# A Data Mining Approach for Detecting Collusion in Unproctored Online Exams

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#### Setting

- Data from the *Descriptive Statistics* course at U Duisburg-Essen, Germany
- Exams consist of arithmetical problems, programming tasks in R, and a short essay task
- Exams are conducted digitally with the e-assessment system JACK
  - Each student receives different randomized numerical values across all tasks
  - Event logs capture students' activities, time stamps, and points during the exams for every subtask

Table 1: Overview of the test and comparison group

	Comparison	Test
Year	18/19	20/21
N	109	151
Style	proctored	unproctored
<b>Total points</b>	60	60
Sub tasks	19	17
Duration	70	70

- The test group (2020/21) took the unproctored exam at home
  - The comparison group (2018/19) took a proctored exam at the university
- Data cleaning is conducted, removing student with
  - Minimal participation
  - Minimal achievement
  - Internet problems

#### Aim of the Paper

Detecting potential collusion with a hierarchical clustering algorithm on event logs and strengthen the analysis with a proctored comparison group

## Methodology

• The study utilizes an agglomerative (bottom-up) hierarchical clustering algorithm characterized by the following equation:

$$D(s_i, s_{i'}, v_i, v_{i'}) = rac{1}{h} \sum_{j=1}^h (w_j^P \cdot d_j^P(s_{ij}, s_{i'j}) + w_j^L \cdot d_j^L(v_{ij}, v_{i'j}))$$

- $D(s_i, s_{i'}, v_i, v_{i'})$  global pairwise dissimilarity
- $d_j^P(s_{ij}, s_{i'j})$  points dissimilarity for each task j
- $d_j^L(v_{ij}, v_{i'j})$  students event patterns dissimilarity for each task j
- $\sum_{j=1}^{h} w_{j}^{P} + w_{j}^{L} = 1$  weight of each attribute h
- We reduce the weights for
  - R-tasks, as these tasks have more noise
  - Essay questions, as comparisons on these kinds of tasks are limited
- Points achieved
- ullet Dissimilarities in points achieved for each task j

$$d_{\,i}^P(s_{ij},s_{i'j})=|s_{ij}-s_{i'j}|$$

- $s_{ij}$  denotes the points achieved by student i in the j-th subtask
- Manhatten metric
- ullet Dissimilarities in the students event patterns (time of submission) for each task j

$$d_{j}^{L}(v_{ij},v_{i'j}) = \sum_{m=1}^{K=70} |v_{ijm} - v_{i'jm}|$$

- $d_i^L(v_{ij}, v_{i'j})$  students event patterns dissimilarity for each task j
- Examination is divided into  $m=1,\ldots,70$  time intervals
- $v_{ijm}$  denotes the number of answers of student i for task j in the m-th interval

### Empirical Results

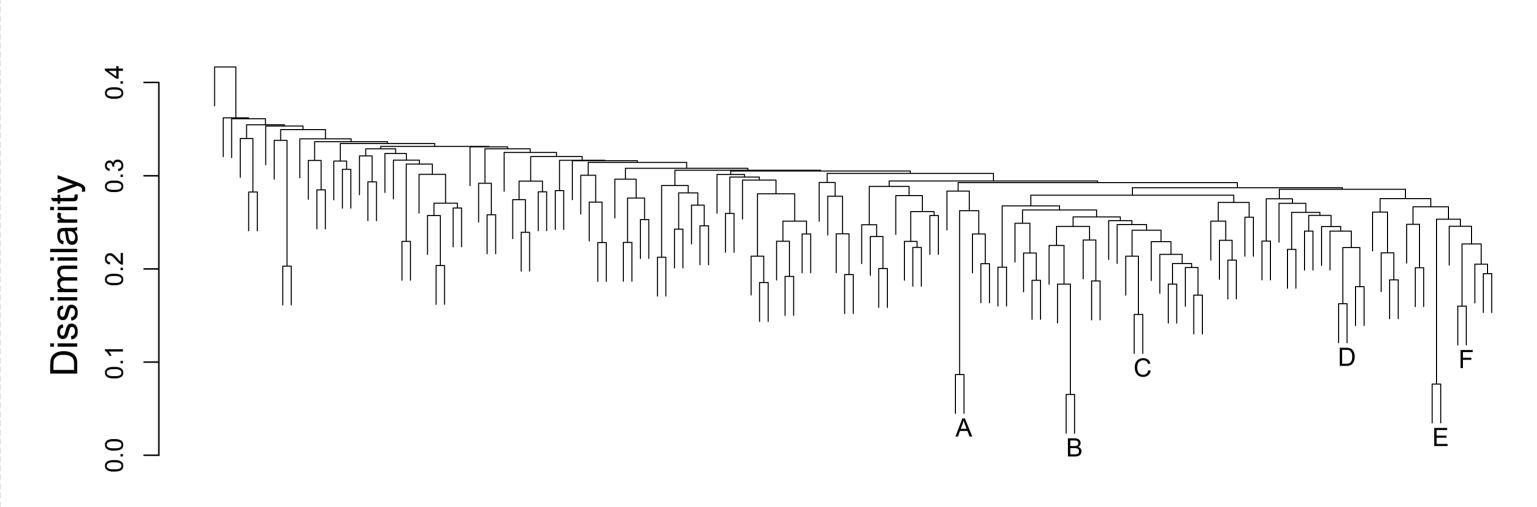


Figure 1: Dendogram produced by average linkage clustering of the unproctored test group (2020/21). **A-F** mark the clusters with the lowest dissimilarity.

- Figure 1 shows the dendrogram of the test group
- Overall a lower level of dissimilarity compared to the comparison group
- Six clusters (A-F) standing out noticeably from the rest of the cohort, suggesting potential collusion
- The distance between notable clusters and the median distance is greater than in the comparison group

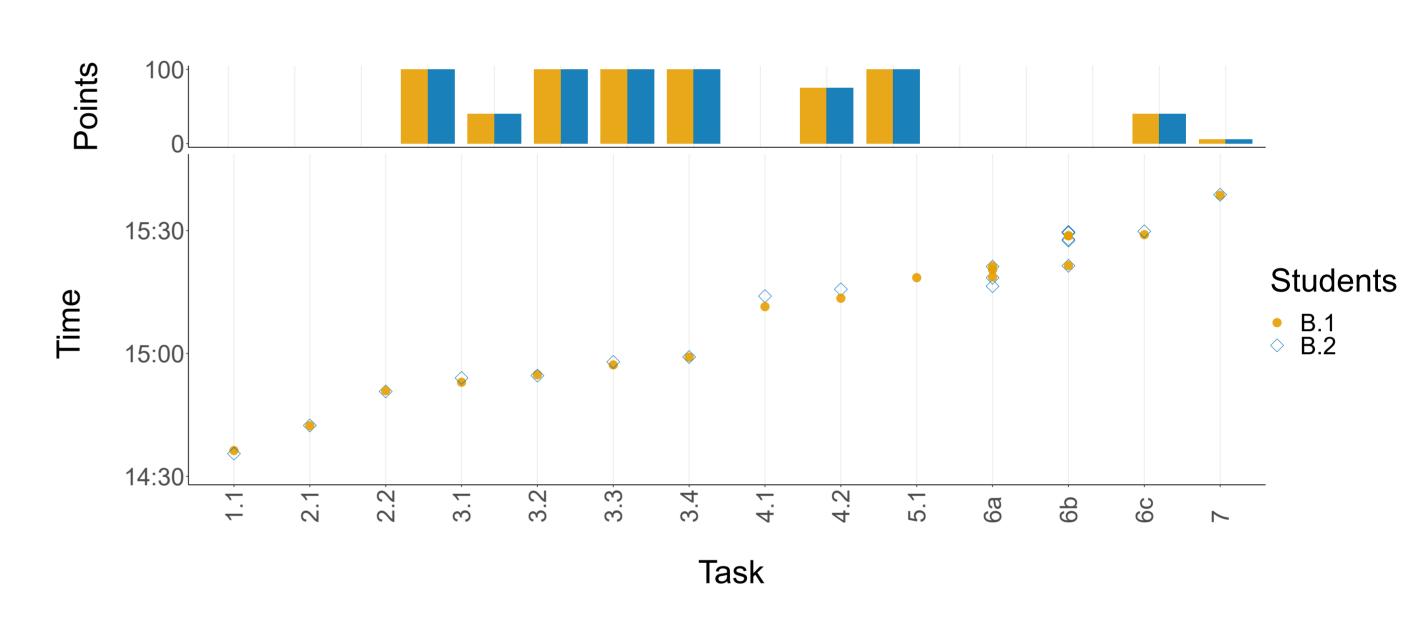


Figure 2: Event logs and achieved points of the cluster **B** from the test group (2020/21). Above the scatter plot, a bar chart is added to compare the points per subtask.

- Figure 2 illustrates the individual comparison of achieved points and event logs of the student cluster with the highest similarity
  - Similar time path
- Achieved same points for each task

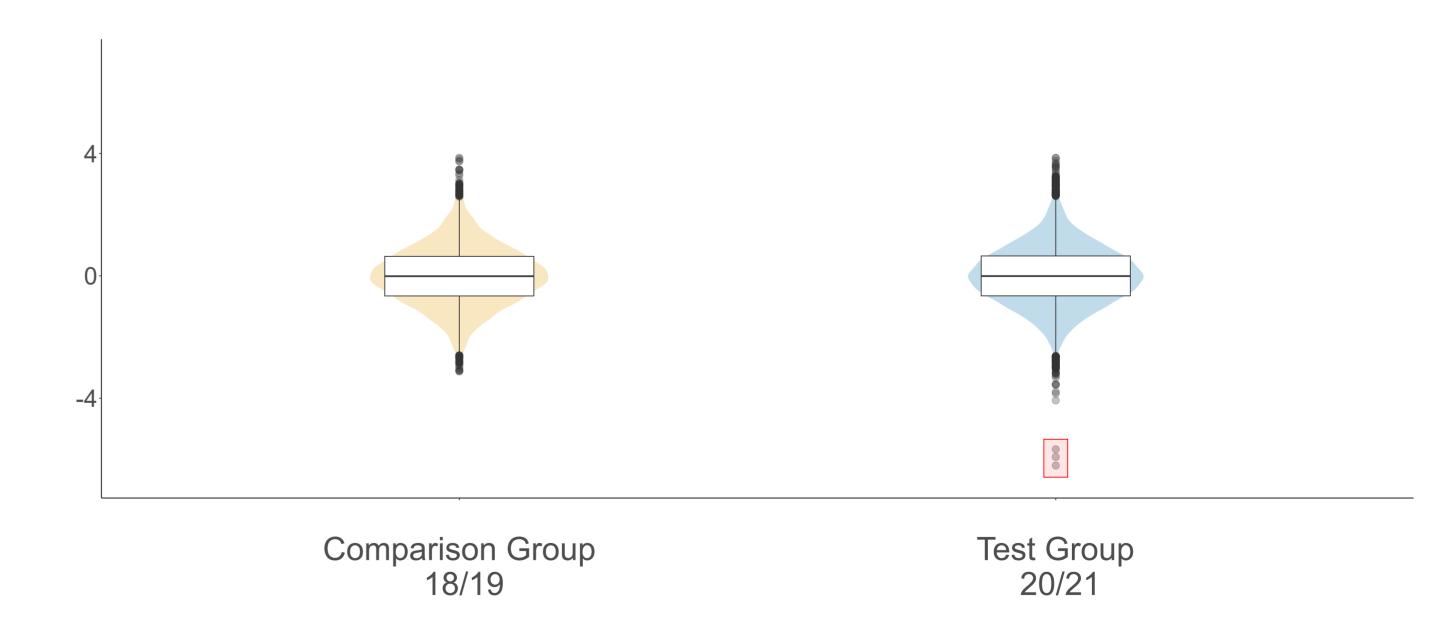


Figure 3: Comparison of the normalized distance measures.

• Figure 3 compares the normalized distributions of the dissimilarity measures between the comparison and test groups

## Discussion

- Six notable clusters (especially A, B, and E), each consisting of two students
- Collusion in larger groups is not found
- Findings do not depend on linkage methods and parameter specifications
- The approach provides a basis for the examination of clusters based on comparison with a reference group