

Exercise 1 :

Solve Exercise 10.1 in PM.

Exercise 2 :

Consider a poker game consisting of two rounds, and where each player is initially dealt three cards. During the first round all three cards can be changed (*FC*), but during the second round at most two cards can be changed (*SC*). When deciding on whether to call or fold you can taken into account the number of cards changed by your opponent as well as your current hand (*MH*). After playing 20 games we have the results in Table 1, where *BH* shows who has the best hand.

| Case number: | <i>BH</i> | <i>MH</i> | <i>FC</i> | <i>SC</i> |
|--------------|-----------|-----------|-----------|-----------|
| 1 | op | no | 3 | 1 |
| 2 | op | 1a | 2 | 1 |
| 3 | draw | 2 v | 1 | 1 |
| 4 | me | 2 a | 1 | 1 |
| 5 | draw | fl | 1 | 1 |
| 6 | me | st | 3 | 2 |
| 7 | me | 3 v | 1 | 1 |
| 8 | me | sfl | 1 | 0 |
| 9 | op | no | 0 | 0 |
| 10 | op | 1 a | 3 | 2 |
| 11 | draw | 2 v | 2 | 1 |
| 12 | me | 2 v | 3 | 2 |
| 13 | op | 2 v | 1 | 1 |
| 14 | op | 2 v | 3 | 0 |
| 15 | me | 2 v | 3 | 2 |
| 16 | draw | no | 3 | 2 |
| 17 | draw | 2 v | 1 | 1 |
| 18 | op | fl | 1 | 1 |
| 19 | op | no | 3 | 2 |
| 20 | me | 1 a | 3 | 2 |

Table 1: Training data for constructing a poker classifier.

- Construct a naive Bayes classifier for the poker domain.
 - Use the data cases to learn the parameters in the model; if you feel comfortable with the estimation procedure, you only need to estimate the probabilities required for solving the exercise below.
 - What class does your classifier assign to a case with $MH=1a$, $FC=1$, and $SC=1$?
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Exercise 3 :

You want to predict whether a person will pay back a loan based on the features *Income*, *Houseowner* and *Marital Status* of the person. Domains and distance functions on the domains of these features are defined as follows:

| <i>Income</i> | <i>low</i> | <i>medium</i> | <i>high</i> |
|---------------|------------|---------------|-------------|
| <i>low</i> | 0 | 1 | 2 |
| <i>medium</i> | 1 | 0 | 1 |
| <i>high</i> | 2 | 1 | 0 |

| <i>Houseowner</i> | <i>yes</i> | <i>no</i> |
|-------------------|------------|-----------|
| <i>yes</i> | 0 | 1 |
| <i>no</i> | 1 | 0 |

| <i>Marital Status</i> | <i>unmarried</i> | <i>married</i> | <i>divorced</i> |
|-----------------------|------------------|----------------|-----------------|
| <i>unmarried</i> | 0 | 1 | 1 |
| <i>married</i> | 1 | 0 | 1 |
| <i>divorced</i> | 1 | 1 | 0 |

Define the distance between two examples by the sum of the distances for the three features.

Your training examples are:

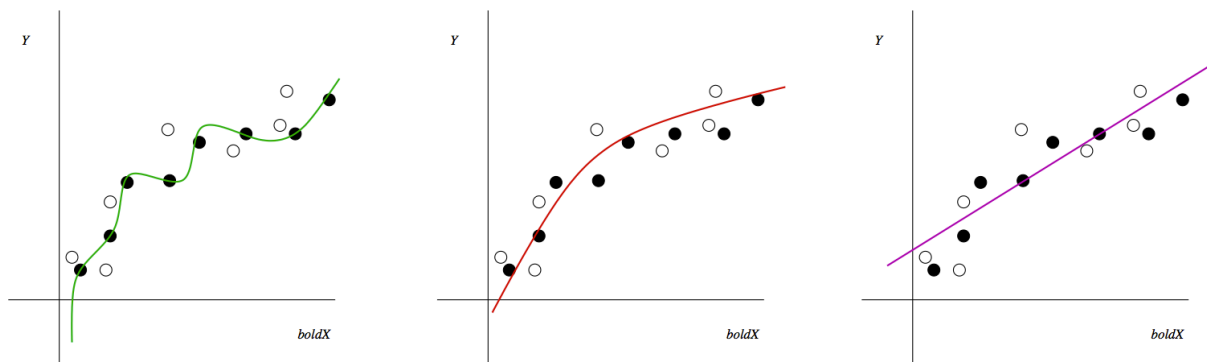
| | <i>Income</i> | <i>Houseowner</i> | <i>Marital Status</i> | <i>Pay back</i> |
|---|---------------|-------------------|-----------------------|-----------------|
| 1 | high | yes | married | yes |
| 2 | high | yes | unmarried | yes |
| 3 | medium | no | divorced | no |
| 4 | low | yes | married | no |
| 5 | low | no | unmarried | no |

Now you want to predict 'Pay back' for a new case with *Income* = high, *Houseowner* = no, *Marital Status* = divorced.

- What is the prediction obtained by the 1-nearest-neighbor rule?
- What is the prediction obtained by the 3-nearest-neighbor rule?
- What could be a sensible modification of the distance function such that you would get a different result from the 1-nearest-neighbor rule?

Exercise 4 :

The following graphs show three regression models learned from training examples (filled dots):



The open dots represent a set of future observations (or a validation set). Which of the three models has the smallest SSE on these future observations? No exact computations required – try to read it (approximately) off the graphs!

Exercise 5 :

Suppose you are working on a spam detection system. You formulated the problem as a classification task where “Spam” is the positive class and “not Spam” is the negative class. Your training set contains $m = 1000$ emails.

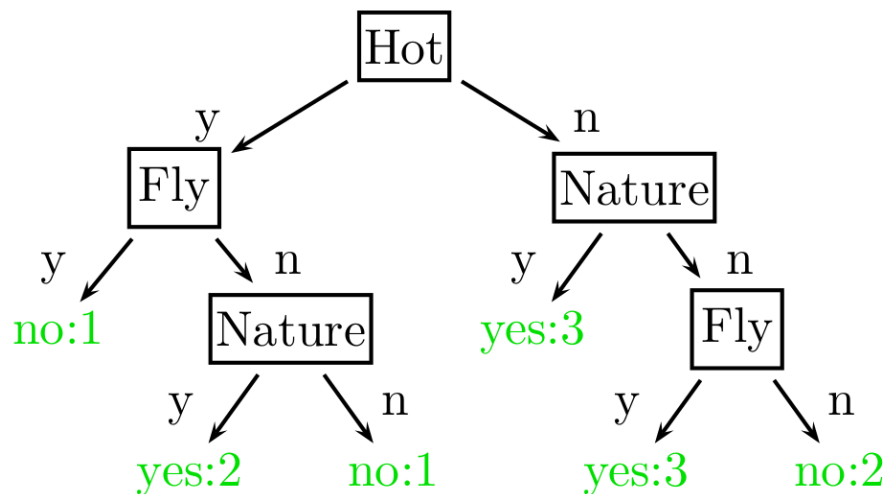
| | Predicted Spam | Predicted not Spam |
|-----------------|----------------|--------------------|
| Actual Spam | 8 | 2 |
| Actual not Spam | 16 | 974 |

Calculate the Accuracy, Recall, Specificity and Precision in this example.

How do your answers change if we now consider “Spam” the negative class and “not Spam” the positive class?

Exercise 6 :

Based on 12 training examples the following decision tree was learned:



Here, for example, the label “yes:2” at the end of the branch $\text{Hot}=y, \text{Fly}=n, \text{Nature}=y$ means that there were two examples in the training set with $\text{Hot}=y, \text{Fly}=n, \text{Nature}=y$, and both examples had class label $\text{Likes}=\text{yes}$. Thus, the decision tree has 100% accuracy on the training data (all leaves are class pure).

Now suppose you have the following 5 examples (not used in the construction of the tree), which you want to use as a validation set:

| Culture | Fly | Hot | Music | Nature | Likes |
|---------|-----|-----|-------|--------|-------|
| no | no | yes | yes | yes | no |
| no | no | yes | no | no | yes |
| yes | yes | no | no | no | yes |
| yes | no | yes | no | yes | yes |
| no | no | no | no | no | no |

Based on these validation examples, we perform post-pruning of the decision tree:

- First check whether the 'Nature' node reached by Hot=y, Fly=n should be pruned (eliminated)
 - If yes, what does the new tree look like after pruning?
 - Continue the pruning process by checking for other nodes whether they should be pruned (in a bottom-up order; the next candidate for pruning could be the 'Fly' node reached by Hot=n, Nature=n).
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Exercise 7 :

Look at this example, introduced in the lecture. Assuming the points are measurements from some experiment and the functions are fitting functions to predict further measurements. The left one is a linear function and the right one is a polynomial function. According to Ockham's razor, which one of these functions is the better pick. Justify your answer briefly (in 2-3 sentences), highlighting why Ockham's razor prefers one of the functions and what the problem of overfitting would be in this case.

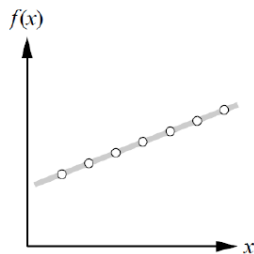


Figure 1: The linear function

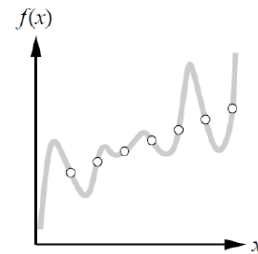


Figure 2: The polynomial function