LEARNING TIME PATTERNS: MANY STUDY TIMES TO CONSIDER WHEN DESIGNING DIGITAL LEARNING

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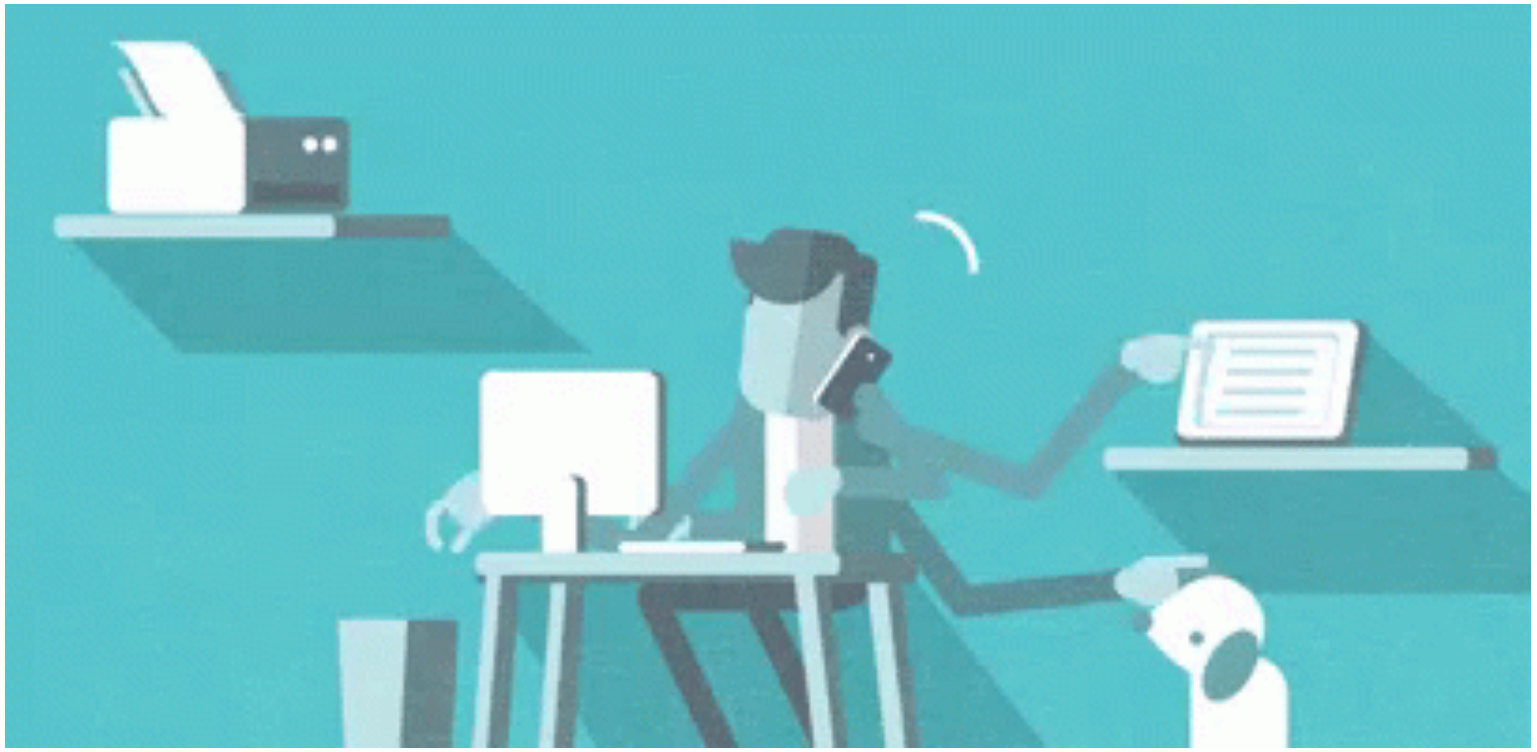
IARIA

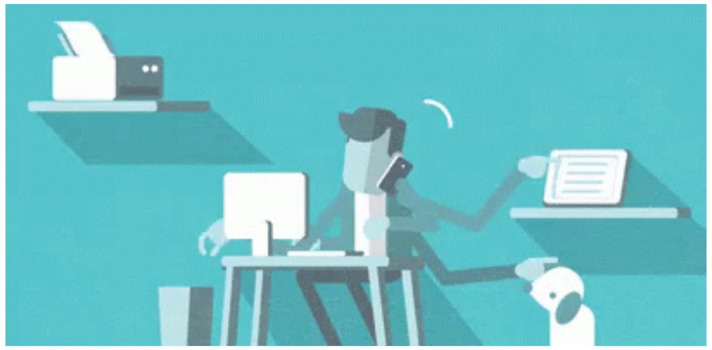
PIAZZA COPERNICO
LEARNING EXPERIENCE EVOLUTION

Sara Zuzzi senior Data Scientist, studies and interprets large amounts of data to derive useful information on which a company can base its strategic actions. By processing Big Data, the data scientist is able to make the information hidden in the data understandable, and to transform the data into new knowledge and opportunities.

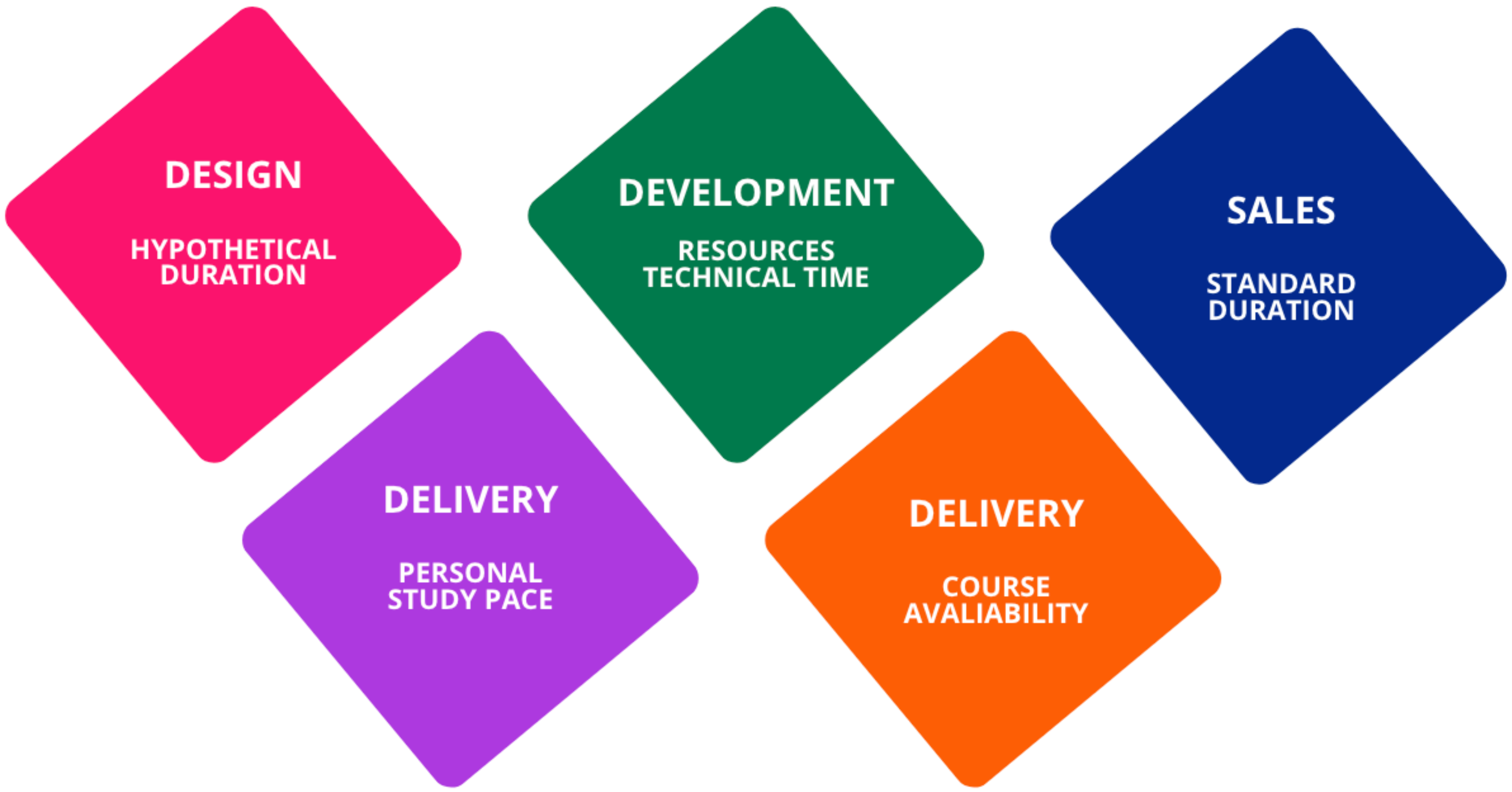
TIME PROBLEM



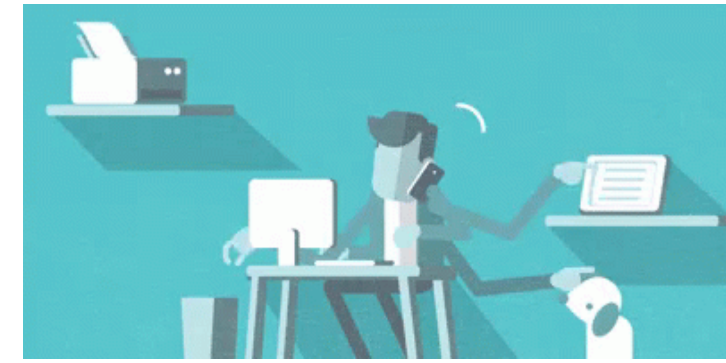
TIME IN DIGITAL LEARNING 1/2



- is a key factor in any training project as it is an important predictor of training outcomes;
- is a driver in the digital content market;
- is also a factor in motivation and engagement.
- There are many dimensions of time in an online course to be taken into account and better investigated



TIME IN DIGITAL LEARNING 2/2



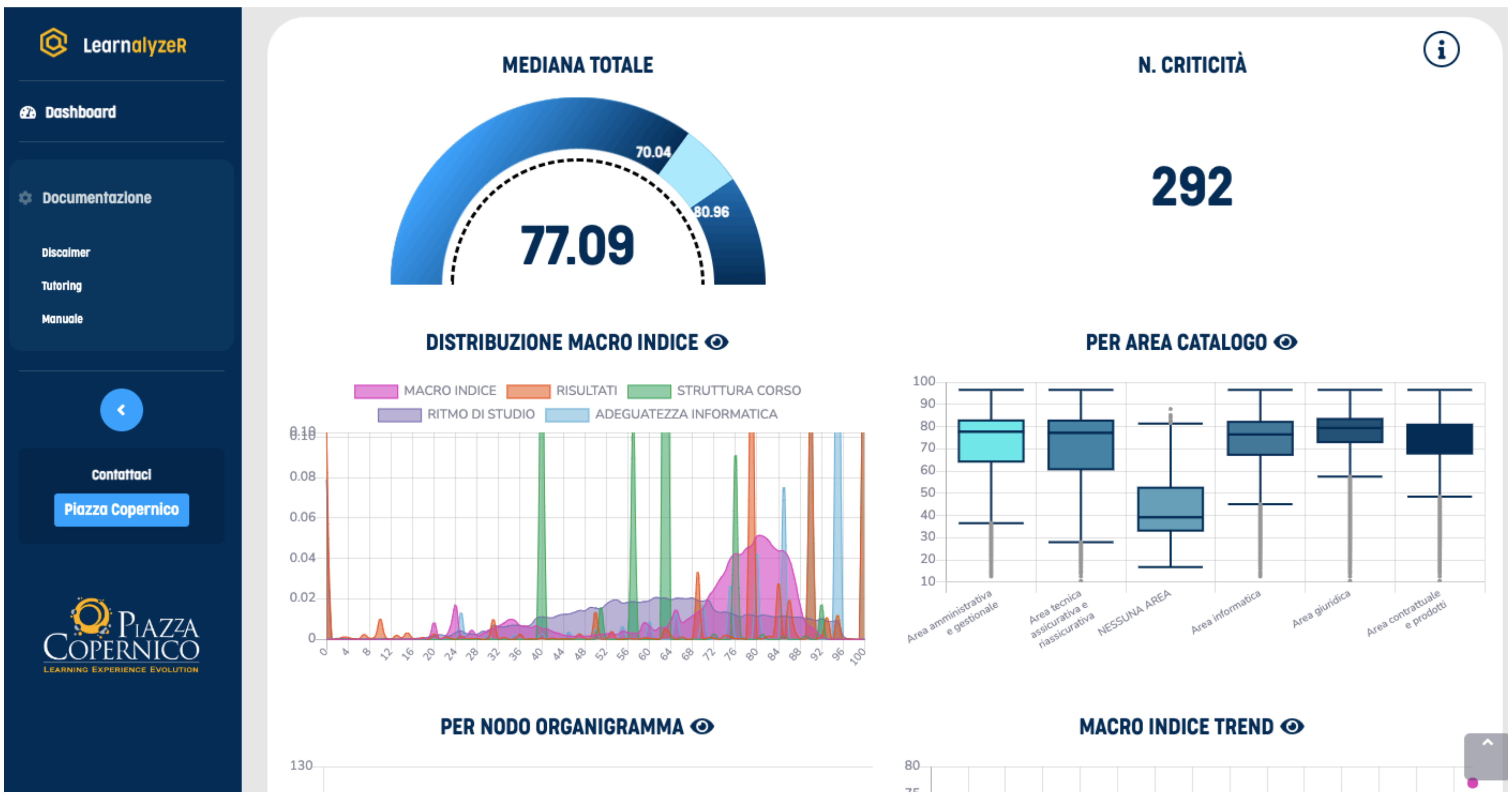
- One of the biggest **problems** in digital learning is understanding the **time dimension** and its **impact** on the **design** and **study** of the **different teaching methodologies**.
- Investigating **time** differences means being able to give **instructional designers** clearer **information to design teaching**, taking into account cognitive load and usage patterns of training materials.
- There are **studies in the literature** on time patterns that focus on analysing the factors that contribute to **effective learning by assessing users results and satisfaction**.

WHAT DO WE WANT TO INVESTIGATE?

METHODS AND TOOLS

- A **comparative examination of time** between teaching methodologies is proposed to investigate whether there are **different patterns of time use**, behavior and performance. The tool we use for the analysis is:

LearnalyzeR



METHODS AND TOOLS

- A **comparative examination of time** between teaching methodologies is proposed to investigate whether there are **different patterns of time use**, behavior and performance. The tool we use for the analysis is:
- LearnalyzeR provides a **performance level** for each user and edition, analysing critical issues and supporting the tutor's daily intervention through the MIP.
  - **Macro Performance Index** (MIP), composite indicator, range [0,100]
  - The sub-indicators of the MIP: **Results** (I_R), **Study Pace** (I_{SP}), **Course Structure** (I_{CS}), **Computer Adequacy** (I_{CA}); each varies in the range [0,100]
  - MIP divides users into **performance classes** (Lukers MIP=[0;30), Latecomers MIP=[30;50), Regulars MIP=[50;70), Hard Workers MIP=[70;80), Top Performers MIP=[80;100]).

DATA

The courses analysed are 12 from the same client, Zurich, held in 2022:

- **Smartlearning 5 courses, 7052 users**
  Slides of the client onto SCORM content pages plotted within LMS, with an accompanying narrative voice created by a professional speaker.
- **Tutorial Storytelling 3 courses, 3545 users**
  The content pages consist of text, images, graphics and sounds; there are games with low-complexity interactions, test pages, exercises, cases and stories to make the content more concrete (soft skills type).
- **Videolearning 4 courses, 5605 users**
  TEACHING PILLS, video lessons with actors or lecturers; static filming.

THE ANALYSIS RESULTS

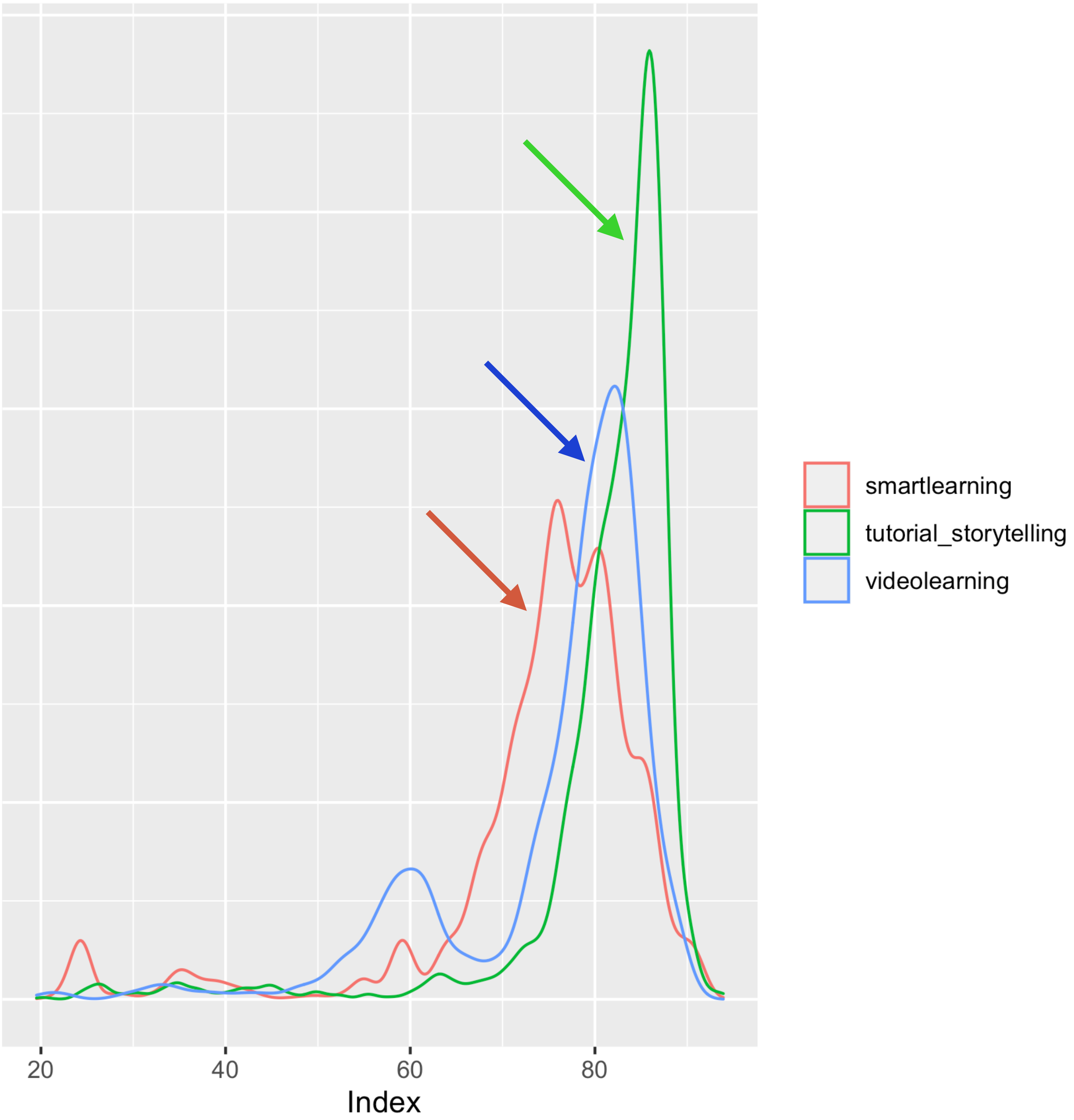
THE ANALYSIS RESULTS 1/7

- **Smartlearning:** MIP has shifted towards performace values below 80; median 76; at least 50% per cent of users are not above the Regulars class.

- **Tutorial storytelling:** MIP narrow peak above 80; median 83 with a fairly homogeneous behaviour of the population (narrow distribution); at least 75% of the users are in the Top Performers class.

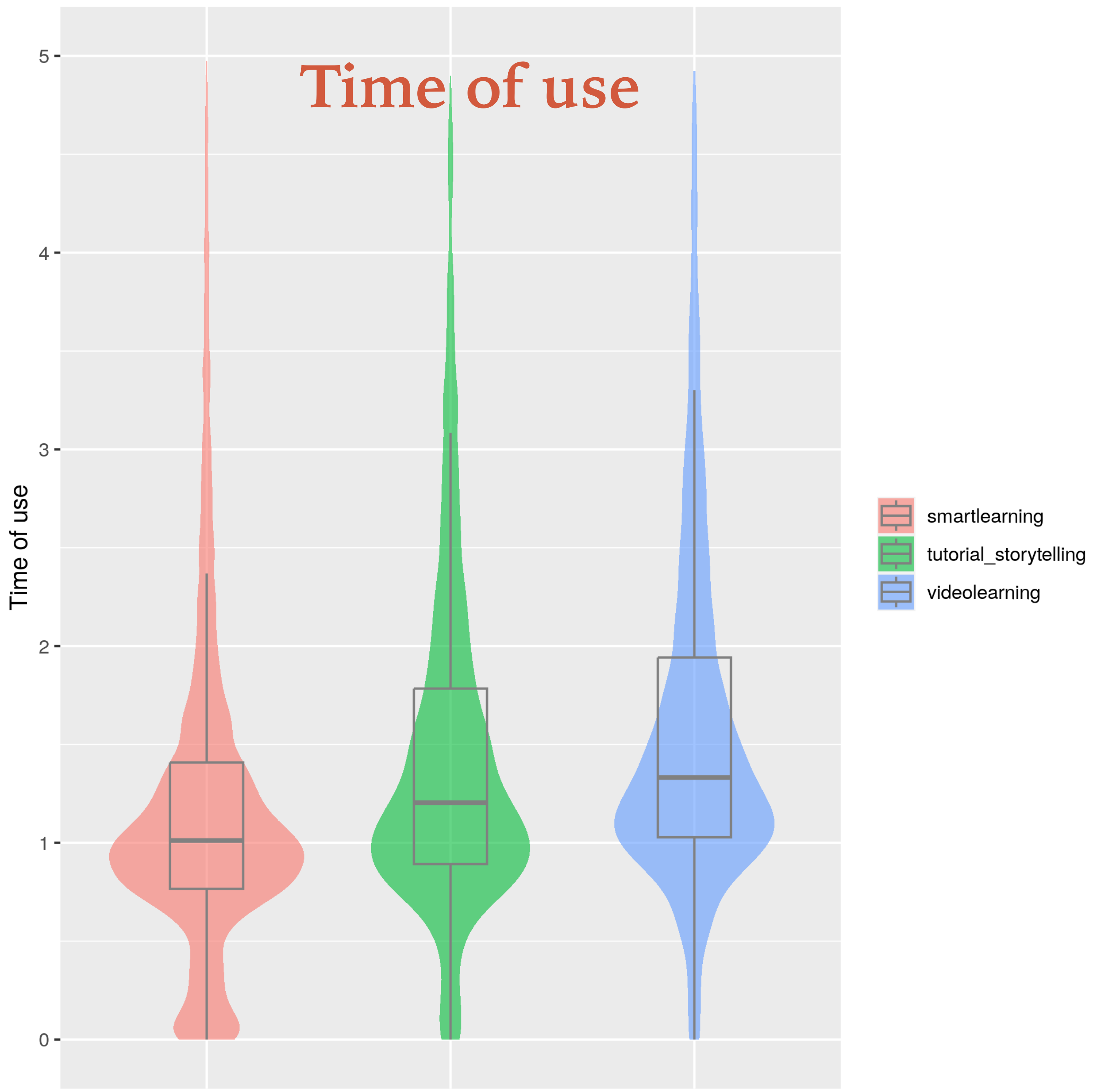
- **Videolearning:** different levels of performance are observed, a narrow peak around 80, a second peak around 60 and a non-negligible left tail (inhomogeneity of performance); median 79; at least 75% of the users are not below the Regulars class.

Performance



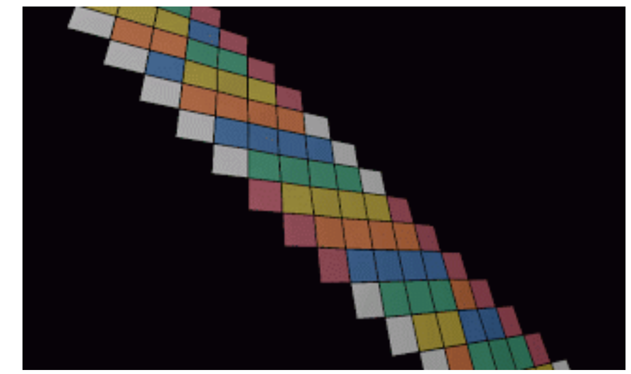
THE ANALYSIS RESULTS 2/7

When analysing the Normalised Use Time (NUT=time of use / expected time), it can be seen that all three course types show an uneven usage behaviour (as in I_{SP}) and there is evidence of long times for a significant percentage of the population (tails upwards).

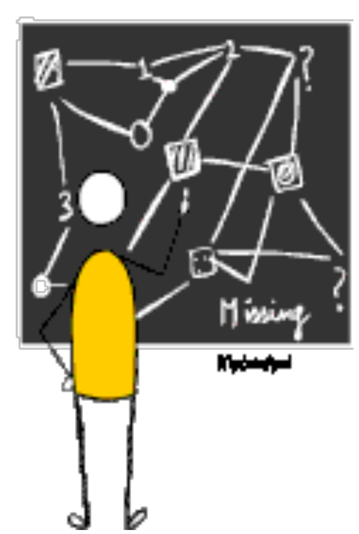


THE ANALYSIS RESULTS 3/7

- To **understand the trends in the MIP** and identify the factors that lead to critical or virtuous behaviour, we open the MIP (composite indicator) and analyse the individual sub-indices **Results** (I_R), **Study Pace** (I_{SP}), **Course Structure** (I_{CS}), **Computer Adequacy** (I_{CA}).



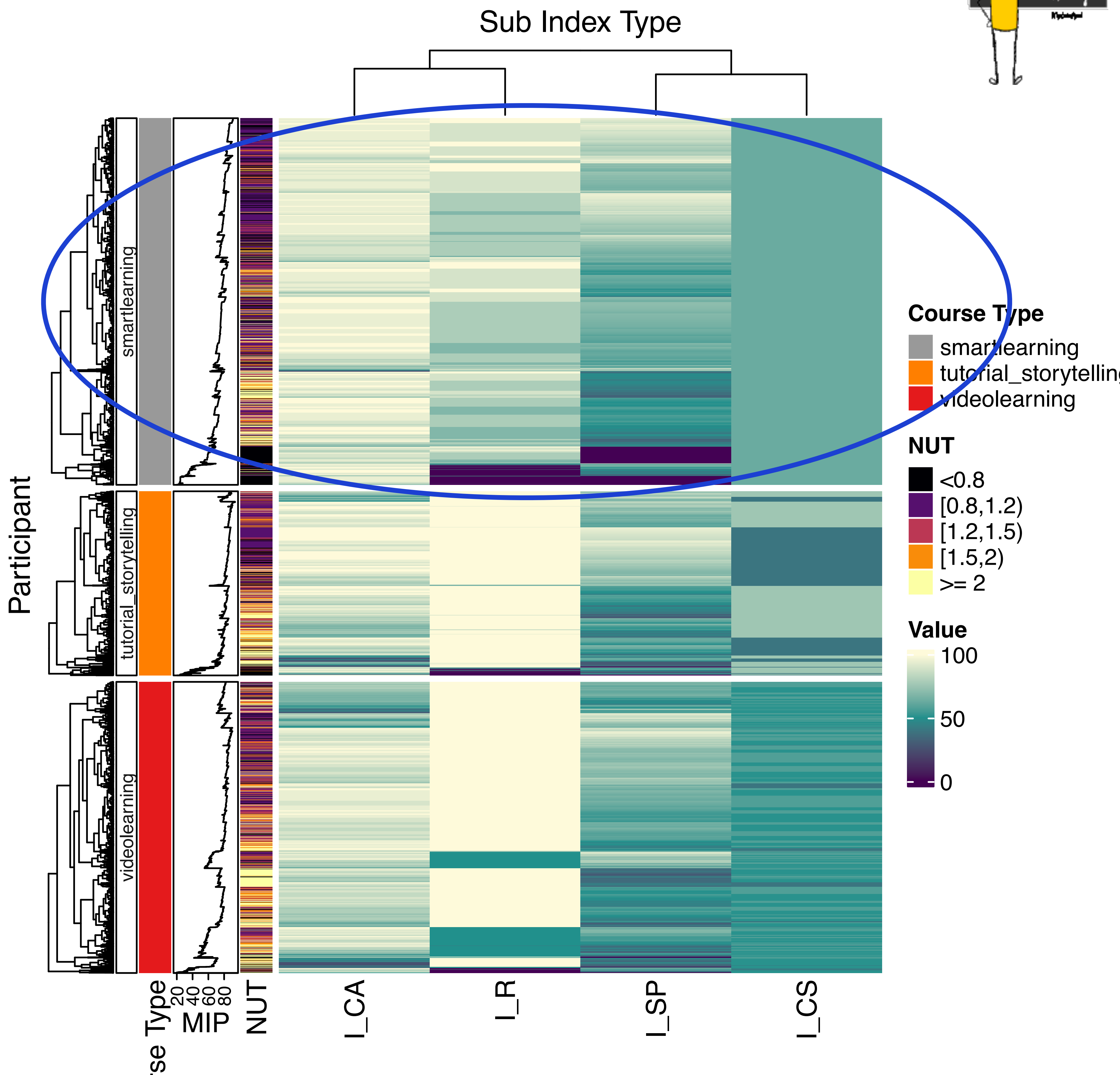
- Finally, we relate the indicators to **Normalized Use Time** (*NUT*).



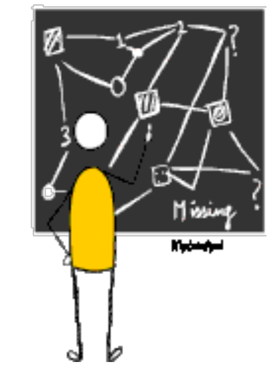
THE ANALYSIS RESULTS 4/7

Heatmap

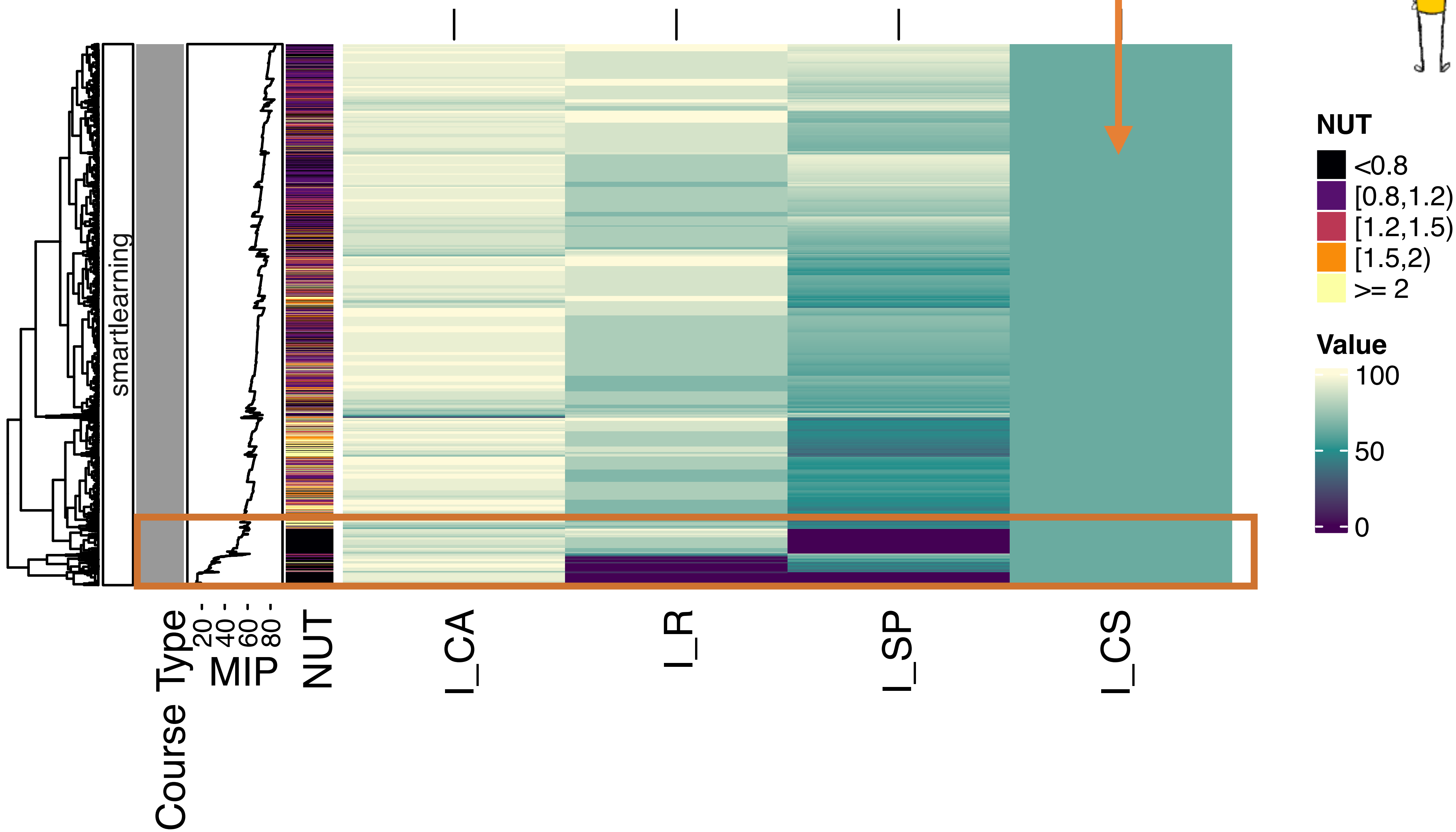
It provides an **overall view** of the analysis performed, highlighting the **presence of intra-type patterns.**



THE ANALYSIS RESULTS 5/7

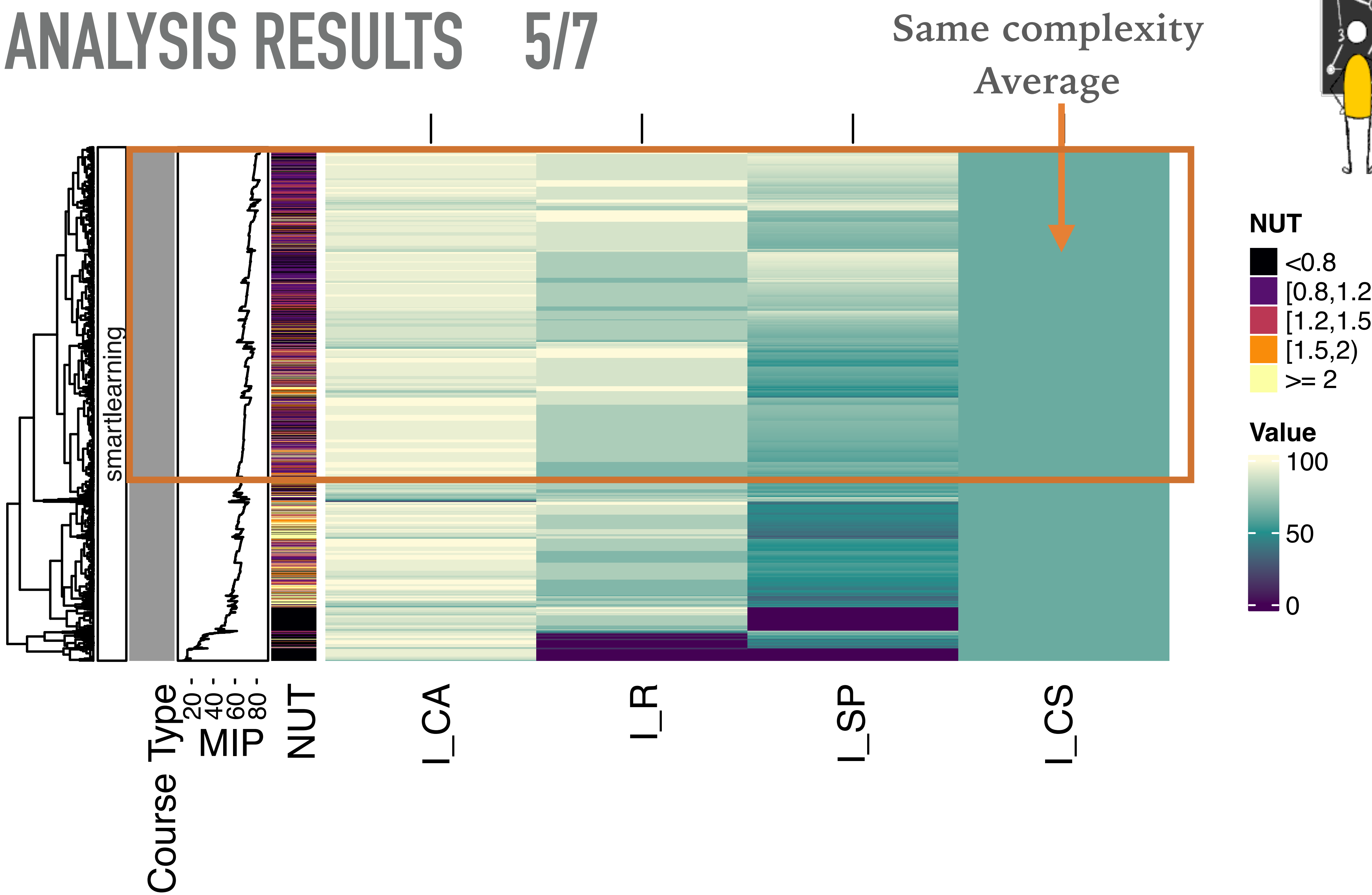


Same complexity
Average



Low MIP values are found in correspondence with dark I_R and I_{SP} (low values) and very dark NUT (less time use than expected); **therefore poor performance (low MIP values) is a consequence of less time use than expected.**

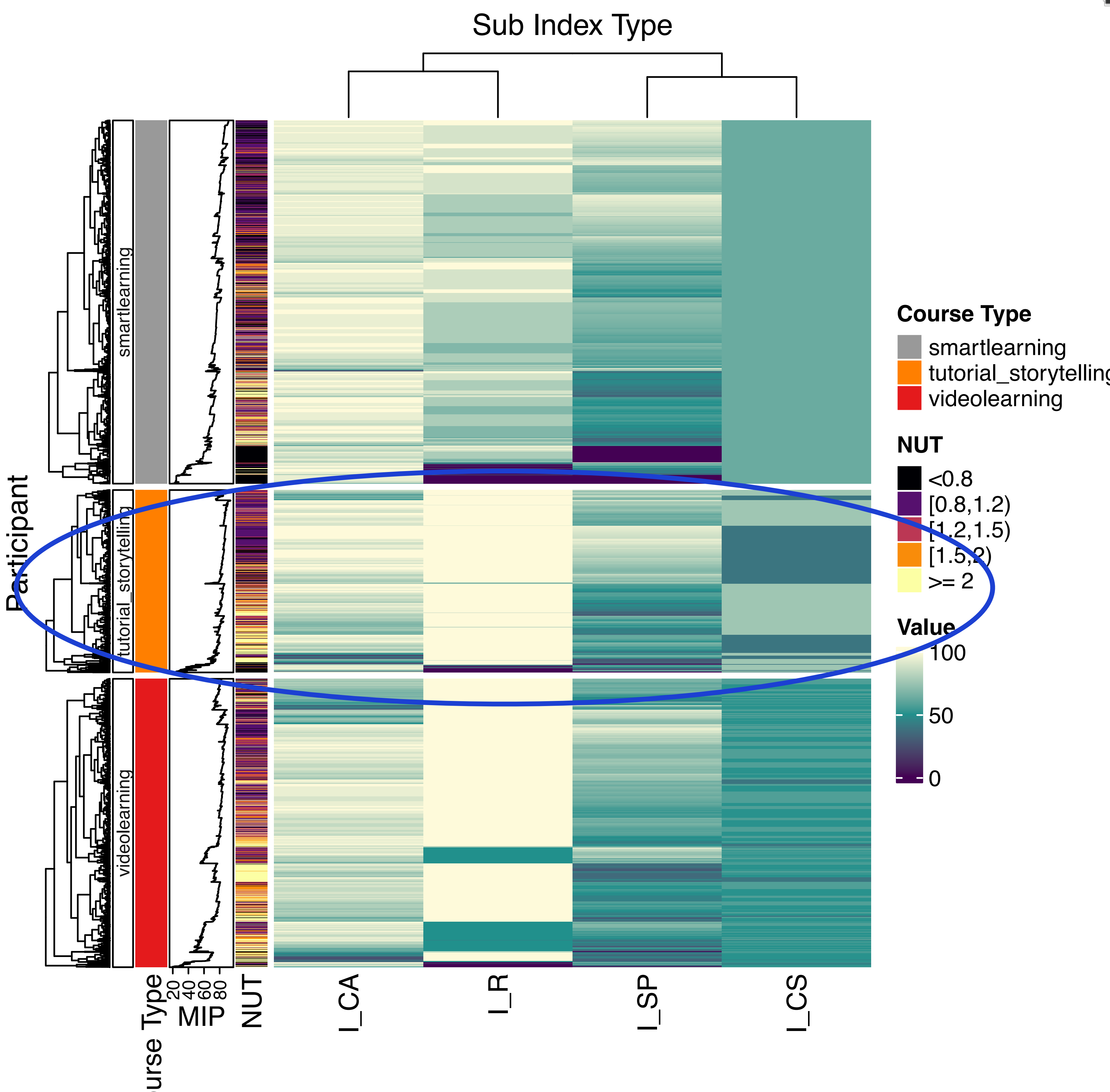
THE ANALYSIS RESULTS 5/7



There are bands where I_R e I_{SP} alternate between light and dark. It can be seen that a good I_{SP} (light bands) corresponds to an adequate NUT (utilisation time equal to that expected), but low I_R values (dark bands) or viceversa. **It can be concluded that in order to obtain the desired results, it is necessary to have a higher time use than expected.**

THE ANALYSIS RESULTS 4/7

Heatmap

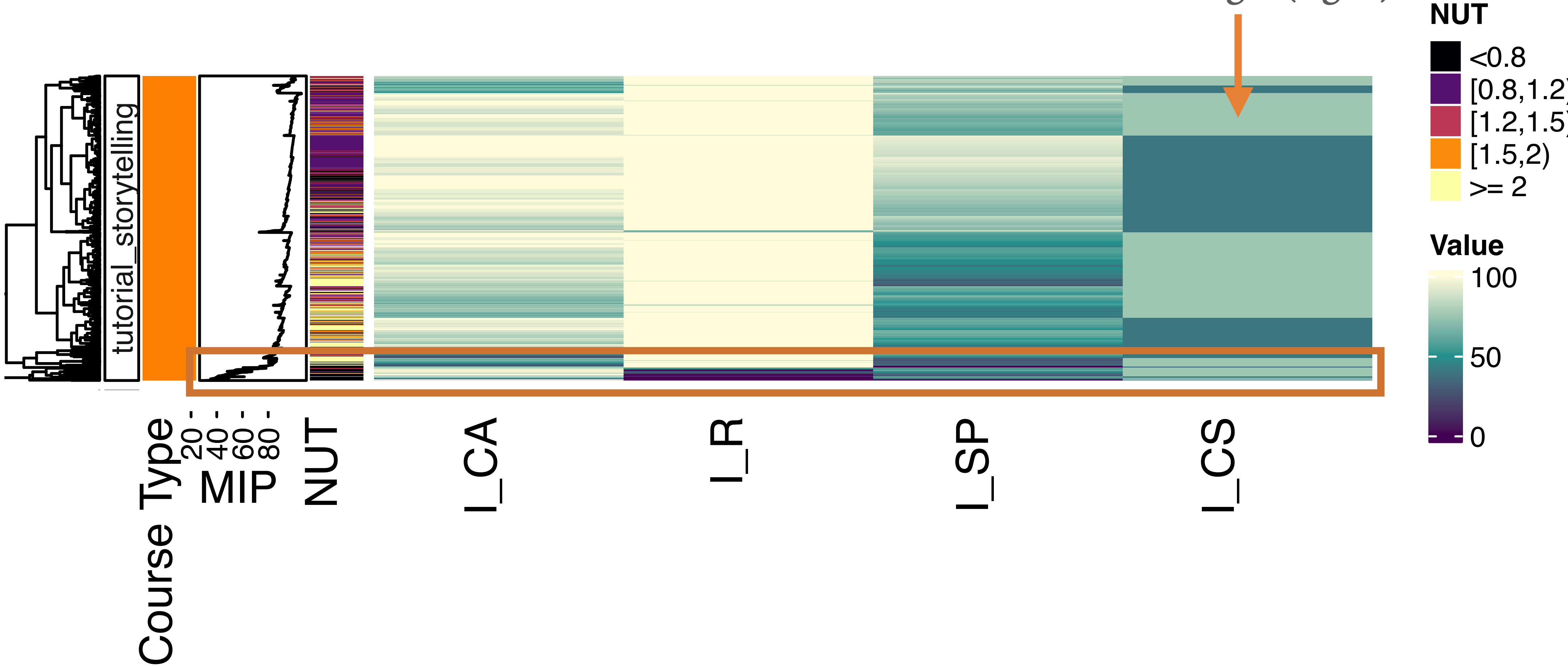


THE ANALYSIS RESULTS 6/7

Uneven complexity

Low (dark)

Medium high (light)



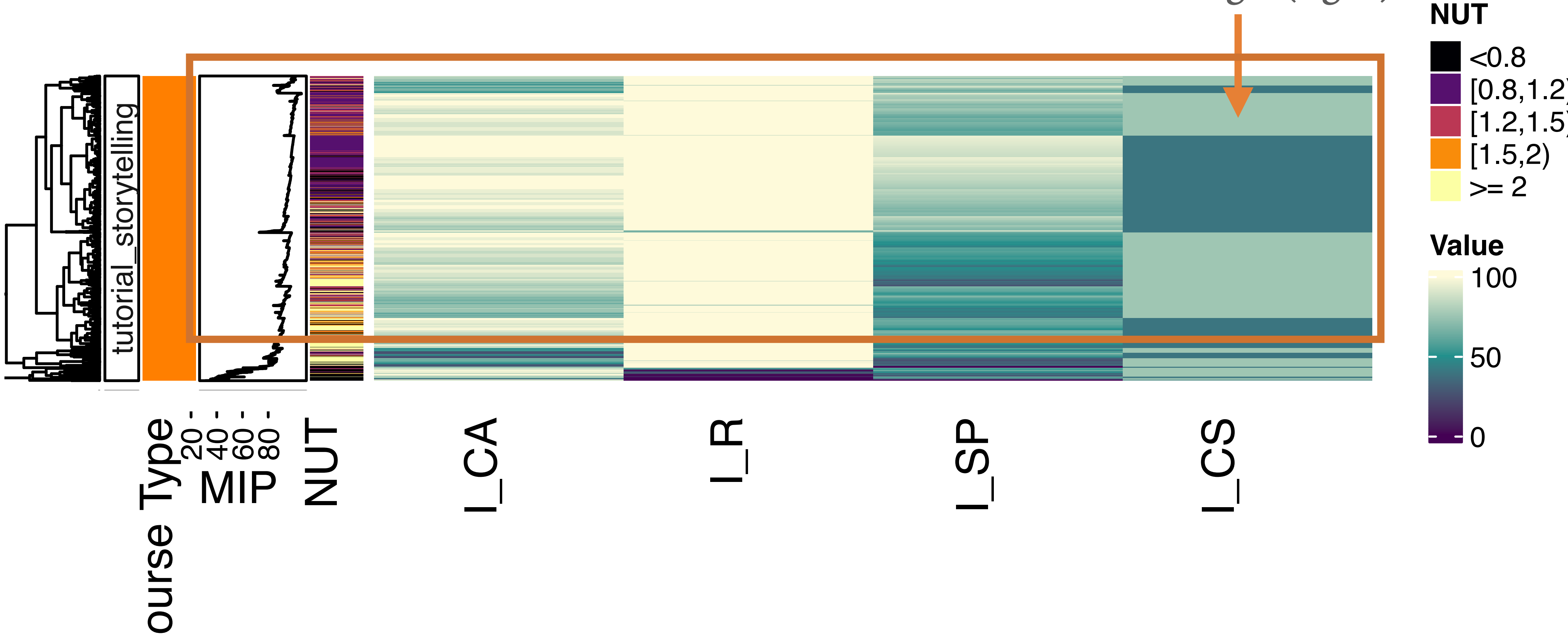
A narrow band has low MIP values at dark I_R and I_{SP} (low values), a very dark NUT (less than expected user time) and a medium to high complexity; this can be said to be punctual because this aggregate contains a small number of users.

THE ANALYSIS RESULTS 6/7

Uneven complexity

Low (dark)

Medium high (light)

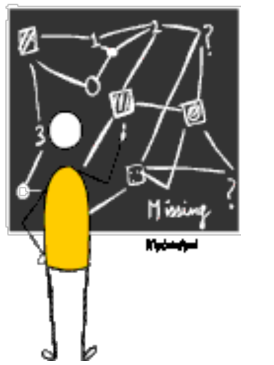


I_R with adequate values (users achieve the required results, light band).

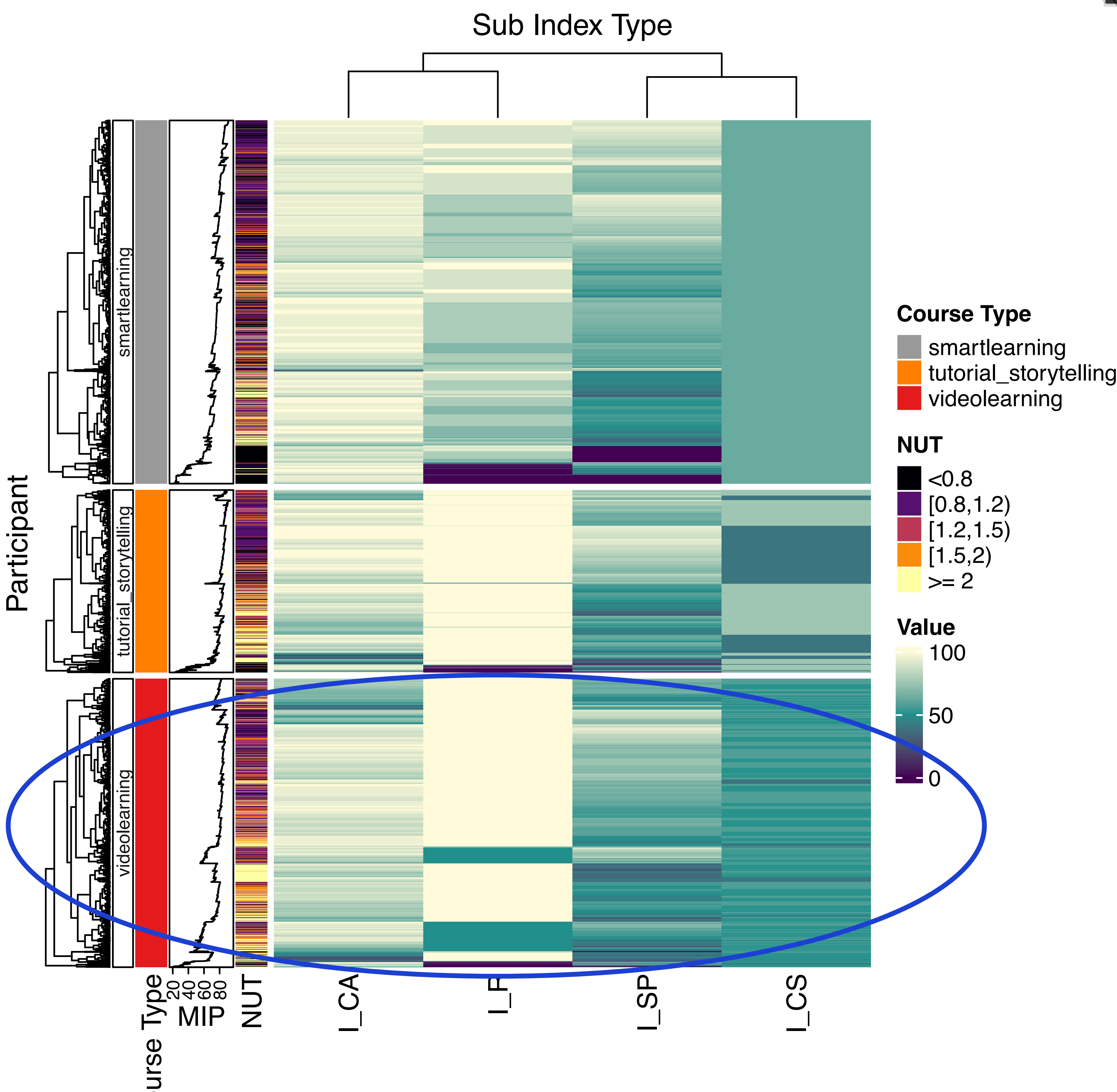
I_{SP} and I_{CS} alternate between light and dark, when complexity is low (low I_{CS} , dark band) there is good I_{SP} (light band) and adequate NUT (user time equal to expected time), while for more complex courses (high I_{CS} , light band) there are low I_{SP} values (dark band) and high NUT (user time much longer than expected time).

We conclude that for low complexity, the results can be achieved with the expected time, whereas as complexity increases, the required results are achieved by increasing the user time from one and a half times to more than twice the expected time.

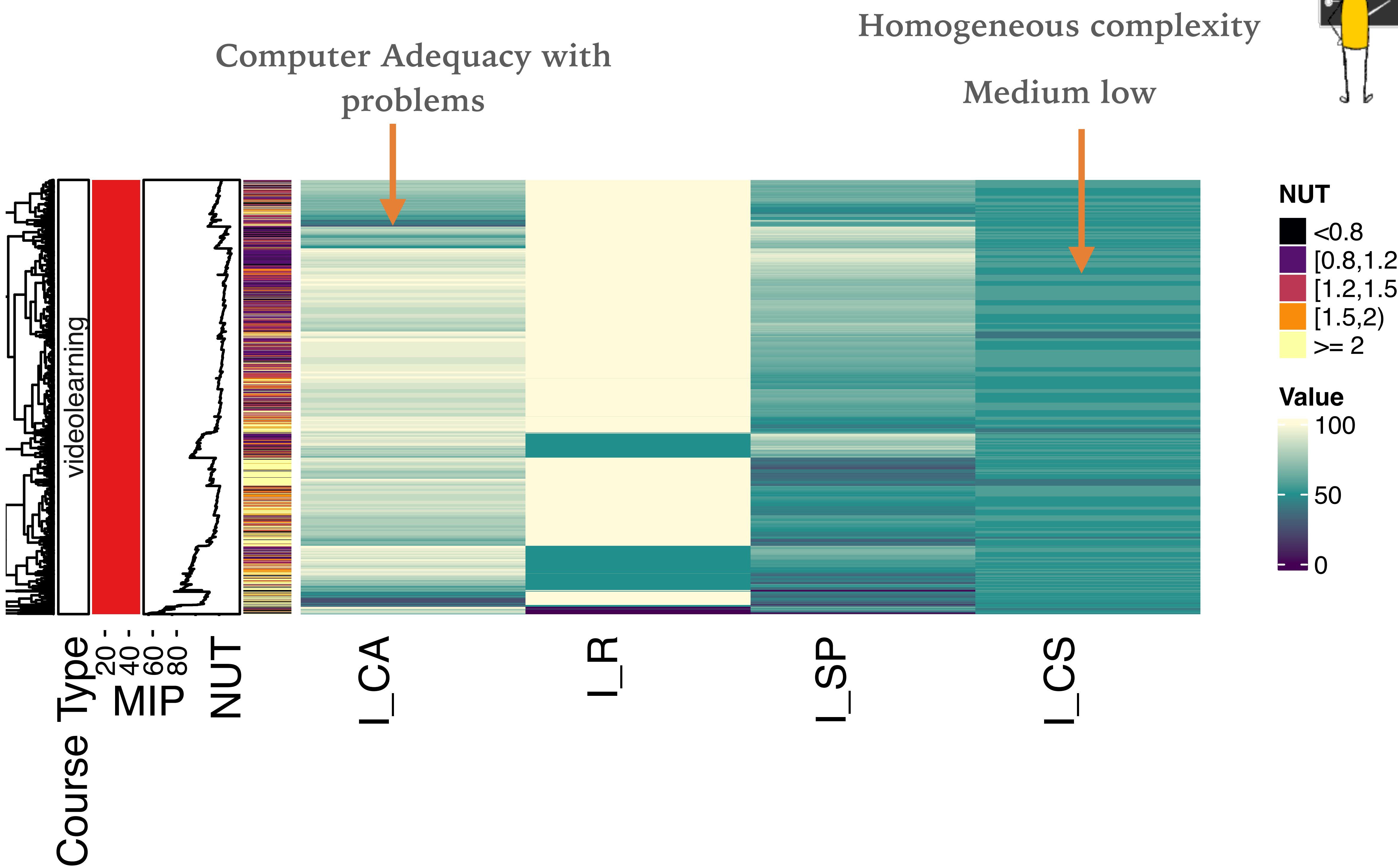
THE ANALYSIS RESULTS 4/7



Heatmap



THE ANALYSIS RESULTS 7/7



Patterns are more confusing; in general, compared to the other course types, it is observed that the NUT values are much clearer, thus **a much longer use time than expected.**

THE VALUE OF LEARNALYZER'S ANALYSIS

CONCLUSIONS

Give time its proper value for:

- ➤ designers,
- ➤ sales people
- ➤ end users, who need to have enough time to learn.

➤ **Storytelling** methodology appropriate and effective from several perspectives, performs best regardless of content and editions. One point of attention is the complexity of the structure directly related to the spent study time.

➤ **Smartlearning** meets the requirements of low time-to-market and low impact on the training budget, but performs less well in terms of results achieved; the use of courses outside working hours does not guarantee their completion, nor an adequate study pace and time.

➤ **Videolearning** performs well, with more than satisfactory results, but against a more difficult and tiring study; improvement in this type of course:

- ➤ technical, for can make Computer Adequacy values higher; ;
- ➤ methodological, in order to manage the high value of time of use:
  - didactic designs
  - create moments of self-assessment and reinforcement of knowledge.

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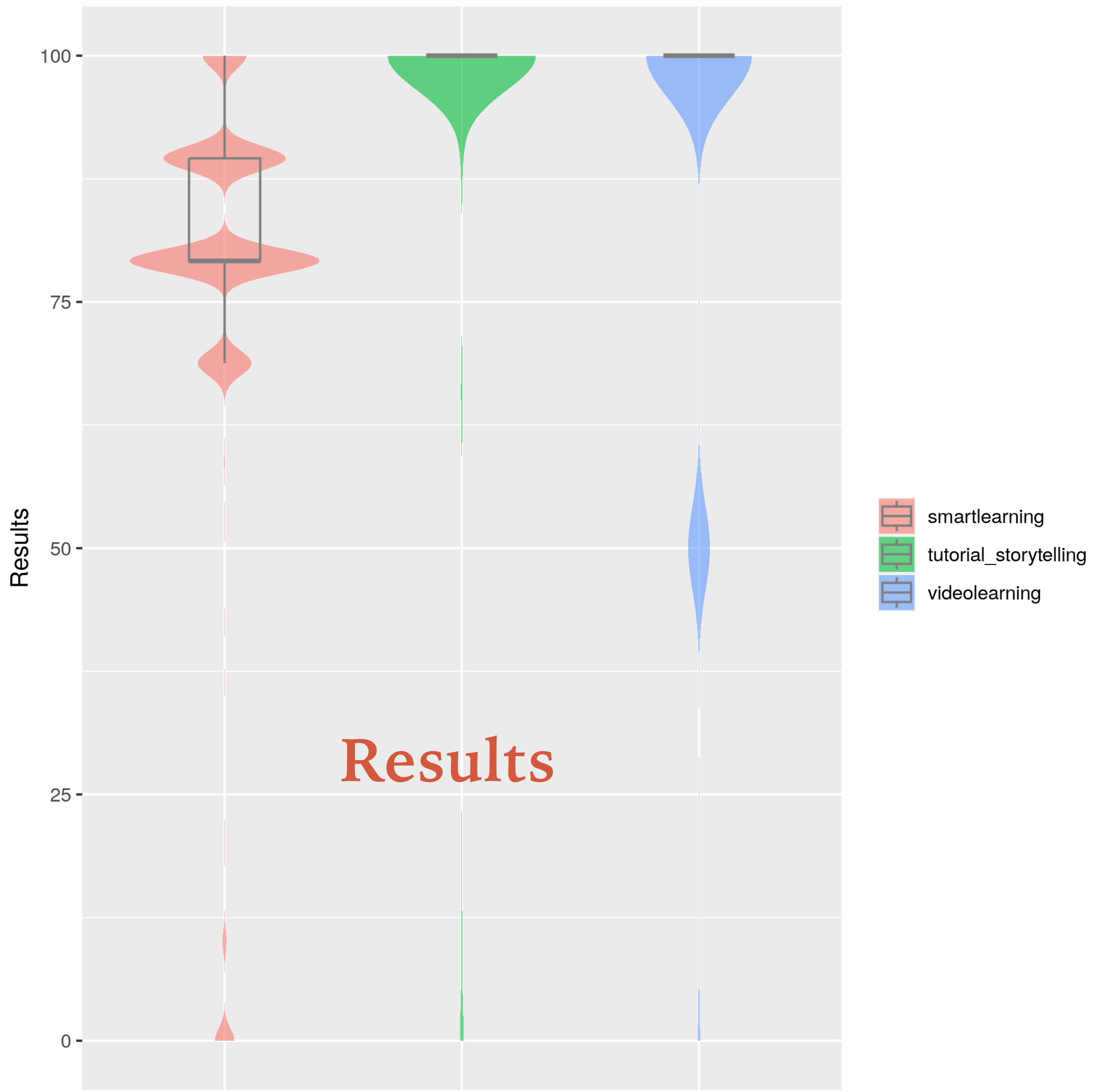
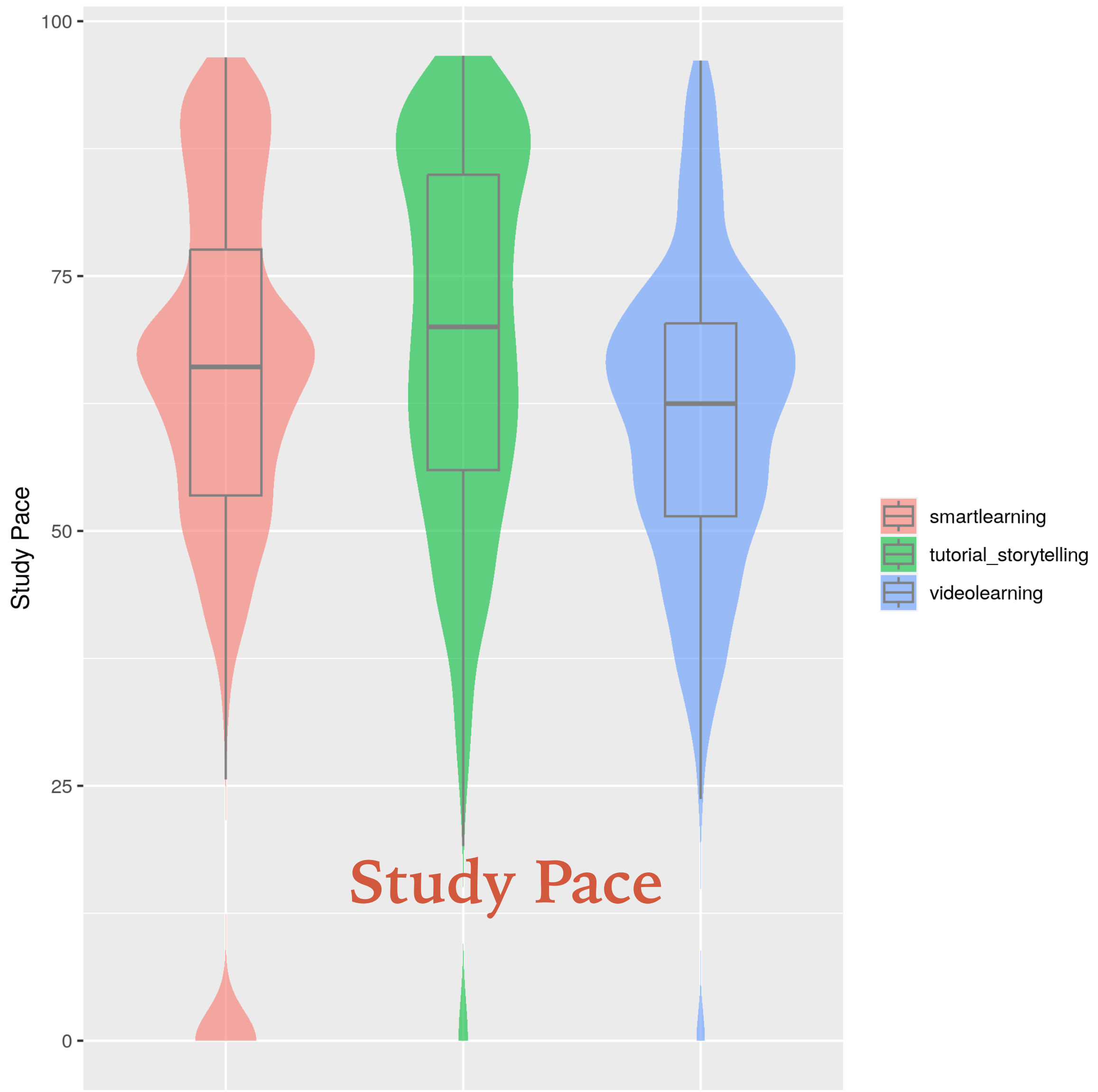
Thanks!

Learnalyzer

APPENDIX RESULTS 1/2





APPENDIX RESULTS 2/2