Что цифровой след может рассказать о студенте?

Дмитрий Аббакумов, PhD
ВШЭ и KU Leuven

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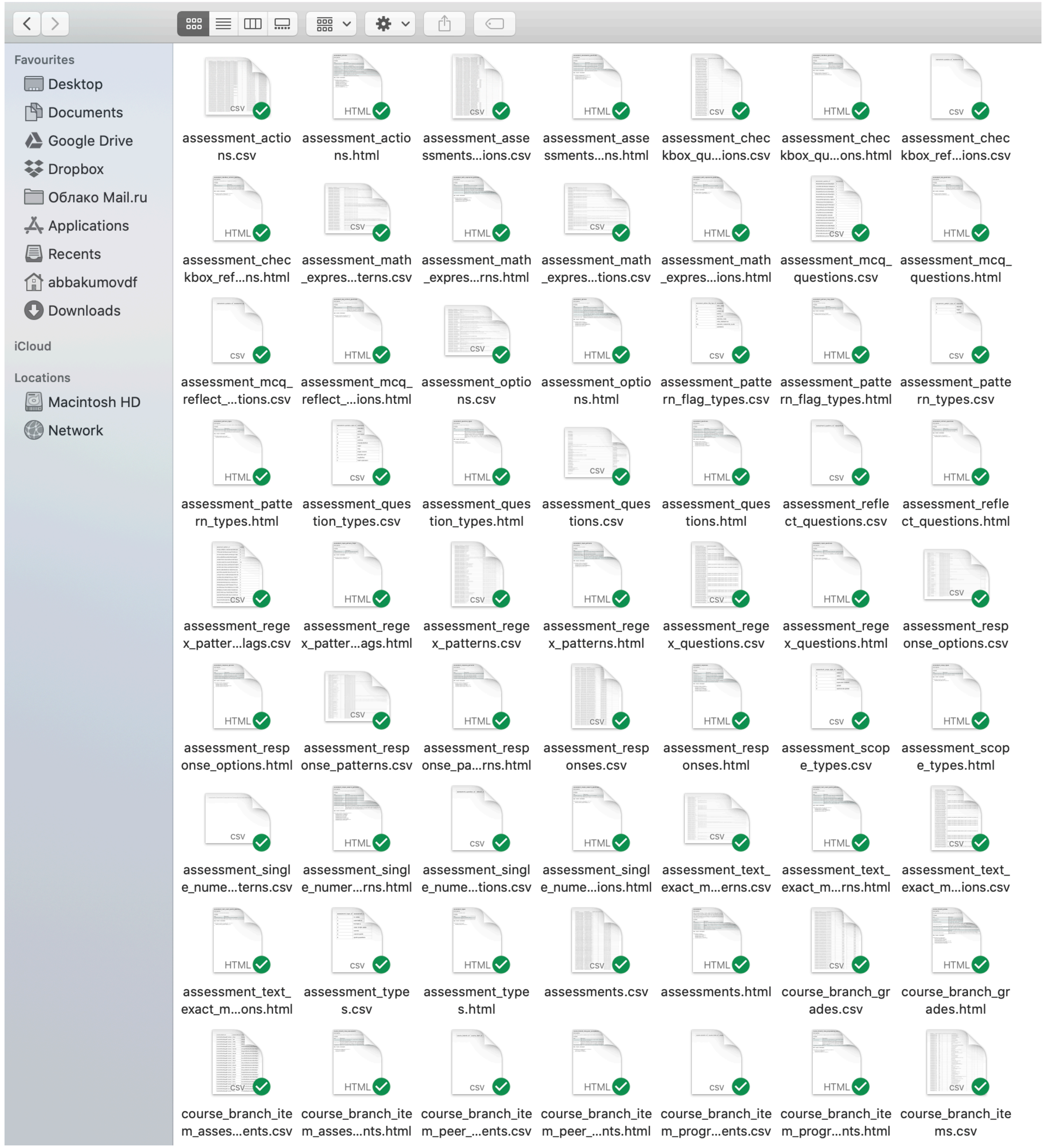

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Измерение подготовленности студентов онлайн-курсов

1. Мотивация
2. Проблема
3. Теоретическая рамка
4. Работа с данными
5. Анализ
6. Интерпретация результатов

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Why measure proficiency in MOOCs?

Proficiency measures

1. mark areas that need additional work within the course
2. show how the course works and evaluate its efficiency
3. give evidence that the learner has mastered the course

FACULTY OF PSYCHOLOGY AND EDUCATIONAL SCIENCES
Methodology of Educational Sciences Research Group
ITEC, imec research group at KU Leuven
KU LEUVEN

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Проблема:

- Частая замена заданий
- Попытки
- Контекстные данные

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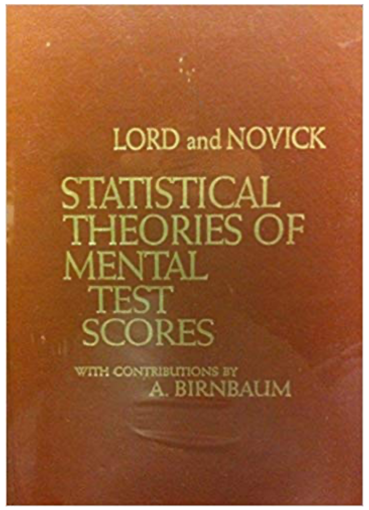
Классическая психометрическая теория

$$X = T + E$$

```
X – наблюдаемый балл
T – истинная подготовленность
E – ошибка измерения
```

Melvin R. Novick (1932–1986)
През. ПО (1979/80)

Frederik M. Lord (1912–2000)
През. ПО (1958/59)



Lord & Novick (1968)

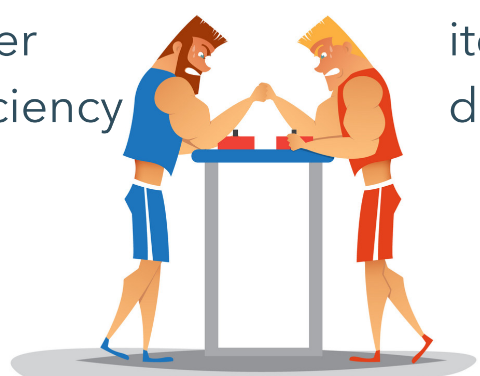
Проблема:

- Частая замена заданий = **классика не подходит!**
- Попытки
- Контекстные данные

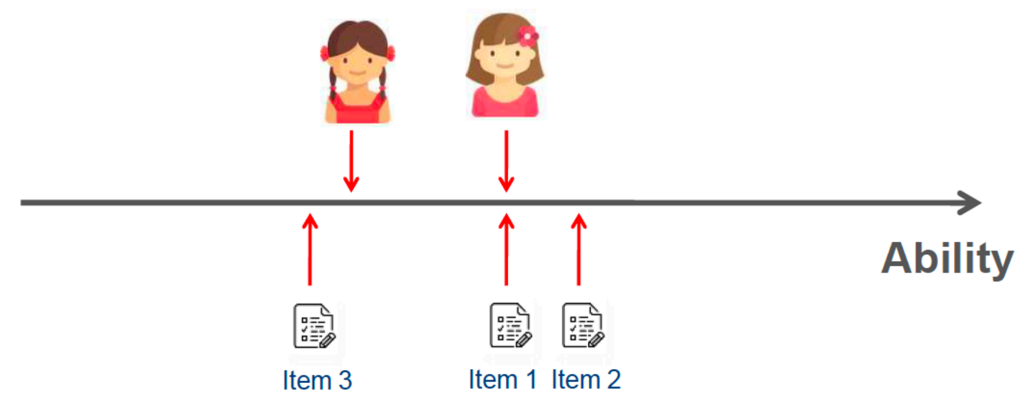
Современная психометрическая теория

Вероятность правильного ответа на задание описывается функцией разности уровня подготовленности студента и уровня трудности задания

learner proficiency



item difficulty



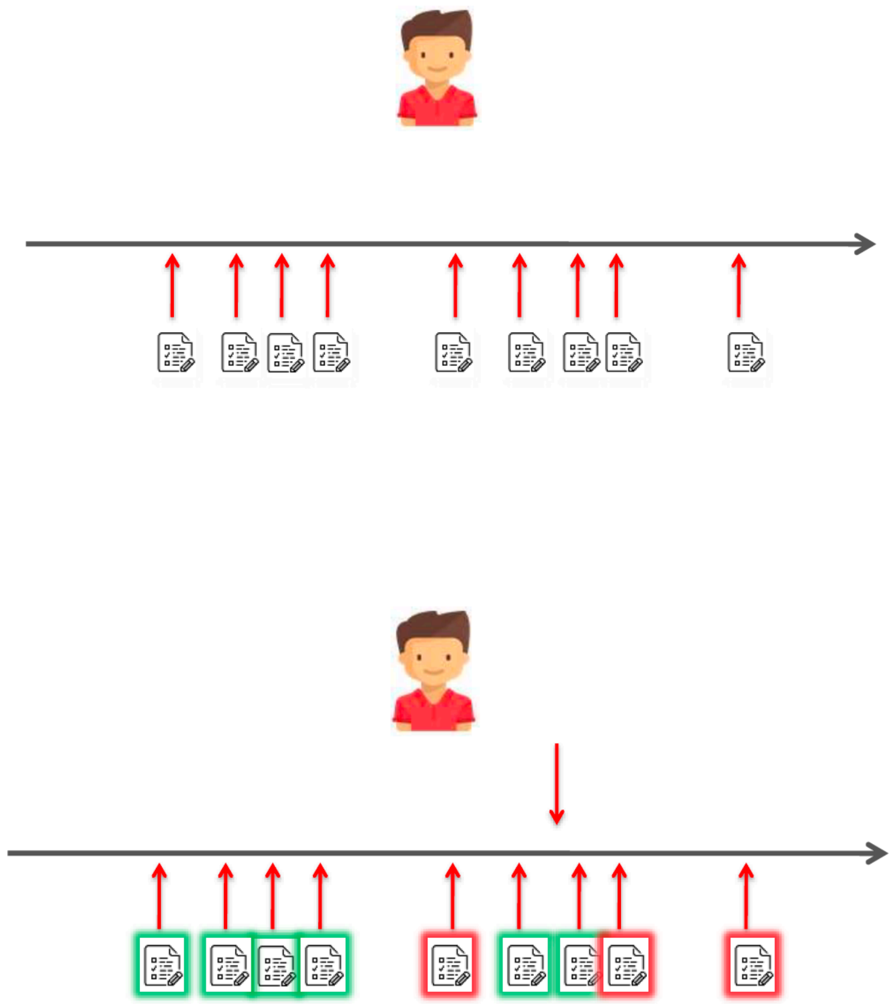
Rasch simple logistic model (SLM)

$$P_{ni} = \frac{e^{(B_n - D_i)}}{1 + e^{(B_n - D_i)}}$$

One-parameter logistic IRT model

$$P_{ni} = \frac{e^{(B_n - D_i)}}{1 + e^{(B_n - D_i)}}$$

Современная психометрическая теория



Проблема:

- Частая замена заданий
- Попытки = **не учтены в современной**
- Контекстные данные = **не учтены в современной**

$$Logit\left(\pi_{ij}\middle|\theta_j\right) = \ln(\pi_{ij}/1 - \pi_{ij}) = \theta_j - \delta_i \; and \; Y_{ij} \sim Bernoulli(\pi_{ij})$$

$$Logit\left(\pi_{ij}\right) = b_0 + u_{1j} + u_{2i},$$

where $u_{1j} \sim N(0, \sigma^2_{u1})$ and $u_{2i} \sim N(0, \sigma^2_{u2})$

Wim Van den Noortgate

Paul De Boeck

През. ПО 1997/98

$$Logit\left(\pi_{ij}\right) = b_0 + (b_{10} + b_{1j})*attempt_{ij} + u_{1j} + u_{2i}$$

$$Logit\left(\pi_{ij}\right) = b_0 + (b_{10} + b_{1j} + b_{1i})*attempt_{ij} + u_{1j} + u_{2i}$$

$$Logit\left(\pi_{ij}\right) = b_0 + (b_{10} + b_{1j} + b_{1i})*attempt_{ij} + b_2*class_j + \ b_3*attempt_{ij}*class_j + u_{1j} + u_{2i}$$

$$Logit\left(\pi_{ij}\right) = b_0 + (b_{10} + b_{1j} + b_{1i})*attempt_{ij} + b_2*class_j + b_3*attempt_{ij}*class_j + \ b_4*formative\,.\,assessment\,.\,performance_j + b_5*lecture\,.\,activity_j + u_{1j} + u_{2i}$$

Проблема:

- Частая замена заданий
- Попытки = ~~не~~ **учтены в современной**
- Контекстные данные = ~~не~~ **учтены в современной**

Измерение подготовленности студентов онлайн-курсов

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{"agent": "Mozilla/5.0 (X11; Linux x86_64) AppleWebKit/537.36 (KHTML, like Gecko)
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item_id	item_4
correctness	0
attempt	0
class	4
form_performance	.4
lect_activity	.6

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```
[1] "MODEL TITLE"
[1] "m0"
glmer(formula = assessment_response_score ~ 1 + (1 | hse_user_id) +
    (1 | assessment_question_id), data = db, family = binomial)
coef.est  coef.se
    0.63     0.22

Error terms:
 Groups                 Name        Std.Dev.
 hse_user_id            (Intercept) 0.78
 assessment_question_id (Intercept) 1.01
 Residual                           1.00
---
number of obs: 51550, groups: hse_user_id, 1609; assessment_question_id, 21
AIC = 58778.7, DIC = 51779.6
deviance = 55276.1
Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']
 Family: binomial  ( logit )
Formula: assessment_response_score ~ 1 + (1 | hse_user_id) + (1 | assessment_question_id)
   Data: db

     AIC      BIC   logLik deviance df.resid
 58778.7  58805.2 -29386.3  58772.7    51547

Scaled residuals:
    Min      1Q  Median      3Q     Max
-4.0952 -0.7526  0.3708  0.6519  4.2011

Random effects:
 Groups                 Name        Variance Std.Dev.
 hse_user_id            (Intercept) 0.6135   0.7833
 assessment_question_id (Intercept) 1.0158   1.0078
Number of obs: 51550, groups:  hse_user_id, 1609; assessment_question_id, 21

Fixed effects:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)   0.6345     0.2215   2.864  0.00418 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

```
[1] "MODEL TITLE"
[1] "m1"
glmer(formula = assessment_response_score ~ 1 + attempt.rec + 
    (1 + attempt.rec | hse_user_id) + (1 | assessment_question_id), 
    data = db, family = binomial)
            coef.est coef.se
(Intercept) 0.27     0.25   
attempt.rec 0.92     0.03   

Error terms:
 Groups                 Name        Std.Dev. Corr 
 hse_user_id            (Intercept) 0.92          
                        attempt.rec 0.60     0.22 
 assessment_question_id (Intercept) 1.12          
 Residual                           1.00          
---
number of obs: 51550, groups: hse_user_id, 1609; assessment_question_id, 21
AIC = 55401, DIC = 44685.6
deviance = 50037.3 
Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']
 Family: binomial  ( logit )
Formula: assessment_response_score ~ 1 + attempt.rec + (1 + attempt.rec |  
    hse_user_id) + (1 | assessment_question_id)
   Data: db

     AIC      BIC   logLik deviance df.resid 
 55401.0  55454.1 -27694.5  55389.0    51544 

Scaled residuals: 
     Min       1Q   Median       3Q      Max 
-11.3243  -0.6525   0.2929   0.6051   6.1629 

Random effects:
 Groups                 Name        Variance Std.Dev. Corr
 hse_user_id            (Intercept) 0.8411   0.9171       
                        attempt.rec 0.3595   0.5996   0.22
 assessment_question_id (Intercept) 1.2541   1.1199       
Number of obs: 51550, groups:  hse_user_id, 1609; assessment_question_id, 21

Fixed effects:
            Estimate Std. Error z value Pr(>|z|)    
(Intercept)  0.26994    0.24557   1.099    0.272    
attempt.rec  0.92466    0.03061  30.211   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:
            (Intr)
attempt.rec -0.007
```

```
[1] "MODEL TITLE"
[1] "m2"
glmer(formula = assessment_response_score ~ 1 + attempt.rec +
    (1 + attempt.rec | hse_user_id) + (1 + attempt.rec | assessment_question_id),
    data = db, family = binomial, control = glmerControl(optCtrl = list(maxfun = 20000)),
    start = ss)
            coef.est coef.se
(Intercept) 0.29     0.27
attempt.rec 0.90     0.06

Error terms:
 Groups                 Name        Std.Dev. Corr
 hse_user_id            (Intercept) 0.96
                        attempt.rec 0.59     0.18
 assessment_question_id (Intercept) 1.22
                        attempt.rec 0.21     -0.58
 Residual                           1.00
---
number of obs: 51550, groups: hse_user_id, 1609; assessment_question_id, 21
AIC = 54928.6, DIC = 43940.5
deviance = 49426.6
Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']
 Family: binomial  ( logit )
Formula: assessment_response_score ~ 1 + attempt.rec + (1 + attempt.rec |
    hse_user_id) + (1 + attempt.rec | assessment_question_id)
   Data: db
Control: glmerControl(optCtrl = list(maxfun = 20000))

     AIC      BIC   logLik deviance df.resid
 54928.6  54999.4 -27456.3  54912.6    51542

Scaled residuals:
    Min      1Q  Median      3Q     Max
-9.0770 -0.6386  0.2920  0.5887  6.9007

Random effects:
 Groups                 Name        Variance Std.Dev. Corr
 hse_user_id            (Intercept) 0.91642  0.9573
                        attempt.rec 0.35181  0.5931   0.18
 assessment_question_id (Intercept) 1.49362  1.2221
                        attempt.rec 0.04462  0.2112   -0.58
Number of obs: 51550, groups:  hse_user_id, 1609; assessment_question_id, 21

Fixed effects:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  0.28628    0.26801   1.068    0.285
attempt.rec  0.89732    0.05587  16.061   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:
            (Intr)
attempt.rec -0.481
```

```
[1] "MODEL TITLE"
[1] "m3"
glmer(formula = assessment_response_score ~ 1 + attempt.rec *
    group + (1 + attempt.rec | hse_user_id) + (1 + attempt.rec |
    assessment_question_id), data = db, family = binomial, control = glmerControl(optCtrl = list(maxfun = 20000)),
    start = ss)
                  coef.est coef.se
(Intercept)        0.65     0.27
attempt.rec        1.34     0.07
group             -0.48     0.03
attempt.rec:group -0.33     0.03

Error terms:
 Groups                 Name        Std.Dev. Corr
 hse_user_id            (Intercept) 0.86
                        attempt.rec 0.52     -0.11
 assessment_question_id (Intercept) 1.22
                        attempt.rec 0.21     -0.59
 Residual                           1.00
---
number of obs: 51550, groups: hse_user_id, 1609; assessment_question_id, 21
AIC = 54487.4, DIC = 44586.9
deviance = 49527.2
Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']
 Family: binomial  ( logit )
Formula: assessment_response_score ~ 1 + attempt.rec * group + (1 + attempt.rec |
    hse_user_id) + (1 + attempt.rec | assessment_question_id)
   Data: db
Control: glmerControl(optCtrl = list(maxfun = 20000))

     AIC      BIC   logLik deviance df.resid
 54487.4  54575.9 -27233.7  54467.4    51540

Scaled residuals:
    Min      1Q  Median      3Q     Max
-8.5593 -0.6367  0.2888  0.5895  6.8981

Random effects:
 Groups                 Name        Variance Std.Dev. Corr
 hse_user_id            (Intercept) 0.73881  0.8595
                        attempt.rec 0.26643  0.5162   -0.11
 assessment_question_id (Intercept) 1.49750  1.2237
                        attempt.rec 0.04468  0.2114   -0.59
Number of obs: 51550, groups:  hse_user_id, 1609; assessment_question_id, 21

Fixed effects:
                  Estimate Std. Error z value Pr(>|z|)
(Intercept)        0.64834    0.26955   2.405   0.0162 *
attempt.rec        1.33564    0.06804  19.630   <2e-16 ***
group             -0.48193    0.02969 -16.235   <2e-16 ***
attempt.rec:group -0.33418    0.02788 -11.987   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:
            (Intr) attmp. group
attempt.rec -0.414
group       -0.091  0.067
attmpt.rc:g  0.024 -0.631 -0.171
```

```
[1] "MODEL TITLE"
[1] "m4"
glmer(formula = assessment_response_score ~ 1 + attempt.rec *
    group + lp + fp + (1 + attempt.rec | hse_user_id) + (1 +
    attempt.rec | assessment_question_id), data = db, family = binomial,
    control = glmerControl(optCtrl = list(maxfun = 20000)), start = ss)
                  coef.est coef.se
(Intercept)       -0.75     0.30
attempt.rec        1.34     0.07
group             -0.42     0.03
lp                 0.32     0.07
fp                 1.16     0.09
attempt.rec:group -0.33     0.03

Error terms:
 Groups                 Name        Std.Dev. Corr
 hse_user_id            (Intercept) 0.77
                        attempt.rec 0.52     -0.07
 assessment_question_id (Intercept) 1.22
                        attempt.rec 0.21     -0.58
 Residual                           1.00
---
number of obs: 51550, groups: hse_user_id, 1609; assessment_question_id, 21
AIC = 54260.2, DIC = 44937
deviance = 49586.6
Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']
 Family: binomial  ( logit )
Formula: assessment_response_score ~ 1 + attempt.rec * group + lp + fp +
    (1 + attempt.rec | hse_user_id) + (1 + attempt.rec | assessment_question_id)
   Data: db
Control: glmerControl(optCtrl = list(maxfun = 20000))

     AIC      BIC   logLik deviance df.resid
 54260.2  54366.4 -27118.1  54236.2    51538

Scaled residuals:
    Min      1Q  Median      3Q     Max
-8.7422 -0.6357  0.2882  0.5888  6.9224

Random effects:
 Groups                 Name        Variance Std.Dev. Corr
 hse_user_id            (Intercept) 0.59150  0.7691
                        attempt.rec 0.26841  0.5181   -0.07
 assessment_question_id (Intercept) 1.49685  1.2235
                        attempt.rec 0.04458  0.2111   -0.58
Number of obs: 51550, groups:  hse_user_id, 1609; assessment_question_id, 21

Fixed effects:
                  Estimate Std. Error z value Pr(>|z|)
(Intercept)       -0.74662    0.29589  -2.523   0.0116 *
attempt.rec        1.33715    0.06808  19.641  < 2e-16 ***
group             -0.41830    0.02778 -15.058  < 2e-16 ***
lp                 0.32347    0.06646   4.867 1.13e-06 ***
fp                 1.15944    0.08885  13.050  < 2e-16 ***
attempt.rec:group -0.33473    0.02800 -11.953  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:
            (Intr) attmp. group  lp     fp
attempt.rec -0.380
group       -0.092  0.069
lp          -0.368  0.005 -0.036
fp          -0.091  0.019  0.148 -0.258
attmpt.rc:g  0.026 -0.632 -0.166 -0.005 -0.020
```

Измерение подготовленности студентов онлайн-курсов

1. Мотивация

2. Проблема

3. Теоретическая рамка

4. Работа с данными

5. Анализ

6. **Интерпретация результатов**

Table 2.3

Probabilities of correct response on an item with average difficulty

	Effect of Attempt: Student-Specific	Effect of Attempt: Item-Specific	Maximum Number of Used Attempts	Watched All Video Lectures and Was Productive with Formative Assessments	Attempt 1	Attempt 2	Attempt 3
Basic Model					.65		
Extension 1	Average				.57	.77	.89
	+ 1 SD				.57	.86	.96
	- 1 SD				.57	.64	.71
Extension 2	Average	Average			.57	.77	.89
		+ 1 SD			.57	.80	.92
		- 1 SD			.57	.73	.84
	+ 1 SD	Average			.57	.86	.96
		+ 1SD			.57	.88	.98
		- 1 SD			.57	.83	.95
	- 1 SD	Average			.57	.65	.71
		+ 1 SD			.57	.69	.79
		- 1 SD			.57	.60	.62
Extension 3	Average	Average	≤ 2		.66	.88	.97
			> 6		.31	.39	.48
Extension 4	Average	Average		Yes	.74	.92	.98
				No	.32	.64	.87

Note: In the table, for the basic model and extensions 1 and 2 the student's proficiency is considered as average.

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Measuring student's proficiency in MOOCs: multiple attempts extensions for the Rasch model

Dmitry Abbakumov • Piet Desmet • Wim Van den Noortgate

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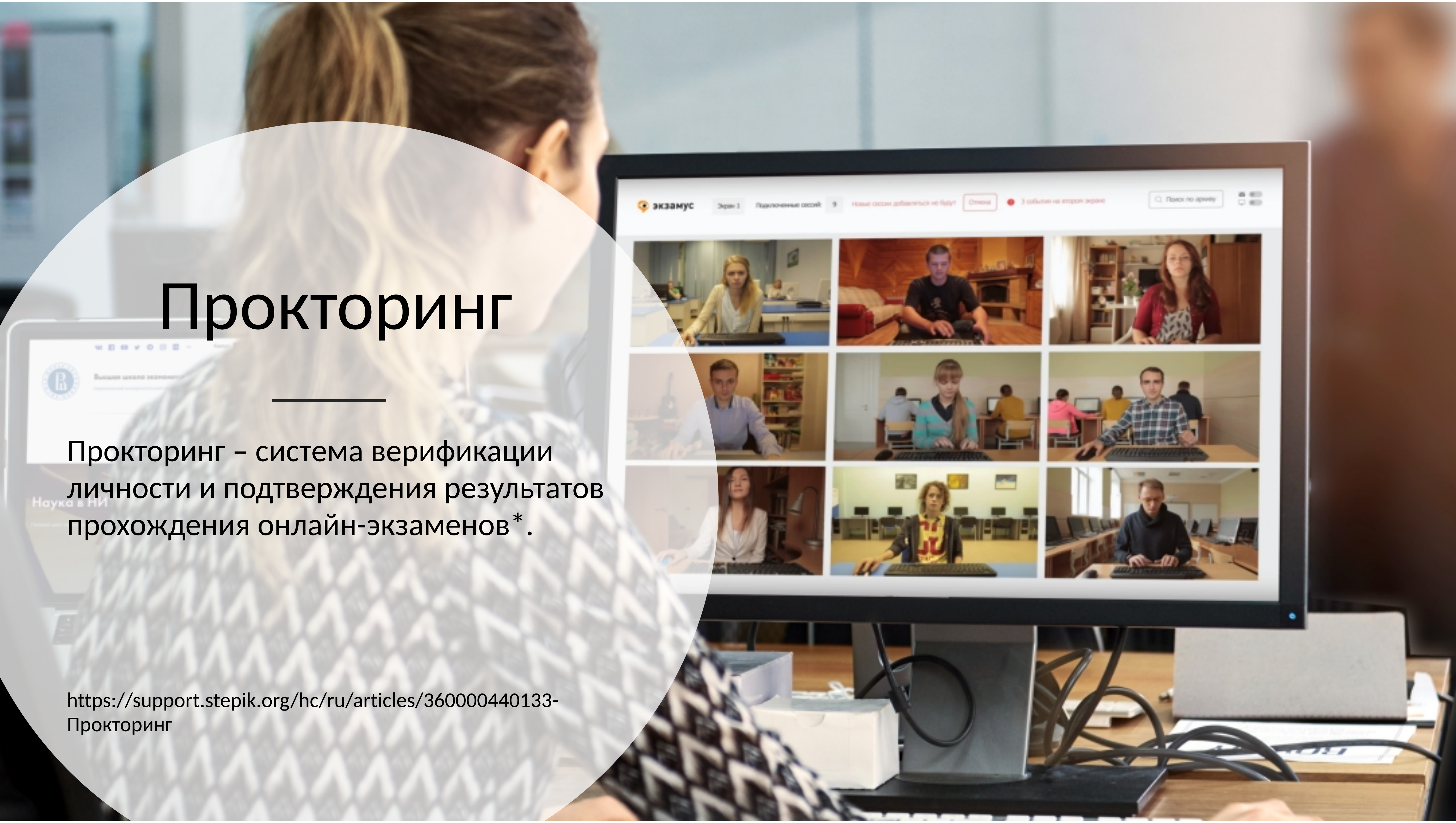
Abstract

Popularity of online courses with open access and unlimited student participation, the so-called massive open online courses (MOOCs), has been growing intensively. Students, professors, and universities have an interest in accurate measures of students' proficiency in MOOCs. However, these measurements face several challenges: (a) assessments are dynamic: items can be added, removed or replaced by a course author at any time; (b) students may be allowed to make several attempts within one assessment; (c) assessments may include an insufficient number of items for accurate individual-level conclusions. Therefore, common psychometric models and techniques of Classical Test Theory (CTT) and Item Response Theory (IRT) do not serve perfectly to measure proficiency. In this study we try to cover this gap and propose cross-classification multilevel logistic extensions of the common IRT model, the Rasch model, aimed at improving the assessment of the student's proficiency by modeling the effect of attempts and by involving non-assessment data such as student's interaction with video lectures and practical tasks. We illustrate these extensions on the logged data from one MOOC and check the quality using a cross-validation procedure on three MOOCs. We found that (a) the performance changes over attempts depend on the student: whereas for some students performance ameliorates, for other students, the performance might deteriorate; (b) similarly, the change over attempts varies over items; (c) student's activity with video

Возможности психометрики для прокторинга



Прокторинг

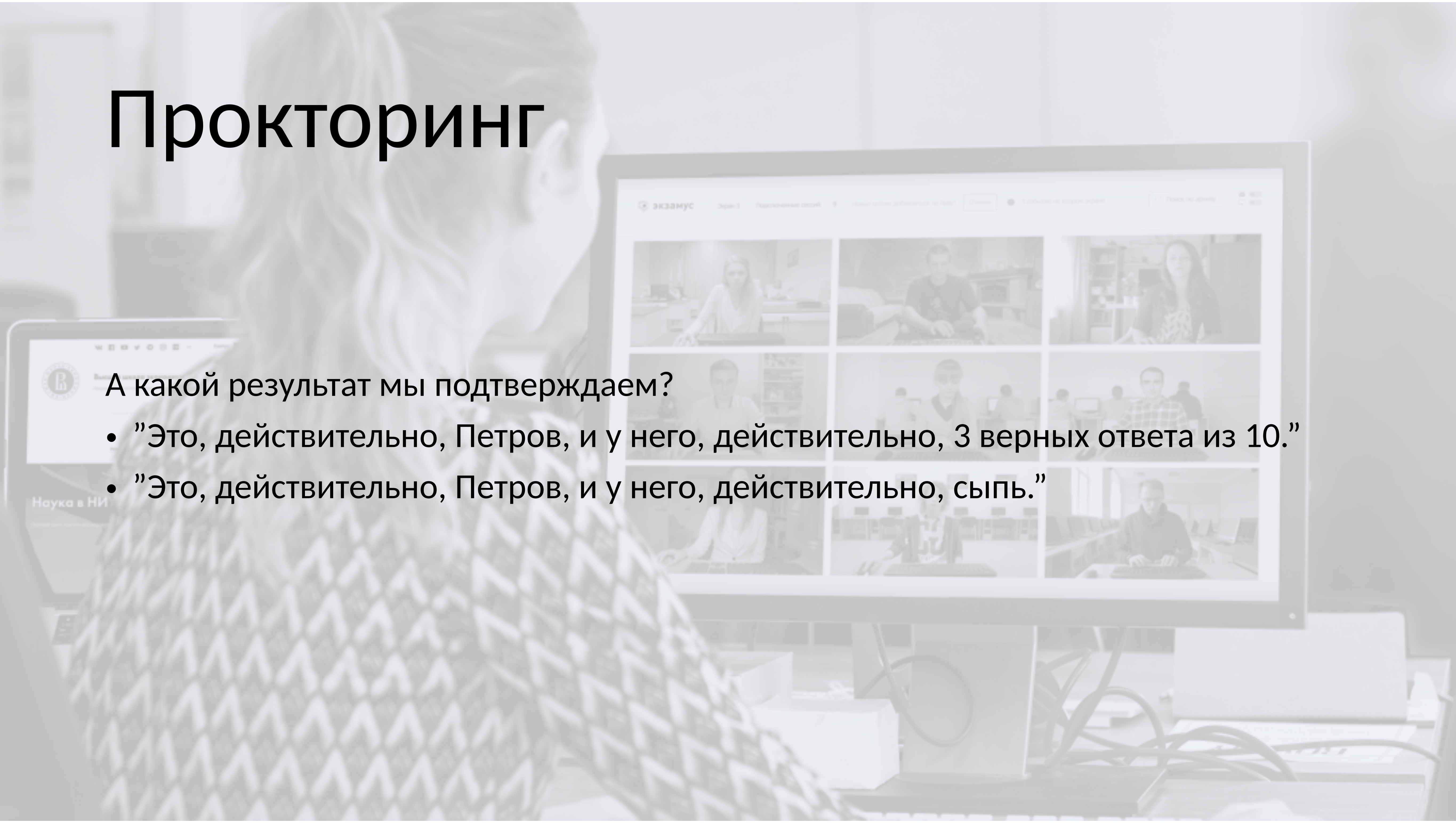
Прокторинг – система верификации личности и подтверждения результатов прохождения онлайн-экзаменов*.

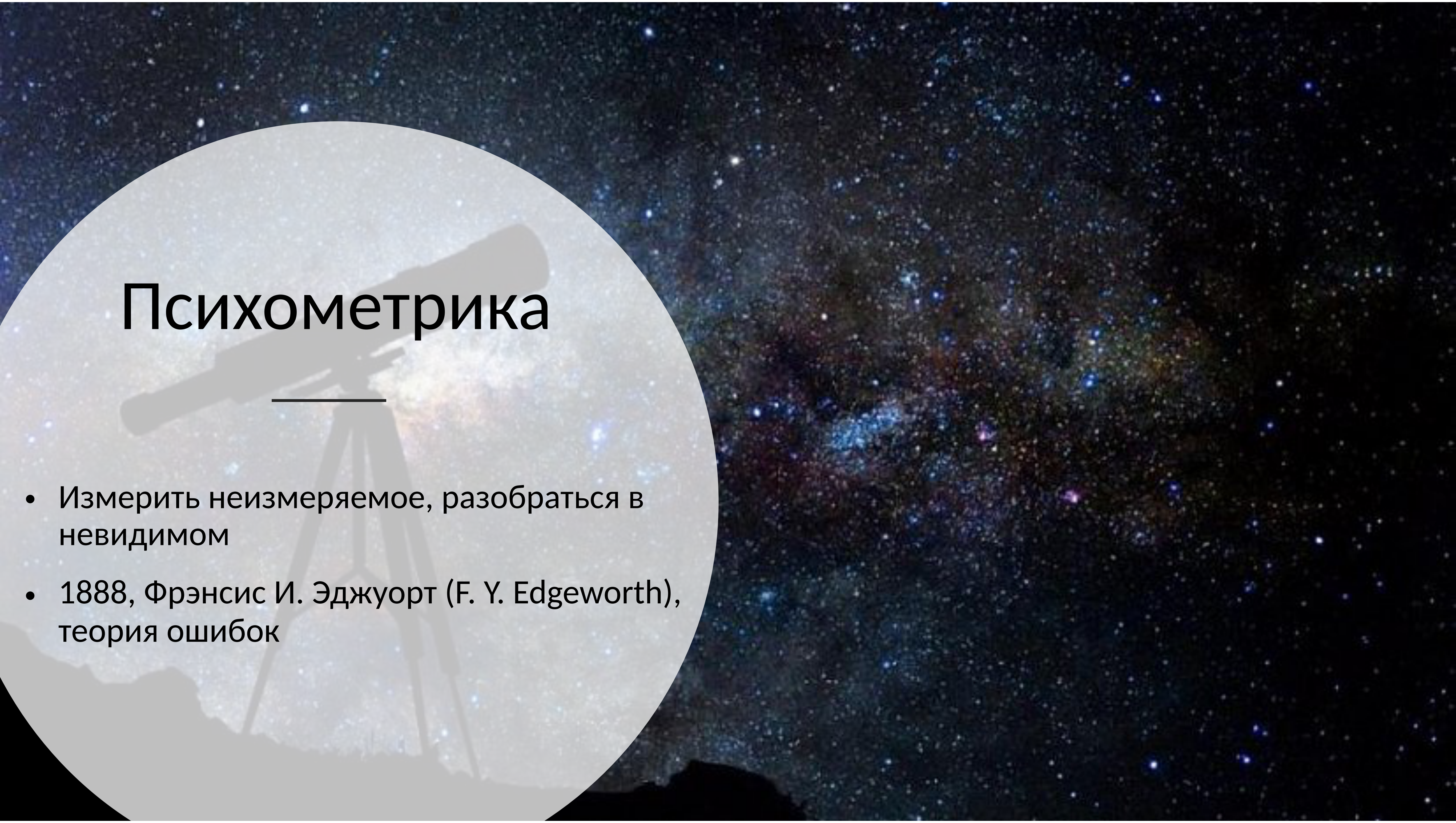
https://support.stepik.org/hc/ru/articles/360000440133-Прокторинг

Прокторинг

А какой результат мы подтверждаем?

- ”Это, действительно, Петров, и у него, действительно, 3 верных ответа из 10.”
- ”Это, действительно, Петров, и у него, действительно, сыпь.”





Психометрика

- Измерить неизмеряемое, разобраться в невидимом
- 1888, Фрэнсис И. Эджуорт (F. Y. Edgeworth), теория ошибок

Психометрика

- 1960-е, Ф. Лорд (F. Lord) и Г. Раш (G. Rasch), теория латентных переменных

Как вы яхту назовете…

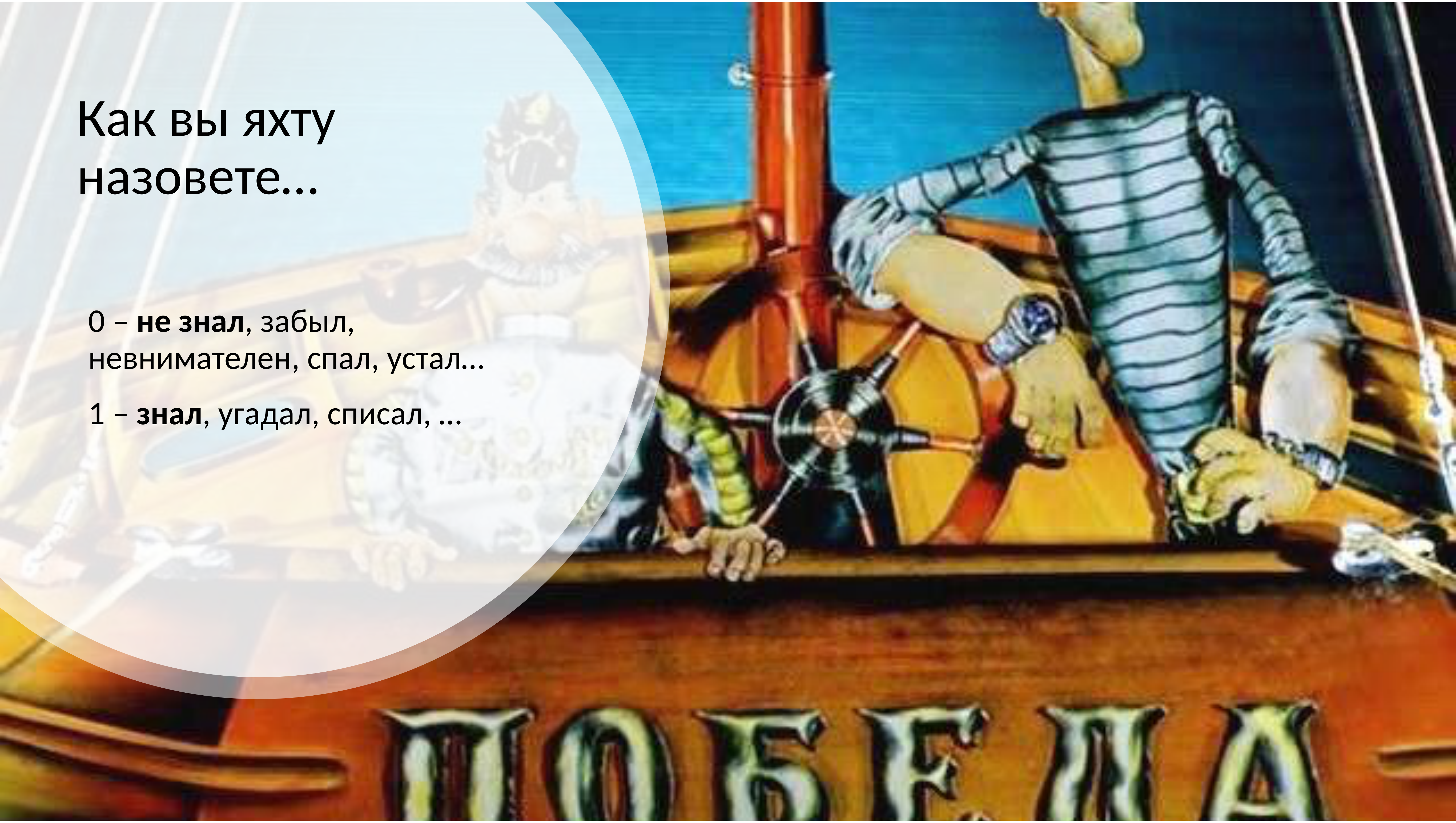
Что стоит за 0 и 1?

Как мы понимаем 0 и 1?

Как вы яхту назовете…

0 – **не знал**, забыл, невнимателен, спал, устал…

1 – **знал**, угадал, списал, …

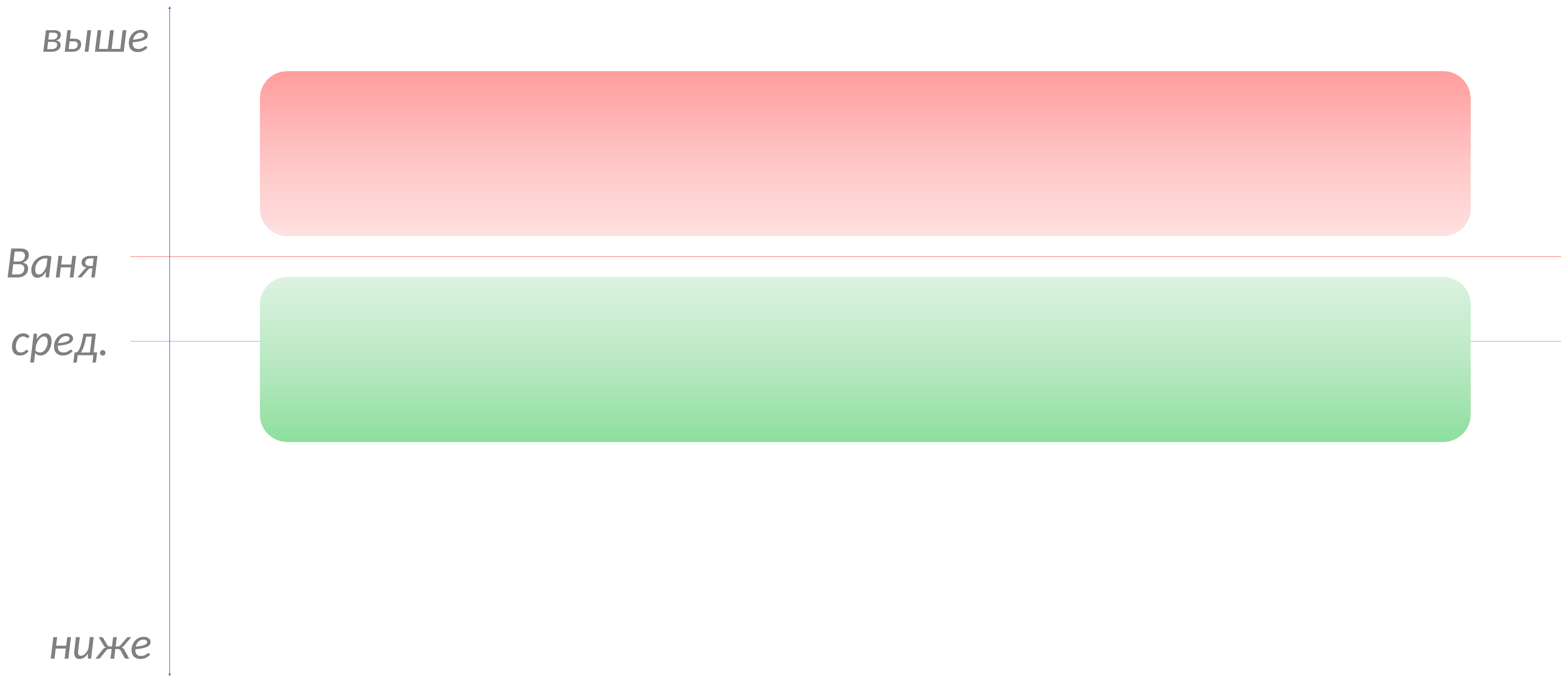


Немного о технологии

- Построение модели (расширения модели Раша):
  - от теории
  - от данных
- Построение ожидаемого паттерна ответов испытуемого в соответствии с моделью
- Анализ расхождений и отклонений в реальном паттерне ответов испытуемого
  - по знаку
  - по локации
  - по предыдущему опыту

Abbakumov, Desmet, & Van den Noortgate (9-13 July 2018) Measuring student's proficiency in MOOCs: Multiple attempts extensions for the Rasch model. *The 2018 International Meeting of the Psychometric Society, NY, USA*

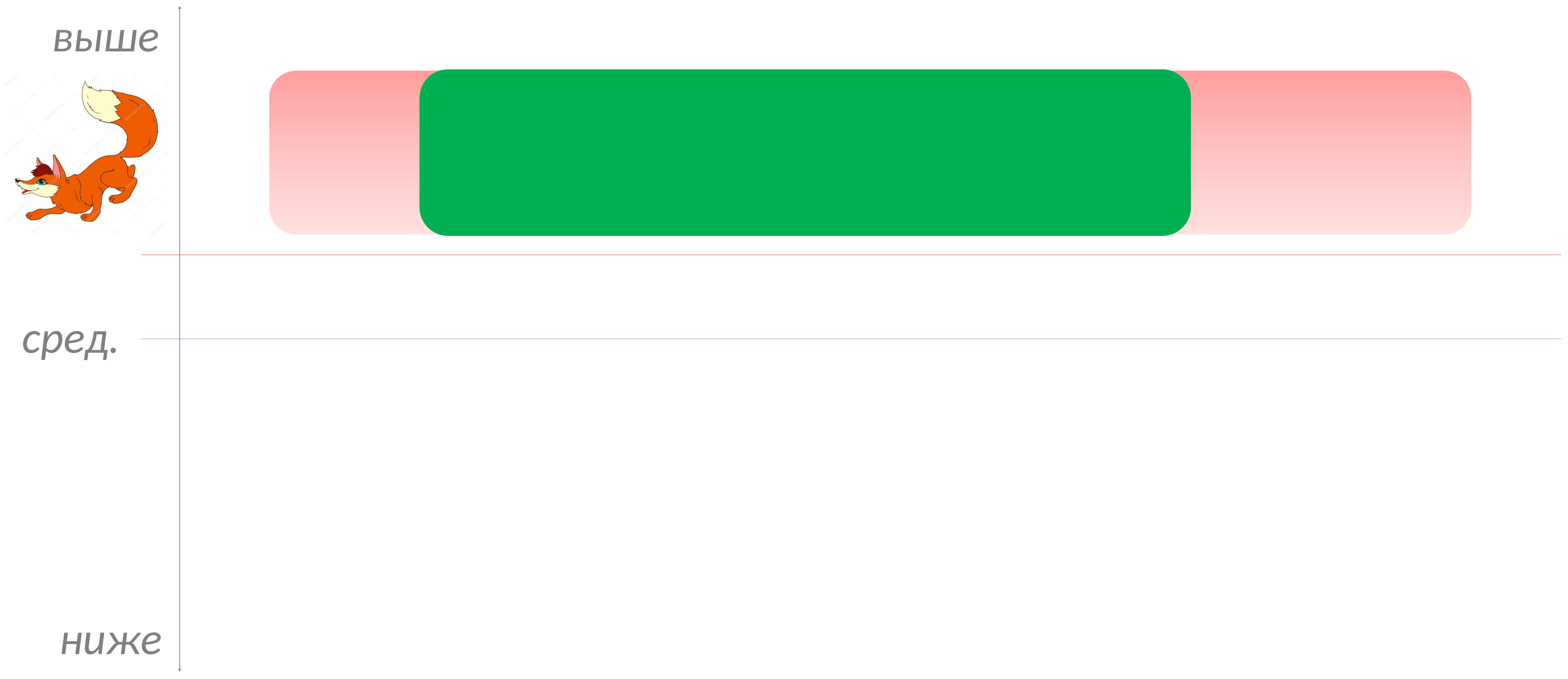
Вероятностный паттерн



Реальный паттерн 1

Реальный паттерн 2

Реальный паттерн 3



Computational Behavioral Science

Behavioral sciences **explore the cognitive processes** within organisms and **the behavioral interactions** between organisms in the natural world. It involves the systematic analysis and investigation of human and animal behavior through the study of the past, controlled and naturalistic observation of the present, and disciplined scientific experimentation and modeling. It attempts to accomplish legitimate, objective conclusions through rigorous formulations and observation. Examples of behavioral sciences include **psychology, psychobiology, anthropology, and cognitive science**. Generally, behavior science deals primarily with human action and often seeks to generalize about human behavior as it relates to society.

Computational science (also scientific computing or scientific computation (SC)) is a rapidly growing multidisciplinary field that uses **advanced computing capabilities to understand and solve complex problems**. It is an area of science which spans many disciplines, but at its core it involves the development of models and simulations to understand natural systems.

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Спасибо!

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