Data analysis of examination papers

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Agenda & introductory comments

- Evaluation of performance analysis overview of some aspects
- Brief discussion of methods
- (not easily transferable) Results
 - rather a pilot study, to show what kinds of questions may by raised and solved
 - technical characteristics: no automated data collection as could be e.g. in e-learning systems with possibility to use built-in analytical reports with predefined structure - > custom design

Exams / Types of analyses

- univariate analysis distribution of total score (response)
- examine structure (+ items to response relation)
- relate performance to other characteristics (socio-demographic, attendance,...)

Analytical questions addressed

- 1) What are the most predictive parts of the test with respect to overall score result in the test?
- 2) Considering performance of students expressed in scores obtained for solution of particular items, are there any significant dependencies between particular problem areas included in the test?
- 3) Are there any groups of students who are similar with respect to performance in test?

Other analyses may include: search for common factors influencing performance in tests, examination of reliability of tests and analysis of sources of variability (incl. investigation of effect of examiners)

Data description

- *N=45* examination papers in a basic "all-in-one" course of mathematics, tests have the same structure 8 tasks each
- Expert classification of tasks (-> analysis of metadata)
- basic linear algebra calculations (denoted LA), matrix algebra task (MA), limit calculation (LF), item focused on rather straightforward derivatives application (D1), item including a more difficult application of derivatives (D2), integral calculation (IN), optimization of a function of two variables (F2) and solving a differential equation (DE)
- overall score (SC) as sum of all 8 evaluations for particular test items

SC = LA + MA + LF + D1 + D2 + IN + F2 + DE

Basic exploratory analysis - histograms



Results / dependency graph

Edges evaluated with Spearman correlation



Results / graphical model

Directed acyclic graph (node represents random variable) and set of density functions – for each node *U* in form *P*(*U*|*parents*(*U*))

Factorization of joint probability function (chain rule):

P(LA,MA,LF,D1,D2,IN,DE,F2) =

 $\mathsf{P}(\mathsf{LA})\mathsf{P}(\mathsf{MA})\mathsf{P}(\mathsf{F2}|\mathsf{MA})\mathsf{P}(\mathsf{LF}|\mathsf{F2})\mathsf{P}(\mathsf{IN}|\mathsf{F2})\mathsf{P}(\mathsf{D1}|\mathsf{IN})\mathsf{P}(\mathsf{D2}|\mathsf{D1})\mathsf{P}(\mathsf{DE}|\mathsf{D2},\mathsf{F2})$

Possibility to capture conditional independence relations



Method: Regression tree

- Predicting value of (continuous) variable SC
- Tree construction by recursive partitioning of input data set according to the variable with the highest discrimination power
- Advantages:
 - Possibility to capture interactions and dependencies valid just for particular subsets of data
 - Weak assumptions; possibility to deal with missing values
 - Easy interpretation of model
 - Identification of important variables

Results / SC prediction - regression tree



DE, LA and F2 variables chosen as predictors

Results / cluster analysis

- 2 groups found (avg. silhouette width 0.26; PAM method)
- "Well-performers" being the more clearly defined group







