  be a set of  $\mathbf{R}^d$  points for which we don't know the labels.

We suppose that  $S$  and  $U$  come from the same ensemble.

We want to assign labels from  $\{-1, 1\}$  to the points of  $U$ .

# Our problem

A lot of ways to solve it :

- generative approach → learning the distribution of individual classes
  - Naives Bayes
  - Logistic regression
  - ...
- discriminative approach → learning the boundaries between classes
  - KNN
  - Random Forest
  - LDA
  - NNets
  - ...

# Our framework

Discriminative approach : KNN

- simple algorithm
- well performing
- non linear

→ we will deal with the multiclass case

# The KNN algorithm

## KNN principle (1)

In order to assign a label to an unknown point :

- 1 find the k-nearest neighbours according to a distance
- 2 take the majority of the corresponding labels ; if equality pick one randomly

## KNN principle (2)

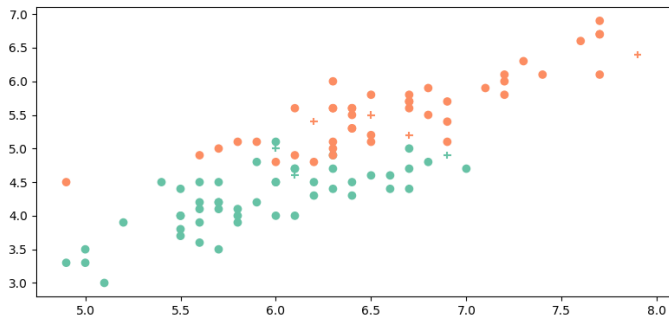


Figure – KNN example

# Naive KNN approach

Given an unknown point  $X$  :

- 1 compute all the distances :  
for  $s \in S, i \in I : \|s_i - X\|$
- 2 sort the distances and select the  $k$ -least
- 3 take the majority of the corresponding labels ; if equality pick one randomly

Given a space dimension  $d$ , research costs for one unknown point (assuming  $k \ll n$ ) :

- $O(d)$  per known point
- $O(nd)$  for the whole data set

Space complexity is  $O(dn)$



## How to improve naive knn ?

- approximate knn
- exact knn

→ based on pre-partitionning the space

# LSH approach

Random hyperplan  $\rightarrow$  hash function

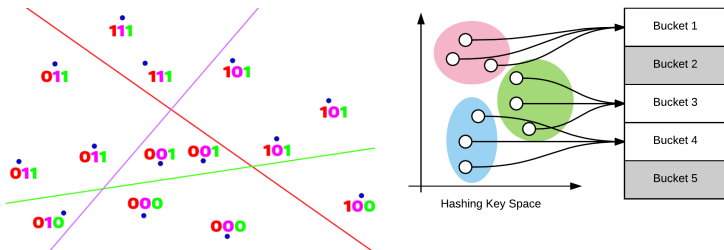


Figure – LSH

The region where falls the new point gives the candidates

Repeat it - gather candidates - compute distances

$$O(kd + \frac{nd}{2^k}) \approx O(d \log(n))$$

- └ KNN improvements
- └ approximate k-NN

# KD trees V1

- Find NNs for new point (7,4)

- find region containing (7,4)
- compare to all points in region

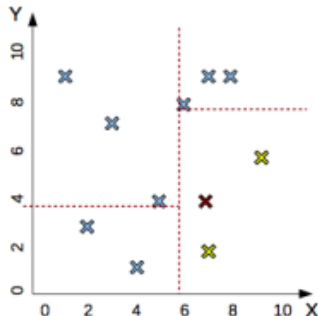
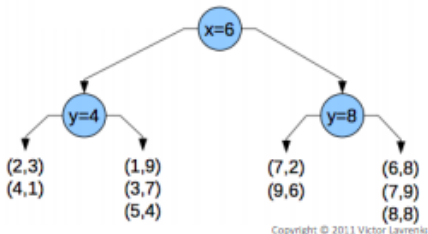


Figure – KD trees V1 (copyright V. Lavrenko)

$$O(\log(n) + kd)$$

## KD trees V2

→ KDtrees with exact NNs : our work !

## A simple example

We have the following dataset in a  $2d$  space :

$$X = \{(1, 3), (1, 8), (2, 2), (2, 10), (3, 6), (4, 1), (5, 4), (6, 8), \\ (7, 4), (7, 7), (8, 2), (8, 5), (9, 9)\}$$

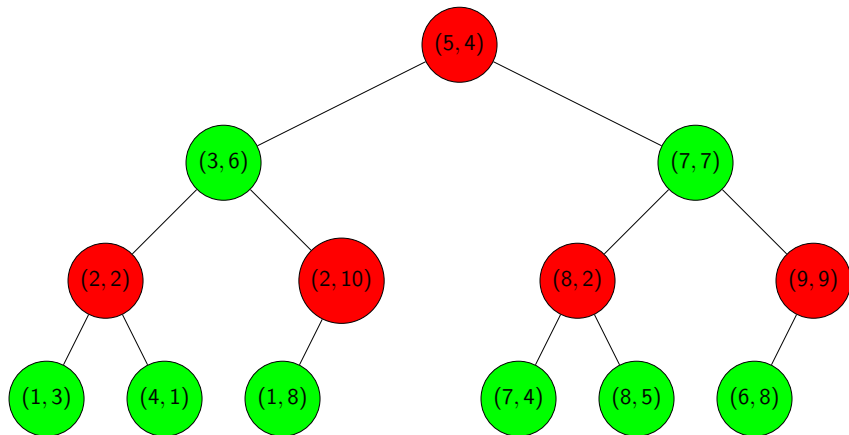
$$Y = \{Blue, Blue, Blue, Blue, Blue, Blue, Red, Red, Red, Red, \\ Red, Red, Red\}$$

We want to assign a color to the following point :  $(4, 8)$

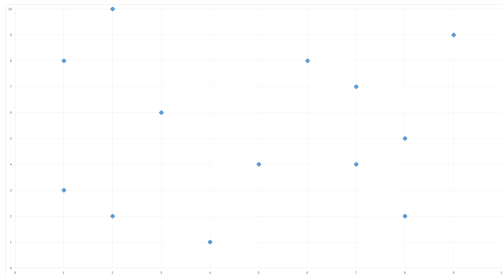
## How to optimize k-nn search

We use a data structure known as a k-d tree.

## building the k-d tree



# How do we partition the space ?

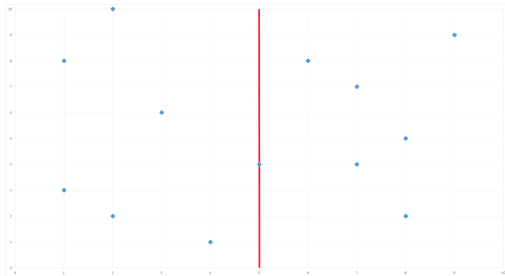




└ KNN improvements

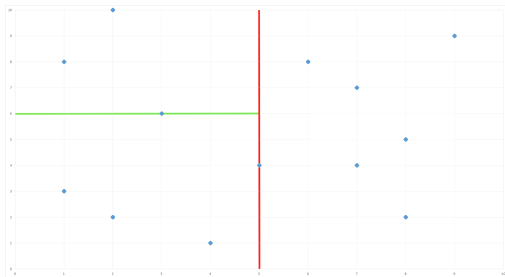
└ Exact knn

## How do we partition the space ?



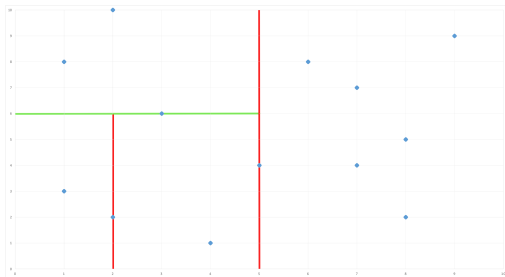
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# How do we partition the space?



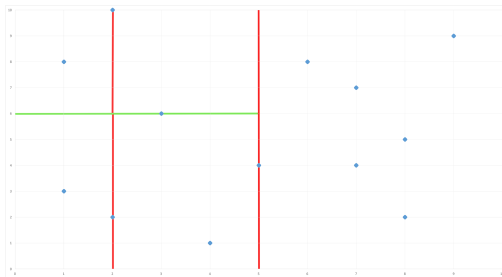
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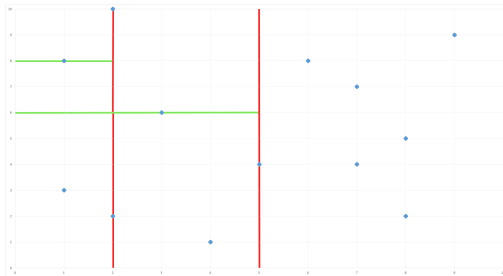
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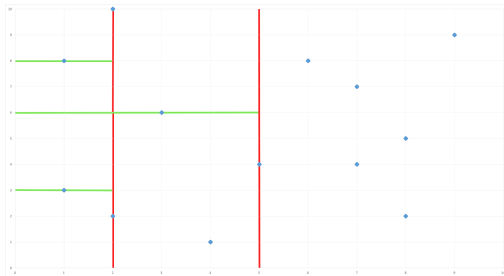
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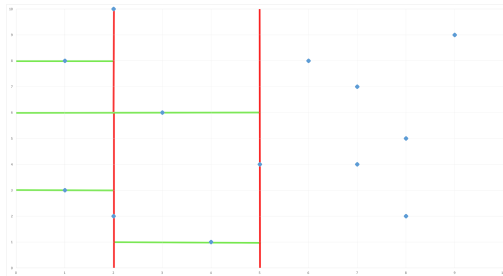


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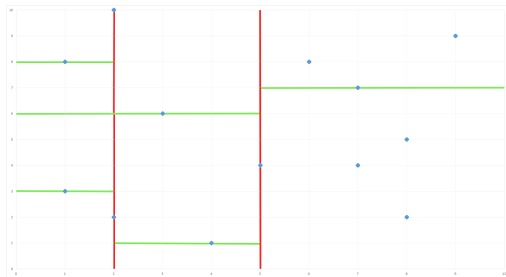


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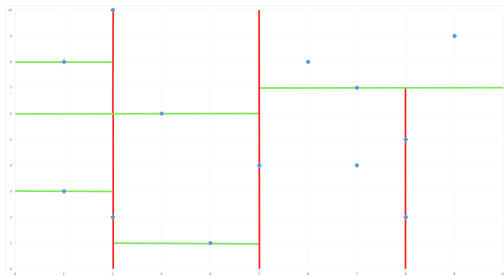
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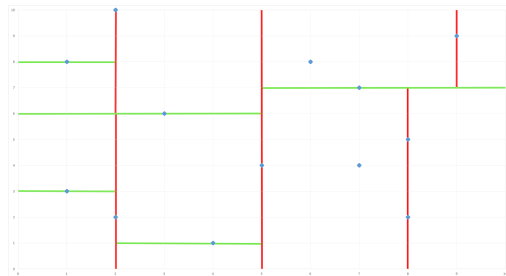
# How do we partition the space?



└ KNN improvements

└ Exact knn

# How do we partition the space?

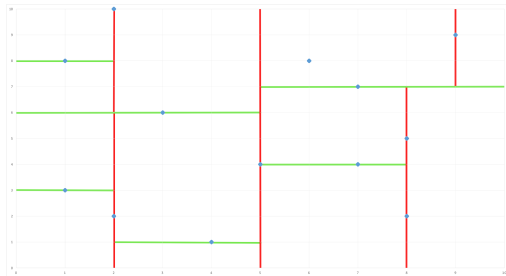


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└ KNN improvements

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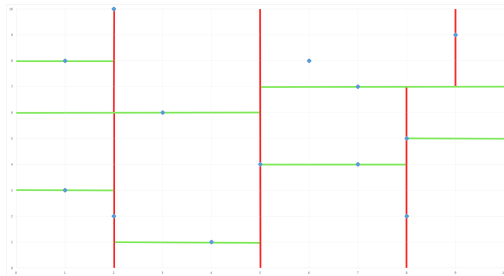


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└ KNN improvements

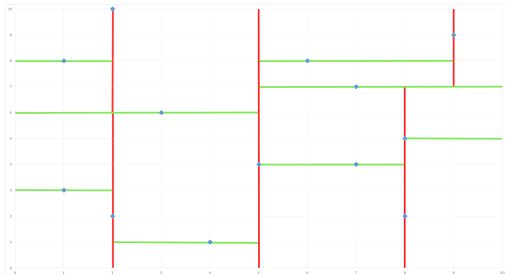
└ Exact knn

# How do we partition the space?



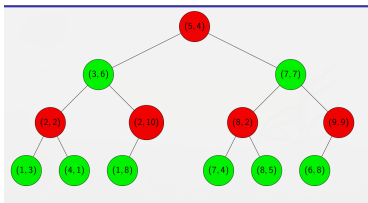
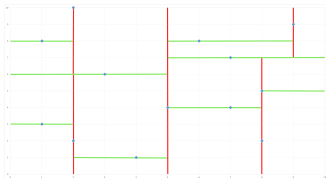
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# How do we partition the space?



4

# how do we find the k nearest neighbours?



# What is the time complexity ?

For the tree creation (best case) :

$$\begin{aligned}
 T(n) &= n \log(n) + 2T\left(\frac{n}{2}\right) \\
 &= n \log(n) + 2\left(\frac{n}{2} \log\left(\frac{n}{2}\right) + 2T\left(\frac{n}{4}\right)\right) \\
 &= n \log(n) + n \log\left(\frac{n}{2}\right) + 4T\left(\frac{n}{4}\right) \\
 &= n \log(n) + n \log\left(\frac{n}{2}\right) + n \log\left(\frac{n}{4}\right) + \dots + n \log\left(\frac{n}{2^{\log(n)}}\right) \\
 &= n \sum_{i=0}^{\log(n)} \log\left(\frac{n}{2^i}\right) \\
 &= O\left(n \sum_{i=0}^{\log(n)} \log(n)\right) \\
 &= O(n \log^2(n))
 \end{aligned}$$

# What is the time complexity ?

For the tree creation (worst case) :

$$\begin{aligned}T(n) &= n^2 + 2T\left(\frac{n}{2}\right) \\&= n^2 + 2\left(\left(\frac{n}{2}\right)^2 + 2T\left(\frac{n}{4}\right)\right) \\&= \sum_{i=0}^{\log(n)} \frac{n^2}{2^i} \\&= n^3(2 - 2^{-\log(n)}) \\&= O(n^3)\end{aligned}$$



# what is the time complexity

time complexity of our full program :

- For the nearest neighbour search :
  - best :  $T(n) = O(\log(n)d)$
  - worst :  $T(n) = O(nd) \equiv \text{depth-first traversal}$
- For k-nearest neighbours of  $p$  points :
  - best :
    - if  $pd > n\log(n) \Rightarrow T(n) = O(pd\log(n))$
    - otherwise  $T(n) = O(n\log^2(n))$
  - worst :
    - if  $pd > n^2 \Rightarrow T(n) = O(pdn)$  (very unlikely)
    - otherwise  $T(n) = O(n^3)$

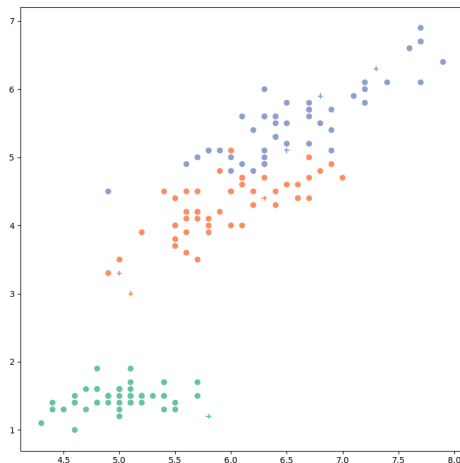
Most of the complexity is due to tree creation.

$k$ -fold cross validation does not increase complexity unless the number of folds is very high.

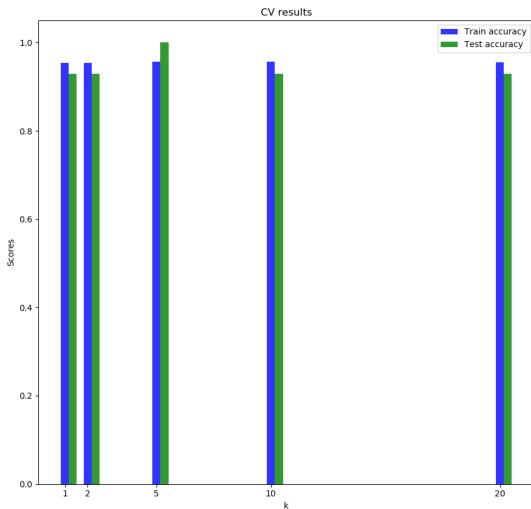
└ KNN improvements

└ Exact knn

# How does our program perform ?



# How does our program perform ?



does it work for bigger spaces?

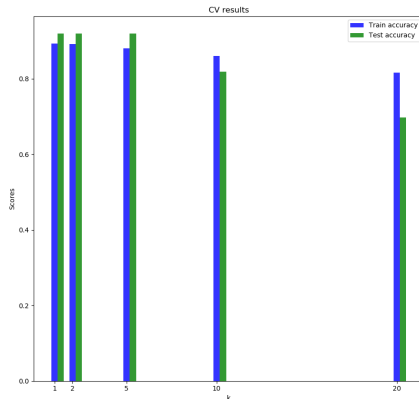


Figure – CV results on leaf dataset ( $d=192$ , 99 classes,  $n=990$ )

- Implement approximative in CV then apply exact Knn with optimal  $k$
- be able to handle categorical data
- implement faster median selection algorithm (for faster tree creation)

## sources |

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