MADS-ML – Machine Learning

Classification

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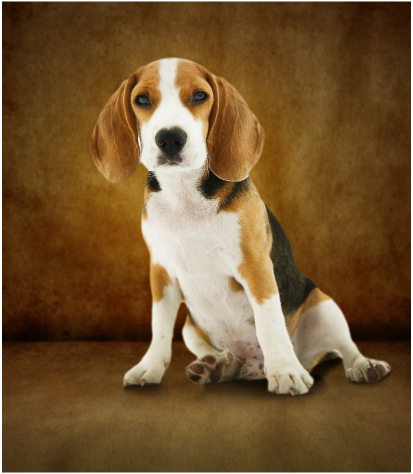
Moodle (WiSe 2024/25)

Motivation



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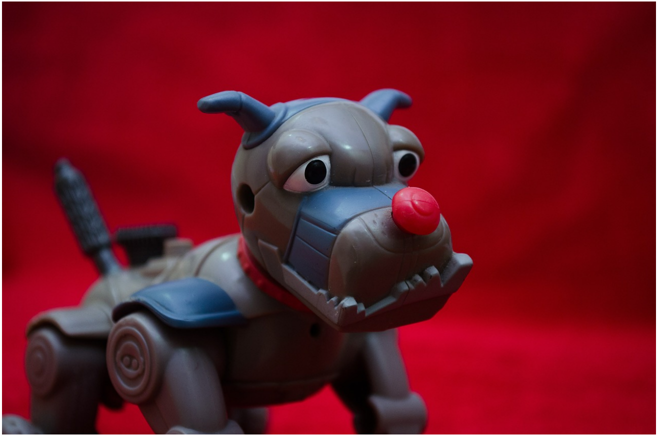

Is this a picture of a dog?

Outline

The classification problem

Definition 1 (The classification problem (abstract))

Setting:

- a universe U of classifiable objects each described with features (attributes) from a common set of features A
- a set of classes C
- a set of labelled examples $O \subseteq U$ (meaning for $o \in O$, $c(o) \in C$ is known).

Task:

- Determine a **classification function** $K : U \rightarrow C$, that maps instances of U onto their respective class!

A classification function implies a partition on U with $|C|$ partitions. Each element belongs to exactly one partition.

Notebook 02_1_classification_digits_walkthrough, Cells 1–7

Labelled Data

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Notebook 02_1_classification_digits_walkthrough, Cells 8–9

The classification problem

For non-trivial classification problems, finding a classification function is impossible or extremely difficult.

Definition 2 (Simplified classification problem)

Instead of finding the actual classification function, determine an approximation that minimizes some quality function assessing how close the approximation is to the actual classification function.

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- Usually, the classification must be fast (**online** performance), while the training should be fast (**offline** performance) and require only small training datasets.
- Creating proper features (e.g. turning numerical features into categorial ones, scaling) is part of the preparation of setting up a classifier.

Toy-Example: Classifying insurance risks

Lets consider the following training dataset of a (simplified) insurance company

ID	age	car type	risk (target)
1	23	family	high
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One possible classification function is:

- if age $>$ 50 then risk $=$low;
- if age $\leq$ 50 and car type $=$ truck then risk $=$ low;
- if age $\leq$ 50 and car type $\neq$ truck then risk $=$ high.

Two phases of a classifier

Offline Phase – Learning

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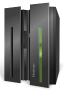
learning
training



yields

classifier

training data

classification-algorithm

Online Phase – Classification

unknown data → consumes → classifier → yields → classification

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- WRONG: Use the same data as for training. Drawback: The algorithm already knows this data and thus the task's solution. ⌛ Details in Classification II ...
  NEVER evaluate predictive performance on training data!
- CORRECT: Before training, split the labelled data into training and test data. Use only the training dataset for the learning phase. Use the test dataset for the evaluation.

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Notebook 02_1_classification_digits_walkthrough, Cells 10–14

Quality Measures for Classifiers

Let K be a classifier, TR the training set, TE the test set and $C(x)$ the correct class of a data instance x.

- classification accuracy:

$$A_{TE}(K) := \frac{|\{x \in TE \mid K(x) = C(x)\}|}{|TE|}$$

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Note, that true and apparent classification error use the same formula on different data sets.

Apparent Classification Error

The apparent classification error is taken on the training data.

- It is not a suitable measure for classification quality!
- It is however interesting to compare to the true classification error
- the comparison informs on overfitting (⌛ tbd.)

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Is **58.5%** accuracy a good result?

Is **99.9%** accuracy a good result?

➔ We cannot judge such a result without a frame of reference!

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Minimum requirement: A classifier should at least outperform random guessing.

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Exercises 1–2

Outline

Example Dataset

- Iris dataset
- often used in benchmarking classification algorithms
- instances are plants of genus iris
- features: 4 measures of petals and sepals (breadth and width)
- now with classes: 3 species (Iris Setosa, Iris Versicolor, Iris Virginica)

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For this lecture, we mostly ignore the domain (in real applications, we don't!).

Referenzen

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