

# ***Data Mining and Machine Learning***

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## LECTURE 10: Supervised classification: k-nn classifiers

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The k nearest neighbors method (Fix y Hodges, 1951) is used to estimate the density function of a random variable.

In the supervised classification context the k-nn method is used to estimate the class conditional density  $f(\mathbf{x}/C_j)$ , of the predictors  $\mathbf{x}$  in a given class  $C_j$ .

k-nn is a nonparametric method since none assumption on the distribution of the predictors is made.

## K-nn univariate density estimation

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- Let  $x_1, x_2, \dots, x_n$  be a random sample from a unknown density function  $f(x)$ , and let  $t$  a real number where  $f$  is going to be estimated.
- Recall that the probability of  $x$  lies in the interval  $(t-h, t+h)$ , can be approximated by  $2hf(t)$ , where  $f$  is the density function and  $h$  is a constant near to zero.

On the other hand, such probability can also be estimated by  $k/n$ , where  $k$  is the number of observations in the interval  $(t-h, t+h)$ . In k-nn estimation,  $k$  is pre-fixed and  $h$  is computed according to  $k$ .

Formally, let  $d(x, y) = |x - y|$  be the usual distance between the points  $x$  and  $y$  of the real line.

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Suppose that we have computed all the distances  $d(x_i, t) = |x_i - t|$  and that these are ordered in an increasing way, such as:

$$d_1(t) \leq d_2(t) \leq \dots \leq d_n(t)$$

- The estimator of the density function at the point  $t$  using  $k$  nearest neighbors is given by:

$$\hat{f}(t) = \frac{k}{2nd_k(t)}$$

## Example: Density estimation

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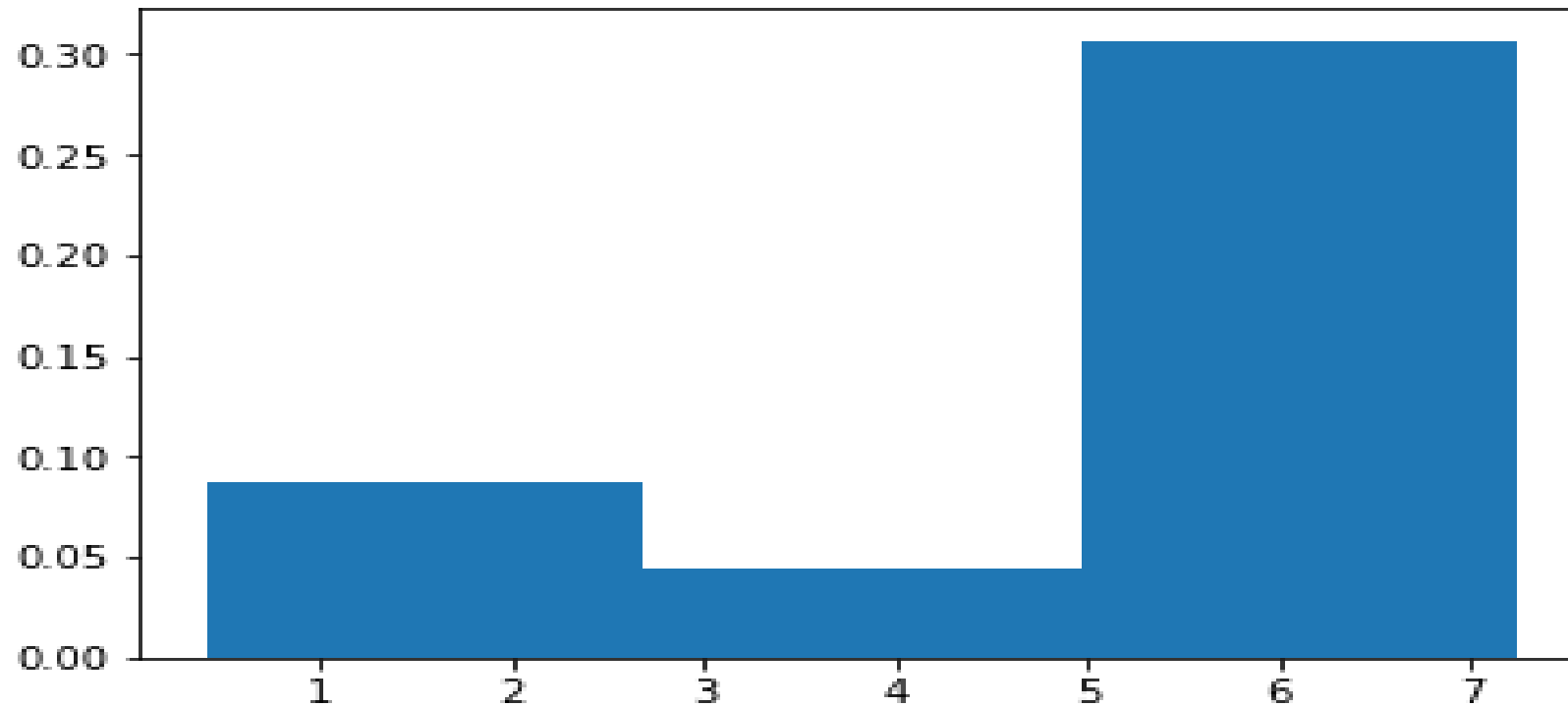
Given the following sample of size  $n=10$ , estimate the its density function

7.03860 6.38018 6.95461 2.25521 7.24608 6.62930 3.92734 0.40701 5.59448 5.05751

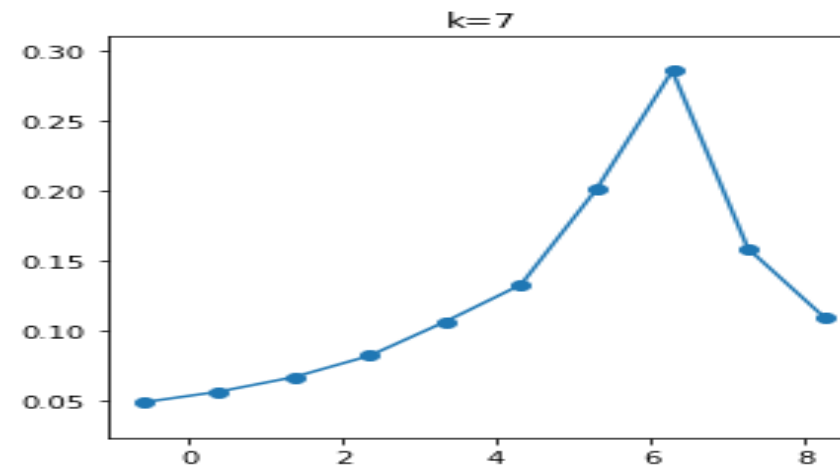
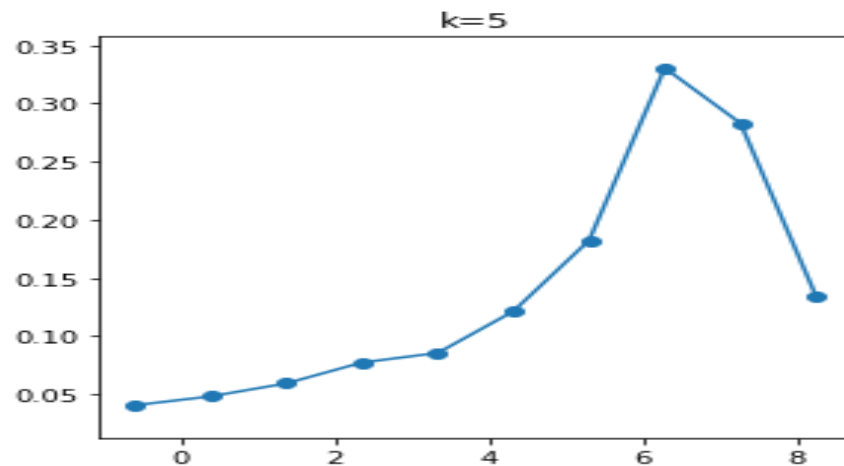
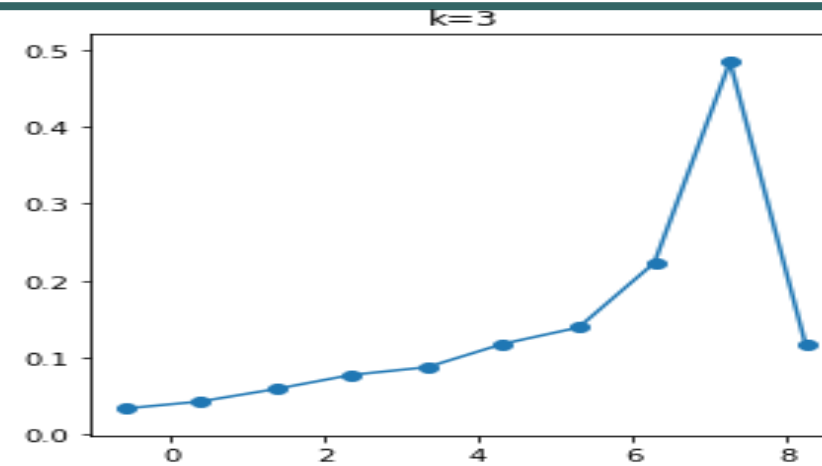
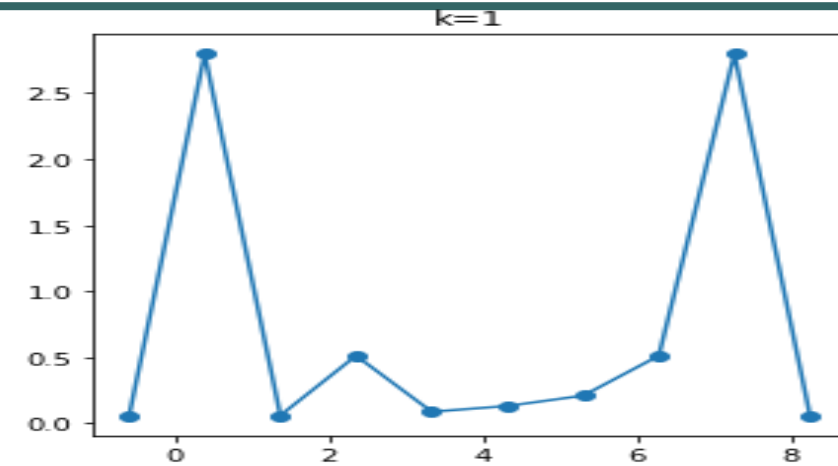
The normalized histogram (area = 1) is shown in the next slide.  
Notice that this density estimator is not continuous.

# Density estimation using histogram

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# Knn density estimation for several values of k



# Multivariate k-nn density estimation

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- The estimate of the density function is given by

$$\hat{f}(\mathbf{x}) = \frac{k}{nv_k(\mathbf{x})}$$

- where  $v_k(\mathbf{x})$  is the volume of the ellipsoid centered at  $\mathbf{x}$  and with radius  $r_k(\mathbf{x})$ , which is the distance of  $\mathbf{x}$  to the  $k$ -th nearest point.



# The k-nn classifier

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In supervised classification the k-nn algorithm is very easy to apply (Cover and Hart, 1967)

In fact, if the conditional density function  $f(\mathbf{x}/C_i)$  of class  $C_i$  that appears in the posterior probability expression

$$P(C_i / \mathbf{x}) = \frac{f(\mathbf{x} / C_i) \pi_i}{f(\mathbf{x})}$$

Is estimated using k-nn, then to classify an object, with measurements given by the vector  $\mathbf{x}$ , into class  $C_i$ , it has to hold

$$\frac{k_i \pi_i}{n_i v_k(\mathbf{x})} > \frac{k_j \pi_j}{n_j v_k(\mathbf{x})}$$

for  $j \neq i$ , where  $k_i$  y  $k_j$  are the  $k$  neighbors in classes  $C_i$  and  $C_j$  respectively.

## The k-nn classifier (cont)

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Assuming proportional priors to the size of the classes ( $n_i/n$  and  $n_j/n$ , respectively) the last equation is equivalent to:

$$k_i > k_j \text{ para } j \neq i$$

Then, the classification of an object  $\mathbf{x}$  will be as it follows:

- 1) Find the  $k$  objects that are closer in distance to the object  $\mathbf{x}$ ,  $k$  usually is an odd number: 1, 3 etc. to avoid ties.
- 2) If the majority of these  $k$  objects belong to class  $C_i$ , then object  $\mathbf{x}$  is assigned to that class.

In case of a tie, the class is assigned randomly.

## The k-nn classifier (cont)

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- The k-nn method has two problems; the distance to be chosen and the election of the number of neighbors  $k$ .
- The most elementary distance that can be chosen is the Euclidean distance given by  $d(\mathbf{x}, \mathbf{y}) = (\mathbf{x} - \mathbf{y})'(\mathbf{x} - \mathbf{y})$ . This distance may cause problems when the predictors have very different scale of measurement. It is a good idea to normalize the data before applying k-nn. Other distance that can be used is the Manhattan distance given by  $d(\mathbf{x}, \mathbf{y}) = |\mathbf{x} - \mathbf{y}|$ .
- When there are attributes of mixed type, there are two options: First, use distance for mixed among records with mixed attributes (Gower distance). Second, encode the nominal attributes into numerical ones and use Euclidean Distance.
- Enas and Choi (1996), using simulation, performed an experiment to determine the optimal value of  $k$  for the two class problem and they found  $k = n^{3/8}$  when the covariance matrices of the two groups are similar and  $k = n^{2/8}$  when the covariance matrices of the two groups are very different. In here,  $n$  = number of instances.

## The k-nn classifier (cont)

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- The bias of the misclassification error increases as  $k$  increases, but the variance decreases.
- Cover and Hart (1967) showed that the misclassification error rate of a  $k$ -nn classifier is at most 2 times the optimal error rate (error of a Bayesian classifier where the posterior are explicitly known).

## Example: Predicting final grade

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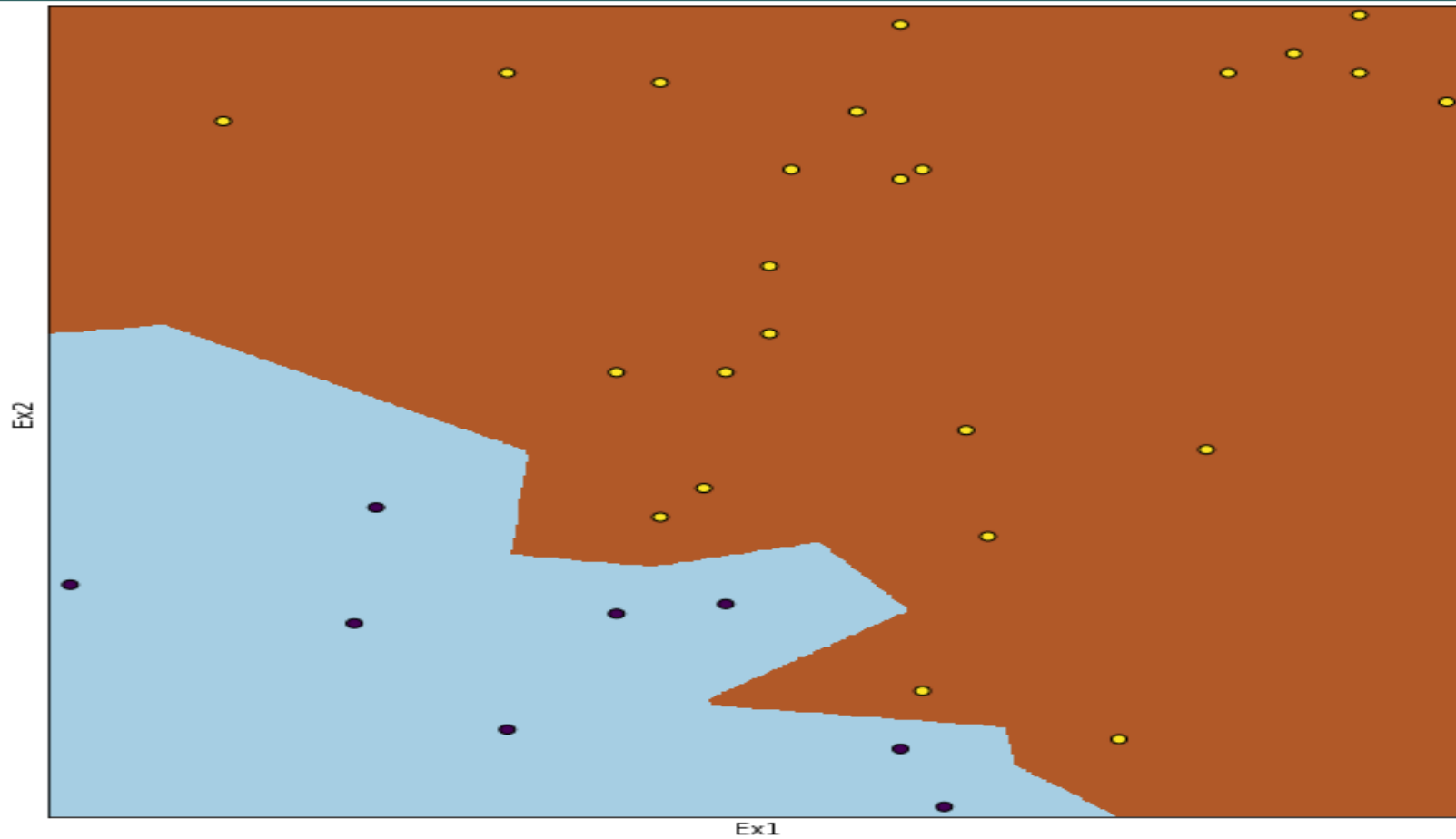
```
df=pd.read_csv("c://PW-PR/eje1dis.csv")
#Extracting the predictor matrix and the class column
y=df['Nota']
X=df.iloc[:,0:2]
#creating a numerical class column "pass"
lb_make = LabelEncoder()
df["pass"] = lb_make.fit_transform(df["Nota"])
#Tambien se puede usar y.as_matrix() para la clasificacion
y1=df["pass"].as_matrix()
X1=X.as_matrix()
#Constructing the classifier
neigh = KNeighborsClassifier(n_neighbors=3)
neigh.fit(X1, y1)
```

## Example: Predicting final grade (cont)

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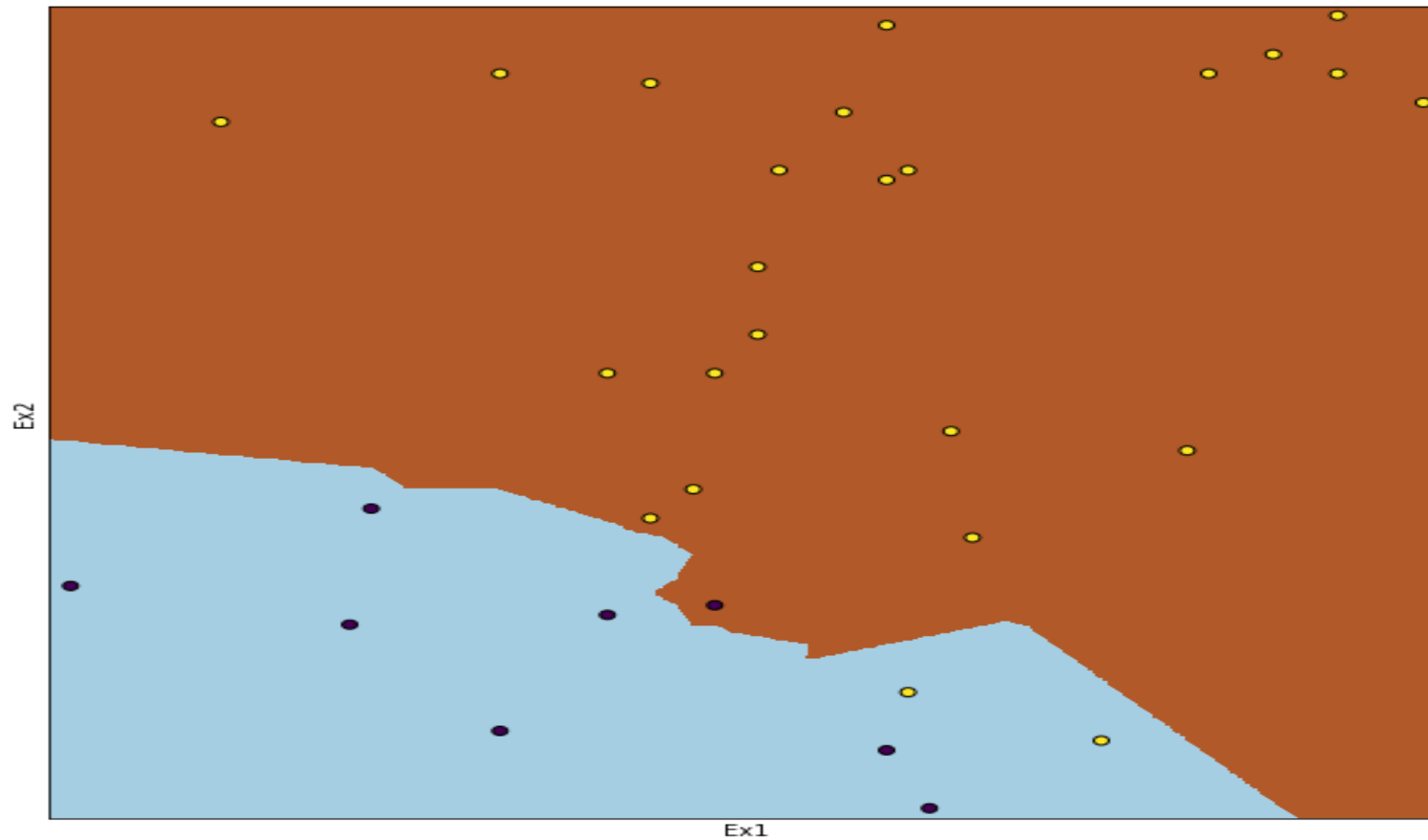
```
#Making the predictions
pred=neigh.predict(X1)
print predprint pred
[1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 0 0 0 0 0 0 0]
#Calculating the number of errors
error=(y!=pred).sum()
print "This is the number of errors=", error
This is the number of errors= 0
```

## Example: Decision boundary( $k=1$ )



## Example: Decision Boundary (k=7)

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## Example: Diabetes

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```
url= "http://academic.uprm.edu/eacuna/diabetes.dat"
names = ['preg', 'plas', 'pres', 'skin', 'test', 'mass', 'pedi', 'age', 'class']
data = pd.read_table(url, names=names)
y=data['class']
X=data.iloc[:,0:8]
y1=y.as_matrix()
X1=X.as_matrix()
#Estimacion de la precision usando k=5 vecinos usando validacion cruzada
from sklearn.model_selection import cross_val_score
neigh = KNeighborsClassifier(n_neighbors=5)
scores = cross_val_score(neigh, X1, y1, cv=10)
scores
ray([ 0.67532468, 0.79220779, 0.71428571, 0.67532468, 0.66233766, 0.74025974, 0.7012987 , 0.79220779,
      0.71052632, 0.75 ])
print("Accuracy using k=5 neighbors: %0.2f (+/- %0.2f)" % (scores.mean(), scores.std() * 2))
Accuracy using k=5 neighbors: 0.72 (+/- 0.09)
```

# Applying k-nn to handwritten digit recognition

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The MNIST dataset was introduced by LeCun and Cortes (1998), The training dataset consists of 60k images of the digits 0 to 9 and the test dataset consists of 10k images. Each row of the datasets has 785 entries containing 784 pixels (28x28)

and the first entry is the digit label.

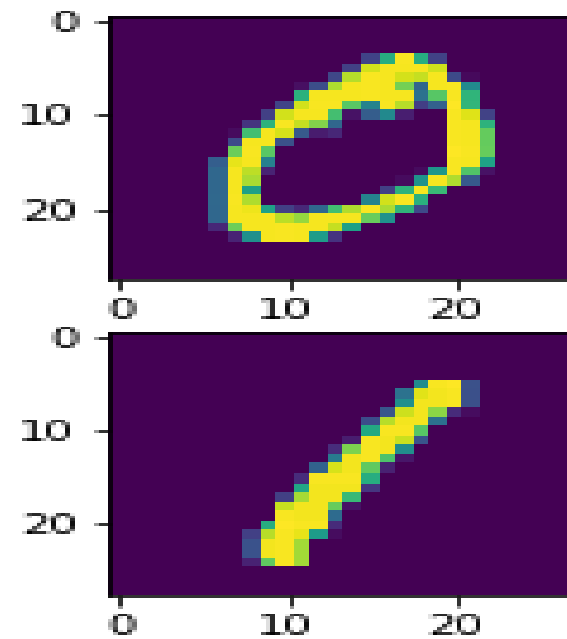
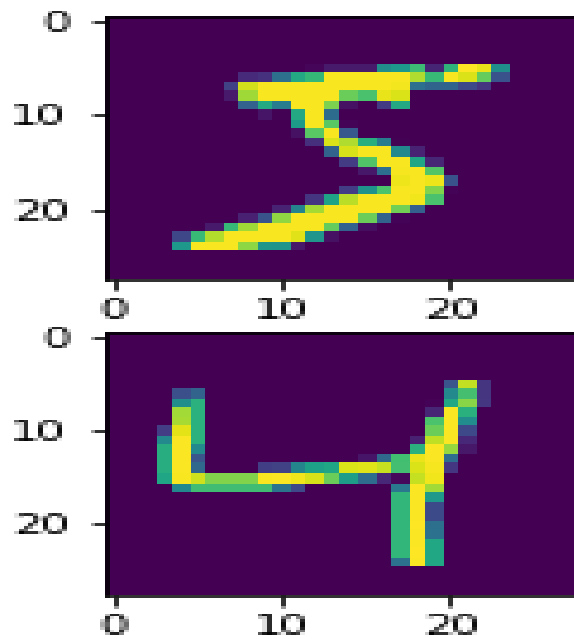
The datasets formatted as csv are available at <https://pjreddie.com/> The training dataset is 104MB and the test is 17MB.

Scikit-learn has a very small subset of the MNIST dataset

Visualizing the digits:

# Visualizing some rows of MNIST

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# Applying Knn to a subset of MNIST

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It takes more than 10 minutes to work with the full dataset, therefore we will use an small subset available in scikit-learn

```
# load el MNIST digits dataset
mnist = datasets.load_digits()
print ("the number of records is:",len(mnist.data))
the number of records is: 1797
# Training and testing split,
# 75% for training and 25% for testing
(trainData, testData, trainLabels, testLabels) = train_test_split(np.array(mnist.data), mnist.target,
test_size=0.25, random_state=42)
# Showing the size of each data split
print("training data points: {}".format(len(trainLabels)))
print("testing data points: {}".format(len(testLabels)))
```

## Applying Knn to a subset of MNIST (cont)

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```
# Applying k-nn with k-5
model = KNeighborsClassifier(n_neighbors=5)
model.fit(trainData, trainLabels)

# Predicting the tesData labels
predictions = model.predict(testData)

# Evaluating the performance of the classifier for each digit
print("EVALUATION ON TESTING DATA")
print(classification_report(testLabels, predictions))
```

# Applying Knn to a subset of MNIST (cont)

---

```
# Applying k-nn with k-5
model = KNeighborsClassifier(n_neighbors=5)
model.fit(trainData, trainLabels)

# Predicting the tesData labels
predictions = model.predict(testData)

# Evaluating the performance of the classifier for each digit
print("EVALUATION ON TESTING DATA")
print(classification_report(testLabels, predictions))
```

# Applying Knn to a subset of MNIST (cont)

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## EVALUATION ON TESTING DATA

precision recall f1-score support

0 1.00 1.00 1.00 43

1 1.00 1.00 1.00 37

2 1.00 1.00 1.00 38

3 1.00 1.00 1.00 46

4 0.98 1.00 0.99 55

5 0.98 0.98 0.98 59

6 1.00 1.00 1.00 45

7 1.00 1.00 1.00 41

8 1.00 1.00 1.00 38

9 0.98 0.96 0.97 48

Most of the digits are predicted with 100% of accuracy

## Other nonparametric classifier

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- Based on kernel density estimation( mixtures of continuous densities). But theirs disadvantage is that they are computationally expensive. The most used is the Gaussian Kernel.
- In general, a nonparametric method suffers of the curse of the dimensionality problem. The number of instances must grow almost exponentially to the number of predictor to have a good estimation.