Instance-based Classifiers

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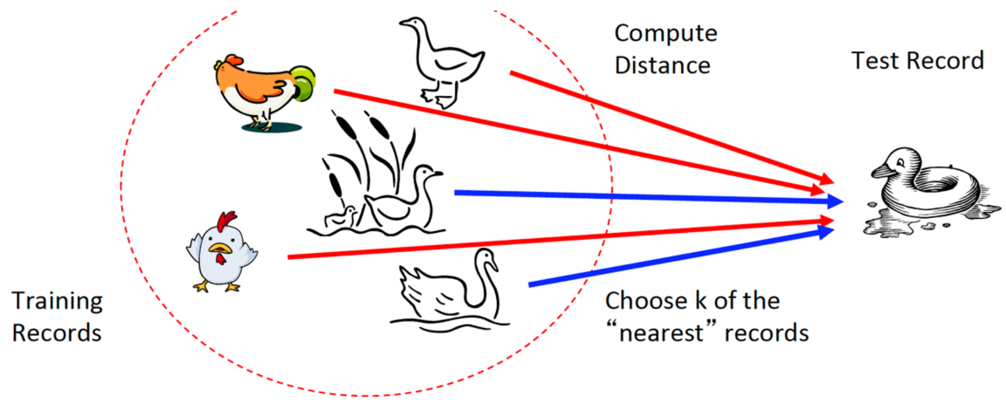
Introduction to Data Mining, 2nd Edition
Chapter 5.2

Instance-based Classifiers

- Instead of performing explicit generalization, compare new instances with instances seen in training, which have been stored in memory.
- Sometimes called **memory-based** learning.
- **Advantages**
  - Adapt its model to previously unseen data by storing a new instance or throwing an old instance away.
- **Disadvantages**
  - Lazy learner: it does not build a model explicitly.
  - Classifying unknown records is relatively expensive: in the worst case, given *n* training items, the complexity of classifying a single instance is *O(n)*.

Nearest-Neighbor Classifier (K-NN)

Basic idea: If it walks like a duck, quacks like a duck, then it's probably a duck.



Requires three things

1. **Training set** of stored records
2. **Distance metric** to compute distance between records
3. **The value of k**, the number of nearest neighbors to retrieve

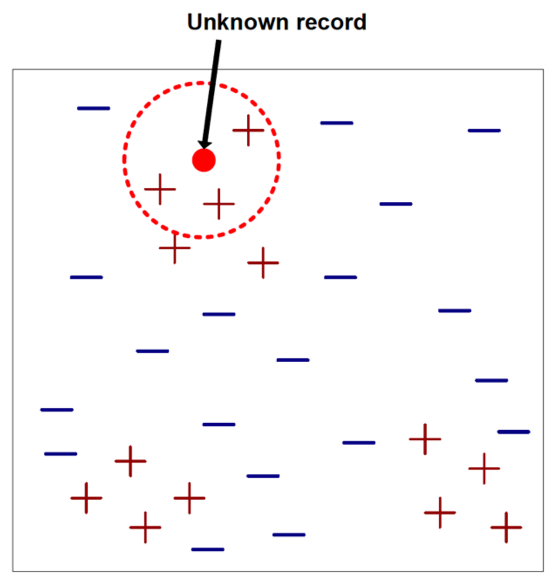
Nearest-Neighbor Classifier (K-NN)

Algorithm 5.2 The k-nearest neighbor classification algorithm.

Let k be the number of nearest neighbors and D be the set of training examples.
for each test example $z = (\mathbf{x}', y')$ **do**
    Compute $d(\mathbf{x}', \mathbf{x})$, the distance between z and every example, $(\mathbf{x}, y) \in D$.
    Select $D_z \subseteq D$, the set of k closest training examples to z.
    $y' = \underset{v}{\operatorname{argmax}} \sum_{(\mathbf{x}_i, y_i) \in D_z} I(v = y_i)$
end for

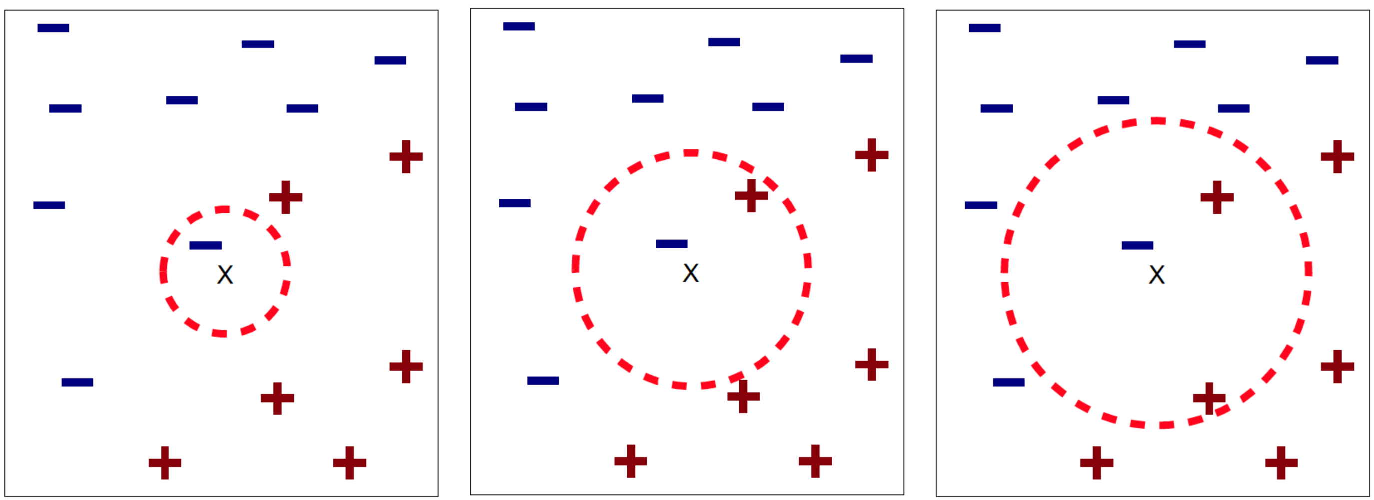
Given a set of training records (memory), and a test record:

1. **Compute the distances** from the records in the training to the test.
2. **Identify the k "nearest" records**.
3. Use class labels of nearest neighbors to **determine the class label** of unknown record (e.g., by taking majority vote).



Definition of Nearest Neighbor

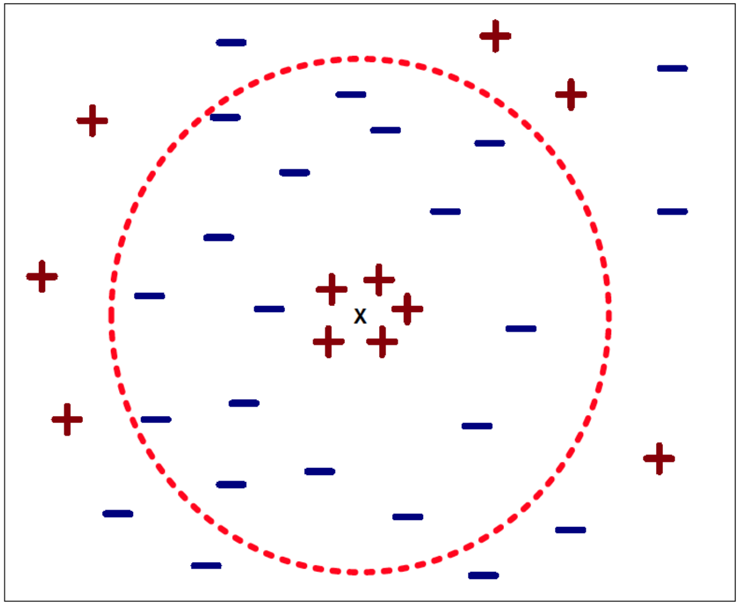
- *K*-nearest neighbors of a record *x* are data points that have the *k* smallest distance to *x*.



(a) 1-nearest neighbor (b) 2-nearest neighbor (c) 3-nearest neighbor

Choosing the Value of K

- If k is too **small**, it is sensitive to **noise** points and it can lead to overfitting to the noise in the training set.
- If k is too **large**, the neighborhood may **include** points from **other classes**.
- General practice **k = sqrt(N)** where N is the number of samples in the training dataset.



Nearest Neighbor Classification

Compute distance between two points:

- Euclidean distance $d(p,q) = \sqrt{\sum_i (p_i - q_i)^2}$

Determine the class from nearest neighbors

- take the majority vote of class labels among the k nearest neighbors
- weigh the vote according to distance (e.g. weight factor, w = $1/d^2$)

$$\text{Distance-Weighted Voting: } y' = \underset{v}{\operatorname{argmax}} \sum_{(\mathbf{x}_i, y_i) \in D_z} w_i \times I(v = y_i).$$

Dimensionality and Scaling Issues

- Problem with Euclidean measure: high dimensional data can cause curse of dimensionality.
  - Solution: normalize the vectors to unit length
- Attributes may have to be scaled to prevent distance measures from being dominated by one of the attributes.
- Example:
  - height of a person may vary from 1.5m to 1.8m
  - weight of a person may vary from 10kg to 200kg
  - income of a person may vary from $10K to $1M

Parallel Exemplar-Based Learning System (PEBLS)

- PEBLS is a nearest-neighbor learning system (k=1) designed for applications where the instances have symbolic feature values
- Works with both continuous and nominal features.
- For nominal features, the distance between two nominal values is computed using Modified Value Difference Metric (MVDM)

$$d(V_1, V_2) = \sum_i \left| \frac{n_{1i}}{n_1} - \frac{n_{2i}}{n_2} \right|$$

- Where n_1 is the number of records that consists of nominal attribute value V_1 and n_{1i} is the number of records whose target label is class i.

Distance Between Nominal Attribute Values

- d(Status=Single, Status=Married) = | 2/4 – 0/4 | + | 2/4 – 4/4 | = 1
- d(Status=Single, Status=Divorced) = | 2/4 – 1/2 | + | 2/4 – 1/2 | = 0
- d(Status=Married, Status=Divorced) = | 0/4 – 1/2 | + | 4/4 – 1/2 | = 1
- d(Refund=Yes, Refund=No) = | 0/3 – 3/7 | + | 3/3 – 4/7 | = 6/7

Tid	Refund	Marital Status	Taxable Income	Cheat
1	Yes	Single	125K	No
2	No	Married	100K	No
3	No	Single	70K	No
4	Yes	Married	120K	No
5	No	Divorced	95K	Yes
6	No	Married	60K	No
7	Yes	Divorced	220K	No
8	No	Single	85K	Yes
9	No	Married	75K	No
10	No	Single	90K	Yes

Class	Marital Status		
	Single	Married	Divorced
Yes	2	0	1
No	2	4	1

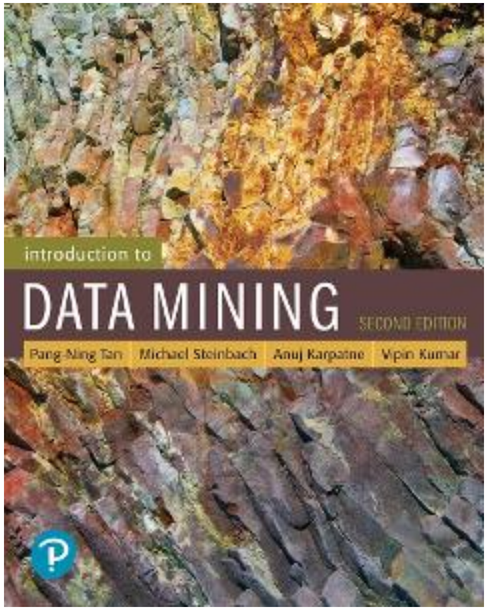
Class	Refund	
	Yes	No
Yes	0	3
No	3	4

Characteristics of Nearest Neighbor Classifiers

- Instance-based learner: makes predictions without maintaining abstraction, i.e., building a model like decision trees.
- It is a lazy learner: classifying a test example can be expensive because need to compute the proximity values between test and training examples.
- In contrast **eager** learners **spend time** in **building** the model but then the classification is fast.
- Make their prediction on local information and for low *k* they are susceptible to noise.
- Can produce wrong predictions if inappropriate distance functions and/or preprocessing steps are performed.

References

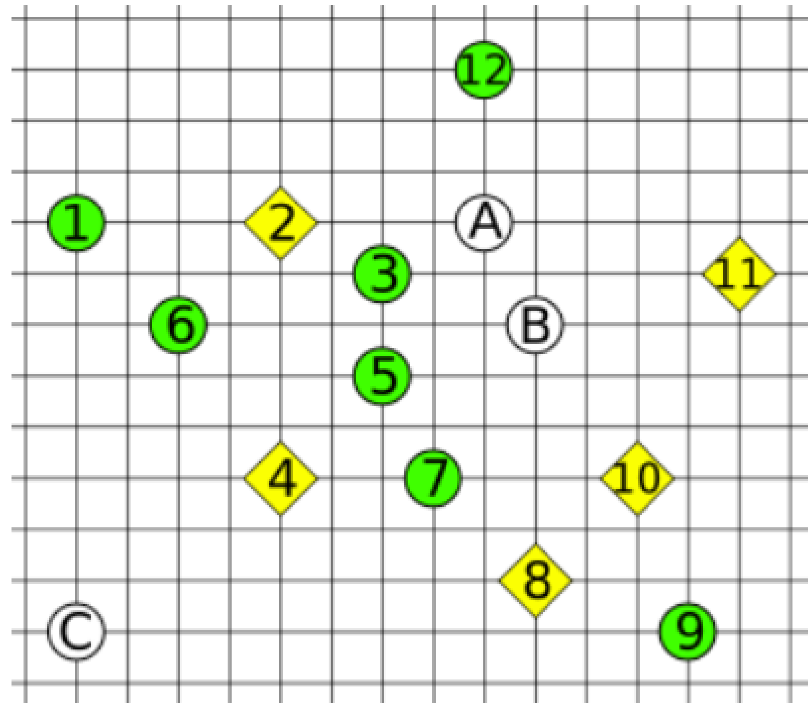
- Nearest Neighbor classifiers. Chapter 5.2. Introduction to Data Mining.



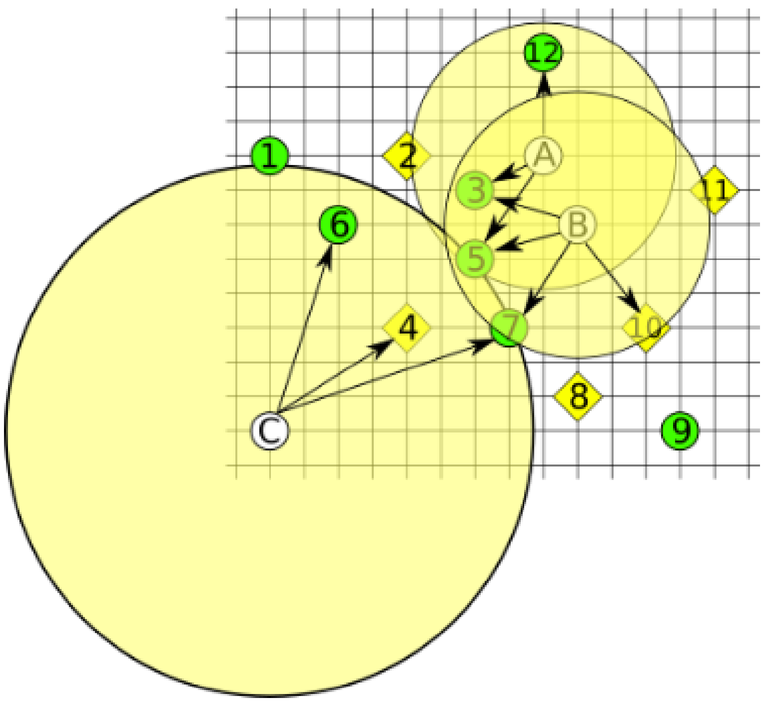
EXERCISES - KNN

b) k-NN (**3 points**)

Given the training set on the right, composed of elements numbered from 1 to 12, and labelled as circles and diamonds, use it to classify the remaining 3 elements (letters A, B and C) using a k-NN classifier with k=3. For each point to classify, list the points of the dataset that belong to its k-NN set.
Notice: A, B and C belong to the test set, not to the training set. Also, the Euclidean distance should be used.



Answer:
kNN(A) = {3, 5, 12} → CIRCLE
kNN(B) = { 3, 5, 7, 10 } → CIRCLE
kNN(C) = { 4, 6, 7 } → CIRCLE



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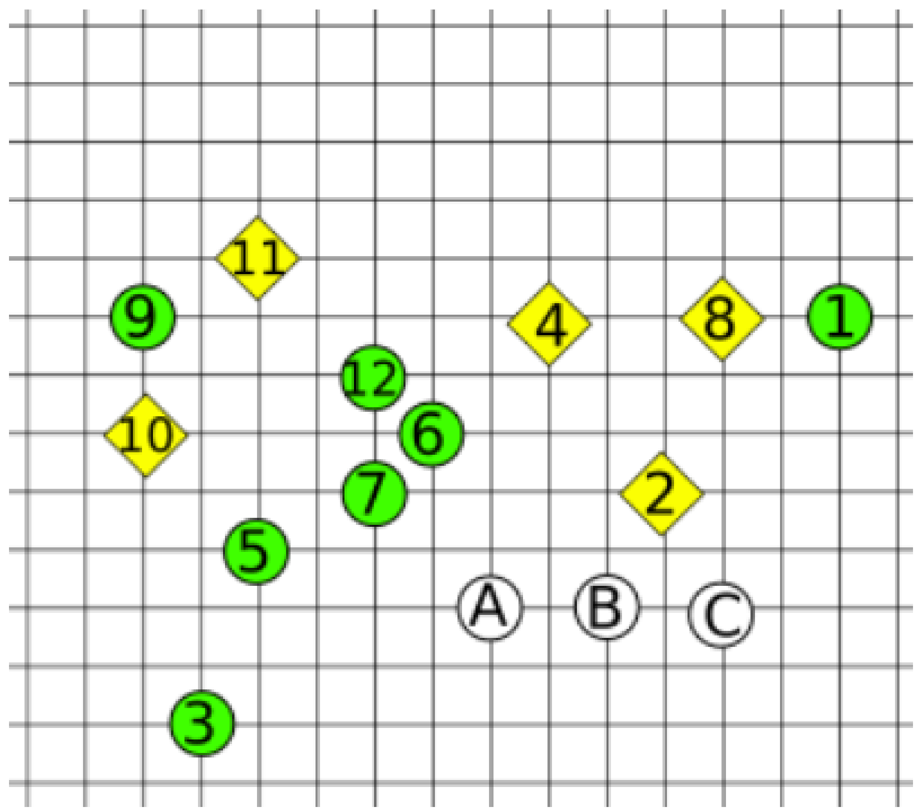

k-Nearest Neighbor Classifier

A medical expert is going to build up a case-based reasoning system for diagnosis tasks. Cases correspond to individual persons where the case problem parts are made up of a number of features describing possible symptoms and the solution parts represent the diagnosis (classification of disease). The case base contains the seven cases provided in the table below.

Training	Fever	Vomiting	Diarrhea	Shivering	Classification
c_1	no	no	no	no	healty (H)
c_2	average	no	no	no	influenza (I)
c_3	high	no	no	yes	influenza (I)
c_4	high	yes	yes	no	salmonella poisoning (S)
c_5	average	no	yes	no	salmonella poisoning (S)
c_6	no	yes	yes	no	bowel inflammation (B)
c_7	average	yes	yes	no	bowel inflammation (B)

Similarity provided by an expert

sim_F

q \ c	no	avg	high
no	1.0	0.7	0.2
avg	0.5	1.0	0.8
high	0.0	0.3	1.0

$sim_V = sim_D = sim_{Sh}$

q \ c	yes	no
yes	1.0	0.0
no	0.2	1.0

Weights

$w_F = 0.3$

$w_V = 0.2$

$W_D = 0.2$

$w_{Sh} = 0.3$

Classify the new instance q = (high; no; no; no) by applying the KNN algorithm with K=1,2,3

Calculate the similarity between all cases from the case base and the new instance q = (high; no; no; no)

c1 = (no; no; no; no):

Sim(q; c1) = 0.3*0.0 + 0.2 *1.0 + 0.2*1.0 + 0.3* 1.0 = 0.70

c2 = (average; no; no; no):

Sim(q; c2) = 0.3* 0.3 + 0.2 *1.0 + 0.2*1.0 + 0.3*1.0 = 0.79

c3 = (high; no; no; yes)

Sim(q; c3) = 0.3*1.0 + 0.2*1.0 + 0.2*1.0 + 0.3*0.2 = 0.76

c4 = (high; yes; yes; no):

Sim(q; c4) = 0.3*1.0 + 0.2*0.2 + 0.2*0.2 + 0.3*1.0 = 0.68

c5 = (average; no; yes; no):

Sim(q; c5) = 0.3*0.3 + 0.2*1.0 + 0.2*0.2 + 0.3*1.0 = 0.63

c6 = (no; yes; yes; no):

Sim(q; c6) = 0.3*0.0 + 0.2*0.2 + 0.2*0.2 + 0.3*1.0 = 0.28

c7 = (average; yes; yes; no):

Sim(q; c7) = 0.3*0.3 + 0.2*0.2 + 0.2*0.2 + 0.3*1.0 = 0.47

sim_F

q \ c	no	avg	high
no	1.0	0.7	0.2
avg	0.5	1.0	0.8
high	0.0	0.3	1.0

$sim_V = sim_D = sim_{Sh}$

q \	yes	no
yes	1.0	0.0
no	0.2	1.0

Weights

$w_F = 0.3$

$w_V = 0.2$

$W_D = 0.2$

$w_{Sh} = 0.3$

KNN Classification for K=1

c1 = (no; no; no; no):

Sim(q; c1) = 0.3*0.0 + 0.2 *1.0 + 0.2*1.0 + 0.3* 1.0 = 0.70

c2 = (average; no; no; no):

Sim(q; c2) = 0.3* 0.3 + 0.2 *1.0 + 0.2*1.0 + 0.3*1.0 = 0.79

c3 = (high; no; no; yes)

Sim(q; c3) = 0.3*1.0 + 0.2*1.0 + 0.2*1.0 + 0.3*0.2 = 0.76

c4 = (high; yes; yes; no):

Sim(q; c4) = 0.3*1.0 + 0.2*0.2 + 0.2*0.2 + 0.3*1.0 = 0.68

c5 = (average; no; yes; no):

Sim(q; c5) = 0.3*0.3 + 0.2*1.0 + 0.2*0.2 + 0.3*1.0 = 0.63

c6 = (no; yes; yes; no):

Sim(q; c6) = 0.3*0.0 + 0.2*0.2 + 0.2*0.2 + 0.3*1.0 = 0.28

c7 = (average; yes; yes; no):

Sim(q; c7) = 0.3*0.3 + 0.2*0.2 + 0.2*0.2 + 0.3*1.0 = 0.47

sim_F

q \ c	no	avg	high
no	1.0	0.7	0.2
avg	0.5	1.0	0.8
high	0.0	0.3	1.0

Weights

w_F=0.3

w_V=0.2

W_D=0.2

w_{Sh}=0.3

Class: Influenza

KNN Classification for K=2

c1 = (no; no; no; no):

Sim(q; c1) = 0.3*0.0 + 0.2 *1.0 + 0.2*1.0 + 0.3* 1.0 = 0.70

c2 = (average; no; no; no):

Sim(q; c2) = 0.3* 0.3 + 0.2 *1.0 + 0.2*1.0 + 0.3*1.0 = 0.79

c3 = (high; no; no; yes):

Sim(q; c3) = 0.3*1.0 + 0.2*1.0 + 0.2*1.0 + 0.3*0.2 = 0.76

c4 = (high; yes; yes; no):

Sim(q; c4) = 0.3*1.0 + 0.2*0.2 + 0.2*0.2 + 0.3*1.0 = 0.68

c5 = (average; no; yes; no):

Sim(q; c5) = 0.3*0.3 + 0.2*1.0 + 0.2*0.2 + 0.3*1.0 = 0.63

c6 = (no; yes; yes; no):

Sim(q; c6) = 0.3*0.0 + 0.2*0.2 + 0.2*0.2 + 0.3*1.0 = 0.28

c7 = (average; yes; yes; no):

Sim(q; c7) = 0.3*0.3 + 0.2*0.2 + 0.2*0.2 + 0.3*1.0 = 0.47

sim_F

q \ c	no	avg	high
no	1.0	0.7	0.2
avg	0.5	1.0	0.8
high	0.0	0.3	1.0

Weights

w_F=0.3

w_V=0.2

W_D=0.2

w_{Sh}=0.3

C2: Influenza

C3: Influenza

Class: Influenza

KNN Classification for K=3

c1 = (no; no; no; no):

Sim(q; c1) = 0.3*0.0 + 0.2 *1.0 + 0.2*1.0 + 0.3* 1.0 = 0.70

c2 = (average; no; no; no):

Sim(q; c2) = 0.3* 0.3 + 0.2 *1.0 + 0.2*1.0 + 0.3*1.0 = 0.79

c3 = (high; no; no; yes):

Sim(q; c3) = 0.3*1.0 + 0.2*1.0 + 0.2*1.0 + 0.3*0.2 = 0.76

c4 = (high; yes; yes; no):

Sim(q; c4) = 0.3*1.0 + 0.2*0.2 + 0.2*0.2 + 0.3*1.0 = 0.68

c5 = (average; no; yes; no):

Sim(q; c5) = 0.3*0.3 + 0.2*1.0 + 0.2*0.2 + 0.3*1.0 = 0.63

c6 = (no; yes; yes; no):

Sim(q; c6) = 0.3*0.0 + 0.2*0.2 + 0.2*0.2 + 0.3*1.0 = 0.28

c7 = (average; yes; yes; no):

Sim(q; c7) = 0.3*0.3 + 0.2*0.2 + 0.2*0.2 + 0.3*1.0 = 0.47

sim_F

q \ c	no	avg	high
no	1.0	0.7	0.2
avg	0.5	1.0	0.8
high	0.0	0.3	1.0

Weights

w_F=0.3

w_V=0.2

W_D=0.2

w_{Sh}=0.3

C1: healty

C2: Influenza

C3: Influenza

Class: Influenza