#### Classification of points in a euclidean space

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#### Our problem

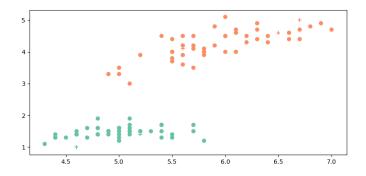


Figure – Classification problem in euclidean space

#### Our problem

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

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

Let U be a set of  $R^d$  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 :

- 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)

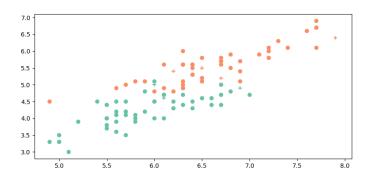


Figure - KNN example

#### Naive KNN approach

Given an unknown point X:

- 1 compute all the distances : for  $s \in S$ ,  $i \in I$  :  $||s_i X||$
- 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
- $\rightarrow$ based on pre-partionning the space

#### LSH approach

#### Random hyperplan →hash function

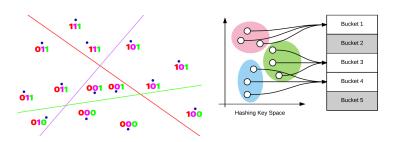


Figure – LSH

The region where falls the new point gives the candidates Repeat it - gather candidates - compute distances  $o(kd + \frac{nd}{2k}) \approx o(dlog(n))$ 

#### KD trees V1

Find NNs for new point (7,4)

- find region containing (7,4)

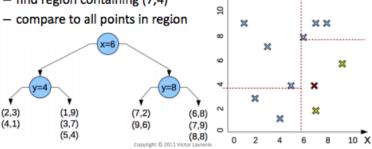


Figure - KD trees V1 (copyright V. Lavrenko)

$$o(log(n) + kd)$$

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└─KNN improvements └─Exact knn

#### KD trees V2

 $\rightarrow$ 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)

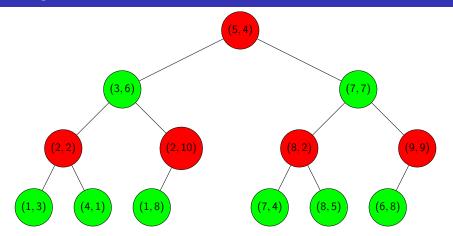
#### How to opitimze k-nn search

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

KNN improvements

Exact knn

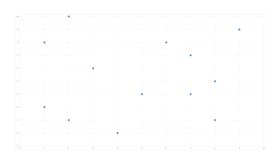
#### building the k-d tree

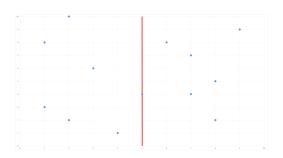


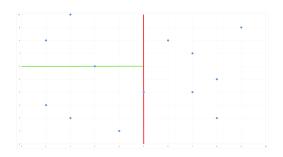
KNN improvements

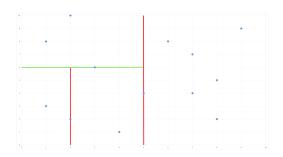
Exact knn

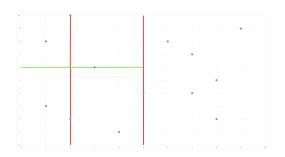
# How do we partition the space?



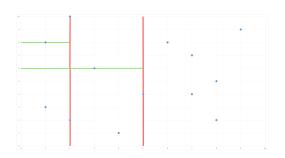


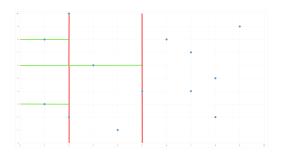


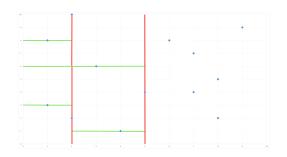


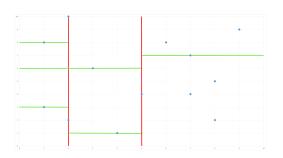


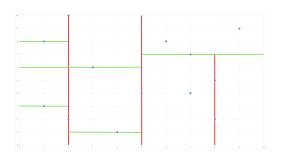
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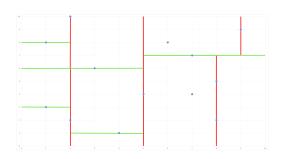


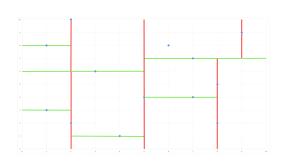


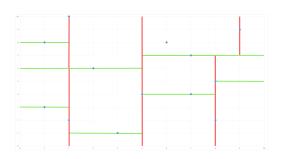


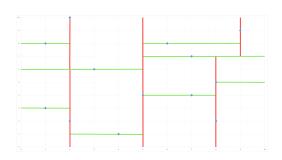








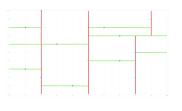


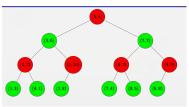


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Exact knn

# how do we find the k nearest neighbours?





# What is the time complexity?

For the tree creation (best case):

$$T(n) = n\log(n) + 2T\left(\frac{n}{2}\right)$$

$$= n\log(n) + 2\left(\frac{n}{2}\log\left(\frac{n}{2}\right) + 2T\left(\frac{n}{4}\right)\right)$$

$$= n\log(n) + n\log\left(\frac{n}{2}\right) + 4T\left(\frac{n}{4}\right)$$

$$= n\log(n) + n\log\left(\frac{n}{2}\right) + n\log\left(\frac{n}{4}\right) + \dots + n\log\left(\frac{n}{2\log(n)}\right)$$

$$= n\sum_{i=0}^{\log(n)}\log\left(\frac{n}{2^{i}}\right)$$

$$= o\left(n\log^{2}(n)\right)$$

$$= o(n\log^{2}(n))$$

### What is the time complexity?

For the tree creation (worst case):

$$T(n) = n^2 + 2T\left(\frac{n}{2}\right)$$

$$= n^2 + 2\left(\left(\frac{n}{2}\right)^2 + 2T\left(\frac{n}{4}\right)\right)$$

$$= \sum_{i=0}^{\log(n)} \frac{n^2}{2^i}$$

$$= n^3(2 - 2^{-\log(n)})$$

$$= o(n^3)$$

### what is the time complexity

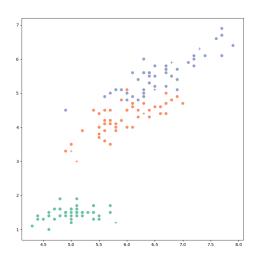
time complexity of our full program:

- For the nearest neighbour search :
  - best : T(n) = o(log(n)d)
  - worst :  $T(n) = o(nd) \equiv depth$ -first traversal
- For k-nearest neighbours of *p* points :
  - best :
    - if  $pd > nlog(n) \Rightarrow T(n) = o(pdlog(n))$
    - 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.

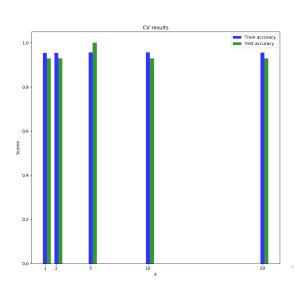
*k*-fold cross validation does not increase complexity unless the number of folds is very high.

# How does our program perform?



└─KNN improvements └─Exact knn

# How does our program perform?



# does it work for bigger spaces?

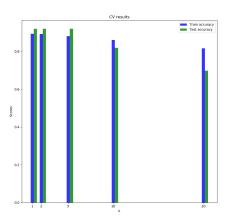


Figure – CV results on leaf dataset (d=192, 99 classes, n=990)

- 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)