An R Package for Adaptive Assessment Utilizing Knowledge Space Theory and Formal Psychological Assessment

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Outline

- Introduction
- 2 mycaas Package
 - Algorithm
 - Shiny
 - Application on RAISE
- Final Remarks









Tests in Education and Clinical Psychology

- Time consuming
- Fatigue effect, social desirability, etc.

(Informal) Definition

A computerized adaptive assessment is an evaluation that adjusts the difficulty and nature of subsequent questions based on the test-taker's responses to previous ones.









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- Increased Efficiency and Accuracy in Assessment:
 - Adaptive systems save time by focusing on the appropriate difficulty level.
- Personalized Learning or Therapy :
 - Feedback can be customized to individuals need.
- Immediate Feedback:
 - Results are available as soon as the assessment is finished.











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- Complexity of Implementation:
 - Requires sophisticated algorithms and data processing infrastructure.
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My computerized adaptive assessment R package

mycaas package

devtools::install_github(''brancaccioandrea/mycaas")

- Based on the strong theoretical foundation
- User-friendly graphical interface made
- Performance analisys to evaluate accuracy and efficiency









Theoretical Framework

Knowledge space theory (KST; Doignon & Falmagne, 1985): The objective is to precisely describe what the individual knows (their knowledge state) in a given domain of knowledge, rather than computing a numerical score.

Formal Psychological Assessment (FPA; Spoto, Stefanutti & Vidotto, 2010): The objective from the clinical perspective is to give an in-depth evaluation of the construct investigated by the questionnaire.





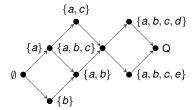




Basic Definitions

Formal definitions of basic concepts encountered so far:

- Domain a either finite or infinite set Q of questions
- State the subset $K \subseteq Q$ of all questions that define the status of individual
- Structure a pair (Q, K), where K is a collection of subset of Q, containing at least the empty set and Q



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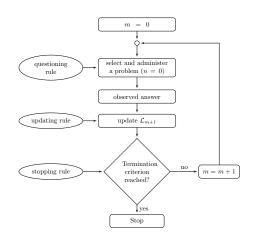


Flowchart of the Adaptive Assessment

Doignon & Falmagne, 1988; Donadello, et al., 2017

The goal of the assessment is to recover the true state of an individual asking the fewest possible questions

- Three rules guide the assessment:
 - Questioning rule
 - Updating rule
 - Termination rule









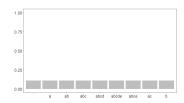


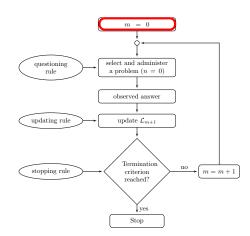
Probability distribution on the states

A probability distribution

$$\mathcal{L}_m:\mathcal{K}\to(0,1)$$

Without prior knowledge is a uniform distribution













Questioning Rule

Half Split Rule

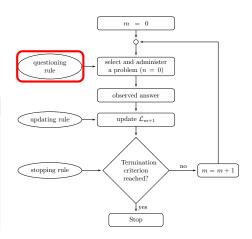
minimize

Select the "best" question to ask

Doignon & Falmagne, 1988

half_split: Let $\mathcal{L}_m(K)$ the likelihood of K at the step m, and the subset $\mathcal{K}_q \subset \mathcal{K}$ such that $q \in K$ for each $K \in K_q$. It selected problem $q \in Q$ that

$$|\mathcal{L}_m(\mathcal{K}_q) - 1/2|$$











Updating Rule

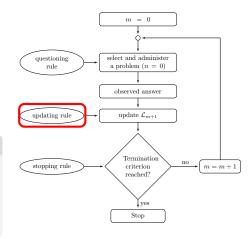
Bayesian Updating Rule

The probability $\mathcal{L}_m(K)$, for each $K \in \mathcal{K}$ is updated in function of the the observed response r_q collected for problem q as follows.

$$\mathcal{L}_{m+1}(K) = \frac{P(r_q|K)\mathcal{L}_m(K)}{\sum_{K' \in \mathcal{K}} P(r_q|K)\mathcal{L}_m(K')}$$

Parameters

$$P(r_q|K) = \begin{cases} \beta_q & \text{if } r_q = 0 \& q \in K; \\ 1 - \eta_q & \text{if } r_q = 0 \& q \notin K; \\ 1 - \beta_q & \text{if } r_q = 1 \& q \in K; \\ \eta_q & \text{if } r_q = 1 \& q \notin K. \end{cases}$$











Termination rule

Heller & Repitsch, 2012

Likelihood Maximization:

The assessment terminate at step m if

$$\max \mathcal{L}_m(K) > SC$$

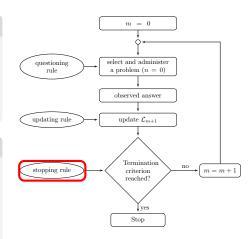
with $SC \in (0.5, 1]$.

Donadello, et al., 2017

Item Discrimination: The assessment terminate at step m if for each $q \in Q$

$$\mathcal{L}_{\textit{m}}(\mathcal{K}_{\textit{q}}) > \textit{SC} \; \text{or} \; \mathcal{L}_{\textit{m}}(\mathcal{K}_{\textit{q}}) < 1 - \textit{SC}$$

with $SC \in [0.5, 1]$.



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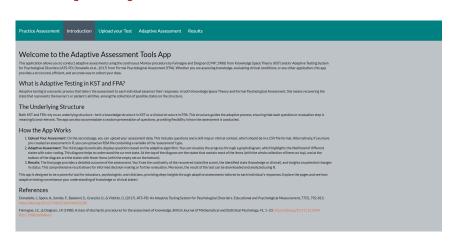
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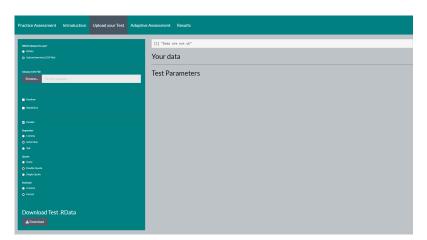










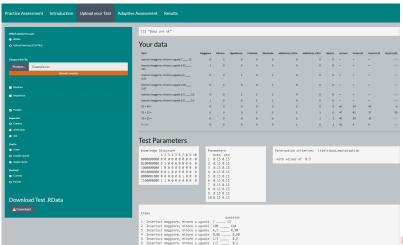










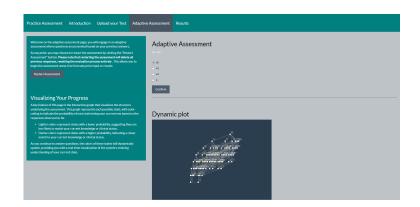










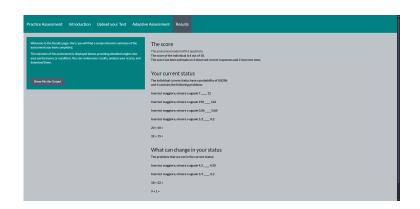












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RAISE - Robotics and AI for Socioeconomic Empowerment

- In collaboration with some middle schools in Lombardia and Liguria
- A pilot test covering the middle school program in in mathematics

Tuning a Test with mycaas

21 items with multiple choice and 595 states

Simulation parameters:

- two termination rules with six stopping criteria $SC = \{.5, .6, .7, .8, .9, 1\}$
- simulate ten response patterns for each $K \in \mathcal{K}$
- lucky guess $\eta_q = .2$ & careless error $\beta_q = .15$









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Performance Analysis

Accuracy and Efficiency Indexes

Given:

- true knowledge state K^w of a student w;
- the probability distribution \mathcal{L}_m at the end of the assessment
- the recovered knowledge state \hat{K}_m^w

The following indexes were computed across simulated subjects:

- The average number of questions asked.
- 2 The average maximum likelihood $\bar{\mathcal{L}}_m(\hat{K}_m)$.
- 3 The average Hamming distance $\bar{D}_m(K, \hat{K}_m)$ computed by

$$\bar{D}_m(K,\hat{K}_m) = \frac{1}{N} \sum_{w=1}^N |K^w \Delta \hat{K}_m^w|,$$

where Δ represents the symmetric set difference.





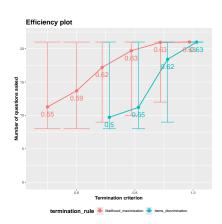


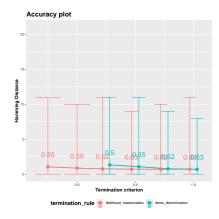




Performance Analysis

performance_simulation(...)













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 - Response: Performance analysis of the test performance_simulation()











Final Remarks

- The Shiny environment is used to make adaptive assessments more accessible and user-friendly.
- Currently the usability of the package is tested within RAISE in Liguria school
- https://github.com/brancaccioandrea/mycass











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