Data Mining (EECS 6412)

K-Nearest Neighbor Classifier (Chapter 9.5)

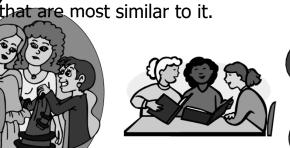
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K-Nearest Neighbor Classifiers

Learning by analogy:

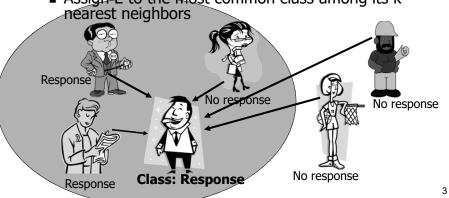
Tell me who your friends are and I'll tell you who you are

A new example is assigned to the most common class among the (K) examples



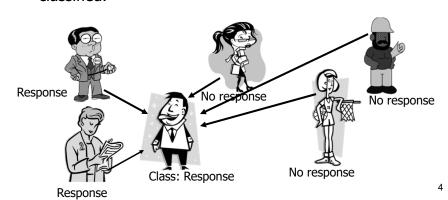
K-Nearest Neighbor Algorithm (k-NN)

- To determine the class of a new example E:
 - Calculate the distance between E and all examples in the training set
 - Select k nearest examples to E in the training set
 - Assign E to the most common class among its k-



K-Nearest Neighbor: Instance **Based Learning**

- No model is built: Store all training examples
- Any processing is delayed until a new instance must be classified.



Distance Between Neighbors

 Each example is represented with a set of numerical attributes



John: Age=35 Income=95K No. of credit cards=3



Rachel: Age=41 Income=215K No. of credit cards=2

- "Closeness" can be defined in terms of the *Euclidean* distance between two examples.
 - The Euclidean distance between $X=(x_1, x_2, x_3,...x_n)$ and $Y=(y_1,y_2, y_3,...y_n)$ is defined as:

$$D(X,Y) = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2}$$

■ Distance (John, Rachel)=sqrt [(35-41)²+(95K-215K)²+(3-2)²]

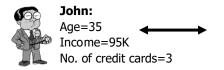
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Example: 3-Nearest Neighbors

Customer	Age	Income	No. credit cards	Response
John 🥻	35	35K	3	No
Rachel ***	22	50K	2	Yes
Hannah	63	200K	1	No
Tom	59	170K	1	No
Nellie 💮	25	40K	4	Yes
David R	37	50K	2	?

Example (3-NN)						
Customer	Age	Income (K)	No.	Response	Distance from David	
John 🚡	35	35	3	No	sqrt [(35-37) ² +(35-50) ² +(3-2) ²]= 15.16	
Rachel ***	22	50	2	Yes	sqrt [(22-37) ² +(50-50) ² +(2-2) ²]= 15	
Hannah	63	200	1	No	sqrt [(63-37) ² +(200- 50) ² +(1-2) ²]= 152.23	
Tom	59	170	1	No	sqrt [(59-37) ² +(170- 50) ² +(1-2) ²]= 122	
Nellie 🍒	25	40	4	Yes	sqrt [(25-37) ² +(40-50) ² +(4-2) ²]= 15.74	
David 🕌	37	50	2	Yes	7	

A Problem and its Solution





Rachel: Age=41 Income=215K No. of credit cards=2

Distance (John, Rachel)= $sqrt [(35-45)^2+(95,000-215,000)^2+(3-2)^2]$

- Distance between examples could be <u>dominated</u> by some attributes with relatively large numbers (e.g., income in our example).
- Important to normalize features (e.g., map numbers to numbers between 0-1)

Example: Income

If Highest income = 200K Lowest income=0

Davis's income is normalized to 50/200, John's income is normalized to 35/200, etc.)

k-NN with Normalization of Variables

Customer	Age	Income (K)	No. cards	Response
John 🥻	55/63= 0.55	35/200= 0.175	³ / ₄ = 0.75	No
Rachel R	22/63= 0.34	50/200= 0.25	2/4= 0.5	Yes
Hannah	63/63=	200/200 =1	½ = 0.25	No
Tom	59/63= 0.93	170/200 =0.85	½ = 0.25	No
Nellie 💮	25/63= 0.39	40/200= 0.2	4/4= 1	Yes
David 🥋	37/63= 0.58	50/200= 0.25	2/4= 0.5	Yes

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Another Problem with k-NN

■ Distance works naturally with numerical attributes $D(Rachel, Johm) = sqrt [(35-37)^2+(35-50)^2+(3-2)^2]=15.16$ What if we have nominal attributes?

Example: married

Customer	Married	Income (K)	No. cards	Response
John	Yes	35	3	No
Rachel	No	50	2	Yes
Hannah	No	200	1	No
Tom	Yes	170	1	No
Nellie	No	40	4	Yes
David	Yes	50	2	

K-NN with Nominal Attributes

- Method 1: Convert nominal attributes to numerical attributes
 - E.g., yes \Rightarrow 1 and no \Rightarrow 0
 - Blue \Rightarrow 1, yellow \Rightarrow 2, red \Rightarrow 3, etc.
 - Problem?
- Method 2:

Distance
$$(x, y) = \sum_{i=1}^{m} dist(x_i, y_i)$$

where $dist(x_i, y_i) = \begin{cases} 0 & \text{if } x_i \text{ and } y_i \text{ are nominal and } x_i = y_i \\ 1 & \text{if } x_i \text{ and } y_i \text{ are nominal and } x_i \neq y_i \\ |norm(x_i) - norm(y_i)| & \text{if } x_i \text{ and } y_i \text{ are continuous} \end{cases}$

and m is the number of attributes

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Example

Distance between David and John:

$$D(David, John) = 0 + |0.25-0.175| + |0.5-0.75|$$

Customer	Married	Income (K)	No. cards	Response
John	Yes	35/200=0.175	³ / ₄ =0.75	No
Rachel	No	50/200=0.25	2/4=0.5	Yes
Hannah	No	200/200=1	1/4=0.25	No
Tom	Yes	170/200=0.85	1/4=0.25	No
Nellie	No	40/200=0.2	4/4=1	Yes
David	Yes	50/200=0.25	2/4=0.5	

K-Nearest Neighbor Classifier

Strengths and Weaknesses

Strengths:

- Simple to implement and use
- Comprehensible easy to explain prediction
- Robust to noisy data by averaging k-nearest neighbors.
- Can learn complex target functions
- Can be used to do regression (how?)

Weaknesses:

- Need a lot of space to store all examples.
- Takes more time to classify a new example than with a model (need to calculate and compare distance from new example to all other examples).

