Datascience: halfway meeting

Datamining

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Paper and pencil exercises: Exercise 2.4

A	B	Number of Instances	
		Y	O
$a1$	$b1$	4	10
$a2$	$b1$	6	2
$a3$	$b1$	8	6
$a1$	$b2$	2	8
$a2$	$b2$	6	2

- Rule of Bayes: $P(A|B) = \frac{P(B|A)\cdot P(A)}{P(B)}$
- so: $P(Y|a3, b2) = \frac{P(a3,b2|Y)\cdot P(Y)}{P(a3,b2)}$ and $P(O|a3, b2) = \frac{P(a3,b2|O)\cdot P(O)}{P(a3,b2)}$
- Unknown: $P(a3, b2|Y)$, $P(a3, b2|0)$ and $P(a3, b2)$
- Since the denominator $P(a3, b2)$ is the same for both $P(Y|a3, b2)$ and $P(O|a3, b2)$ we could ignore it when determining how to classify with Naive Bayes someone with $a3$ and $b2$. But for educational purposes we will show how to calculate it.

Naive Bayes

A	B	Number of Instances	
		Y	O
$a1$	$b1$	4	10
$a2$	$b1$	6	2
$a3$	$b1$	8	6
$a1$	$b2$	2	8
$a2$	$b2$	6	2

- Naive Bayes: $a3$ and $b2$ are conditional independence which means: $P(a3, b2|Y) = P(a3|Y) \cdot P(b2|Y)$
- $P(a3|Y)$ and $P(b2|Y)$ are known from the data, e.g.: $P(a3|Y) = \frac{8}{26}$
- Next: $P(a3, b2) = P(a3, b2|Y) \cdot P(Y) + P(a3, b2|O)P(O)$
- Since $P(a3, b2|Y) = P(a3|Y) \cdot P(b2|Y)$ and $P(a3, b2|O) = P(a3|O) \cdot P(b2|O)$

$$P(a3, b2) = P(a3|Y)P(b2|Y) \cdot P(Y) + P(a3|O)P(b2|O) \cdot P(O) = \frac{8}{26} \cdot \frac{8}{26} \cdot \frac{26}{54} + \frac{6}{28} \cdot \frac{10}{28} \cdot \frac{28}{54}$$

Paper and pencil exercises: Exercise 2.5

A	Y	O	label	number of errors
$a1$	6	18	O	6
$a2$	12	4	Y	4
$a3$	8	6	Y	6

- classification error rate for attribute A equals $\frac{16}{54} = 0.296$
- Gini index for attribute A: $GI(\text{node } m) = \sum_{k=1}^{K} \hat{p}_{mk}(1 - \hat{p}_{mk})$, where $\hat{p}_{mk}$ is the proportion of class k observations in node m
  - $GI(a1) : \frac{6}{24} \times \frac{18}{24} + \frac{18}{24} \times \frac{6}{24} = 0.375$
  - $GI(a2) : 2 \times \frac{12}{16} \times \frac{4}{16} = 0.375$
  - $GI(a3) : 2 \times \frac{8}{14} \times \frac{6}{14} = 0.490$
  - Overall Gini index for attribute A: $GI(A) = \frac{24}{54} \times 0.375 + \frac{16}{54} \times 0.375 + \frac{14}{54} \times 0.490 = 0.4048$

Exercise 2.5 (II)

B	Y	O	label	number of errors
$b1$	18	18	O	18
$b2$	8	10	Y	8

- classification error rate for attribute B equals $\frac{26}{54} = 0.481$
- Gini index for attribute B:
  - $GI(b1) : \frac{18}{36} \times \frac{18}{36} + \frac{18}{36} \times \frac{18}{36} = 0.5$
  - $GI(b2) : 2 \times \frac{8}{18} \times \frac{10}{18} = 0.4938$
  - Overall Gini index for attribute B:
    $GI(B) = \frac{36}{54} \times 0.5 + \frac{18}{54} \times 0.4938 = 0.498$

Projects

- PSCD (DPV / DM)
- MOCHA (primary DPV)
- COVID (DM)

DM project: PSCD

The dataset contains data of 4087 real surgeries of patients.

Aim:

- identify patterns in surgical case durations
- derive prediction models for the surgery time in order to decrease overtime at the TCT

Suggestions:

- Focus on a subset of the surgeries (the most prevalent, or only one type)
- Recode the surgeries into less categories
- Focus on patient characteristics or process characteristics (e.g. the physicians)

Challenges:

- a lot of missing data (multiple imputation with `mice()`)

DPV project: MOCHA

The dataset contains data of 2640 questionnairs.

Aim: What are the priorities of European citizens in assessing the quality of primary care for children in Europe?

Suggestions:

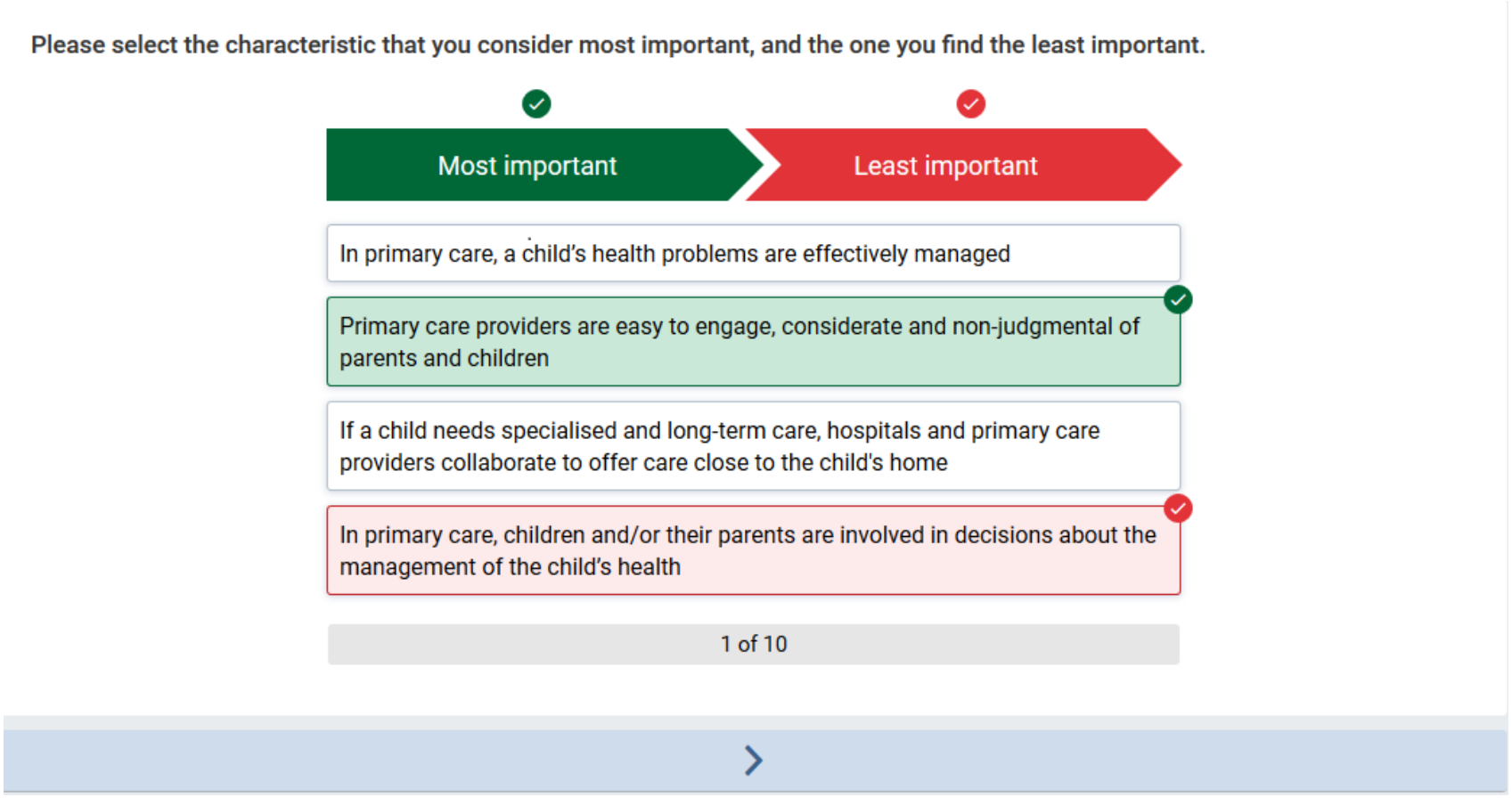
- Calculate best-worst counts (e.g. per country) for all attribute-items
- Look at differences between countries or other background characteristics

Challenges:

- merge the information in the separate datasets to get clear tables for a star schema.

Best-worst questions

Every respondent answered 20 questions (two sets of 10) with each 4 characteristics from which they had to choose the best and worst.



COVID19

The dataset contains data of 375 patients.

Aim: Develop a prediction model for the mortality of COVID-19 patients based on the biomarkers that are available in the data

Suggestions:

- choose e.g. 3 appropriate machine learning models, train the models and compare their accuracy on one or more appropriate accuracy measures.
- validate all model steps: so including the feature selection

Challenges:

- extract the latest measurement per patient (or use all data, when you get a longitudinal dataset)

Obligitory items in your DM project

- Identify what kind of DM problem it is
- Well formulated research questions
- Design of a valid DM pipeline (including feature construction and selection)
- Comparison of different DM models
- Assessment of the performance of the constructed DM models in a sound way (with test/train set, Cross-validation or bootstrap)
- Critical reflection: strenghts and weaknesses of the methodology, results: place the results in the context of the problem