# Quelle recherche en education pour des labos d'informatique ?

P. Dillenbourg, EPFL

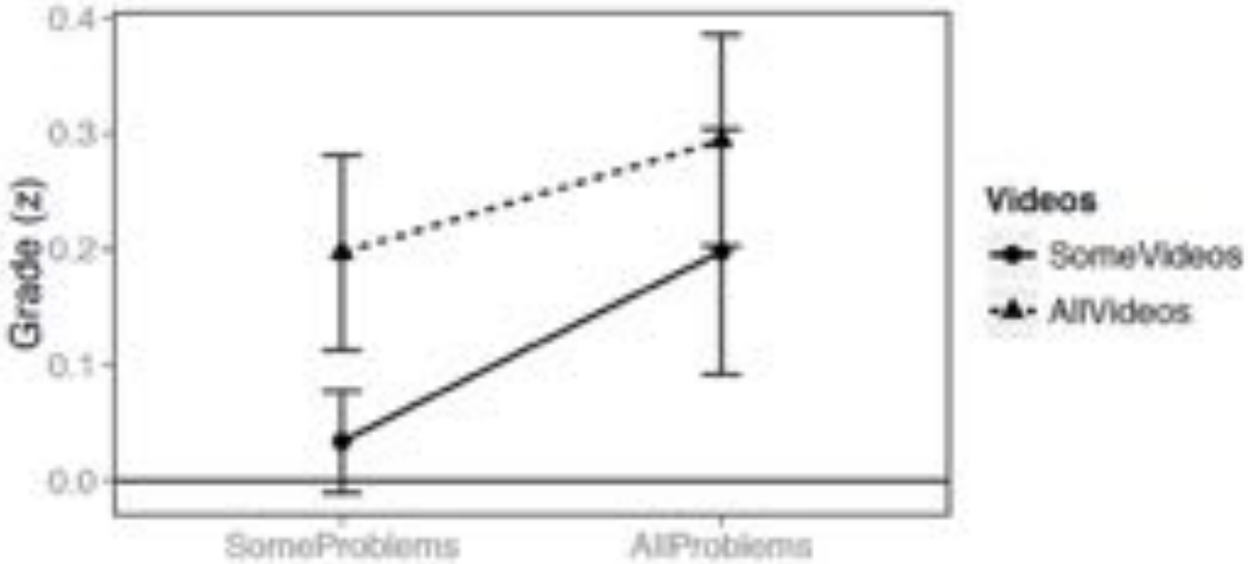

MOOC ONLINE COURSES
Registrations per city

MOOC Services

*Center for Digital Education*

Production

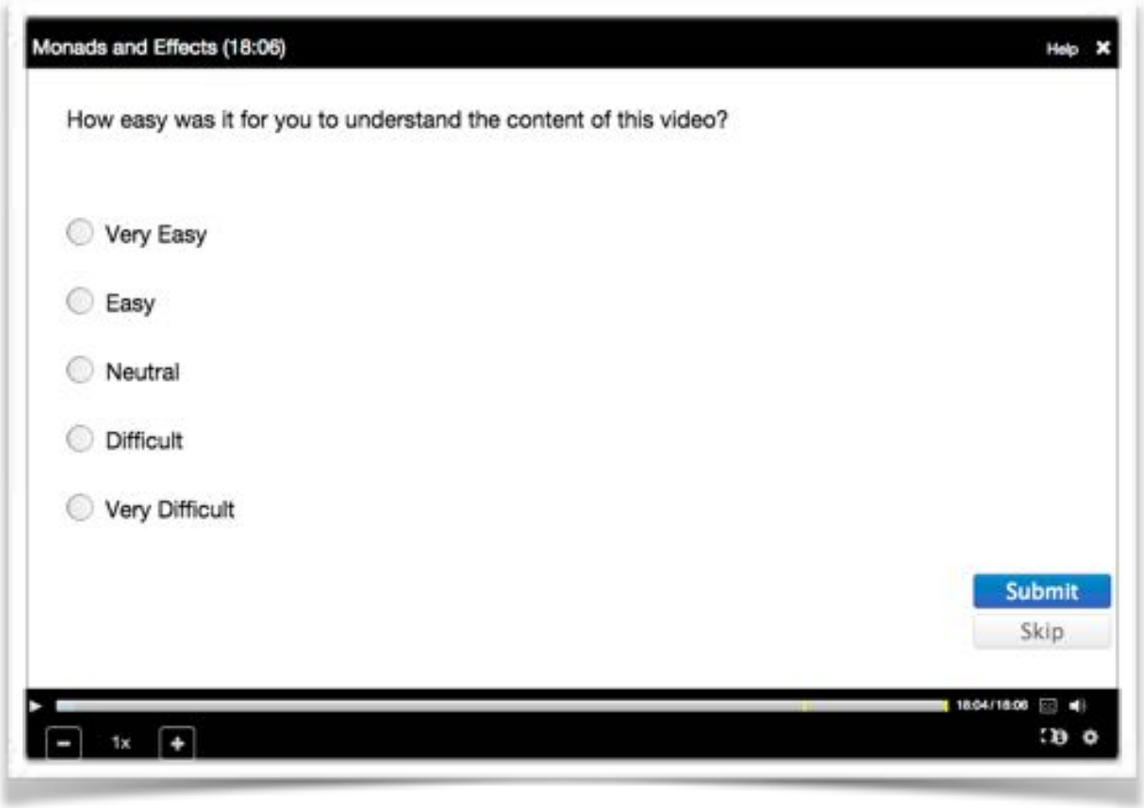

Analytics




*CHILI Lab*

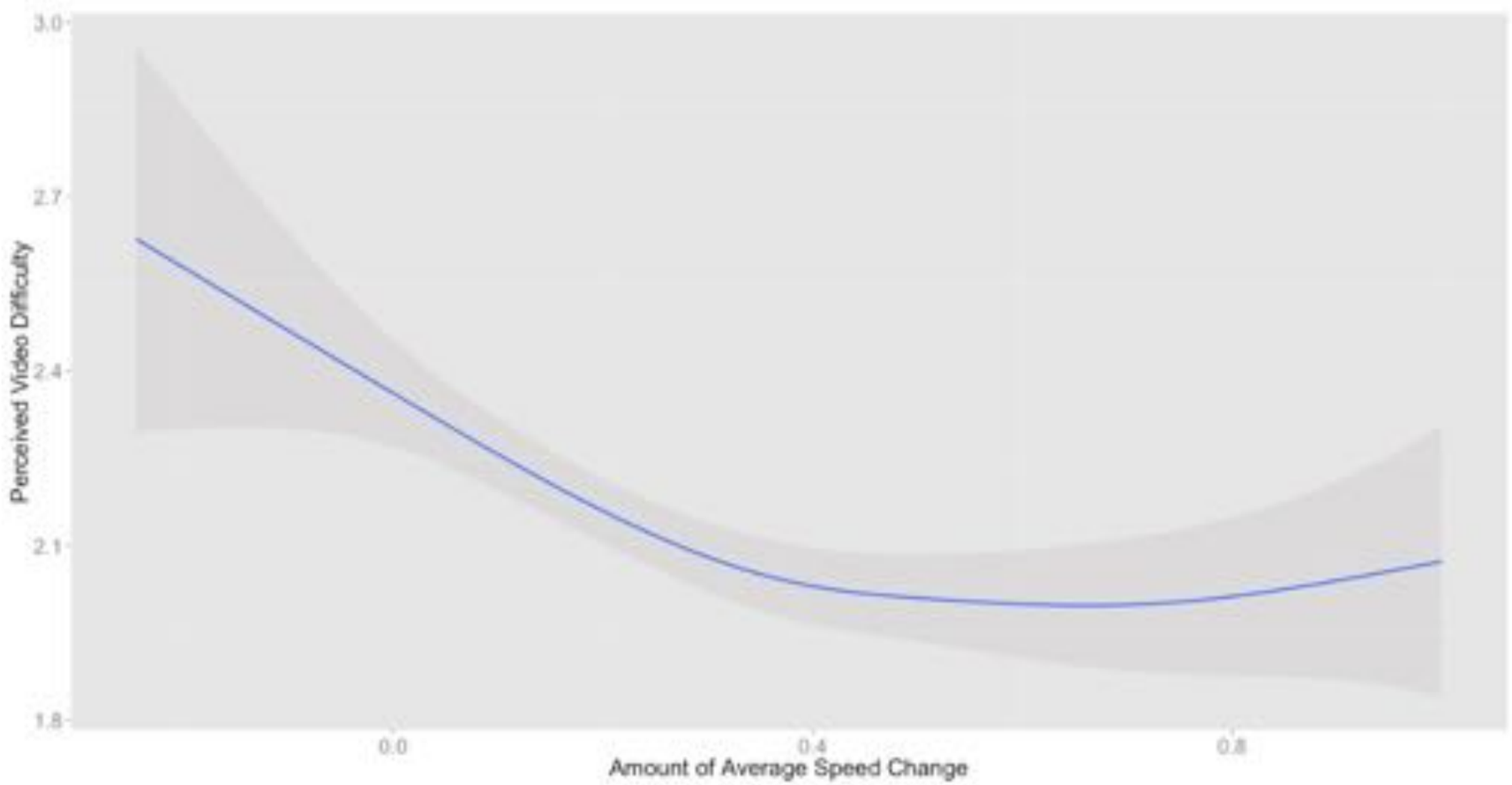
Experiments

MOOC Research

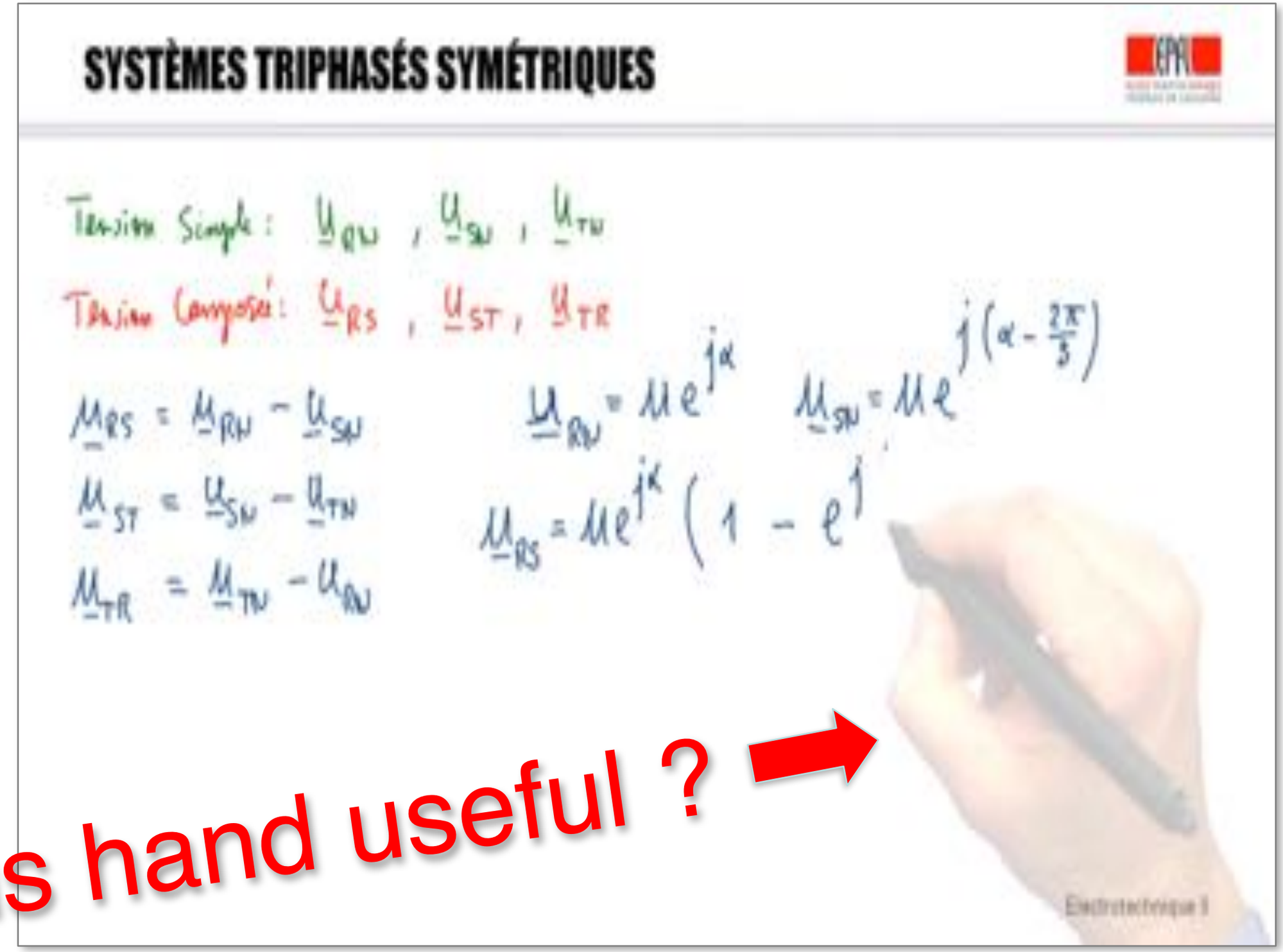



# MOOC Research

The amount of average speed increase has a negative effect saturated at 0.4




- Non-linear relationship (GAM)
- Effect saturates at 0.4




# Is this hand useful ?

Kshitij Sharma, Patrick Jermann, Pierre Dillenbourg

EPFL Center for Digital Education

# Eye tracking experiment on MOOC Video

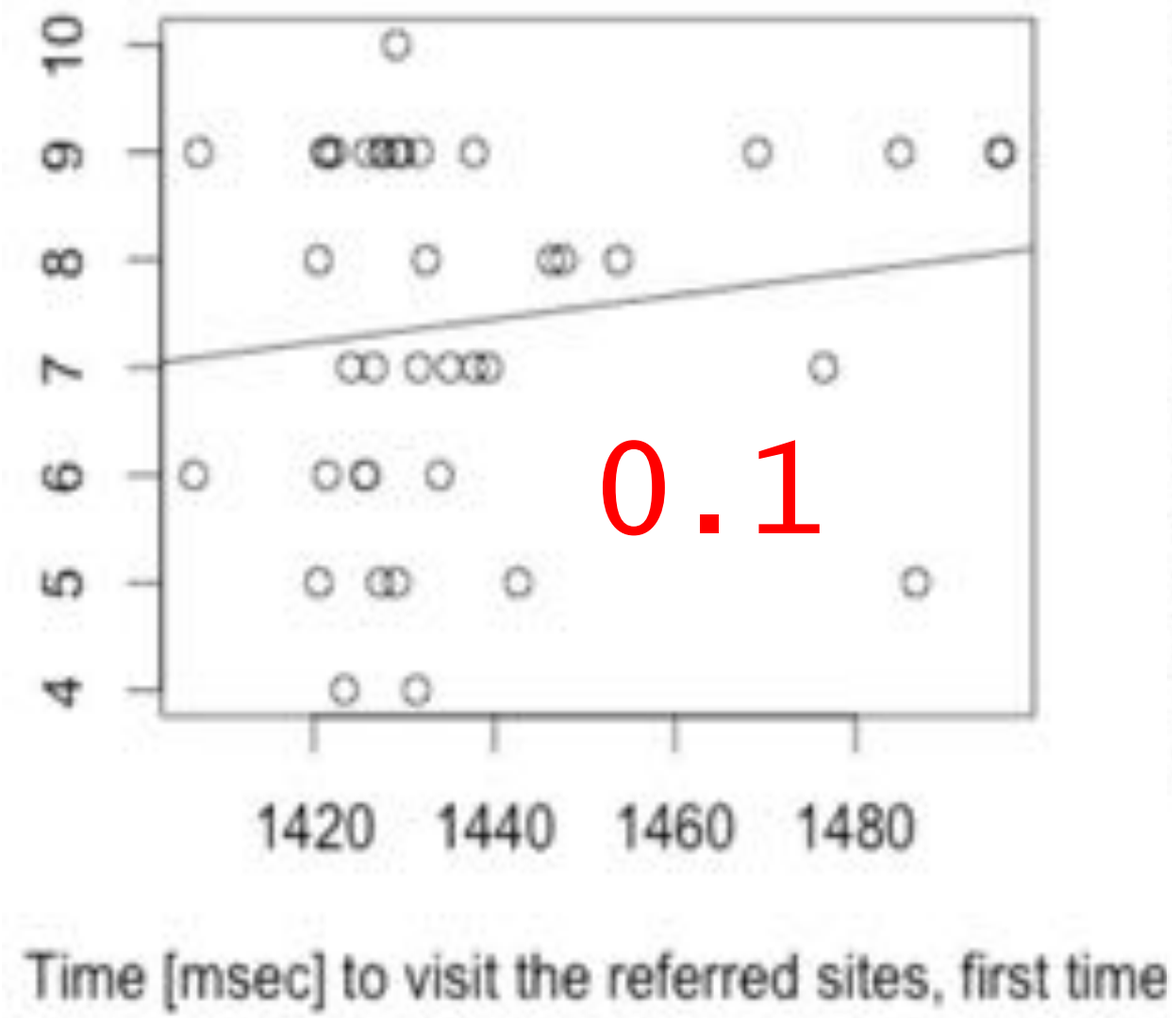
## Following teacher's references

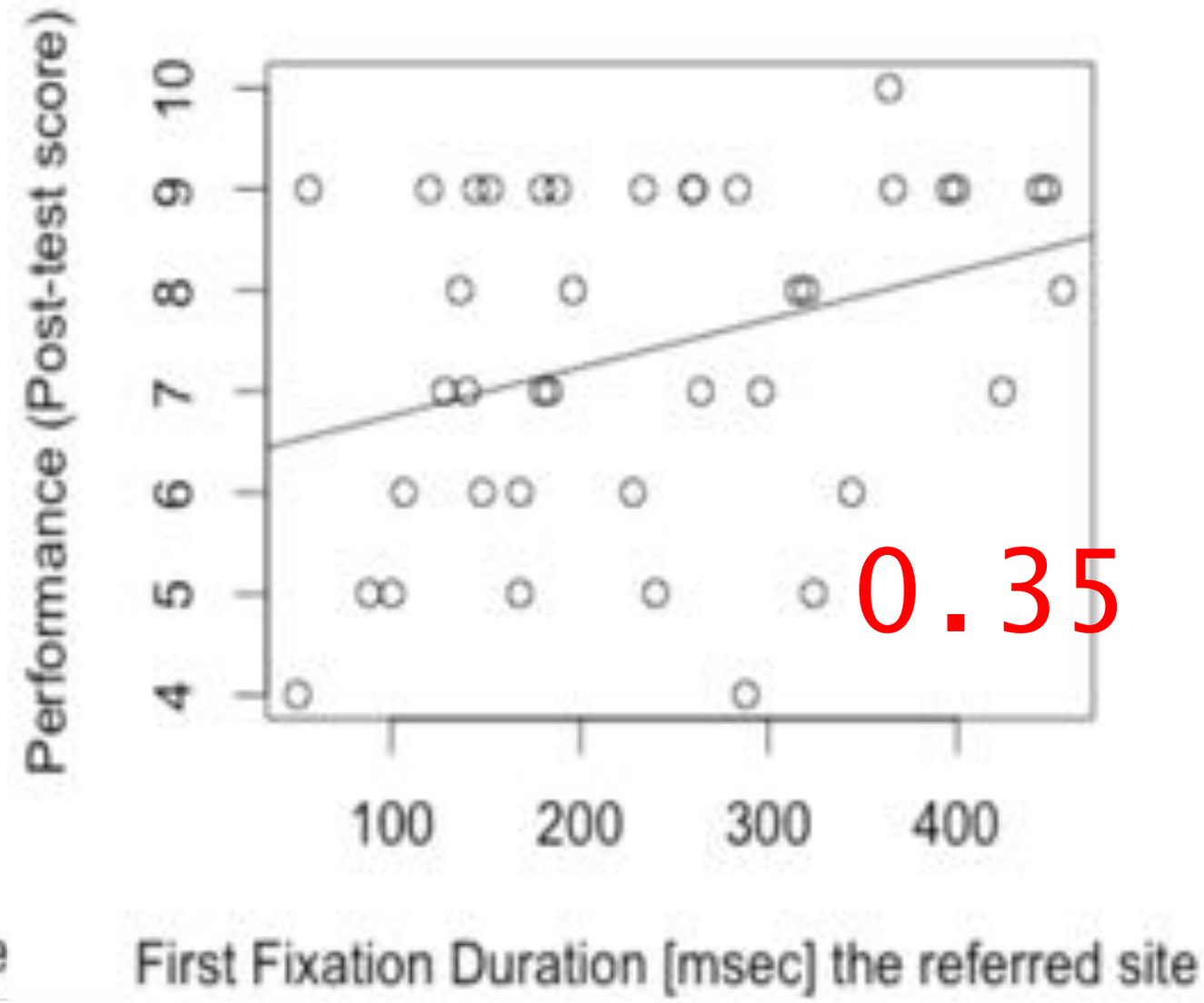
Gaze of students' watching Scala course by Prof. Martin Odersky (EPFL, Switzerland)

ÉCOLE POLYTECHNIQUE FÉDÉRALE DE LAUSANNE

K. Sharma, P. Jermann, P. Dillenbourg
@ CHILI – http://chili.epfl.ch
Supported by the Swiss National Science Foundation
(Grants CR1211_132996 and PZ00P2_126611)

# « withmeness »



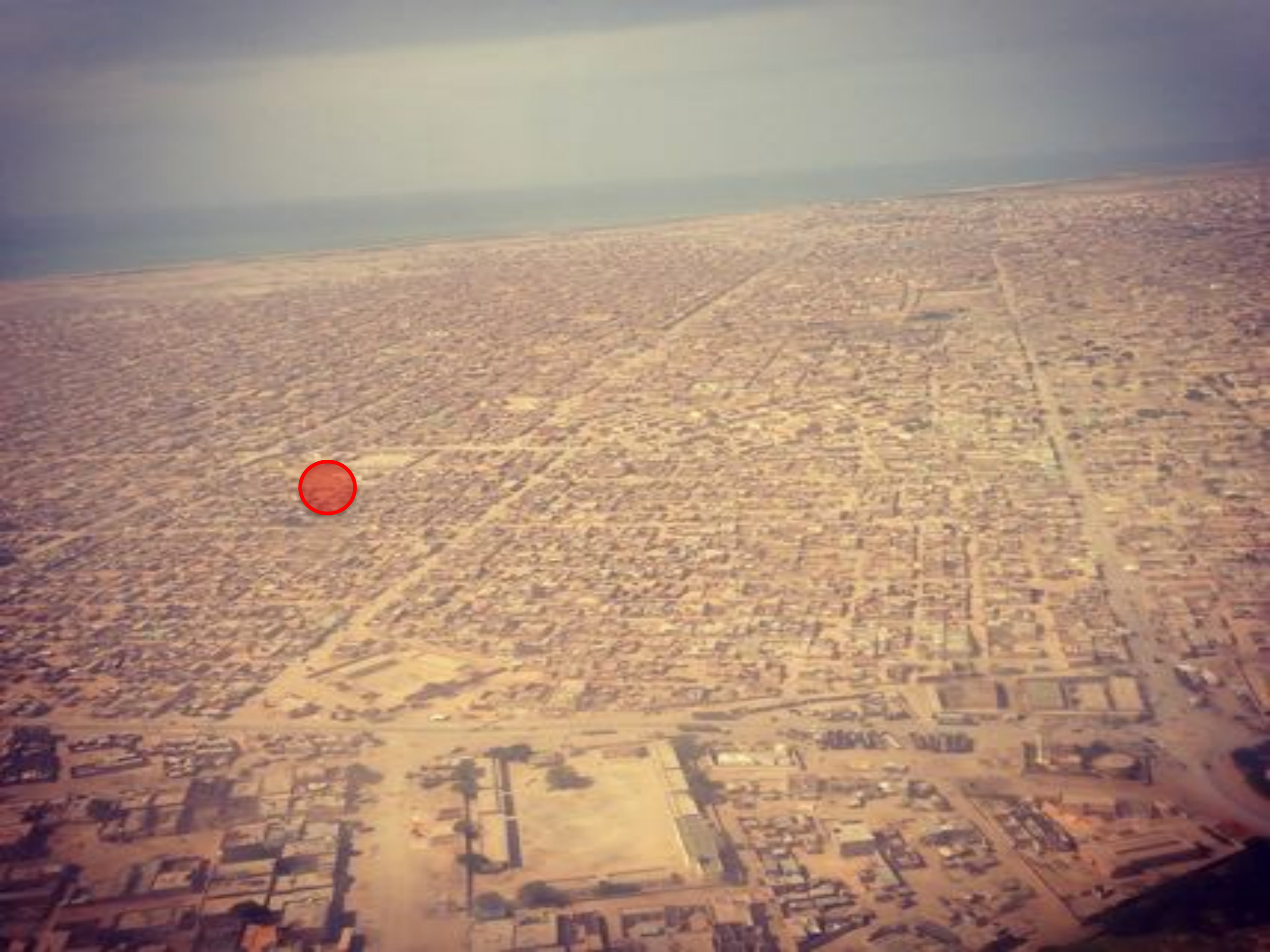




Kshitij Sharma, Patrick Jermann, Pierre Dillenbourg

EPFL Center for Digital Education

gaze (learner) = *f* (deictics (teacher))

withmeness

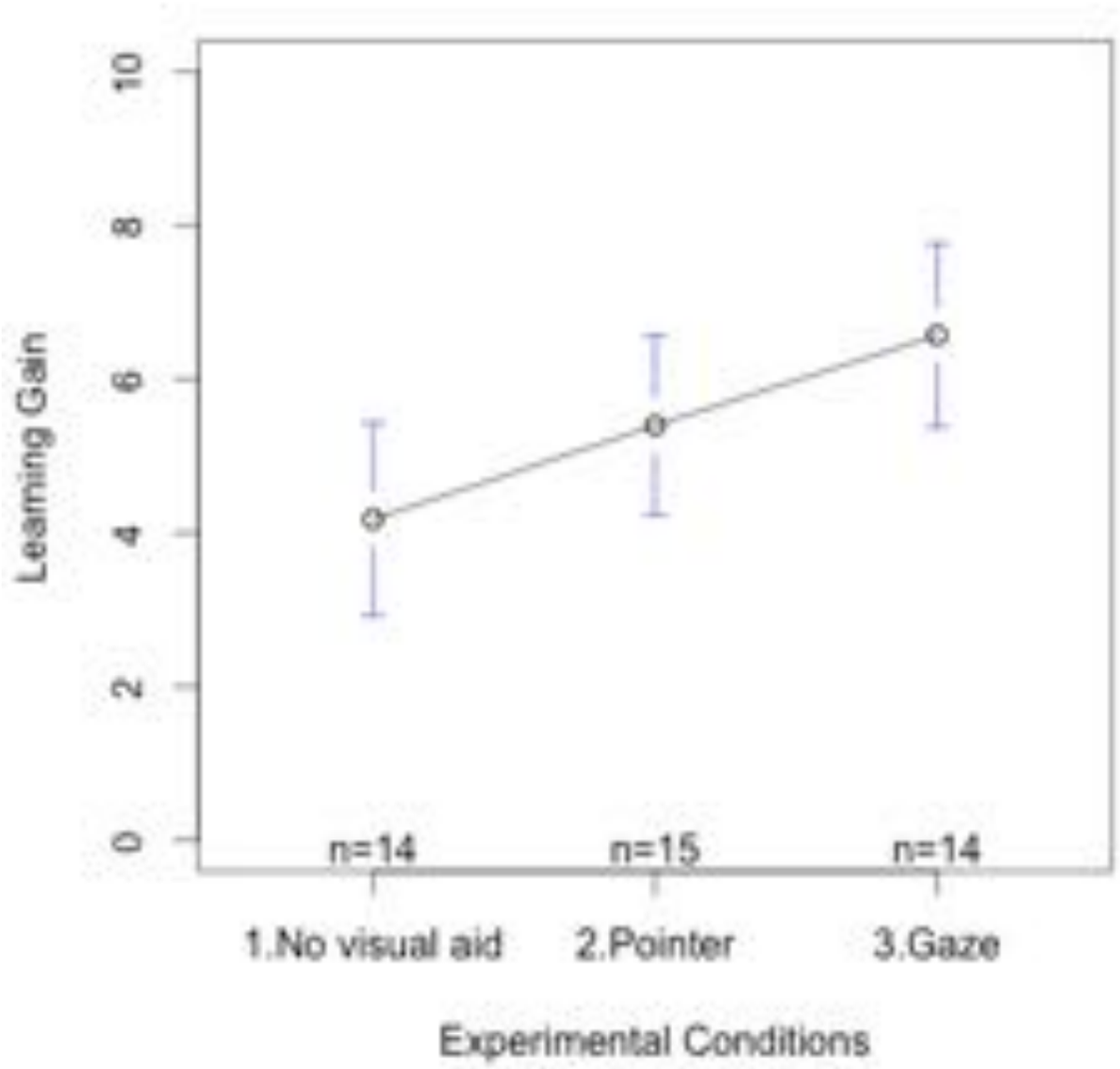



"...they look like a bunch of little grains arranged together...typically a group of very small elements"

Sarah d'Angelo, Kshitij Sharma, Darren Gergle, Pierre Dillenbourg (2016)

# MOOC research

Do finger-based or gaze-based deictics enhance learning ?




Sarah d'Angelo, Kshitij Sharma, Darren Gergle, Pierre Dillenbourg (2016)

gaze (learner) = *f* (gaze (teacher))

Gaze Awareness Tools

# Learning Science**s** ?

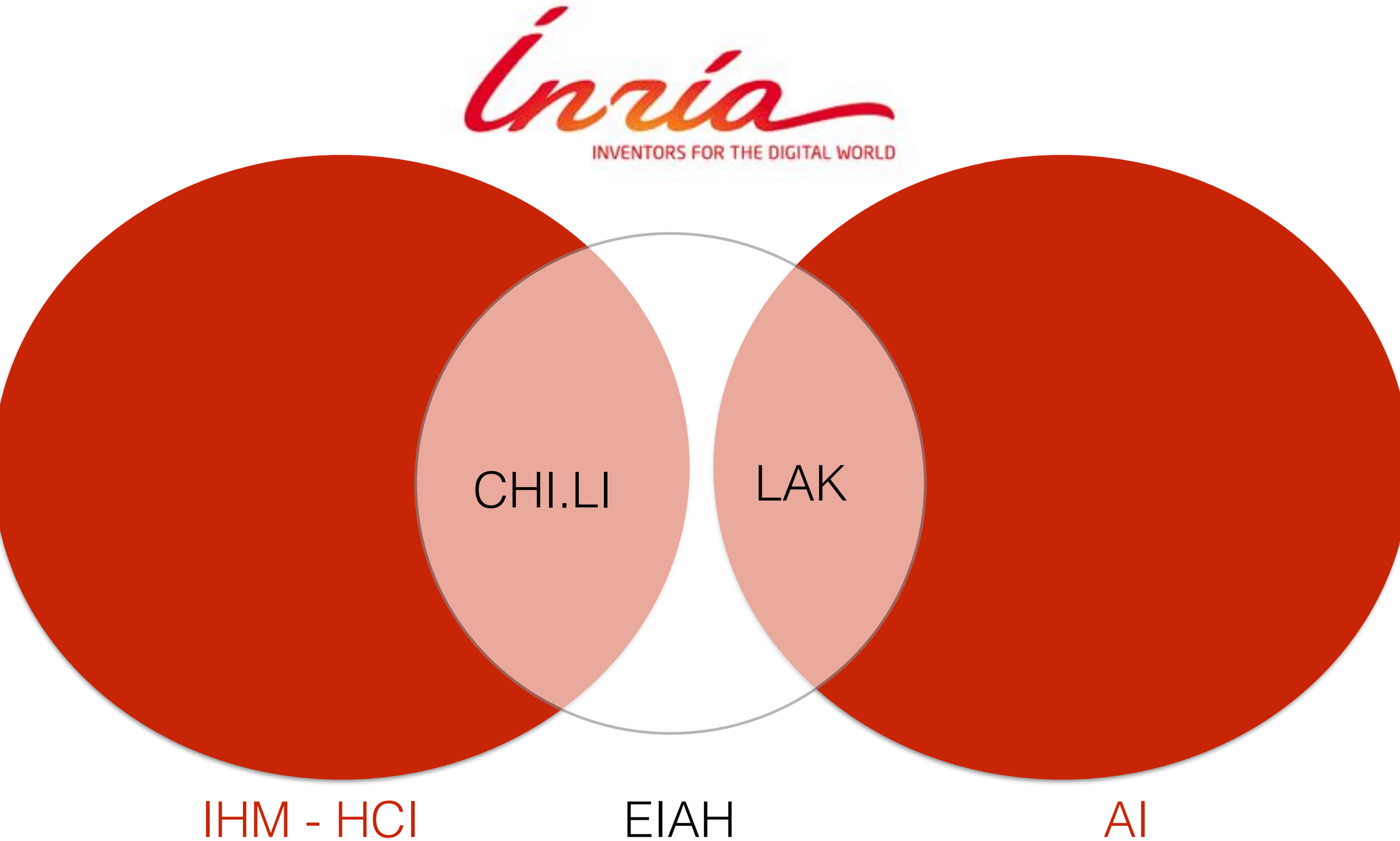
Education Research / Learning Sciences

- Sociology of education (e.g. social / gender inequity)
- Politics of education (e.g. analysis of systems)
- History of education (e.g. industrial revolution)
- Philosophy of education (e.g. economical drive)
- Docimologie / Psychometry
- Audiences: special, adult, lifelong, pre-school,…
- …
- Didactics of disciplines:
  - maths, sciences, F1, F2,…,Wirtschaft Pädagogik
  - CS / computational thinking

- Instructional psychology (how people learn)
- Instructional design
- Learning Technologies
- Distance Education

Learning Technologies Conferences/Journals

- Learning Sciences
- Computer-Supported Collaborative Learning
- AI & Education
- Learning Analytics
- Educational DataMining
- …
- ECTEL
- EdMedia
- OnLine Educa
- 100 more / year


INVENTORS FOR THE DIGITAL WORLD
CHI.LI
LAK
IHM - HCI
EIAH
AI

# What have these men in common ?

Sergio Emotti

CEO UBS (60’000 employees)

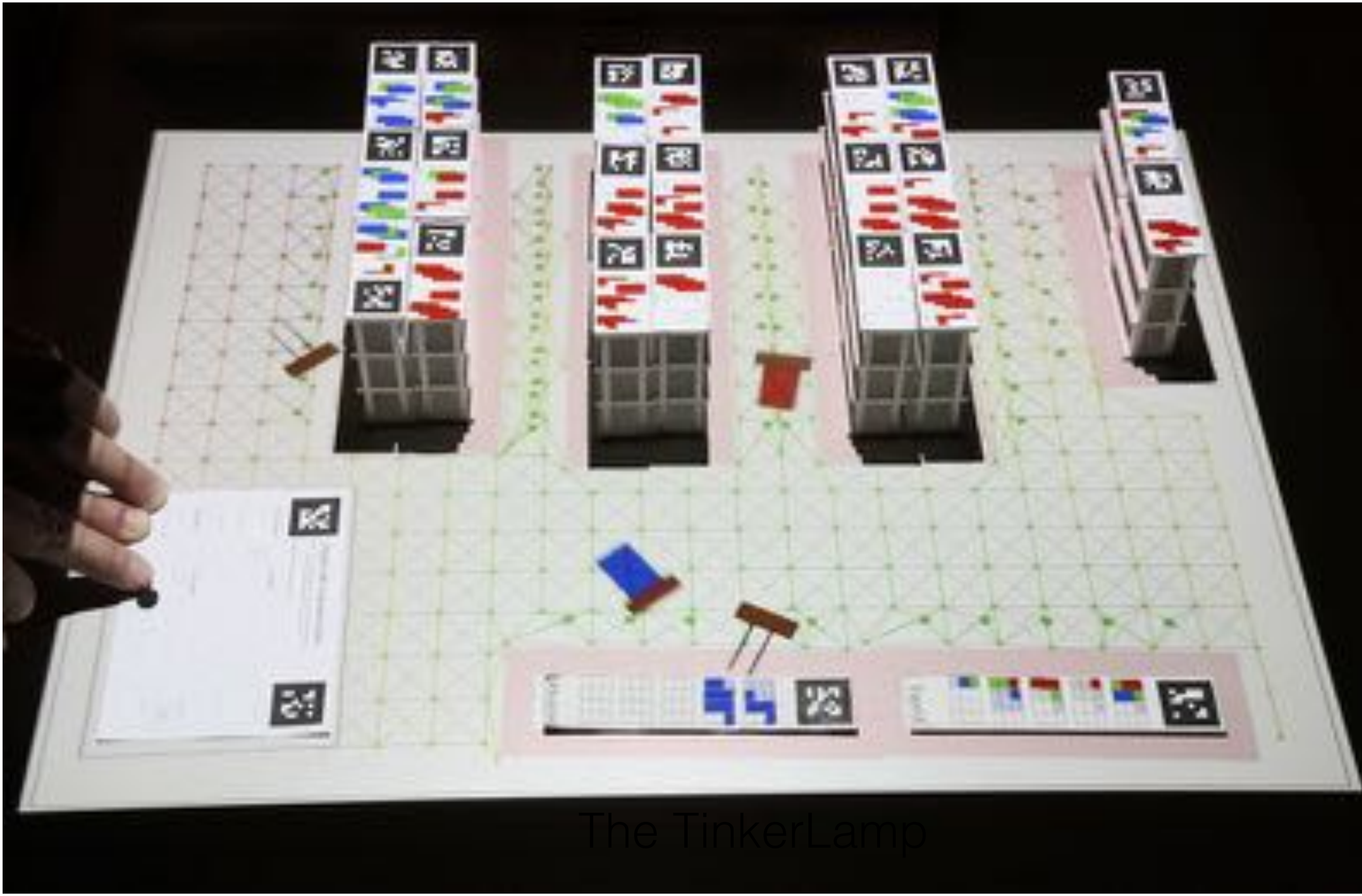
Ueli Maurer

Swiss Minister of Defense

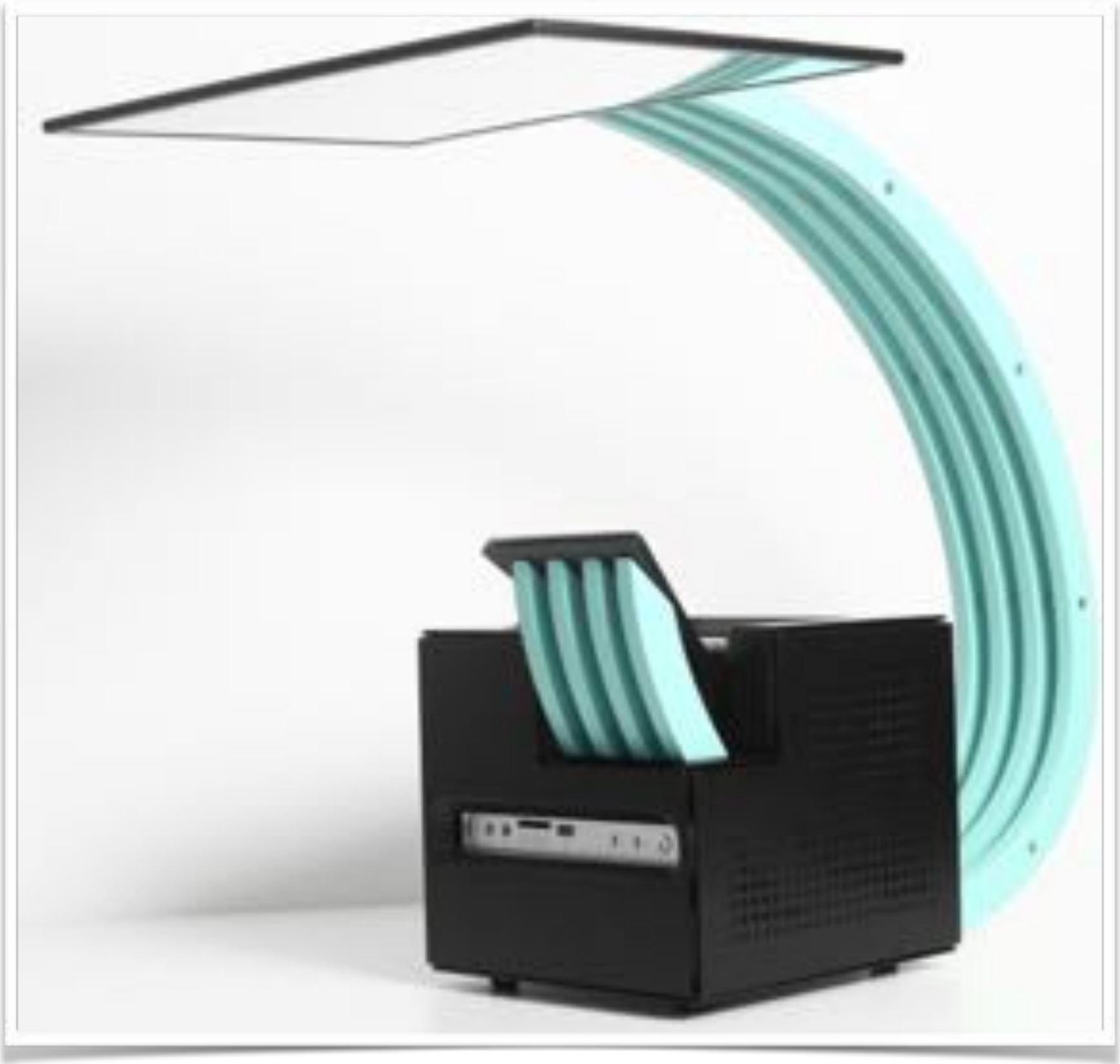
Claude Nobs

Montreux Jazz Festival

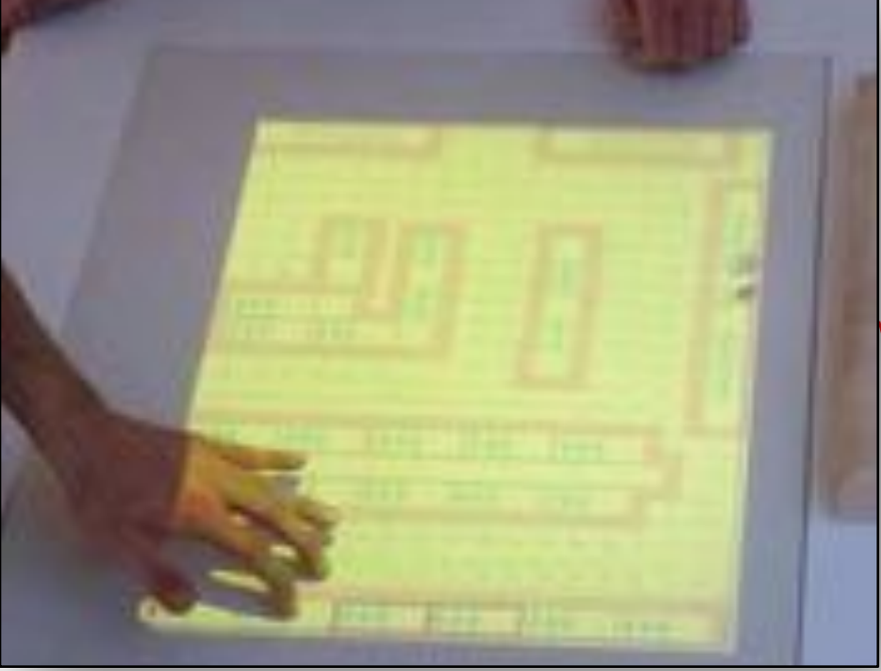

Logistics assistants (warehouse employees)

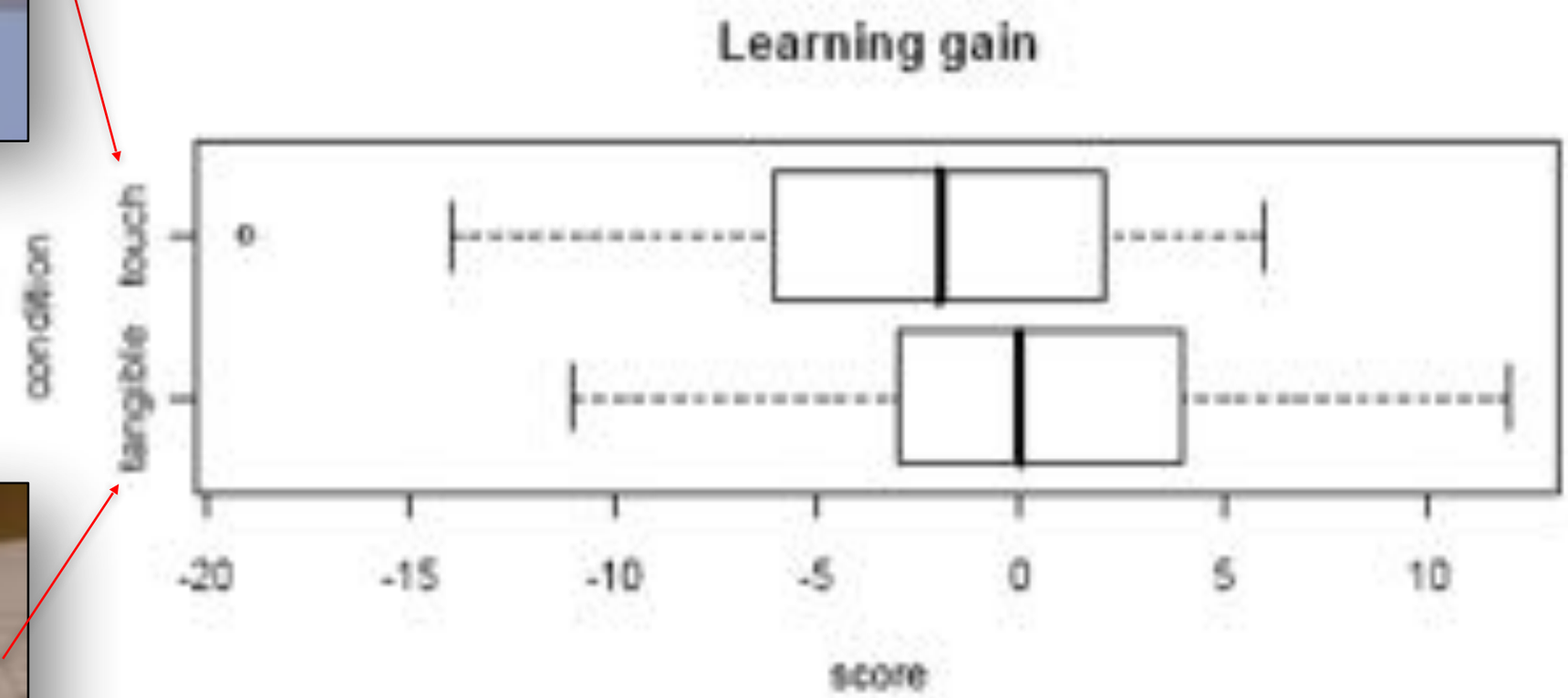



Guillaume Zufferey, Patrick Jermann, Pierre Dillenbourg (EPFL)



Simpliquity

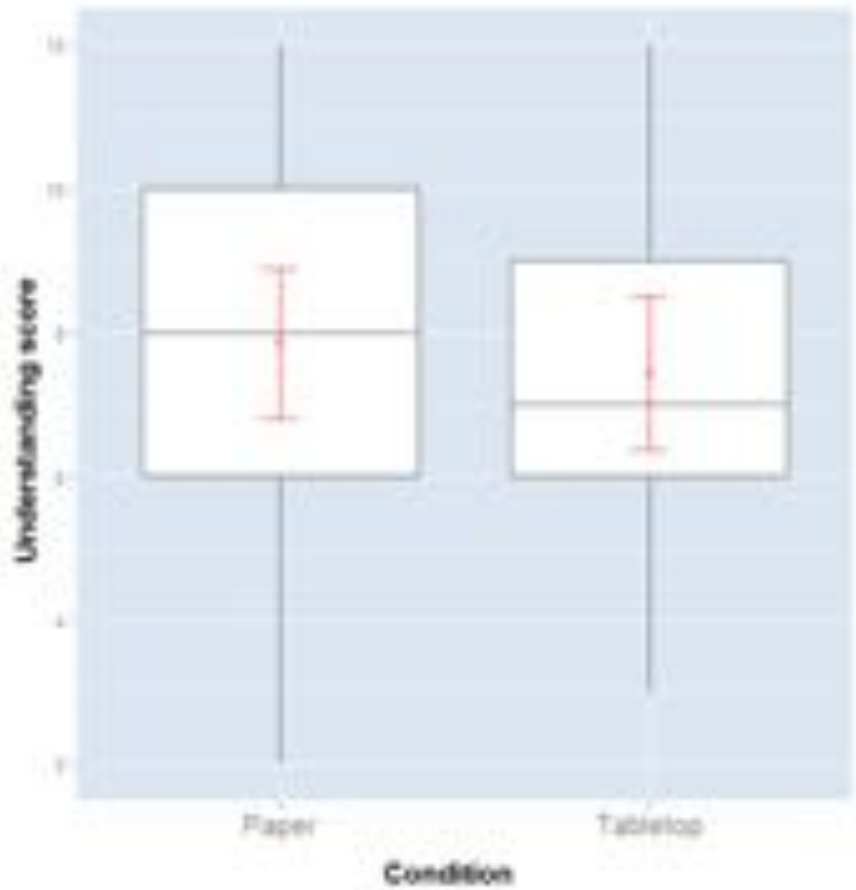





$F(1,37) = 6.68,\ p < .05$

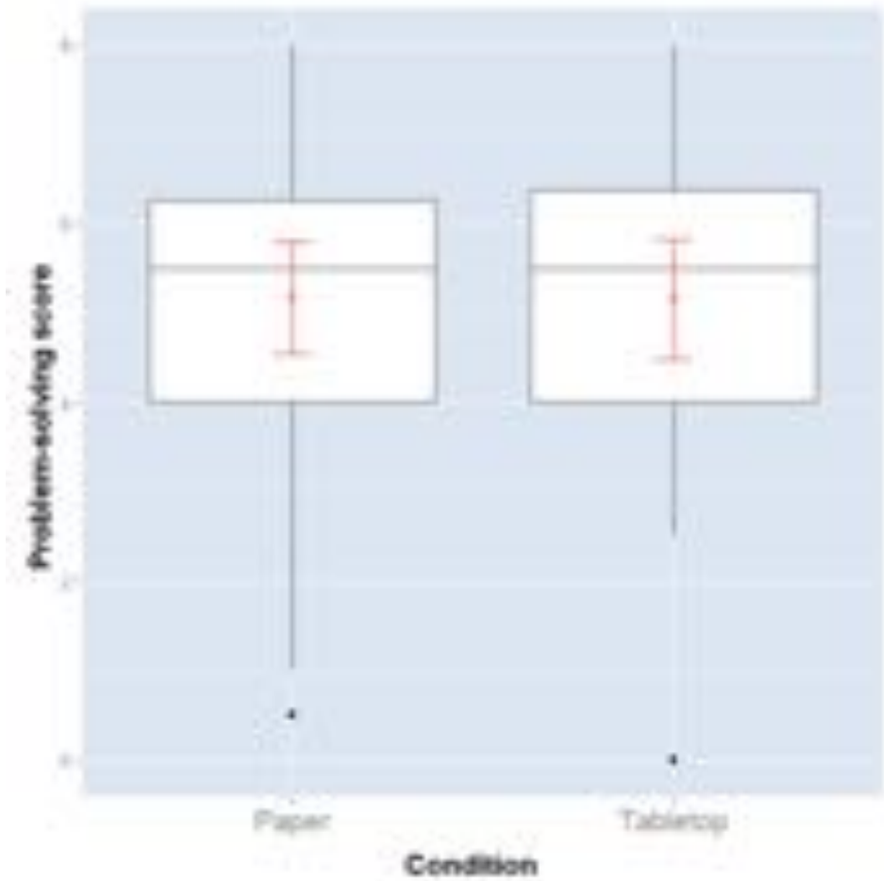
Bertrand Schneider, Aurelien Lucchi

No sign. effect in understanding




mean = 7.84 vs. mean = 7.43
F(1,14) = .25; p > .05

No sign. effect in problem-solving

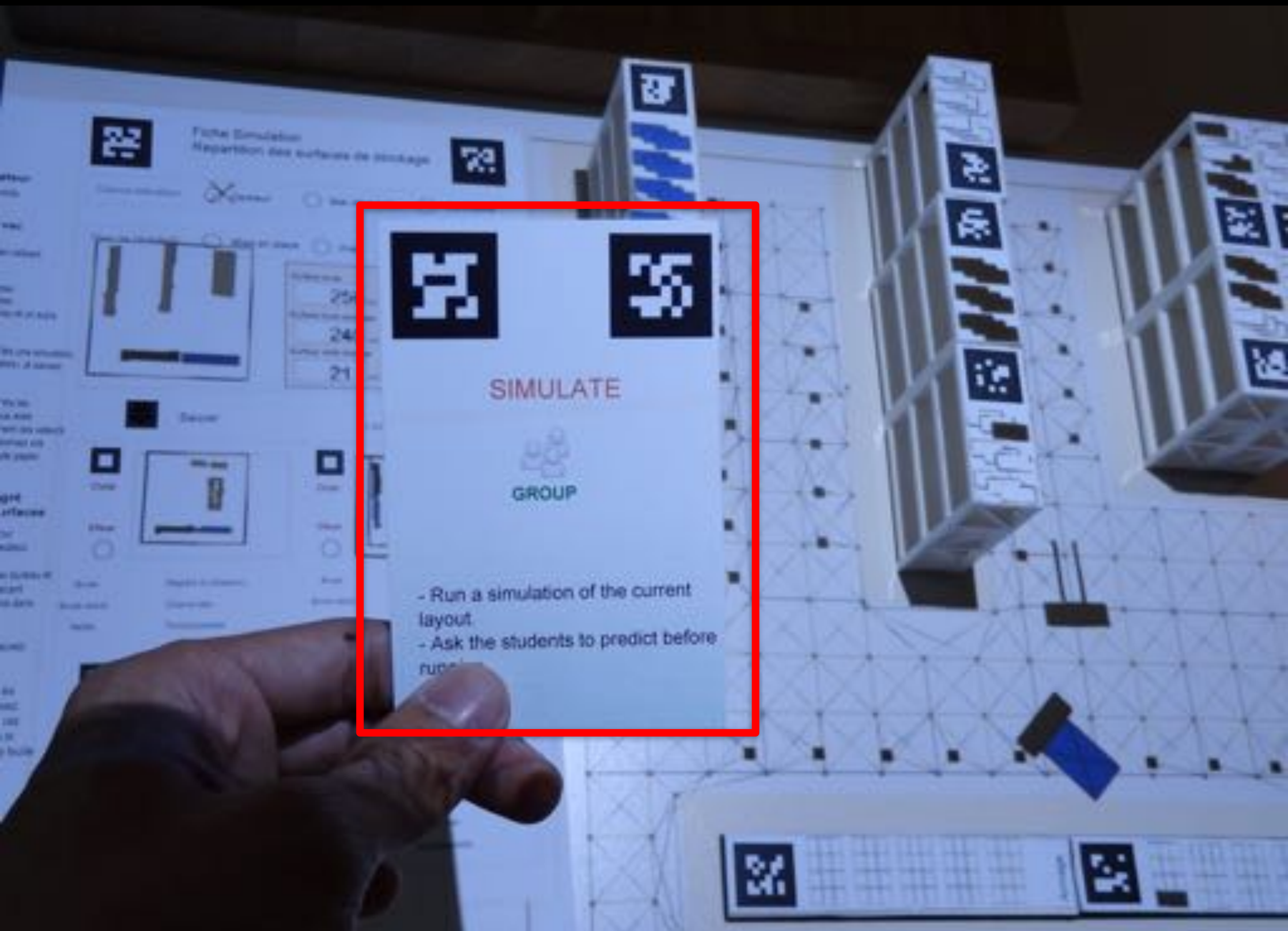



mean = 5.16 vs. mean = 5.15
F(1,14)=.06, p>.05

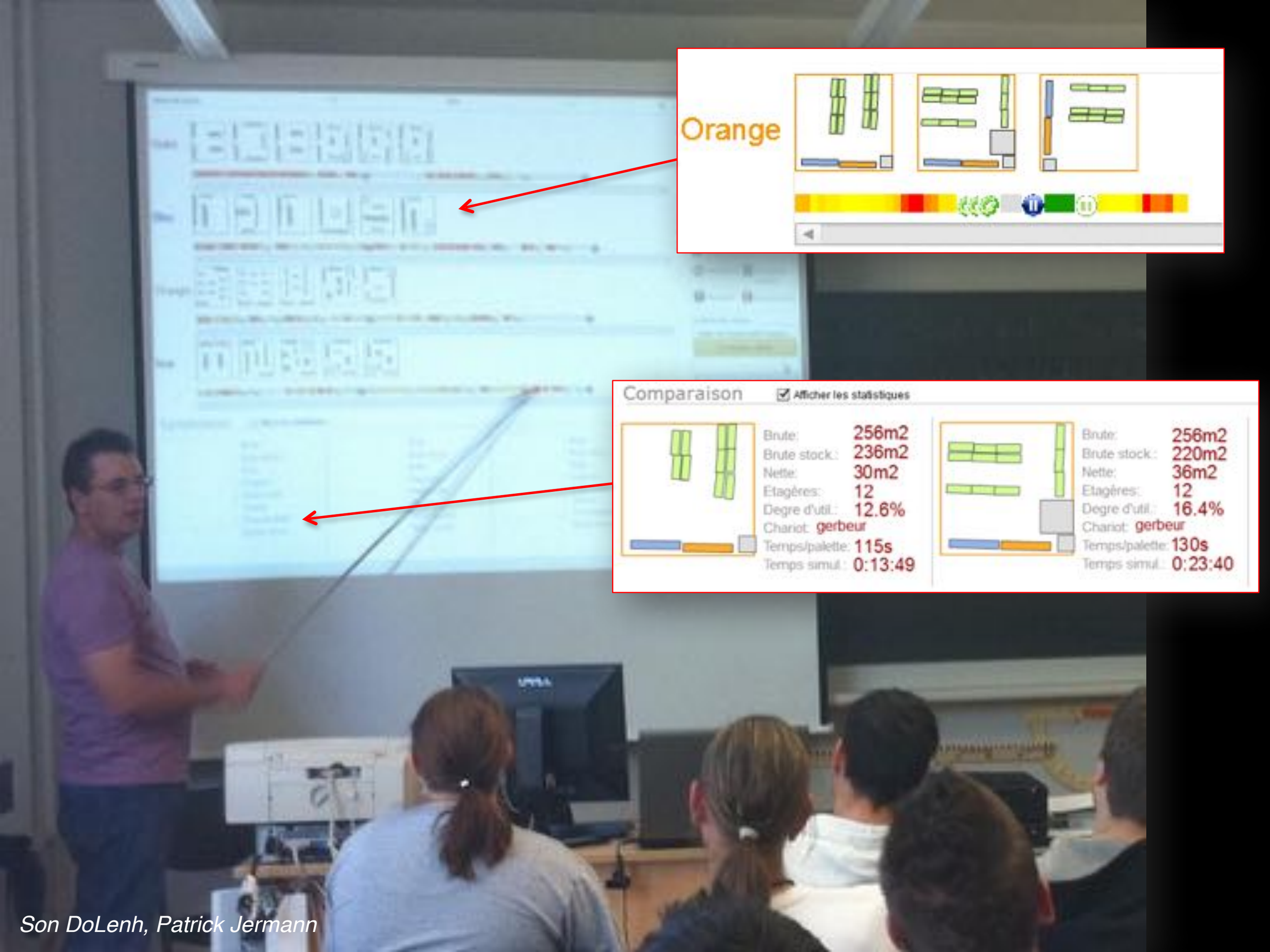
C’est pas parce qu’une technologie est cool

que les apprenants apprennent !

# “Manipulation temptation”!


SIMULATE
GROUP
- Run a simulation of the current layout
- Ask the students to predict before

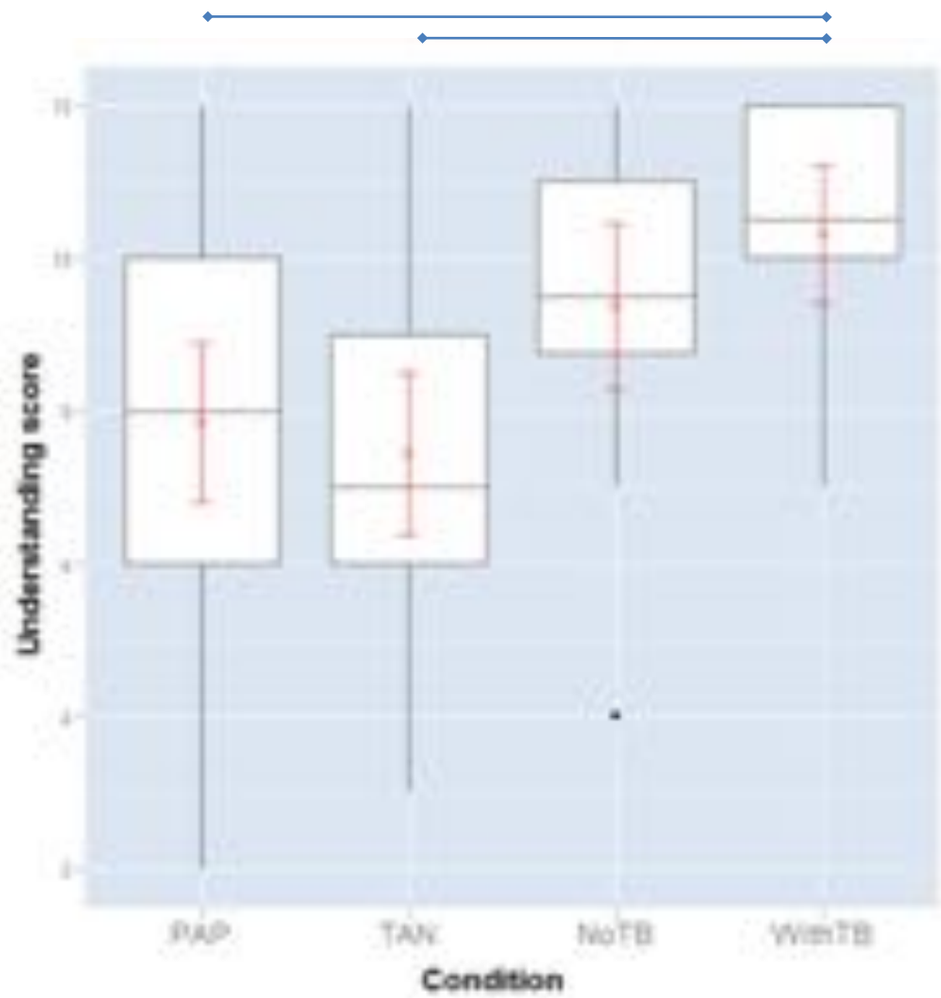

PAUSE CLASS
CLASS
- Pause all the actions (simulation, building model, etc.) in the whole class



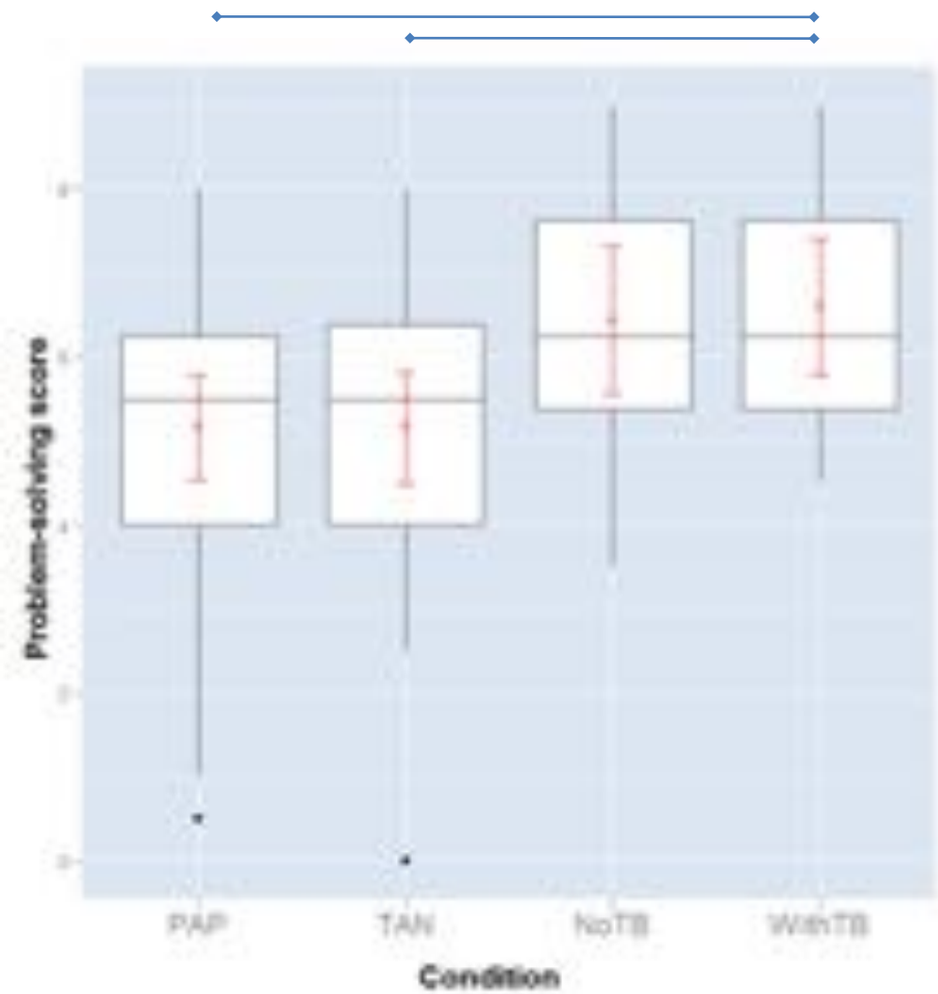

*Son DoLenh, Patrick Jermann*

# Post-test

Sign. effect in understanding

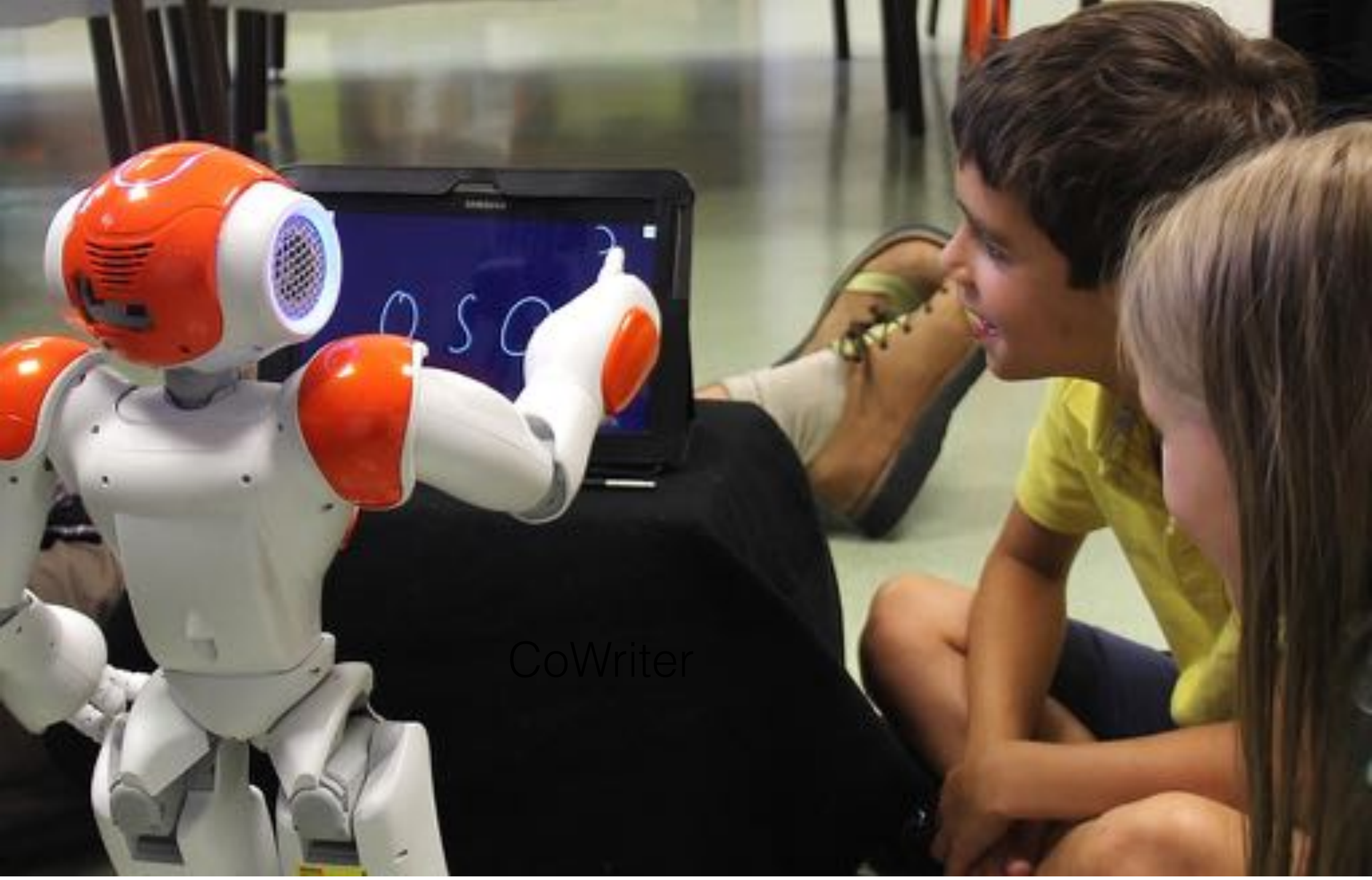



Sign. effect in problem-solving




| Measures | Warehouse study's conditions | | Evaluation of TinkerLamp 2.0 conditions | |
|---|---|---|---|---|
| | Paper/pen | TinkerLamp 1.0 | TinkerLamp 2.0 WithTinkerBoard | TinkerLamp 2.0 NoTinkerBoard |
| *Understanding score* | 7.84(2.85) | 7.43(2.82) | 9.38(2.03) | 10.31(1.70) |
| *Problem-solving score* | 5.16(1.70) | 5.15(1.78) | 6.44(1.65) | 6.59(1.53) |

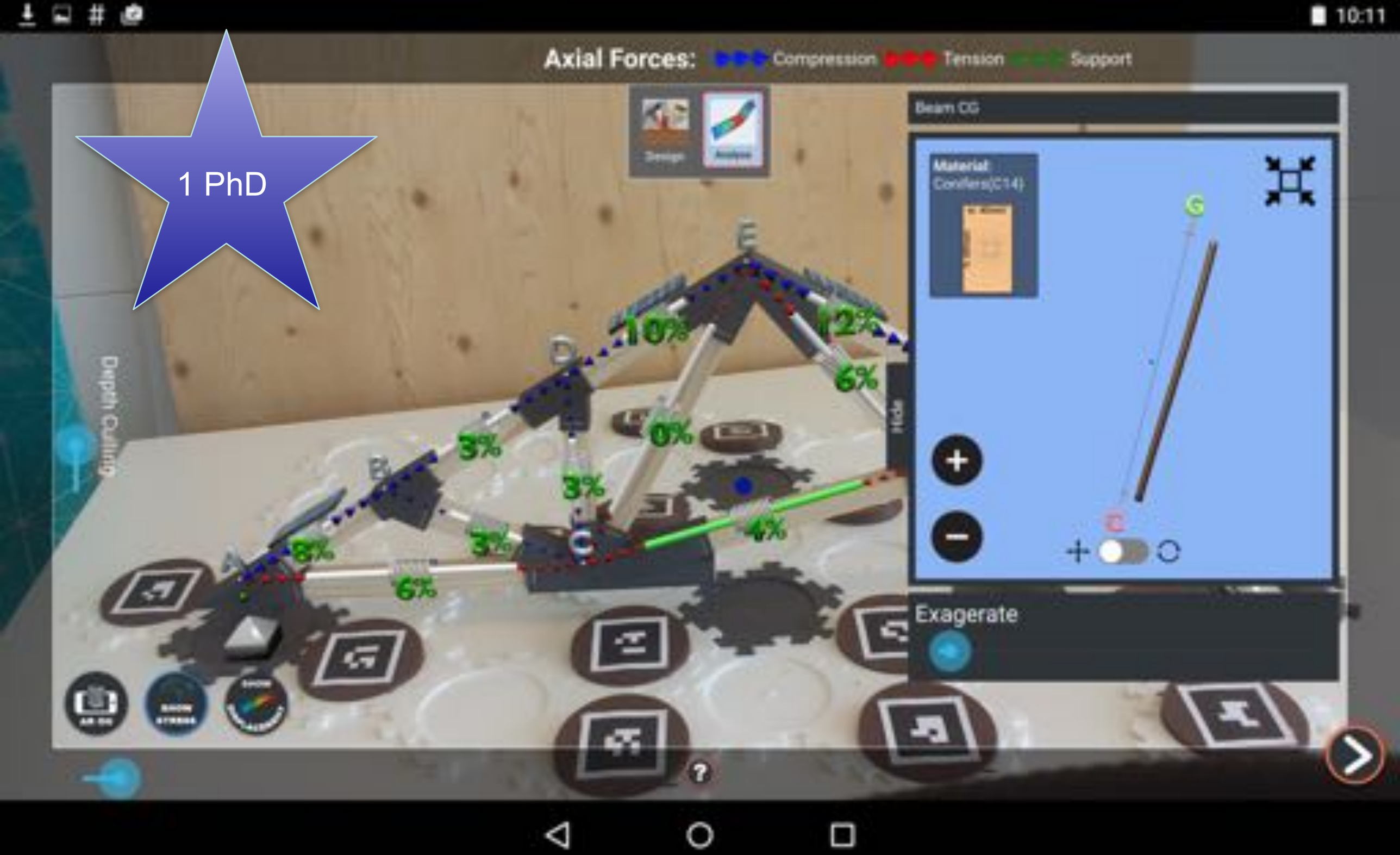
# Classroom orchestration : Circles of Usability




Johal, Lemaignan, Asselborn, Jacq, Billard, Paiva, Dillenbourg

robotics

Swiss National
Centre of Competence
in Research




Augmented Reality for Training Carpenters (L. Lucignano)

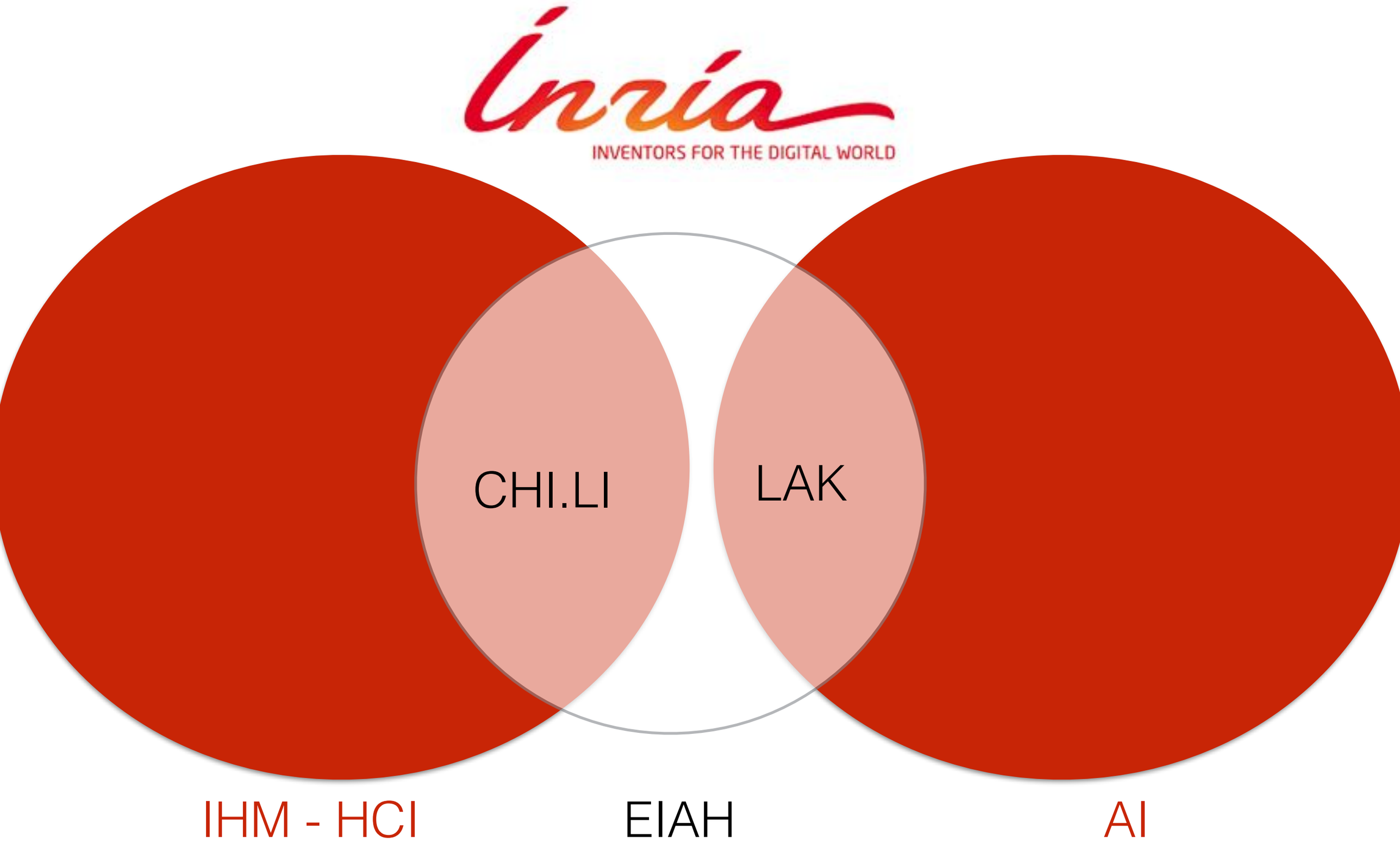
# Physics 101: Exercises Session

Problems are delicious

# Reflect

C’est pas parce que c’est de l’éducation

que cela doit être chiant !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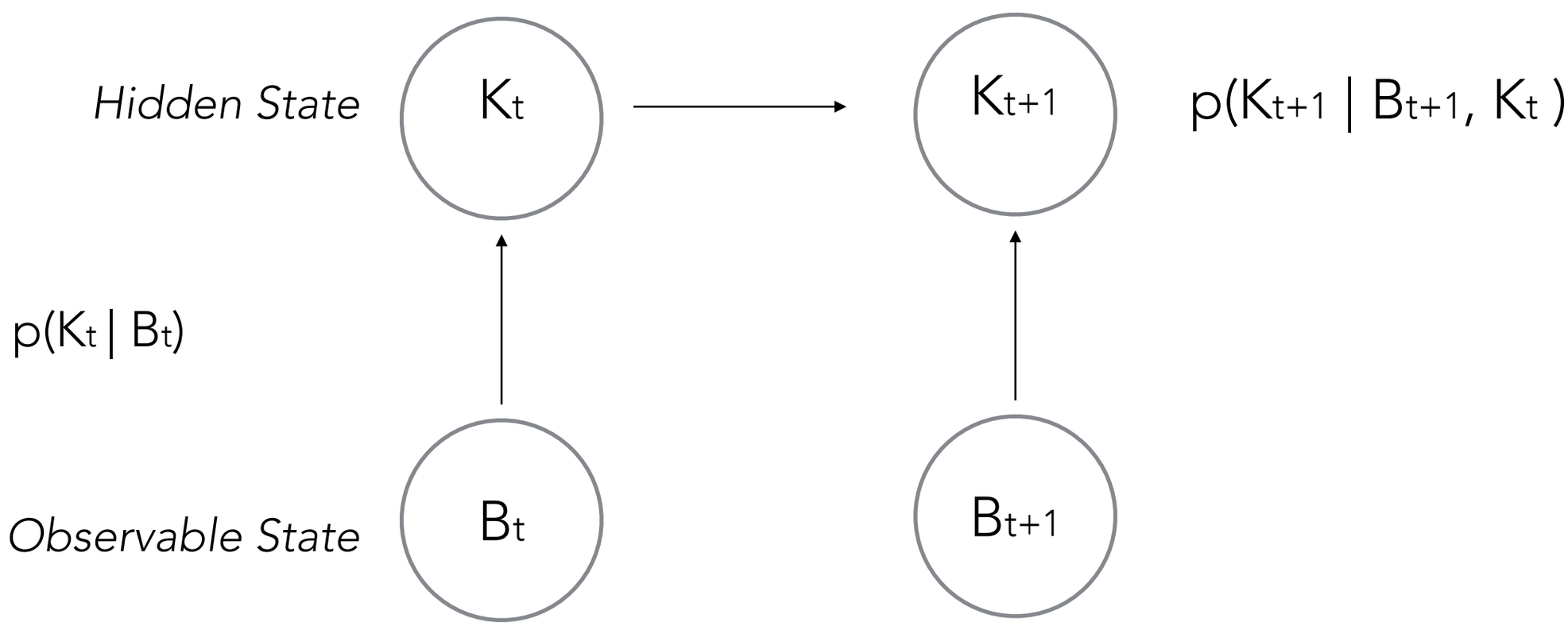
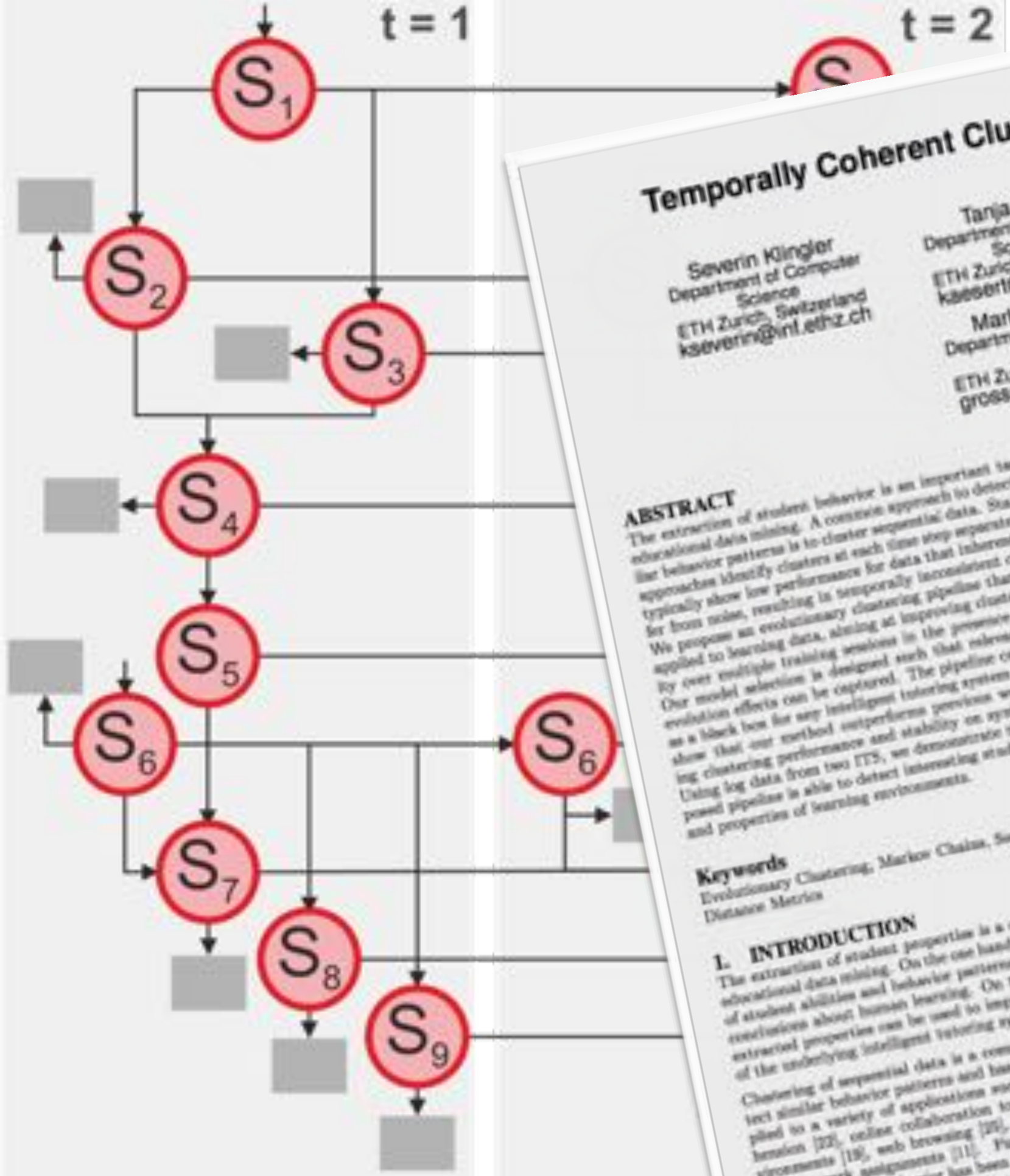
# Modelling in Education




*Bayesian Knowledge Tracing*




# Temporally Coherent Clustering of Student Data

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**ABSTRACT**

The extraction of student behavior is an important task in educational data mining. A common approach to detect similar behavior patterns is to cluster sequential data. Standard approaches identify clusters at each time step separately and typically show low performance for data that inherently suffer from noise, resulting in temporally inconsistent clusters. We propose an evolutionary clustering pipeline that can be applied to learning data, aiming at improving cluster stability over multiple training sessions in the presence of noise. Our model selection is designed such that relevant cluster evolution efforts can be captured. The pipeline can be used as a black box for any intelligent tutoring system (ITS). We show that our method outperforms previous work regarding clustering performance and stability on synthetic data. Using log data from two ITS, we demonstrate that the proposed pipeline is able to detect interesting student behavior and properties of learning environments.

**Keywords**
Evolutionary Clustering, Markov Chains, Sequence Mining, Distance Metrics

## 1. INTRODUCTION

The extraction of student properties is a central element in educational data mining. On the one hand, the identification of student abilities and behavior patterns allows us to draw conclusions about human learning. On the other hand, the extracted properties can be used to improve the adaptation of the underlying intelligent tutoring system (ITS).

Clustering of sequential data is a common approach to detect similar behavior patterns and has been successfully applied to a variety of applications such as reading comprehension [22], online collaboration tools [24], table-top environments [18], web browsing [20], physics simulations [6], work assignments [11]. Furthermore, a variety of

or Hidden Markov models (HMM) [5, 6]. Sequential pattern mining techniques have been contextualized using piecewise linear segmentation [14]. Others have employed semi-supervised graph clustering using the predictions from a student model as additional constraints [20]. Clustering sequential data employing similarity measures on state sequences was used in [4, 8]. These state sequences can be aggregated into Markov Chains modeling the state transitions [17]. HMM have been employed to extract stable groups from temporal data by joint optimization of the model parameters and the cluster count [18].

While the previous work discussed above analyze student clusters at a given point in time, a temporal analysis would allow to identify how interaction patterns change over time and how groups of similar students evolve. Temporal efforts of cluster evolution have been analyzed in [15], based on static clustering at each time step. Static approaches are sensitive to noise in the data and may result in temporally inconsistent clusters. Evolutionary clustering methods [7] address this problem as they consider multiple subsequent time steps. The temporal smoothing increases the resulting cluster stability notably and allows for a better analysis of the clusters, i.e., the student properties and interaction patterns. Recently, an evolutionary clustering approach called AFFECT [27] has been introduced that smoothe proximities of students over time followed by static clustering. AFFECT was shown to outperform static clustering algorithms.

In this paper, we present a complete processing pipeline for evolutionary clustering that can be used as a black box for any ITS. We incorporate a variation of the AFFECT method into our pipeline and demonstrate that temporal smoothing has beneficial properties for extracting student behavior groups from educational data. We propose several extensions of the original method tailored towards learning data. Our approach is articulated in four steps. In a first step, we extract action sequences from ITS log data and cluster them using Markov Chains. We show that the Markov representation of the actions is superior to direct clustering mining techniques [8, 13] with respect to noise robustness and the ability to identify groups of students with similar behavior. The second step consists of computing distances between the Markov Chains. While the choice of sim-

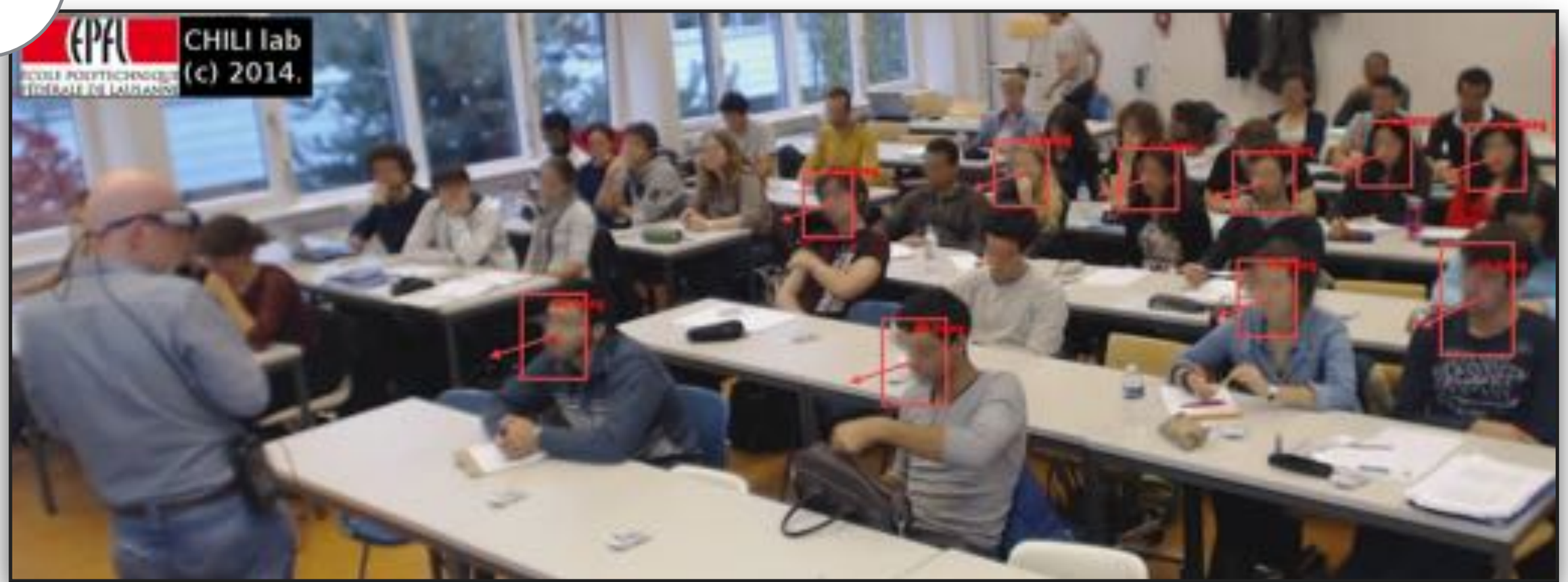
$K_t$

State = ?

$B_t$

# Modelling Education

$K_t$

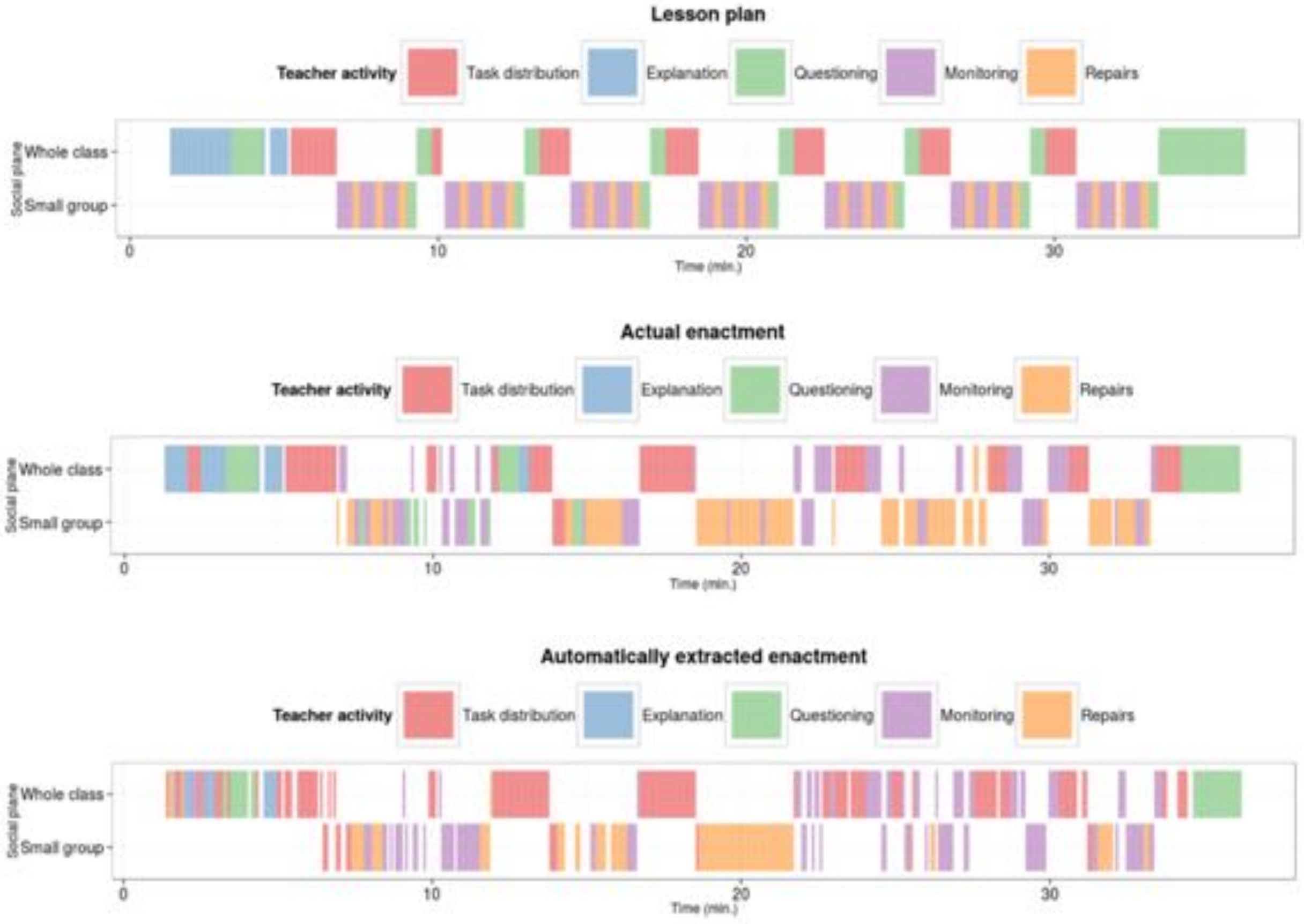



| Kernel | Features | Score | Cohen's kappa |
|---|---|---|---|
| RBF(c=1.31, g=0.0211) | Distance, Head travel norm., Num. still periods | 61.86% | 0.30 |
| RBF(c=1.21, g=0.11) | Period, Row, Head travel norm., Mean duration still | 61.72% | 0.32 |
| RBF(c=1.11, g=0.061) | Head travel norm., Mean duration still | 60.42% | 0.28 |
| RBF(c=1.4, g=0.04) | Period, Distance, Row, Mean duration still | 59.23% | 0.30 |

$B_t$

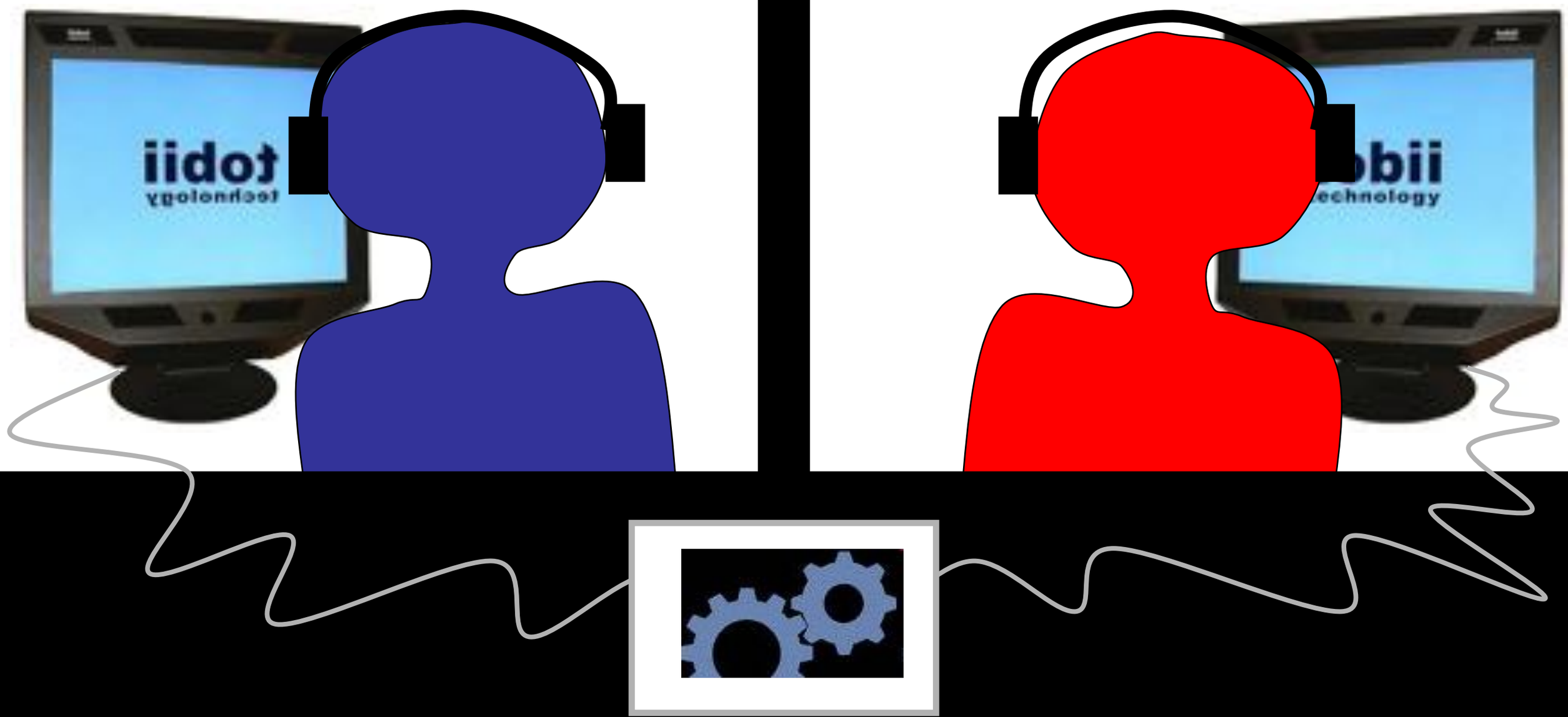
# Modelling Education

| Data source | Features | Best model | In-session perf. | | Out-of-session perf. | |
|---|---|---|---|---|---|---|
| | | | Accuracy | $\kappa$ | Accuracy | $\kappa$ |
| Eye-tracking only | All | Gradient Boosted T. | 87.5% | 0.75 | 86.1% | 0.72 |
| EEG only | All | Gradient Boosted T. | 55.1% | 0.08 | 50.9% | −0.02 |
| Accelerometer only | All | Gradient Boosted T. | 67.6% | 0.34 | 61.2% | 0.19 |
| Audio only | All | Gradient Boosted T. | 81.4% | 0.62 | 79.3% | 0.58 |
| Video only | All | Gradient Boosted T. | 81.7% | 0.63 | 81.9% | 0.63 |
| All | All | Gradient Boosted T. | 90.6% | 0.81 | 89.6% | 0.79 |
| Audio+video | All | Gradient Boosted T. | 86.1% | 0.72 | 84.8% | 0.69 |
| All | Top 5 | (SVM) | | | 88.2% | 0.76 |
| **All** | **Top 81** | **Gradient Boosted T.** | **90.6%** | **0.81** | **89.9%** | **0.80** |




Modelling Education

# Gaze Recurrence



DUET - Dual Eye-Tracking
Pair programming experiment

# Low gaze recurrence

ÉCOLE POLYTECHNIQUE FÉDÉRALE DE LAUSANNE

P. Jermann, M.-A. Nüssli & P. Dillenbourg


Supported by the Swiss National Science Foundation (grants #K-12K1-117909 and #P200P_126611)

DUET - Dual Eye-Tracking
Pair programming experiment

# High gaze recurrence

ÉCOLE POLYTECHNIQUE FÉDÉRALE DE LAUSANNE

P. Jermann, M.-A. Nüssli & P. Dillenbourg
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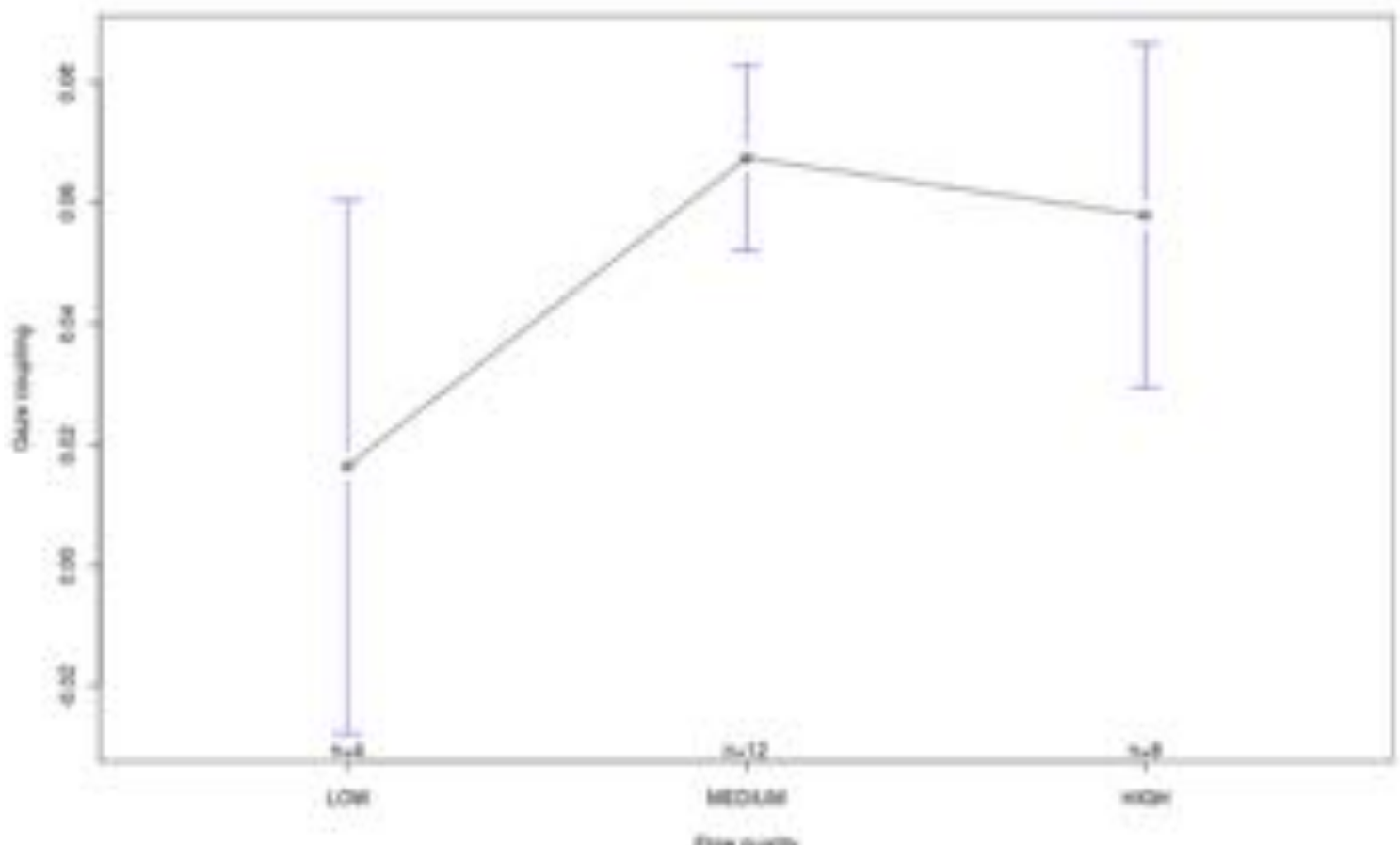
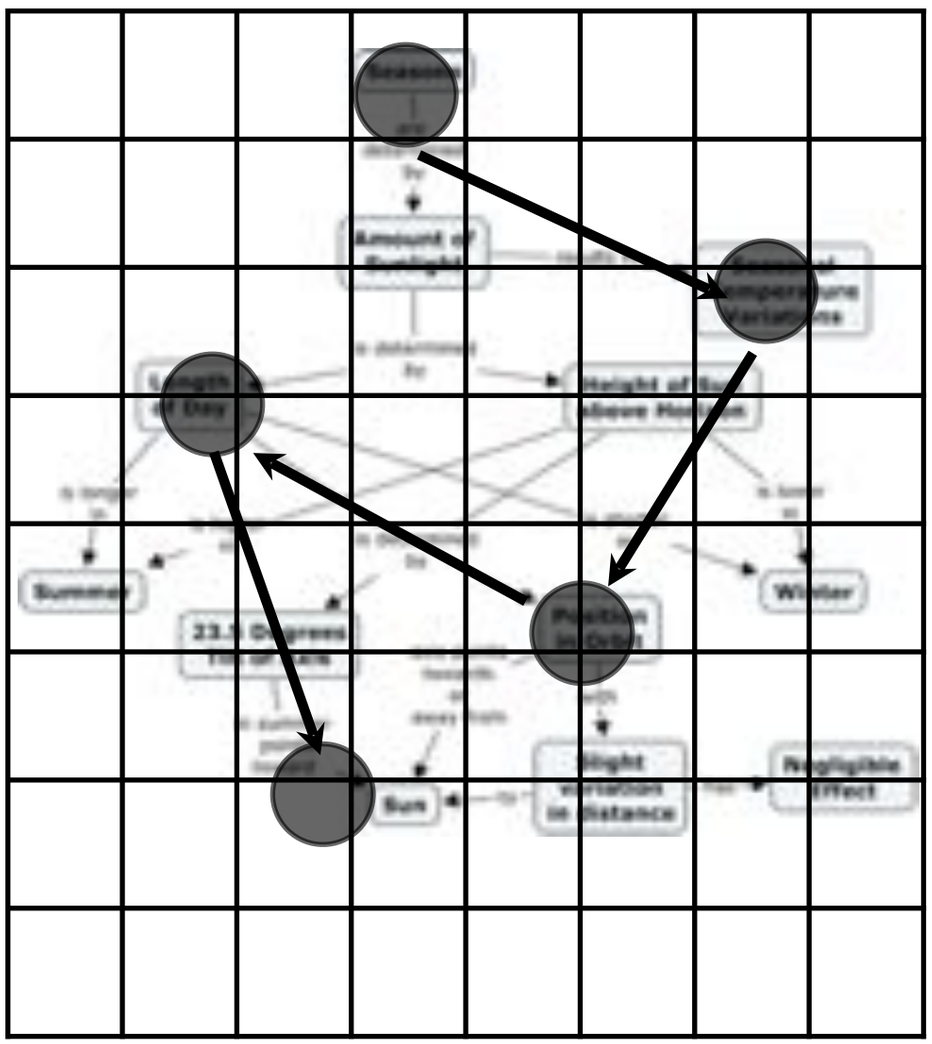
Supported by the Swiss National Science Foundation (grants #K-12K1-117909 and #P200P_126611)




Nüssli, Jermann & Mullins

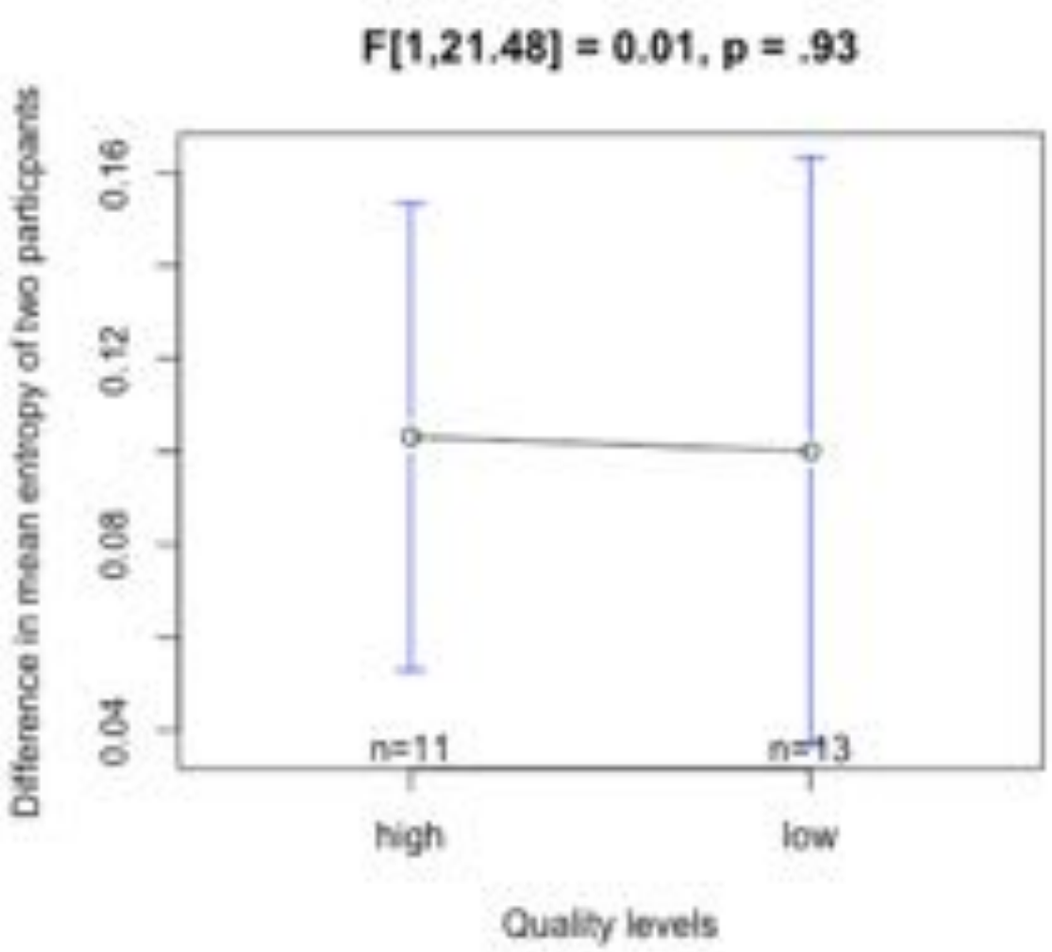
# Spatial Entropy of Gazes

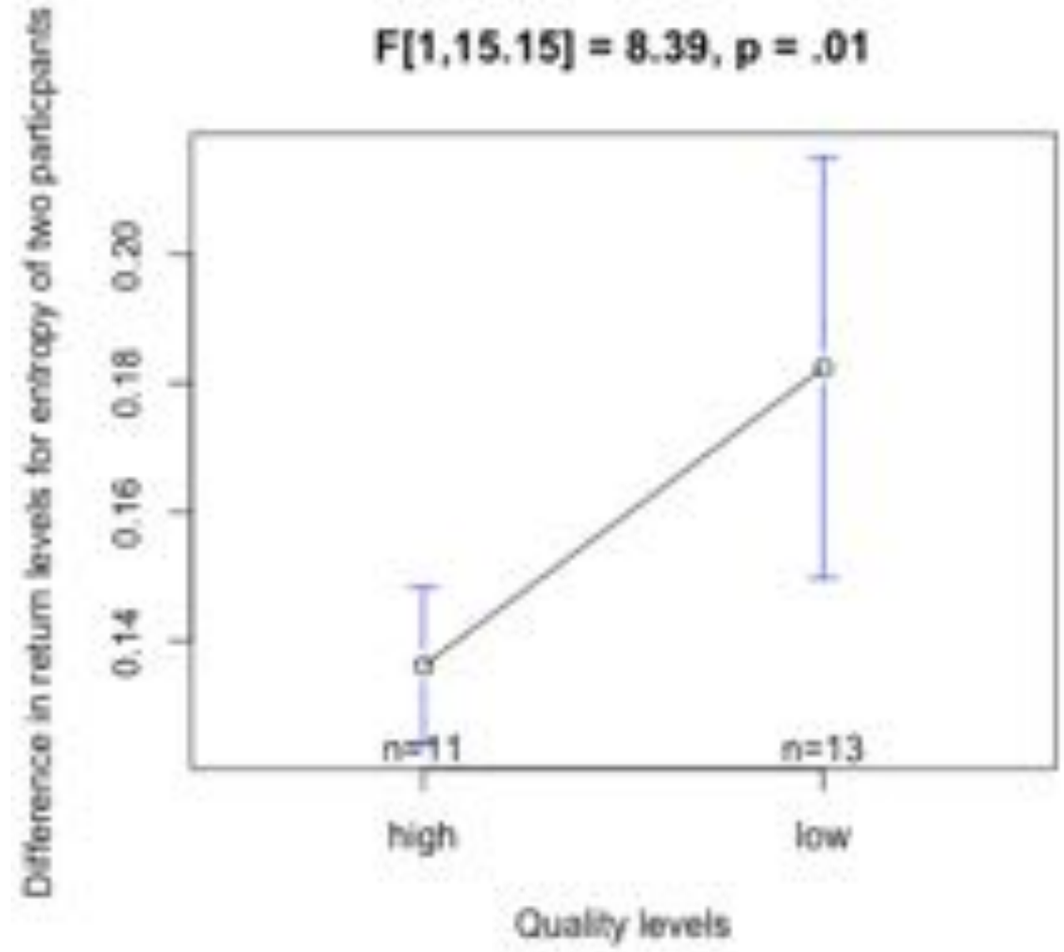


| | A | B | C | D | E |
|---|---|---|---|---|---|
| t = 0 | 0.3 | 0.3 | 0 | 0.3 | 0.1 |
| t = 1 | 0.2 | 0.2 | 0.2 | 0.2 | 0.2 |
| t = 2 | 1 | 0 | 0 | 0 | 0 |

# Extreme Value Theory

## Intra-pair difference of gaze spatial entropy




Means

5% highest values for episodes of 10 seconds

Kshitij Sharma, Valerie Chavez, EPFL & University of Lausanne


Computational Biology

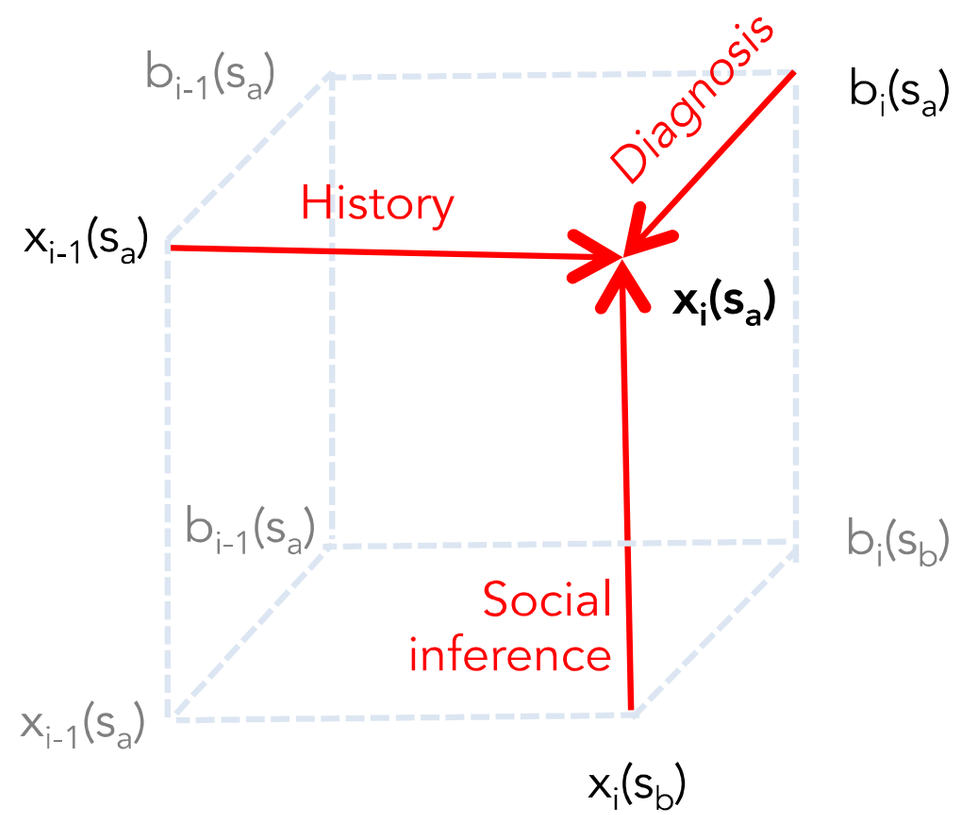
Computational Linguistics

Computational Sociology

Computational Education

Learning Analytics

Educational Design




# Computational Modeling for Learning Sciences

✓ MedTech

✓ GenTech

✓ FinTech

✓ SpaceTech

✓ CleanTech

**EdTech ?**

# EdTech Collider

Simpliquity

HappyNumbers.com

SpeakUp

better study
quiz en comptabilité et économie

IDEAO

Innova Kids
Association for Encouraging Innovation In Tomorrows' Generation

weare playlab

Graasp.eu

coorpacademy

lillup LifeLong Learning

headswap

Lundi 14 novembre, 10:19