

Machine Learning - Sheet 3

Deadline: 18.05.2017 - 23:55

Task 1: Random Forests

(10 Points)

In this task, you are supposed to compare the performance of decision trees with random forests on the car dataset (http://archive.ics.uci.edu/ml/datasets/Car+Evaluation).

- (a) What is the relation between bagging and random forests? Briefly describe both methods, point out the differences.
- (b) Make yourself familar with classification in WEKA (http://www.cs.waikato.ac.nz/ml/weka/) either using the graphical user interface or the API.
- (c) Analyze how the performance of WEKA's random forest is affected when using different numbers of trees (e.g., 1, 5, 10, 20, ...). To do so, use the car dataset and a very simple procedure: Randomly split the dataset into a training set and a test set (two thirds and one third). Take the first to train the random forest. Afterwards, use the test set to compute the percentage of correctly classified instances.
- (d) Compare the performance of WEKA's random forests with your decision tree implementation.

Task 2: Probability Distributions On Finite Sets

(10 Points)

Let Ω be a finite set. We call a function $\mathbb{P}[\{\bullet\}]: \Omega \to [0,1]$ a probability mass function, if it has the following property:

$$\sum_{\omega\in\Omega}\mathbb{P}\left[\left\{ \omega\right\} \right]=1.$$

We call elements ω of Ω elementary events, and we call subsets $A \subseteq \Omega$ events. We extend the notation to the (non-elementary) events $A \subseteq \Omega$ as follows:

$$\mathbb{P}\left[A\right] := \sum_{\omega \in A} \mathbb{P}\left[\left\{\omega\right\}\right].$$

Furthermore, for events $A, B \subseteq \Omega$, we define conditional probability of A given B as follows:

$$\mathbb{P}[A|B] := \begin{cases} \frac{\mathbb{P}[A \cap B]}{\mathbb{P}[B]} & \text{if} \quad \mathbb{P}[B] > 0\\ 0 & \text{otherwise.} \end{cases}$$

Prove the following statements:

1. Let $n \in \mathbb{N}$ and $A_1, \ldots, A_n \subseteq \Omega$ be pairwise disjoint events. By pairwise disjoint we mean that for all $i \neq j$ the events A_i and A_j are disjoint, that is, $A_i \cap A_j = \emptyset$. We write $\biguplus_{i=1}^n A_i$ for $\bigcup_{i=1}^n A_i$ to emphasize that it is the union of disjoint sets.

Prove that
$$\mathbb{P}\left[\biguplus_{i=1}^{n} A_i\right] = \sum_{i=1}^{n} \mathbb{P}\left[A_i\right].$$

Hint: It's a single chain of equations, where each step follows immediately from the above definitions.

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2. Let $A, B \subseteq \Omega$ be two (not necessarily disjoint) events. Show the sum rule:

$$\mathbb{P}\left[A \cup B\right] = \mathbb{P}\left[A\right] + \mathbb{P}\left[B\right] - \mathbb{P}\left[A \cap B\right].$$

Hint: Subdivide $A \cup B$ into three pairwise disjoint sets. Draw a Venn diagram, if necessary.

- 3. Show that for all events A it holds: $\mathbb{P}[A|\Omega] = \mathbb{P}[A]$.
- 4. Let $n \in \mathbb{N}$ and for i = 1, ..., n let $H_i \subseteq \Omega$ be such that $\biguplus_{i=1}^n H_i = \Omega$. Let A be some event. Show the *law of total probability*:

$$\mathbb{P}[A] = \sum_{i=1}^{n} \mathbb{P}[A | H_i] \mathbb{P}[H_i].$$

Hint: Use the fact that $A = A \cap \Omega$, apply distributivity of \cap over \cup .

5. Let A, B be two events with $\mathbb{P}[B] > 0$. Prove the *Bayes' theorem*:

$$\mathbb{P}[A|B] = \frac{\mathbb{P}[B|A]\mathbb{P}[A]}{\mathbb{P}[B]}.$$

6. Let B, H_1, \ldots, H_n be such that $\biguplus_{i=1}^n H_i = \Omega$. Show that for each $j = 1 \ldots n$ it holds:

$$\mathbb{P}[H_j | B] = \frac{\mathbb{P}[B | H_j] \mathbb{P}[H_j]}{\sum_{i=1}^n \mathbb{P}[B | H_i] \mathbb{P}[H_i]}.$$

Hint: Combine the basic version of Bayes' theorem and the law of total probability.

7. Let A_1, \ldots, A_n be some events. Show the *chain rule of conditional probabilities*:

$$\mathbb{P}\left[\bigcap_{i=1}^n A_i\right] = \prod_{i=1}^n \mathbb{P}\left[A_i \left| \bigcap_{j=1}^{i-1} A_j\right.\right].$$

Hint: Split $\bigcap_{i=1}^n A_i$ into $A_n \cap \bigcap_{i=1}^{n-1} A_i$, apply induction over n; $\bigcap_{j=1}^0 A_j = \Omega$.