Techniques of Artificial Intelligence
Exercises – Naïve Bayes Classifier & WEKA

Dipankar Sengupta
Dipankar.Sengupta@vub.ac.be

Roxana Rădulescu
Roxana.Radulescu@vub.ac.be

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23. **Bayes theorem**
For the course X, we experienced that on average one out of ten students passes. We also noticed over the last couple of years that from all the students who passed, 90% did attend the exercise sessions. From all the students who did not pass, 95% did not attend the exercise sessions; they preferred to go to the university pub. Are your chances for passing course X increased by attending the exercise sessions?

Answer:

$P(pass) = 0.1 \rightarrow P(fail) = 0.9$

$P(exercise|pass) = 0.9 \rightarrow P(pub|pass) = 0.1$

$P(pub|fail) = 0.95 \rightarrow P(exercise|fail) = 0.05$

From this we can calculate $P(exercise)$ as follows (theorem of total probability):
$P(exercise) = P(exercise|pass)P(pass) + P(exercise|fail)P(fail) = 0.9 \times 0.1 + 0.05 \times 0.9 = 0.135$

$P(pass|exercise) = \frac{P(exercise|pass)P(pass)}{P(exercise)} = \frac{0.9 \times 0.1}{0.135} = \frac{2}{3} = 0.66$

So: The probability of passing the course is 0.1. If you attend the exercise sessions, the probability of passing is 0.66. Yes, attending exercise sessions does pay off.

24. **Bayes theorem**
An HIV test gives a positive result with probability 98% when the patient is indeed affected by HIV, while it gives a negative result with 99% probability when the patient is not affected by HIV. If a patient is drawn at random from a population in which 0.1% of individuals are affected by HIV and he is found positive, what is the probability that he is indeed affected by HIV?

Answer:

$P(positive|HIV) = 0.98 \rightarrow P(negative|HIV) = 0.02$

$P(negative|\neg HIV) = 0.99 \rightarrow P(positive|\neg HIV) = 0.01$

$P(HIV) = 0.001 \rightarrow P(\neg HIV) = 0.999$

From this we can calculate $P(positive)$ as follows (theorem of total probability):
$P(positive) = P(positive|HIV)P(HIV) + P(positive|\neg HIV)P(\neg HIV) = 0.98 \times 0.001 + 0.01 \times 0.999 = 0.01097$

$P(HIV|positive) = \frac{P(positive|HIV)P(HIV)}{P(positive)} = \frac{0.98 \times 0.001}{0.01097} = 0.08933$

25. **Naïve Bayes classifier**
At the parking lot of company X, a lot of cars get stolen. See below for an overview of the last 10 cars which were parked. I now park my brand new RED DOMESTIC SUV, what is the maximum a posteriori hypothesis (MAP): will the car be stolen or not according to a naïve bayes classifier?

Answer:

An initial idea is to compare the probability that the car will be stolen, given the fact that the car is a red, domestic, SUV with the probability that the car will not be stolen, given the fact that the car is a red, domestic, SUV:
$P(stolen|\text{red domestic SUV})$? $P(\neg stolen|\text{red domestic SUV})$

Example Number	Color	Type	Origin	Stolen?
1	Red	Sports	Domestic	Yes
2	Red	Sports	Domestic	No
3	Red	Sports	Domestic	Yes
4	Yellow	Sports	Domestic	No
5	Yellow	Sports	Imported	Yes
6	Yellow	SUV	Imported	No
7	Yellow	SUV	Imported	Yes
8	Yellow	SUV	Domestic	No
9	Red	SUV	Imported	No
10	Red	Sports	Imported	Yes

$P(stolen|\text{red domestic SUV}) = \frac{P(\text{red domestic SUV}|stolen)P(stolen)}{P(\text{red domestic SUV})}$
$P(\neg stolen|\text{red domestic SUV}) = \frac{P(\text{red domestic SUV}|\neg stolen)P(\neg stolen)}{P(\text{red domestic SUV})}$
NB allows us to just look at:
$H(stolen) = P(\text{red domestic SUV}|stolen)P(stolen)$ and
$H(\neg stolen) = P(\text{red domestic SUV}|\neg stolen)P(\neg stolen)$,
such that we can drop $P(\text{red domestic SUV})$, as it is a constant independent of our possible classes.

The NB ouput class will then be:
$c_{NB} = argmax(H(stolen), H(\neg stolen))$

$$\begin{aligned} H(stolen) &= P(\text{red domestic SUV}|stolen)P(stolen) \\ &= P(red|stolen)P(domestic|stolen)P(suv|stolen)P(stolen) \\ &= \frac{3}{5} \times \frac{2}{5} \times \frac{1}{5} \times \frac{1}{2} = \frac{6}{250} = 0.024 \end{aligned}$$

$$\begin{aligned} H(\neg stolen) &= P(\text{red domestic SUV}|\neg stolen)P(\neg stolen) \\ &= P(red|\neg stolen)P(domestic|\neg stolen)P(suv|\neg stolen)P(\neg stolen) \\ &= \frac{2}{5} \times \frac{3}{5} \times \frac{3}{5} \times \frac{1}{2} = \frac{18}{250} = 0.072 \end{aligned}$$

$H(\neg stolen) > H(stolen)$, thus it is more likely that the car will not be stolen.

Note that by normalizing the obtained results to sum to one, we can calculate the conditional probabilities for each of our classes, given the observed attribute values (red, domestic, SUV). For $stolen$ this is: $\frac{0.024}{0.024+0.072} = 0.25$ and for $\neg stolen$: $\frac{0.072}{0.024+0.072} = 0.75$.

26. **Getting to know WEKA**
Using WEKA you can load datasets, process them and apply classifiers on them. Open the "weather.nominal.arff" dataset, inspect it and run the ID3 algorithm on it. What is the performance of the classifier?

27. **Explorer (Naïve Bayes and cross validation)**
Use "blood_fat_corrupted.arff" dataset.

    - How many attributes and instance are there? What are the possible categorical values?
    - Identify the corrupted values. (instance and attributes)
    - Rectify the corrupted values (ask the instructor for correct values).
    - Apply a Naïve Bayes classifier with 5-fold cross validation, increment it by 5 and iterate it till 40-fold. Describe and motivate observed trend in the performance.

28. **Naïve Bayes in WEKA**
Open the "splice.arff" dataset.

    - Investigate the performance of the Naïve Bayes learner.

- The dataset contains 3190 instances. Successively apply the“RemovePercentage” filter, such that the dataset size is reduced successively up to 50 instances. At each step, investigate the performance of the classifier. Describe and motivate the observed trend in the performance.

29. **ID3 and WEKA**

    - Using the same dataset, show that ID3 does not manage to classify the data. Why is that? Investigate the data in the editor (preprocess tab).
    - You can solve the problem by applying the correct filter on the data. (preprocess tab, choose an unsupervised attribute filter). Show that performance is increased in an important manner.