# STATISTICAL METHODS IN DATA MINING

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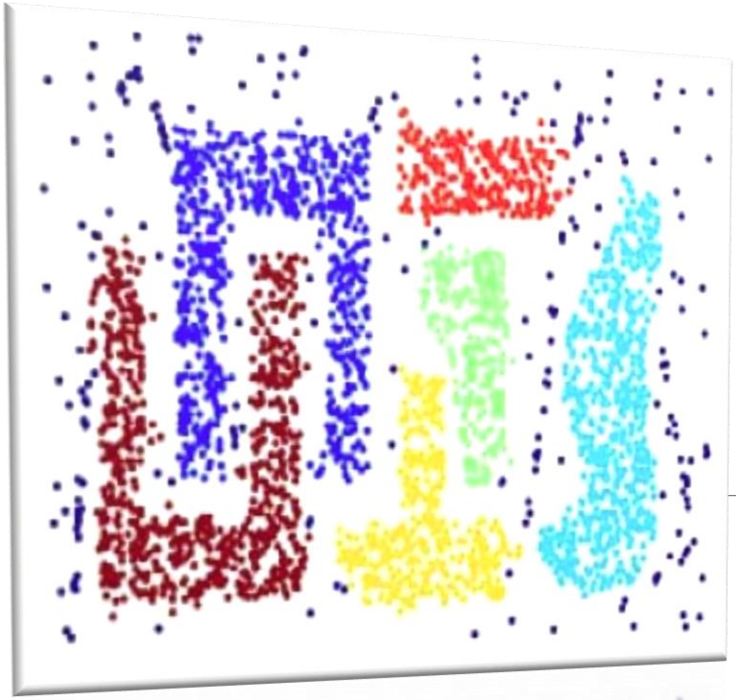
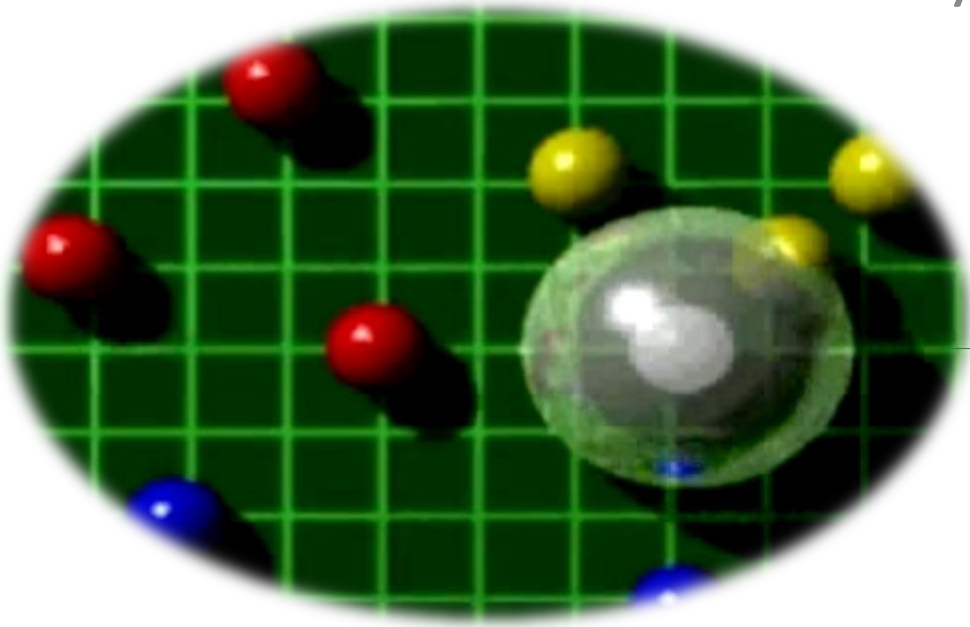
# *Previously on Course…*

- ✓Exploring Data,
- ✓Summary Statistics,
- ✓Data Visualization,
- ✓Measure of Similarity,
- ✓Hierarchical Clustering,
- ✓K-means Clustering
- ✓Density Based Clustering
- ✓Grid Based Clustering
- ✓Model Based clustering



# Today...

- ✓ Classification
  - ✓ K-nearest neighborhood
  - ✓ Bayesian Classification



# Supervised – Unsupervised Learning

- **Supervised learning**
  - is a ***machine learning*** technique for creating a function from training data.
  - The ***training data*** consist input objects (typically vectors), and desired outputs.
  - The output can be a continuous value (called ***regression***), or can predict a class label of the input object (called ***classification***).
  - The task of the supervised learner is to predict the value of the function for any valid input object after having seen a number of training examples.
  - The learner has to generalize from the presented data to unseen situations in a "reasonable" way
- **Unsupervised learning**
  - is a method of ***machine learning*** where a model is fit to observations.
  - It is distinguished from ***supervised learning*** by the fact that there is ***no a priori*** output.
  - In unsupervised learning, a data set of input objects is gathered. Unsupervised learning then typically treats input objects as a set of ***random variables***. A joint density model is then built for the data set.

# Classification

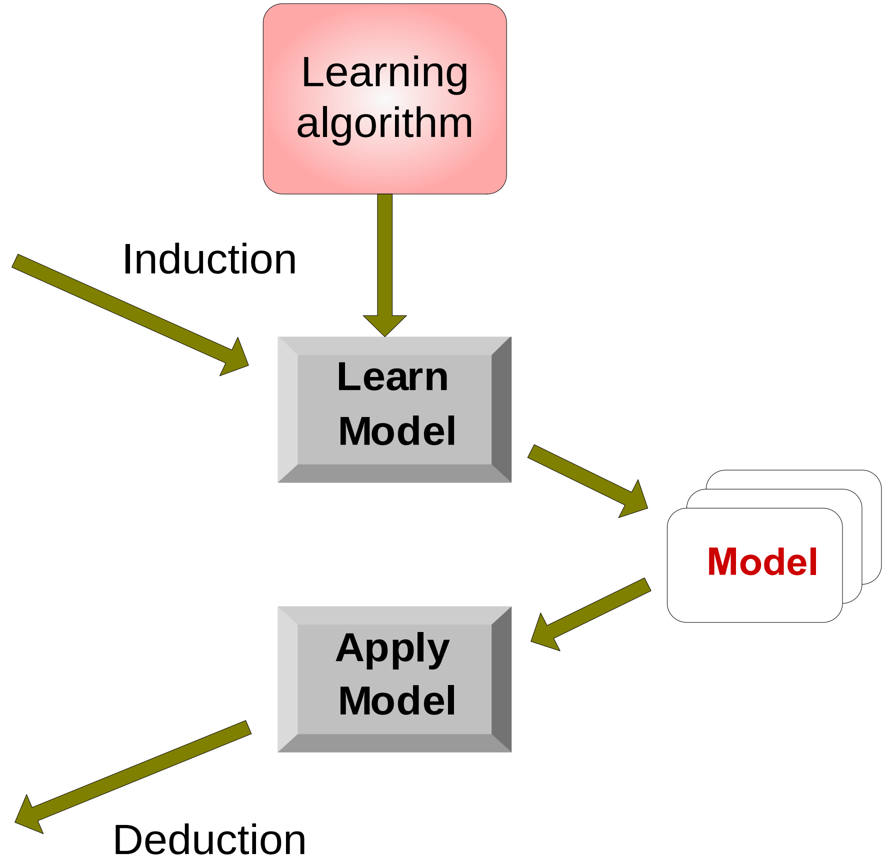
- ✓ The task of assigning *previously unseen* objects to one of several *predefined categories.*
- ✓ Finding a model for class attribute as a function of other attributes.
- ✓ Predicts categorical labels (unlike estimation or prediction).
- ✓ Is a 2-step process:

1. **Model construction**
   - Each tuple/sample is assumed to belong to a predefined class, as determined by the class label attribute,
   - The set of tuples used for model construction is training set,
   - The model is represented as classification rules, trees, or mathematical formulae.
2. **Model usage** (Classifying future or unknown objects)
   - Estimate accuracy rate of the model on a test set,
   - If the accuracy is acceptable, use the model to classify data tuples whose class labels are not known.

# Illustrating Classification Task

| *Tid* | Attrib1 | Attrib2 | Attrib3 | Class |
|---|---|---|---|---|
| 1 | Yes | Large | 125K | No |
| 2 | No | Medium | 100K | No |
| 3 | No | Small | 70K | No |
| 4 | Yes | Medium | 120K | No |
| 5 | No | Large | 95K | Yes |
| 6 | No | Medium | 60K | No |
| 7 | Yes | Large | 220K | No |
| 8 | No | Small | 85K | Yes |
| 9 | No | Medium | 75K | No |
| 10 | No | Small | 90K | Yes |

Training Set

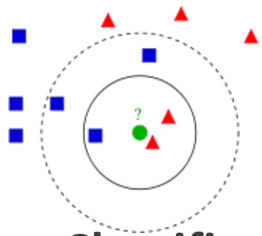



| *Tid* | Attrib1 | Attrib2 | Attrib3 | Class |
|---|---|---|---|---|
| 11 | No | Small | 55K | ? |
| 12 | Yes | Medium | 80K | ? |
| 13 | Yes | Large | 110K | ? |
| 14 | No | Small | 95K | ? |
| 15 | No | Large | 67K | ? |

Test Set

# Classification Techniques

1. **K-Nearest Neighbor**

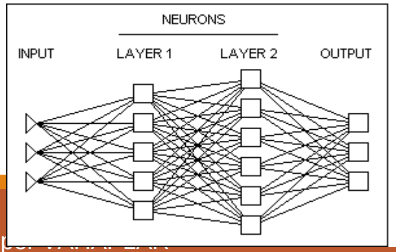



2. **Bayesian Classification**

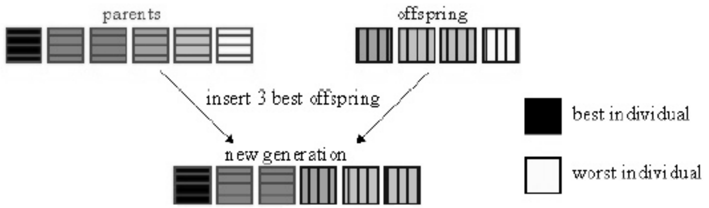
$$c = \max_{c_j} \frac{p(c_j)}{p(d)} \prod_{i=1}^{n} p(a_i \mid c_j)$$

3. **Decision Trees**

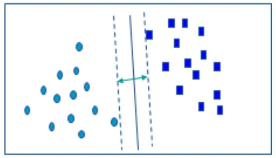

4. **Neural Networks**



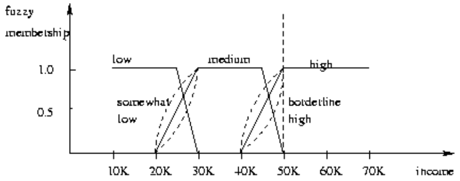

5. **Genetic Algorithms**




6. **Support Vector Machines (SVM)**

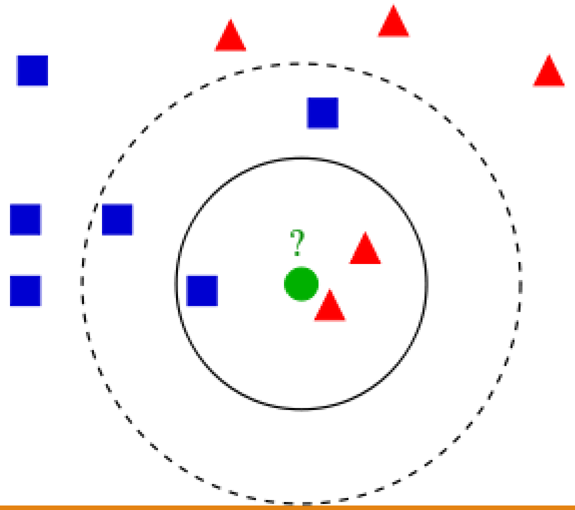


7. **Fuzzy Set Approaches**

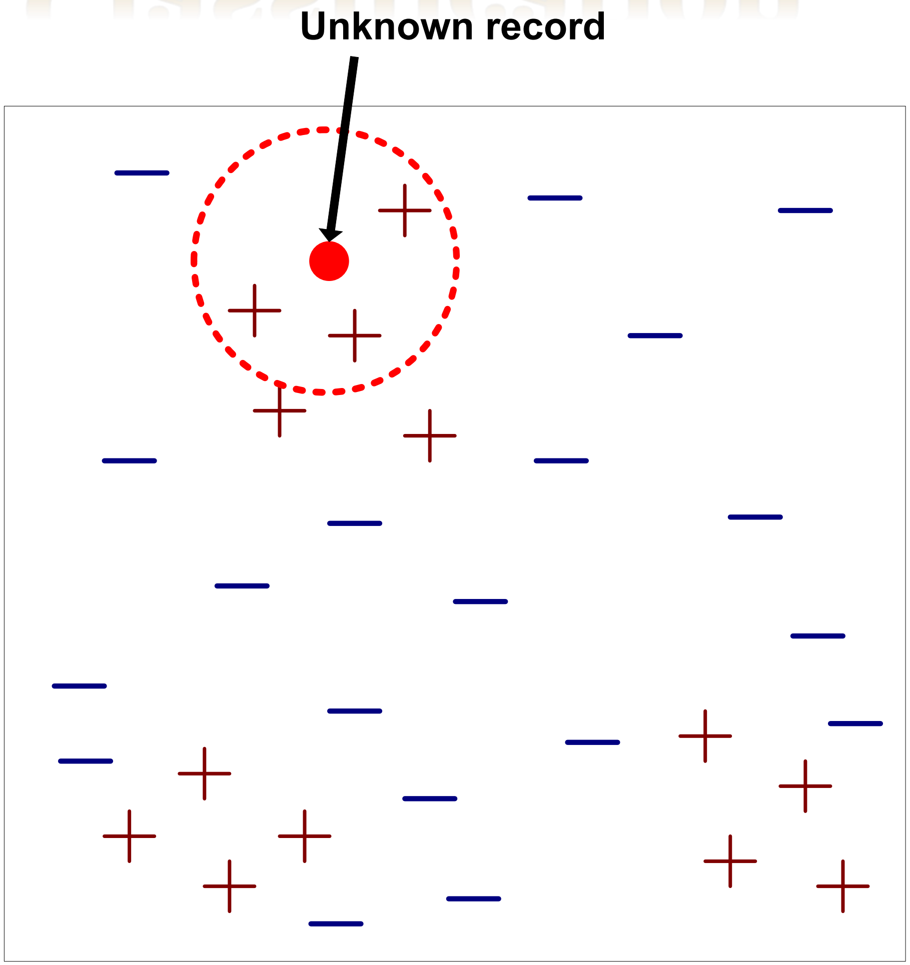


# k-nearest Neighborhood Classification

- Is an example of instance based learning,
- Lazy learner – not an eager learner ,
- Training data set is stored,
- Classification for a new unclassified record is found by comparing it to ***k*** most similar records in the training set.
- If $k = 1$, then the object is simply assigned to the class of its nearest neighbor.



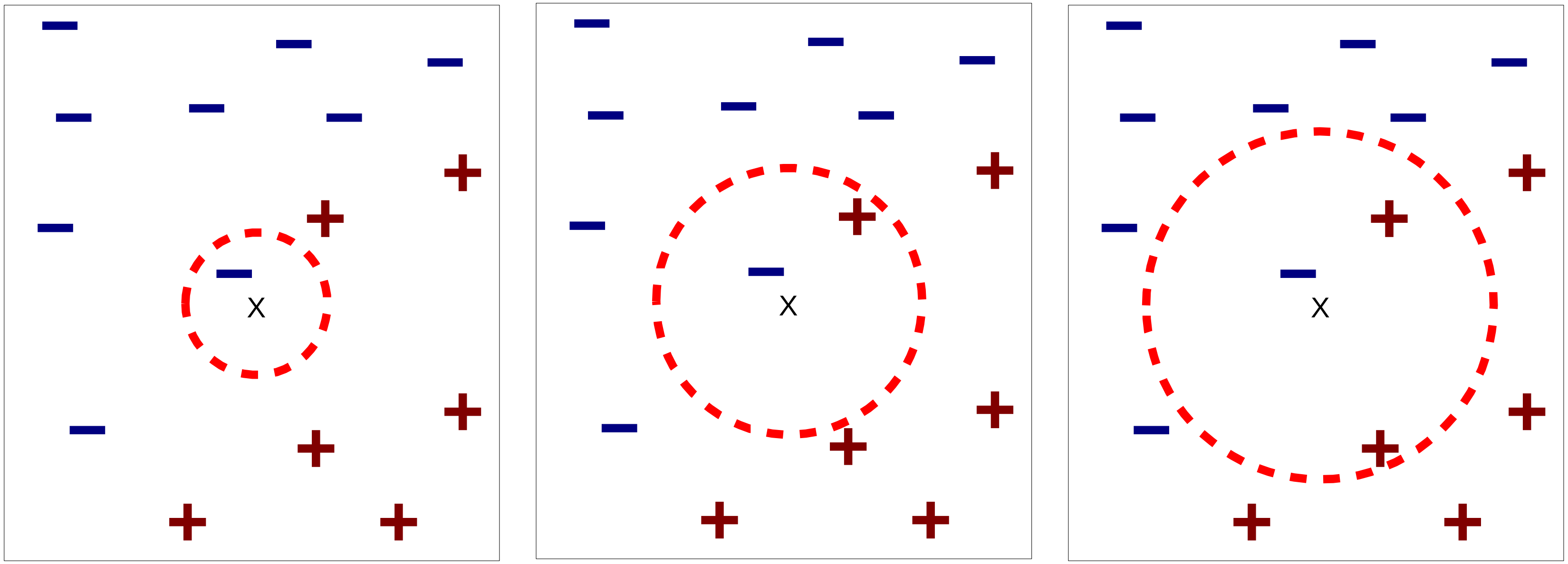
# k-nearest Neighborhood Classification




- Requires three things
  - The set of stored records
  - Distance Metric to compute distance between records
  - The value of *k*, the number of nearest neighbors to retrieve

- To classify an unknown record:
  - Compute distance to other training records
  - Identify *k* nearest neighbors
  - Use class labels of nearest neighbors to determine the class label of unknown record (e.g., by taking majority vote)

# k-nearest Neighborhood Classification

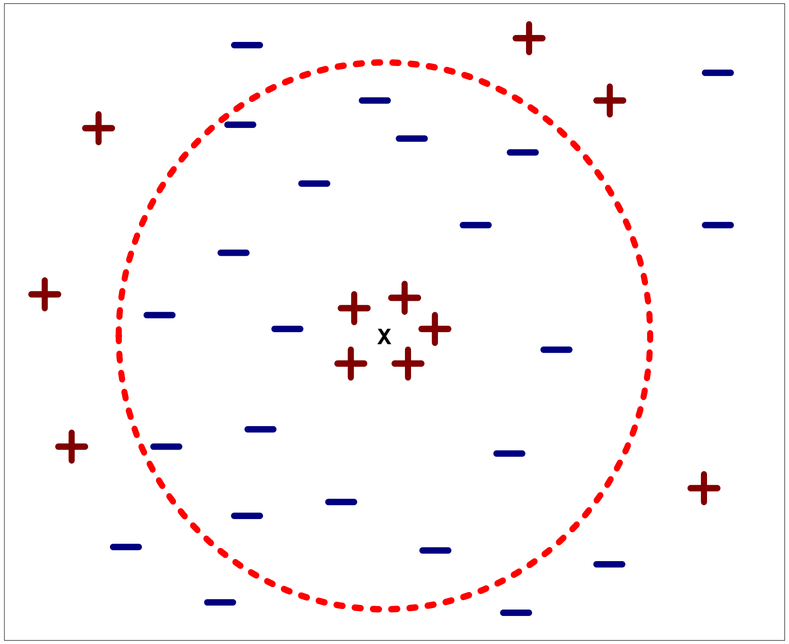



(a) 1-nearest neighbor (b) 2-nearest neighbor (c) 3-nearest neighbor

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

# k-nearest Neighborhood Classification

- Choosing the value of k:
  - If k is too small, sensitive to outliers or noise.
  - If k is too large, locally interesting behaviour will be overlooked.



# k-nearest Neighborhood Classification

- Advantages:
  - No model is built,
  - Building model is cheap,
  - Simple technique, easily implemented,
  - Well suited for records with multiple class labels,
  - Can sometimes be the best method
- Disadvantages:
  - Hard to decide *k*,
  - Requires computation of a distance for all new records.

# K-NN Example

- Using iris data find the class of the following for k=2, k=3, and k=4.

| sepal-length | sepal-width | petal-length | petal-width | class |
|---|---|---|---|---|
| 5.1 | 2.6 | 5.5 | 1.1 | ??? |

# k-NN for Estimation and Prediction

- k-NN may be used for estimation and prediction as well as for *continuous* valued target variables.
- Locally Weighted Averaging

$$\hat{y}_{\text{new}} = \frac{\sum_i w_i y_i}{\sum_i w_i} \qquad w_i = 1/\mathrm{d}(\text{new}, x_i)^2$$

# k-NN for Estimation and Prediction

| Record | Age | Na/K | BP | $Age_{MMN}$ | $Na/K_{MMN}$ | Distance |
|---|---|---|---|---|---|---|
| New | 17 | 12.5 | ? | 0.05 | 0.25 | — |
| A | 16.8 | 12.4 | 120 | 0.0467 | 0.2471 | 0.009305 |
| B | 17.2 | 10.5 | 122 | 0.0533 | 0.1912 | 0.17643 |
| C | 19.5 | 13.5 | 130 | 0.0917 | 0.2794 | 0.09756 |

$$\hat{y}_{\text{new}} = \frac{\sum_i w_i y_i}{\sum_i w_i} = \frac{\frac{120}{0.009305^2} + \frac{122}{0.17643^2} + \frac{130}{0.09756^2}}{\frac{1}{0.009305^2} + \frac{1}{0.17643^2} + \frac{1}{0.09756^2}} = 120.0954.$$

# k-NN for Estimation and Prediction

| | sepal-length | sepal-width | petal-length | petal-width |
|---|---|---|---|---|
| | ???? | 2.3 | 3.3 | 1.2 |
| **1** | 4.9 | 2.4 | 3.3 | 1 |
| **2** | 5.1 | 2.5 | 3 | 1.1 |
| **3** | 5 | 2 | 3.5 | 1 |
| **4** | 5.5 | 2.4 | 3.7 | 1 |

# Bayesian Classifiers

- A probabilistic framework for solving classification problems
- Conditional Probability:

$$P(C \mid A) = \frac{P(A,C)}{P(A)} \qquad P(A \mid C) = \frac{P(A,C)}{P(C)}$$

- Bayes theorem:

$$P(C \mid A) = \frac{P(A \mid C)P(C)}{P(A)}$$

# Example of Bayes Theorem

- Given:
  - A doctor knows that meningitis causes stiff neck 50% of the time
  - Prior probability of any patient having meningitis is 1/50,000
  - Prior probability of any patient having stiff neck is 1/20

- If a patient has stiff neck, what's the probability he/she has meningitis?

$$P(M \mid S) = \frac{P(S \mid M)P(M)}{P(S)} = \frac{0.5 \times 1/50000}{1/20} = 0.0002$$

# Bayesian Classifiers

- Consider each attribute and class label as random variables
- Given a record with attributes ($A_1$, $A_2$,…,$A_n$)
  - Goal is to predict class C
  - Specifically, we want to find the value of C that maximizes P(C| $A_1$, $A_2$,…,$A_n$ )

$$P(C|A_1, A_2\,, A_3\,\ldots\,, A_n) = \frac{P(A_1,A_2,A_3\ldots\,,\,A_n\,|C)P(C)}{P(A_1,A_2,A_3\ldots\,,\,A_n)}$$

- Equivalent to choosing value of C that maximizes

$$P(A_1, A_2, \ldots, A_n|C)\, P(C)$$

# Bayesian Classifiers

- X = (age <= 30 , income = medium, student = yes, credit_rating = fair)
- P(C|X) = ?

$P(C_1)$: P(buys_computer = "yes") = 9/14 = **0.643**
$P(C_2)$: P(buys_computer = "no") = 5/14= **0.357**

- Compute $P(X|C_i)$ for each class
  P(age = "<=30" | buys_computer = "yes") = 2/9 = **0.222**
  P(age = "<= 30" | buys_computer = "no") = 3/5 = **0.6**
  P(income = "medium" | buys_computer = "yes") = 4/9 = **0.444**
  P(income = "medium" | buys_computer = "no") = 2/5 = **0.4**
  P(student = "yes" | buys_computer = "yes) = 6/9 = **0.667**
  P(student = "yes" | buys_computer = "no") = 1/5 = **0.2**
  P(credit_rating = "fair" | buys_computer = "yes") = 6/9 = **0.667**
  P(credit_rating = "fair" | buys_computer = "no") = 2/5 = **0.4**

| age | income | student | credit_rating | buys_computer |
|---|---|---|---|---|
| <=30 | high | no | fair | no |
| <=30 | high | no | excellent | no |
| 31…40 | high | no | fair | yes |
| >40 | medium | no | fair | yes |
| >40 | low | yes | fair | yes |
| >40 | low | yes | excellent | no |
| 31…40 | low | yes | excellent | yes |
| <=30 | medium | no | fair | no |
| <=30 | low | yes | fair | yes |
| >40 | medium | yes | fair | yes |
| <=30 | medium | yes | excellent | yes |
| 31…40 | medium | no | excellent | yes |
| 31…40 | high | yes | fair | yes |
| >40 | medium | no | excellent | no |

**$P(X|C_1)$ :** P(X|buys_computer = "yes") = 0.222 x 0.444 x 0.667 x 0.667 = **0.044**
**$P(X|C_2)$ :** P(X|buys_computer = "no") = 0.6 x 0.4 x 0.2 x 0.4 = **0.019**

**$P(X|C_i)*P(C_i)$ :** P(X|buys_computer = "yes") * P(buys_computer = "yes") = **0.028**
P(X|buys_computer = "no") * P(buys_computer = "no") = **0.007**

**Therefore, X belongs to class ("buys_computer = yes")**

# Bayesian Classifiers

| Name | Give Birth | Can Fly | Live in Water | Have Legs | Class |
|---|---|---|---|---|---|
| human | yes | no | no | yes | mammals |
| python | no | no | no | no | non-mammals |
| salmon | no | no | yes | no | non-mammals |
| whale | yes | no | yes | no | mammals |
| frog | no | no | sometimes | yes | non-mammals |
| komodo | no | no | no | yes | non-mammals |
| bat | yes | yes | no | yes | mammals |
| pigeon | no | yes | no | yes | non-mammals |
| cat | yes | no | no | yes | mammals |
| leopard shark | yes | no | yes | no | non-mammals |
| turtle | no | no | sometimes | yes | non-mammals |
| penguin | no | no | sometimes | yes | non-mammals |
| porcupine | yes | no | no | yes | mammals |
| eel | no | no | yes | no | non-mammals |
| salamander | no | no | sometimes | yes | non-mammals |
| gila monster | no | no | no | yes | non-mammals |
| platypus | no | no | no | yes | mammals |
| owl | no | yes | no | yes | non-mammals |
| dolphin | yes | no | yes | no | mammals |
| eagle | no | yes | no | yes | non-mammals |

A: attributes

M: mammals (7)

N: non-mammals (13)

$$P(A|M) = \frac{6}{7} \times \frac{6}{7} \times \frac{2}{7} \times \frac{2}{7} = 0.06$$

$$P(A|N) = \frac{1}{13} \times \frac{10}{13} \times \frac{3}{13} \times \frac{4}{13} = 0.0042$$

$$P(A|M)P(M) = 0.06 \times \frac{7}{20} = 0.021$$

$$P(A|N)P(N) = 0.004 \times \frac{13}{20} = 0.0027$$

| Give Birth | Can Fly | Live in Water | Have Legs | Class |
|---|---|---|---|---|
| yes | no | yes | no | ? |

P(A|M)P(M) > P(A|N)P(N)

=> Mammals

# Next…

- ✓Decision Trees
- ✓CART,
- ✓C4.5 – C5