

MMLA: Challenges, Opportunities and Techniques



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June 7, 2020



UNIVERSITY OF
COPENHAGEN

Agenda

- 9:00 Intro to the session
- 9:15 Seminar: Designing MMLA:
Research Methods, Ethics & Privacy
from the group work
- 10: Break
- 10:15 Working with MMLA Data
- 12:00 Lunch
- 12:45 Working with MMLA Data
- 13:45 Next Steps

Learning Aims

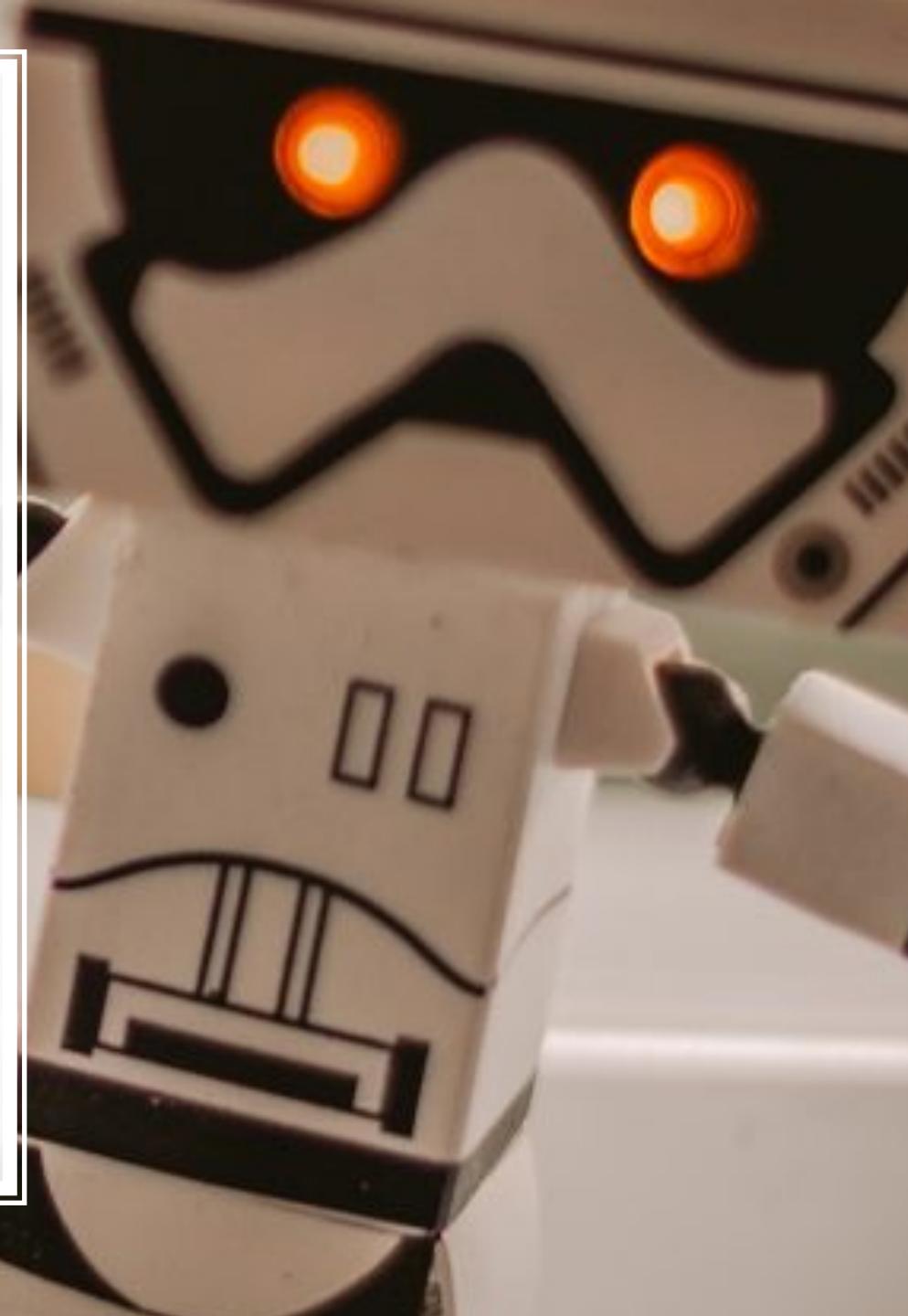
Critical understanding of MMLA

Introduction to some types of ML tools to look at MMLA Data

General ideas of how we can use MMLA to support learning

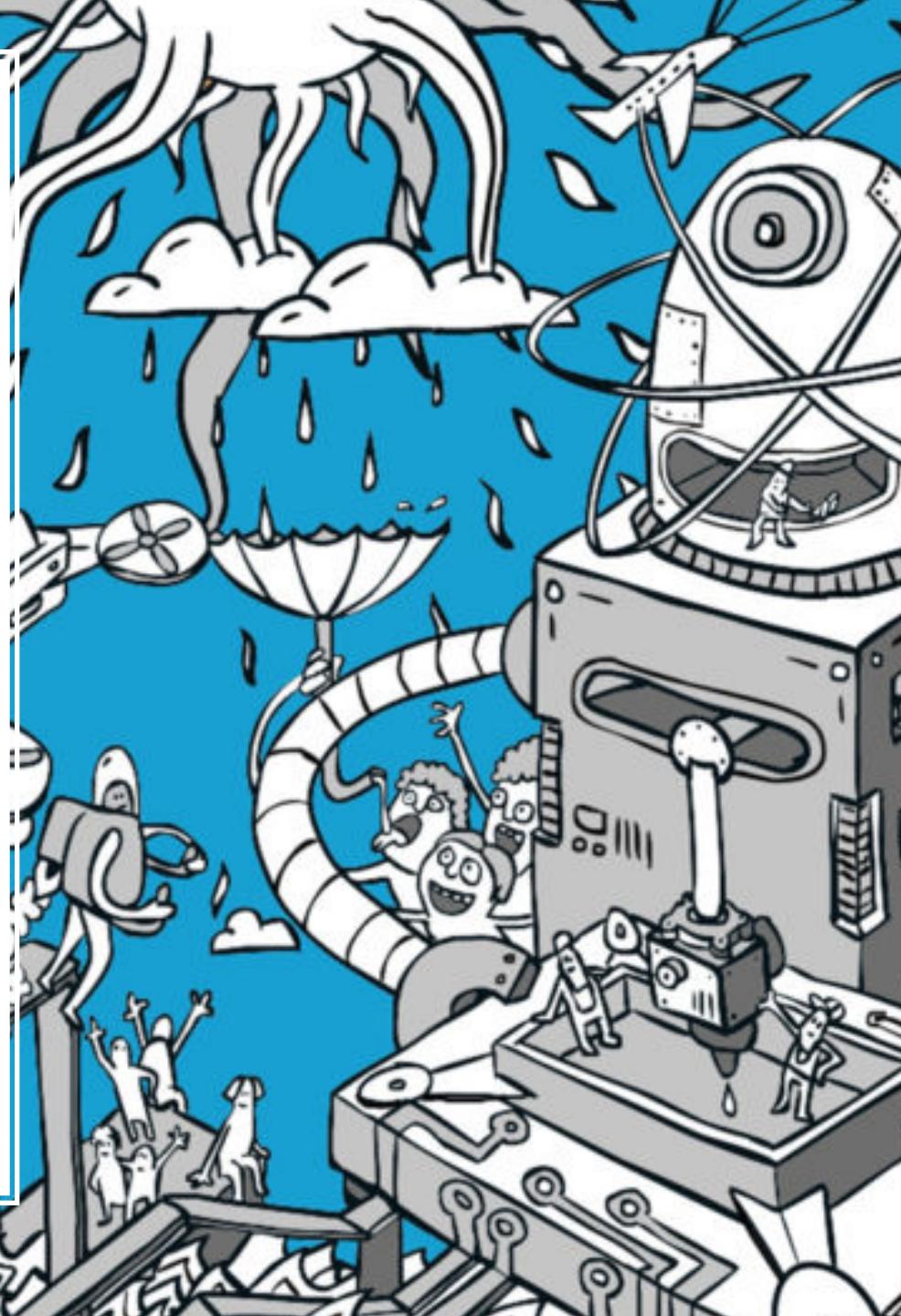
June 7 Pre-Seminar Work

1. Self-organize! Break into roughly 6 teams (4-5 people in a group) and plan to meet up virtually.
2. Do the Preliminary work in week 22 (May 31 - June 5) or earlier
3. Before your group meetings choose at least 1 or more articles (that you are interested in, individually to read, more is better) from the Literature.
4. For your group session conduct an open workshop using Speculative Design Fiction -
<https://www.invisionapp.com/inside-design/speculative-design/>
<https://speculativeedu.eu/approaches-methods-and-tools-for-speculative-design/>
<https://medium.com/demagsign/8-spectacular-speculative-designs-44fb129eb4e2>
5. The idea is to imagine, the good, the bad, and the ugly of MMLA - for instance how would brain implants work with Learning Analytics, what would be the ramifications across social-economic levels, or even more importantly learning self-regulation.
6. The idea is to be inspired by mood boards (https://en.wikipedia.org/wiki/Mood_board (Links to an external site.)) and future thinking in terms of ethics and privacy while considering the benefits and challenges of LA.



Outputs Expectations

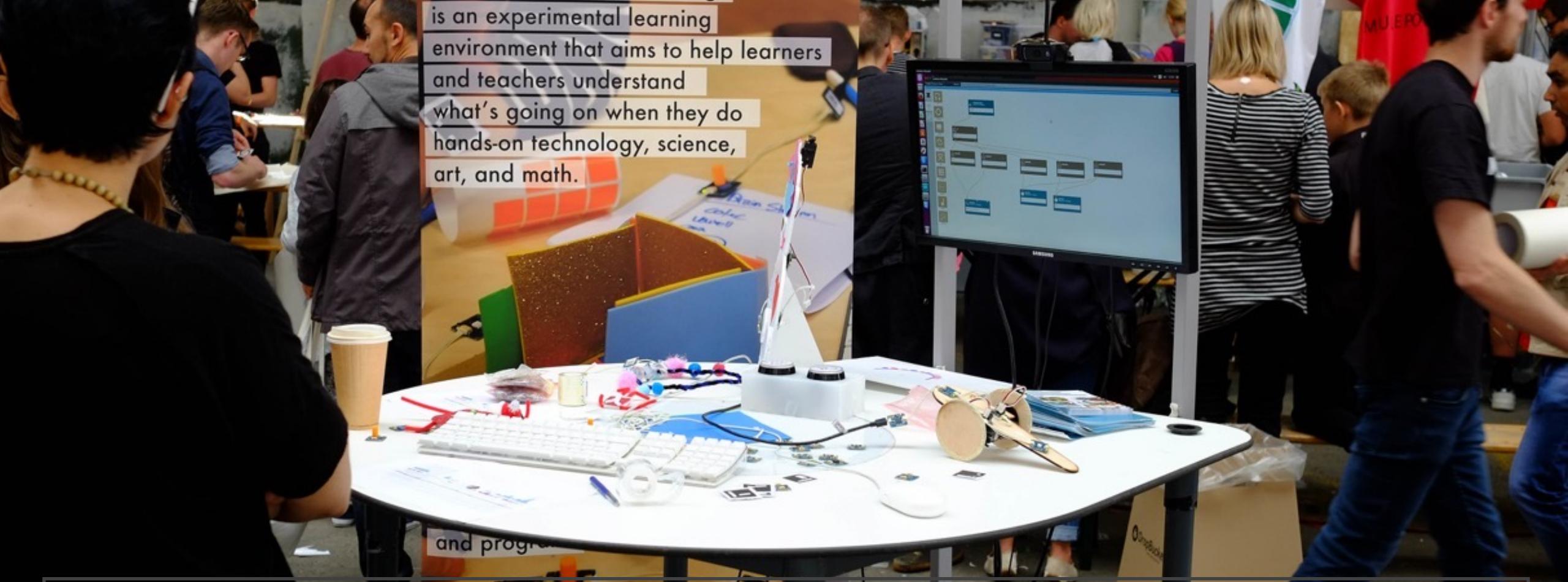
- Each team elect a spokesperson(s) be prepared to discuss with everyone your group's speculative design fiction for MMLA
- Keep in mind the playful nature of this exercise and you go between utopia and dystopia
- We are playing designers, so a broad and shallow approach required instead of a deep and narrow academic view of the world.



Literature

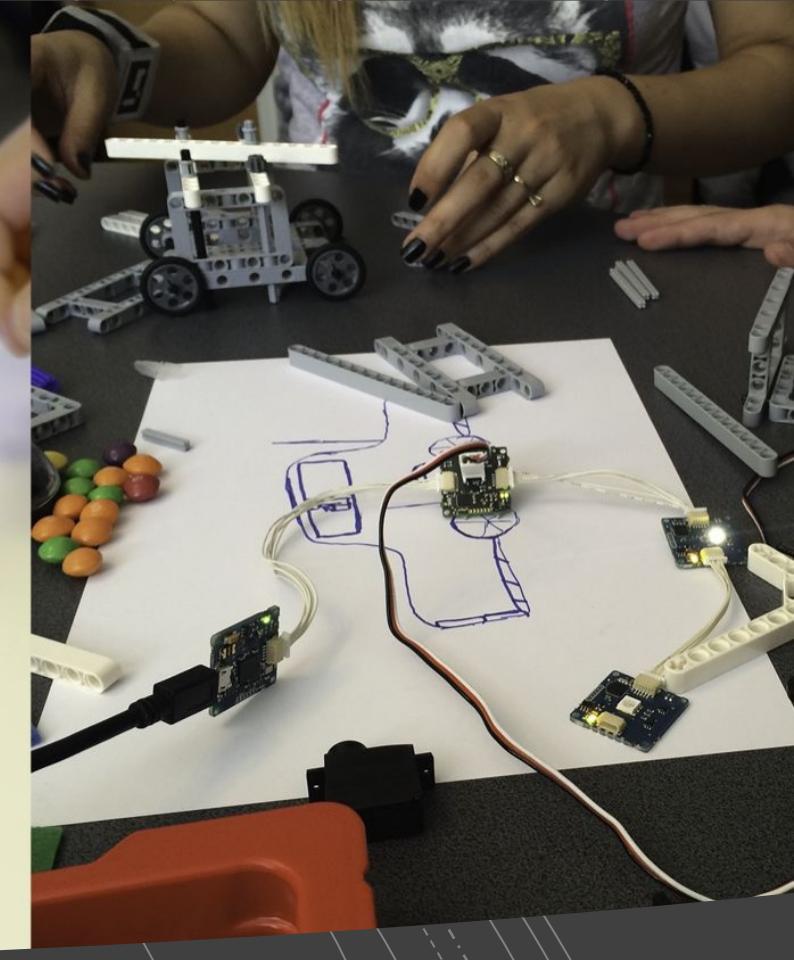
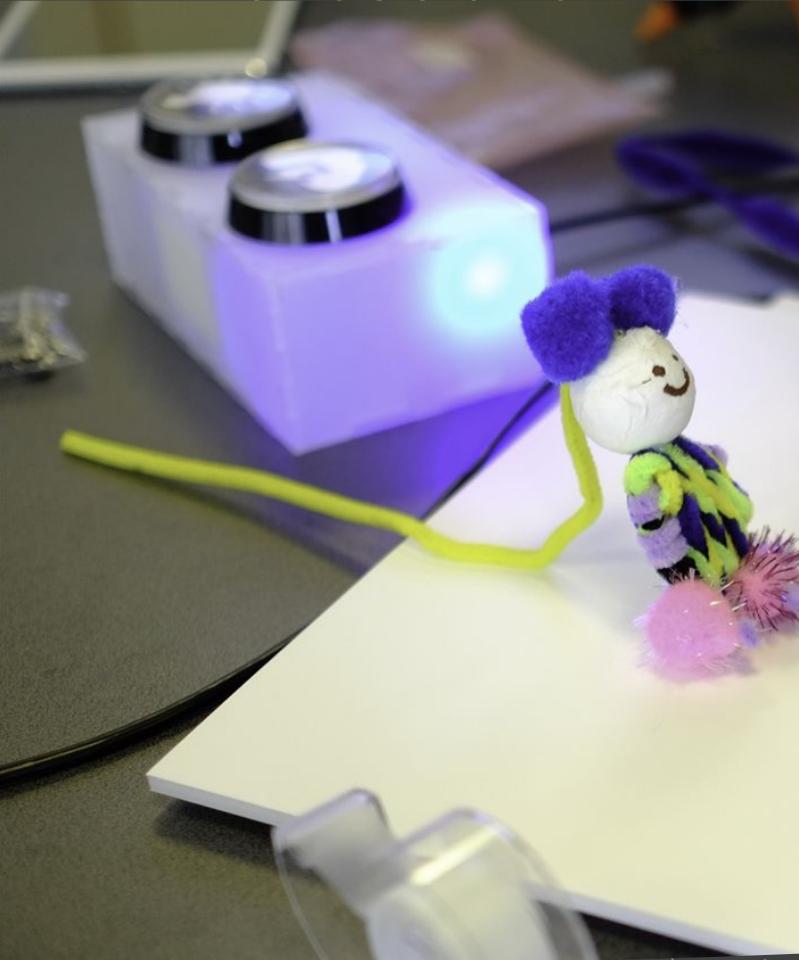
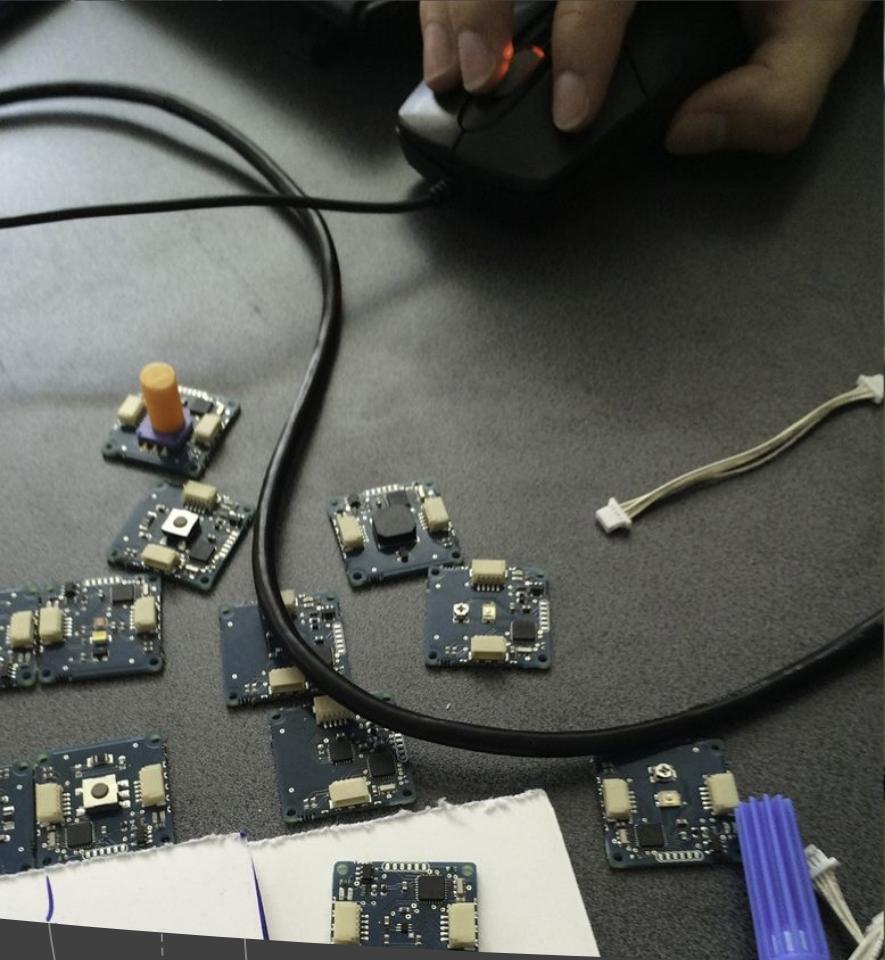
- Blikstein, P., & Worsley, M. (2016). Multimodal Learning Analytics and Education Data Mining: using computational technologies to measure complex learning tasks. *Journal of Learning Analytics*, 3(2), 220-238. doi:10.18608/jla.2016.32.11
- Buckingham Shum, S. J., & Luckin, R. (2019). Learning analytics and AI: Politics, pedagogy and practices. *British Journal of Educational Technology*, 50(6), 2785-2793. doi:10.1111/bjet.12880
- Cukurova, M., Giannakos, M., & Martinez-Maldonado, R. (2020). The promise and challenges of multimodal learning analytics. *British Journal of Educational Technology*, 51(5), 1441-1449. doi:10.1111/bjet.13015
- Di Mitri, D., Schneider, J., Specht, M., & Drachsler, H. (2018). From signals to knowledge: A conceptual model for multimodal learning analytics. *Journal of Computer Assisted Learning*, 34(4), 338-349. doi:10.1111/jcal.12288
- Martinez-Maldonado, R., Echeverria, V., Fernandez Nieto, G., & Buckingham Shum, S. (2020). From Data to Insights: A Layered Storytelling Approach for Multimodal Learning Analytics. <https://doi.org/10.1145/3313831.3376148>
- Shankar S.K., Ruiz-Calleja A., Prieto L.P., Rodríguez-Triana M.J., Chejara P. (2019) An Architecture and Data Model to Process Multimodal Evidence of Learning. In: Herzog M., Kubincová Z., Han P., Temperini M. (eds) *Advances in Web-Based Learning – ICWL 2019*. ICWL 2019. Lecture Notes in Computer Science, vol 11841. Springer, Cham. https://doi.org/10.1007/978-3-030-35758-0_7
- Vujoovic, M., Hernández-Leo, D., Tassani, S., & Spikol, D. (2020). Round or rectangular tables for collaborative problem solving? A multimodal learning analytics study. *British Journal of Educational Technology*, 51(5), 1597-1614. doi:10.1111/bjet.12988

Seminar Discussion



is an experimental learning environment that aims to help learners and teachers understand what's going on when they do hands-on technology, science, art, and math.

PELARS Project



Practice Based Learning Analytics for Research and Support (PELARS)

- What new types of learning analytics can be derived from the hands-on learning of STEM and STEAM subjects?
- How can we use this data to understand and provide avenues for formative assessment constructivist and practice-based learning?
- How can we better understand how the design of physical space and furniture influence learning interventions?

Key Collaborators

- Mutlu Cukurova, UCL Knowledge Lab, United Kingdom
- Emanuele Ruffaldi, Giacomo Dabisias & Lorenzo Landolfi, Scuola Superiore Sant'Anna, Italy
- David Cuartielles, Ardunio Verkstad, Sweden
- Bato Vogel, Malmö University, Sweden
- Donal Healion & Sam Russell, National College of Art and Design, Ireland
- Eva-Sophie Katterfeldt, Bremen University, Germany
- Nina Valkanova, Copenhagen Institute for Interaction Design, Denmark
- Simon Denehey and Phil Hamilton, PERCH, Ireland
- European Network of Living Labs



This project has received funding from the European's Seventh Framework Programme for research technological development and demonstrations under grant agreement 619738



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PERCH

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National College
of Art & Design

Different Approach for Learning Analytics



Less intrusive data collection - Multimodal Learning Analytics (MMLA)



Focus on non-verbal interactions between people and objects



Collect data in real-world settings



Explore different techniques for data analysis



Explore how to design environments for improved collaboration



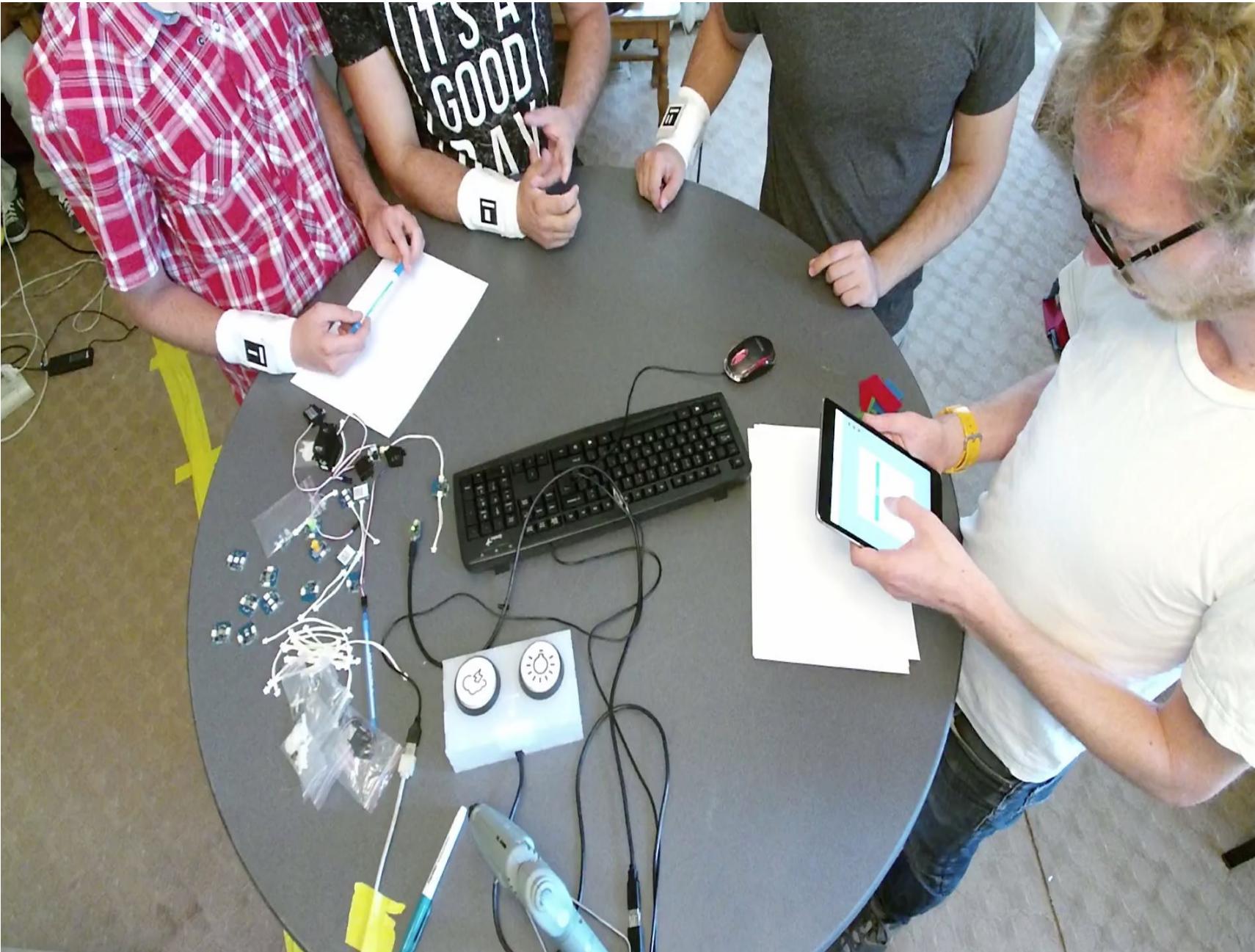
What we did...

- LAS system for collecting diverse traces (data):
 - Computer vision systems for capturing and analyzing “collaboration”
 - Mobile and Web-based tools for student self-documentation and research on-the fly coding
 - Visual Programming Platform including sensors and actuators
 - Sentiment feedback devices
- Learning Analytics
 - Logic and Reasoning based on the data collected
 - Visualizations
 - Specially designed furniture



What the groups did – the interventions

- Focus on groups of 3 students
 - open-ended design task
 - 57 minutes (mean of each session)
- Specially developed learning scenarios
 - Interactive toy
 - Color sorter
 - Autonomous vehicle



Data Collected

MMLA FEATURES (Independent)	Approach	How do these features affect the student outputs of collaboration patterns(Dependent)
<p>FLS - Number of faces looking at screen</p> <p>DBF - Mean distance between faces</p> <p>DBH - Mean distance between hands</p> <p>HMS - Mean hand movement speed</p> <p>AUD - Mean audio level</p> <p>HP - Mean hand positions</p> <p>ACA - Mean Arduino components activity</p> <p>DEC - Number of connected Arduino components</p> <p>SB - Sentiment Buttons</p> <p>PWR - Student Work Phases</p>	<ol style="list-style-type: none">1. Data Processing2. Clustering3. Regression4. Variable refinement5. Regression6. Deep Learning	<p>ASQ- Artefact grade</p> <p>CPS - Score IA, PE & IPV</p>

Briefly the Results

- Artefact solution (What the groups created)
 - Dependent variables – score of the solution
 - Features Distance between Hands, (DBH), Distance between Learners (DBL), and Audio (AUD) can predict after 30 minutes
- Collaborative Problem Solving Framework (How the groups worked together)
 - Dependent variables - Individual Accountability, Physical Engagement, and Synchronicity
 - Individual Accountability (IA) and Synchrony (SYN) are strong features for prediction with Distance between hands (DBH)
 - Synchronicity - DBH is an important feature with Faces Looking at Screen (FLS)
 - Physical Engagement (PE) is a strong feature for Hand Distance (DBH)

Spikol, D., Ruffaldi, E., Dabisias, G., & Cukurova, M. (2018). Supervised machine learning in multimodal learning analytics for estimating success in project-based learning. *Journal of Computer Assisted Learning*, 34(4), 366-377. doi:10.1111/jcal.12263

Vujovic, M., Hernández-Leo, D., Tassani, S., & Spikol, D. (2020). Round or rectangular tables for collaborative problem solving? A multimodal learning analytics study. *British Journal of Educational Technology*, 51(5), 1597-1614. doi:10.1111/bjet.12988

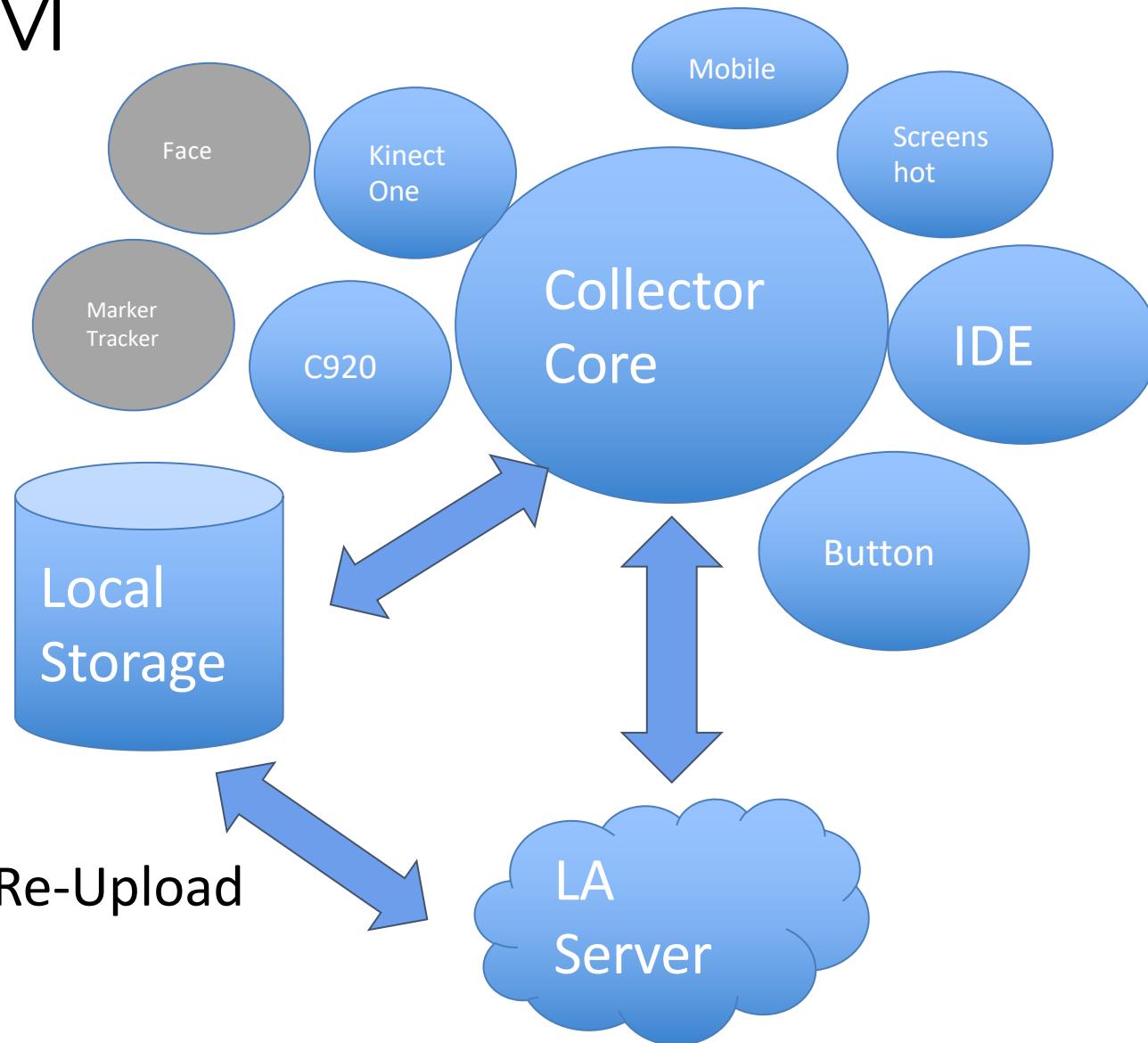
Spikol, D., Ruffaldi, E., Dabisias, G., Cukurova, M. Supervised machine learning in multimodal learning analytics for estimating success in project-based learning. *Journal of Computer Assisted Learning*. 2018; 34: 366– 377. <https://doi.org/10.1111/jcal.12263>

D. Spikol, E. Ruffaldi, L. Landolfi and M. Cukurova, "Estimation of Success in Collaborative Learning Based on Multimodal Learning Analytics Features," 2017 IEEE 17th International Conference on Advanced Learning Technologies (ICALT), Timisoara, Romania, 2017, pp. 269-273, doi: 10.1109/ICALT.2017.8229020.

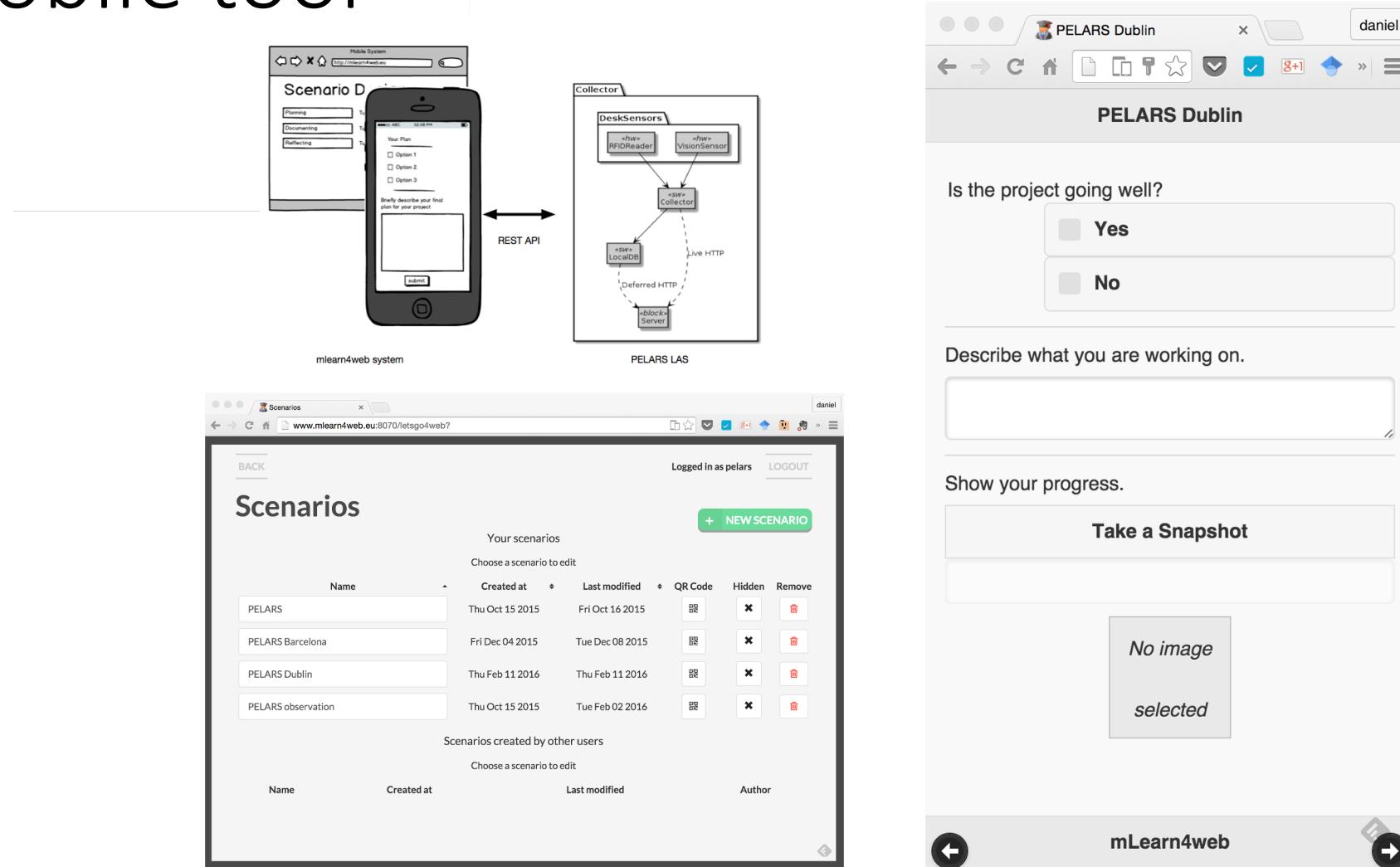


Visualizations

PELARS SYSTEM



Mobile tool



Mobile tool

mLearn4web | Visualization × daniel

www.mlearn4web.eu:8070/visualization/56bc504d7094db7f5484f5c0#

Group: Pillow talk
Interactive image

Text Media

Group: Pillow talk

Group: Pillow talk

Text Media Graph

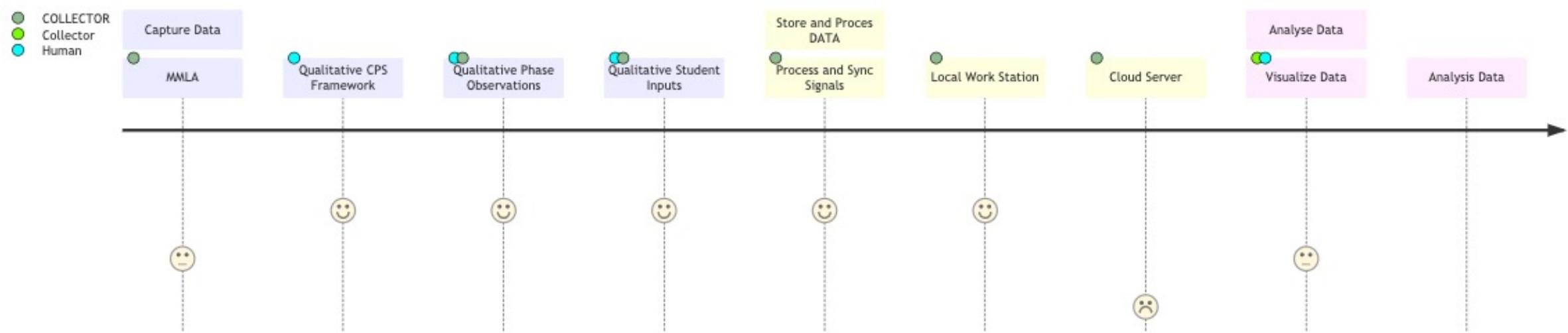
Group: Pillow talk
Not exactly

Group: Pillow talk
More interactivity, spend more time on the code

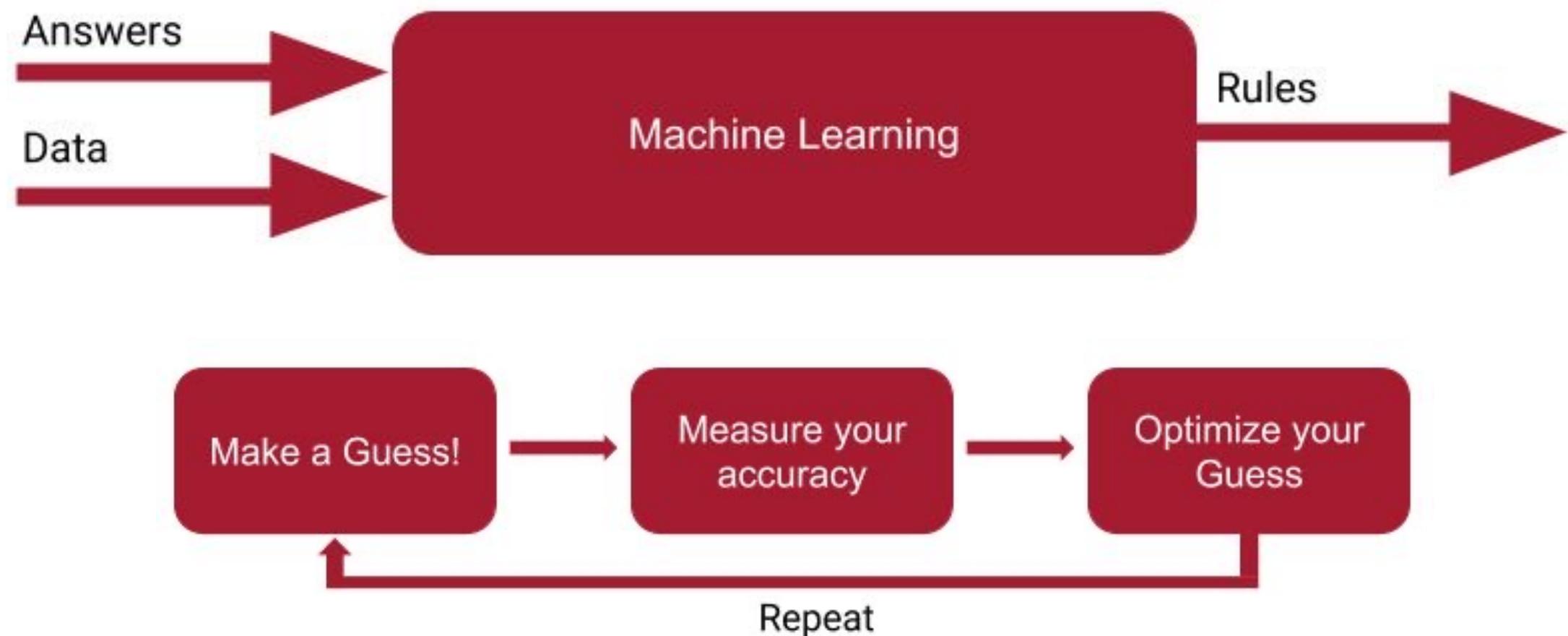
Text Media Graph

Data Journey

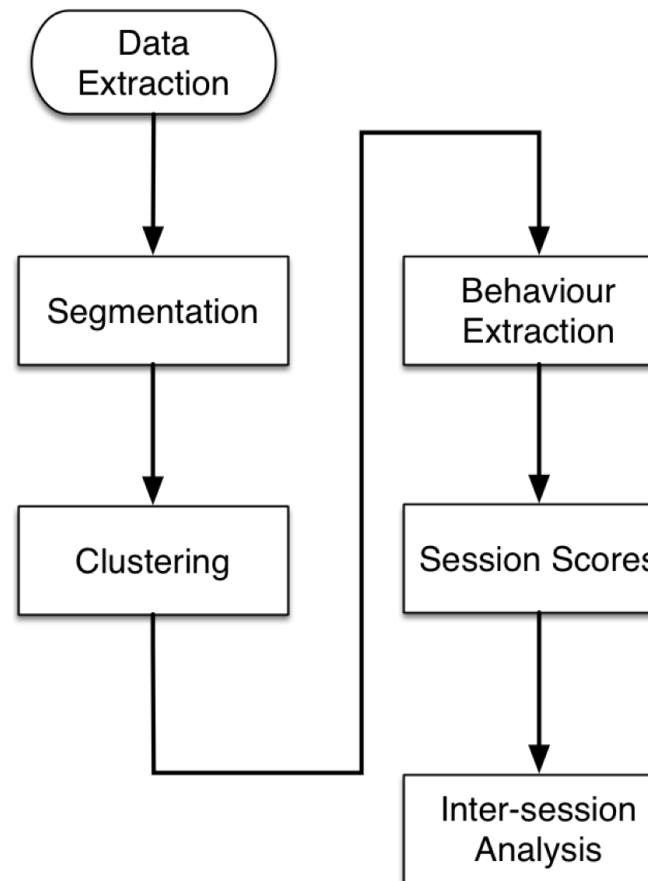
PLELARS DATA COLLECTION PROCESS



Machine Learning Approach (Results)



PELARS MMLA



Segmentation

- Splitting segments into pieces

Clustering

- puts similar types of segments together

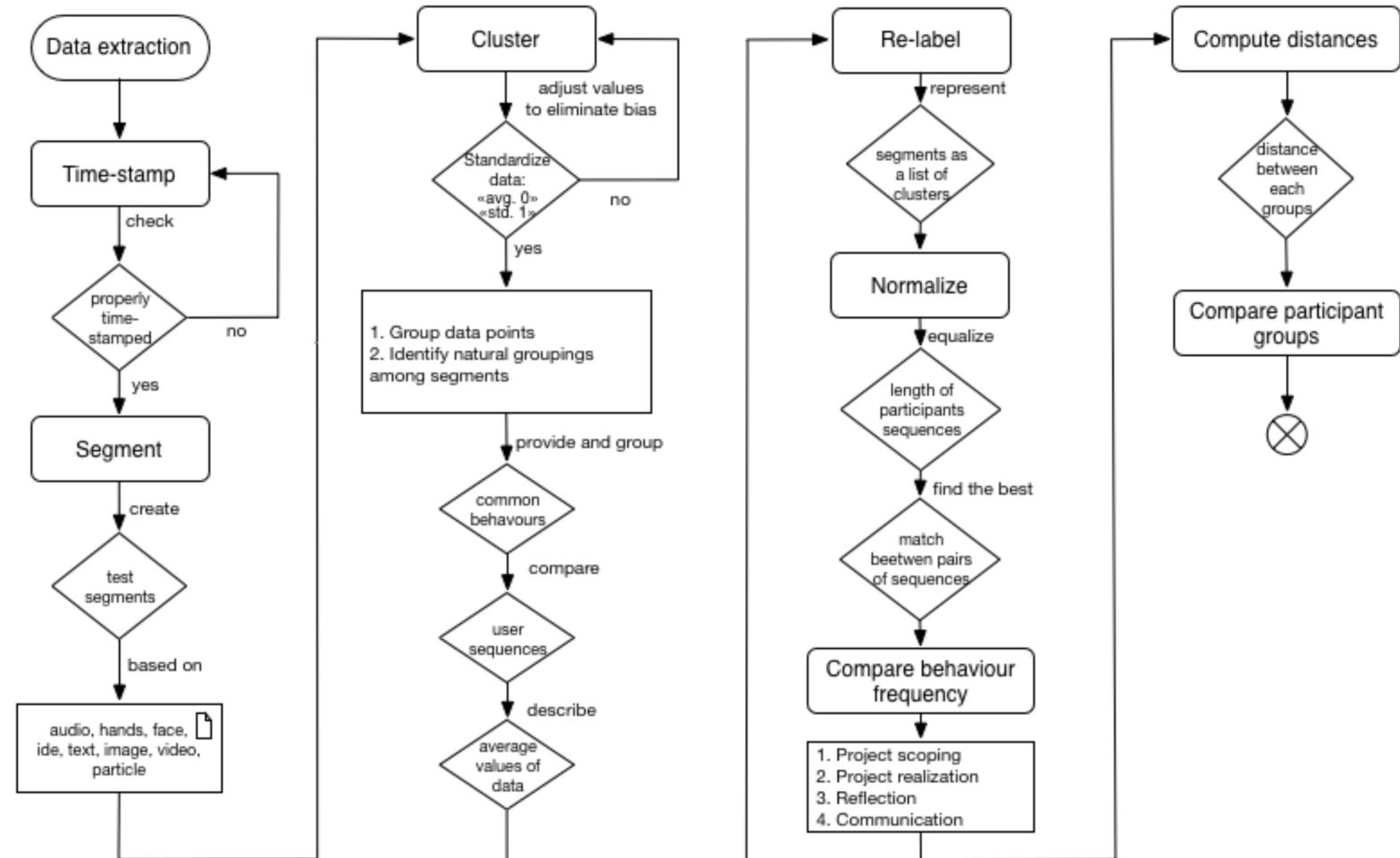
Behaviour Extraction

- Process- duration normalization, comparison of the different clusters

Analysis

- Various methods for comparison for the different “experimental “ conditions

PELARS



PELARS: Initial Understanding

ID	Photo	Planning Sketch	Planning Text	Design Stages	Task Solution	Reflection Text						
Design Students Trial id 497			The cat-teddy is an interactive face. It looks like a monster and the user can make it come to life.	<table border="1"><tr><td>Planning</td><td>45%</td></tr><tr><td>Building</td><td>36%</td></tr><tr><td>Reflecting</td><td>19%</td></tr></table>	Planning	45%	Building	36%	Reflecting	19%		Almost. We had to unplug the hub because the rgb did not work. We planned the sensors the same as we did the logic. That was confusing because it was not the same actually. Less scary toy. Try out more functions. Like heat, Accelerometer. I would not have started planning so much in the beginning. Try out more"
Planning	45%											
Building	36%											
Reflecting	19%											
Engineering Students Trial id 538			To make the red light up if the button connected to the sound are pressed.	<table border="1"><tr><td>Building</td><td>76%</td></tr><tr><td>Planning</td><td>18%</td></tr><tr><td>Reflecting</td><td>6%</td></tr></table>	Building	76%	Planning	18%	Reflecting	6%		Almost Check all logical functions, how they work
Building	76%											
Planning	18%											
Reflecting	6%											
High School Trial id 587			We are working on the disco lights.	<table border="1"><tr><td>Building</td><td>57%</td></tr><tr><td>Planning</td><td>32%</td></tr><tr><td>Reflecting</td><td>11%</td></tr></table>	Building	57%	Planning	32%	Reflecting	11%		If it worked as planned but warned that perhaps something was wrong in presenting the disco. What would be different especially the presentation
Building	57%											
Planning	32%											
Reflecting	11%											

TABLE 6 Best network results for the different network configurations

Layers	Error	Window (s)
1024	0.186	360
1024, 512	0.174	360
1024, 512, 256	0.129	240

TABLE 7 Best error scores after removing isolated features

Removed feature	Best result
No features removed	0.129
All faces data	0.21
All Arduino data	0.21
DBF	0.15
DBH	0.21
HMS	0.19
AUD	0.18
Hand pos	0.21
Arduino comp	0.19

TABLE 3 Results for the 120s window, 0.242 overall accuracy

120s window	Loc	InTh	CorPi	DoWo	QuaOS	OG
Mean	0.182	0.238	0.166	0.197	0.155	0.228
Var	0.074	0.112	0.069	0.076	0.061	0.099

Note. CorPi = corresponds with plan; DoWo = does it work?; InTh = independent thinking; Loc = level of clarity; QuaOS = quality of solution.

TABLE 4 Results for the 240s window, 0.129 overall accuracy

240s window	Loc	InTh	CorPi	DoWo	QuaOS	OG
Mean	0.086	0.175	0.150	0.175	0.154	0.084
Var	0.074	0.056	0.084	0.092	0.062	0.048

Note. CorPi = corresponds with plan; DoWo = does it work?; InTh = independent thinking; Loc = level of clarity; QuaOS = quality of solution.

TABLE 5 Results for the 360s window, 0.193 overall accuracy

360s window	Loc	InTh	CorPi	DoWo	QuaOS	OG
Mean	0.213	0.077	0.237	0.147	0.196	0.181
Var	0.097	0.006	0.083	0.063	0.071	0.057

Note. CorPi = corresponds with plan; DoWo = does it work?; InTh = independent thinking; Loc = level of clarity; QuaOS = quality of solution.

TABLE 2 Machine learning tasks performed over data

Method	Deep learning	Traditional
Task	Regression	Classification
Input	18 variables	9 variables per window
Output	6 scores over 5 levels	1 score with 3 levels
Metrics	Regression score	Classifier accuracy
Widnowing	120,240 and 360 s	10,20,30,90 min
Phase exclusion	Reflection	Reflection
Method	Multiple layers	NB, LR, SVML, and SVMR

Note. NB = naive Bayesian; LR = logistic regression; SVML = support vector machines with linear kernel; SVMR = support vector machines for regression.

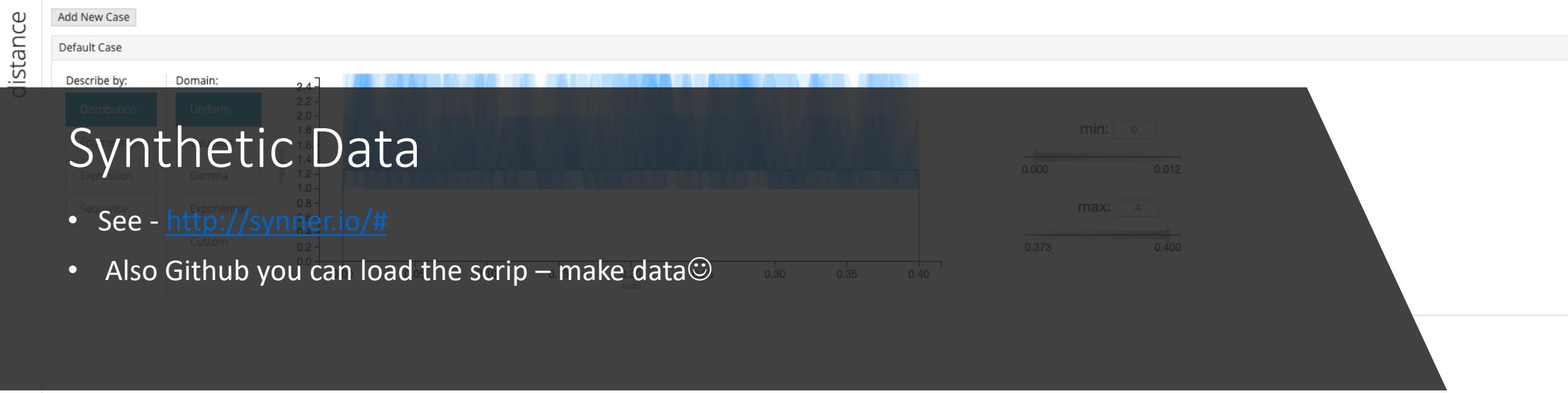
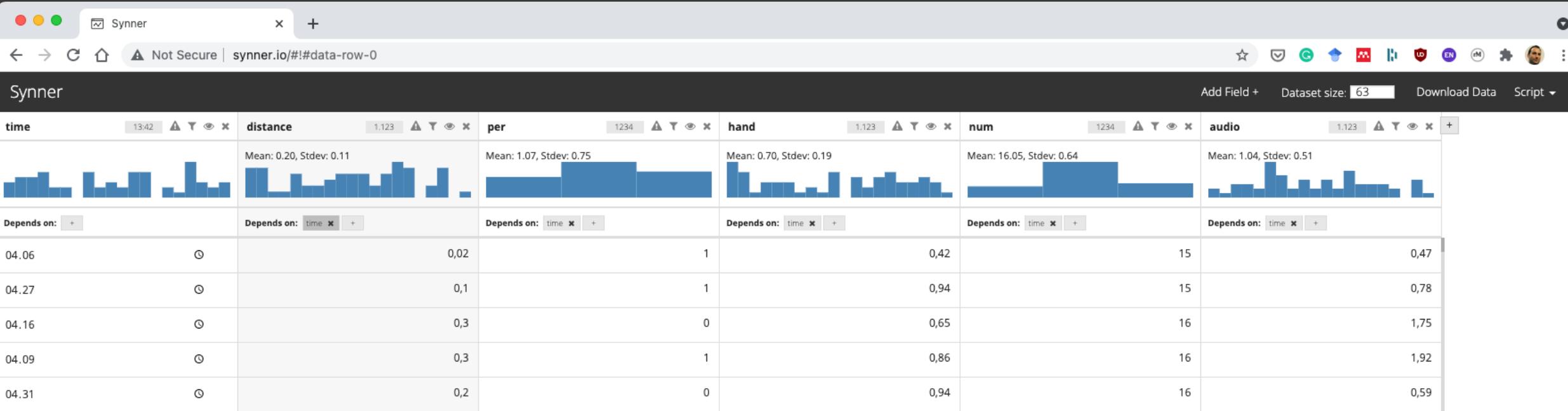
ML approaches to PELARS



MMLA systems

- Labstreaming Layers -
<https://labstreaminglayer.readthedocs.io/info/intro.html>
- Multimodal Learning - Hub
<https://www.springerprofessional.de/en/multimodal-learning-hub-a-tool-for-capturing-customizable-multim/16068602>
- Timeflux - <https://timeflux.io/>
- SSI - <https://hcai.eu/projects/ssi/>
- PSI -<https://www.microsoft.com/en-us/research/project/platform-situated-intelligence/>
- iMotions and Noldus (Commercial) - <https://imotions.com/> & <https://www.noldus.com/>
- PELARS – (Not working) - <http://pelars-doc.readthedocs.org/en/latest/>

Data Workshops

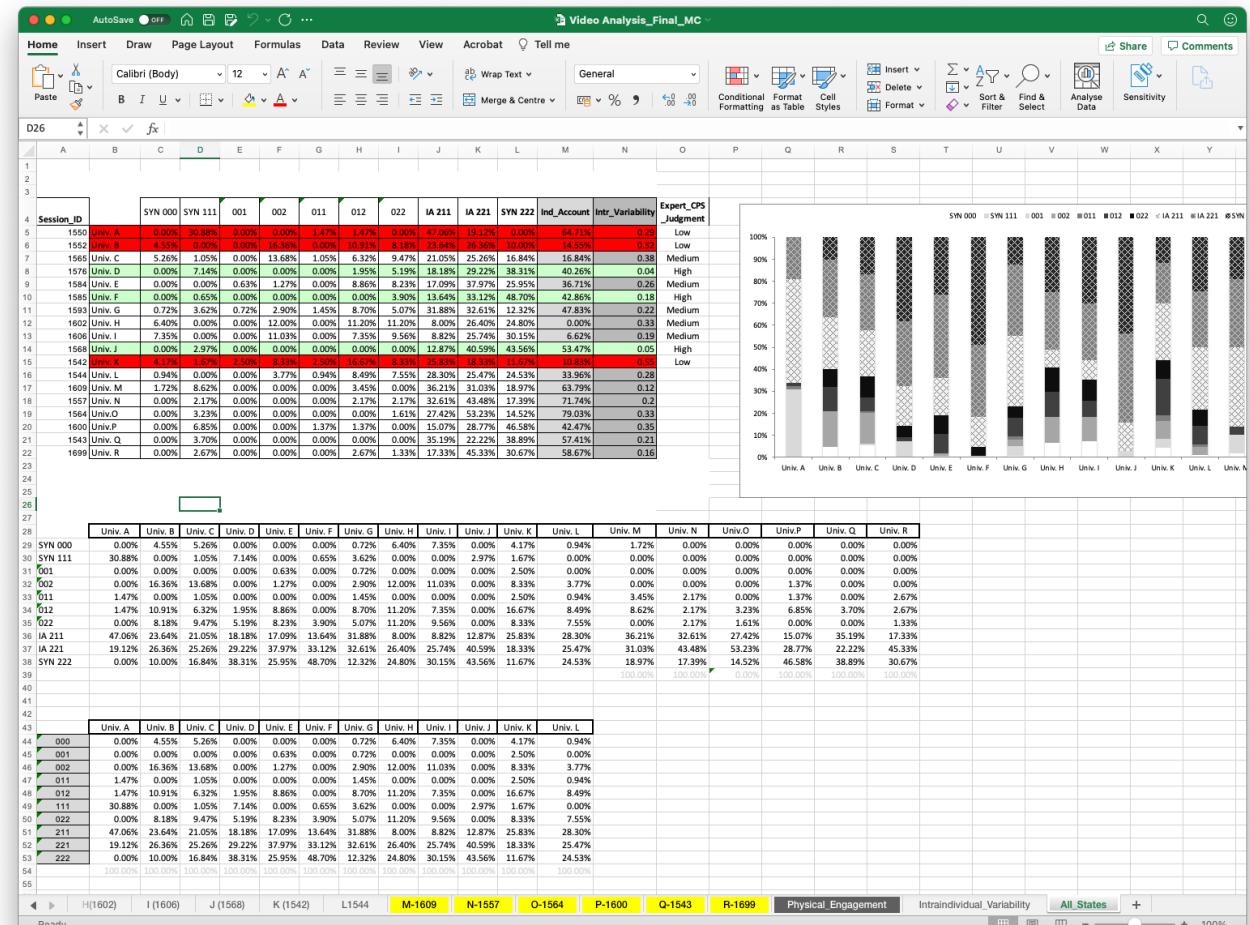


We have over analysed the data

```

session_1564.json
[{"data_id": "711054", "distance": 1.297992706298828, "num": 0, "pos_x0": -0.151622, "pos_x1": -0.11704, "pos_x2": -0.147694, "pos_y0": 0.184005, "pos_y1": -0.0102355, "pos_y2": -6.63504E-4, "pos_z0": 0.596823, "pos_z1": 0.424734, "pos_z2": 0.07172, "session": 1564, "time": 1.467877984394E12, "type": "face"}, {"data_id": "711062", "distance": 1.51432478427887, "num": 0, "pos_x0": -0.366437, "pos_x1": -0.331855, "pos_x2": -0.362509, "pos_y0": 0.224972, "pos_y1": 0.0307316, "pos_y2": 0.0403035, "pos_z0": 0.561699, "pos_z1": 0.38961, "pos_z2": 0.572048, "session": 1564, "time": 1.467877986525E12, "type": "face"}, {"data_id": "711071", "distance": 1.297992706298828, "num": 0, "pos_x0": -0.150256, "pos_x1": -0.115673, "pos_x2": -0.146327, "pos_y0": 0.187946, "pos_y1": -0.00629439, "pos_y2": 0.00327757, "pos_z0": 0.587889, "pos_z1": 0.4158, "pos_z2": 0.598238, "session": 1564, "time": 1.467877988273E12, "type": "face"}, {"data_id": "711081", "distance": 1.297992706298828, "num": 0, "pos_x0": -0.150667, "pos_x1": -0.116085, "pos_x2": -0.146739, "pos_y0": 0.190259, "pos_y1": -0.00398201, "pos_y2": 0.00558995, "pos_z0": 0.589938, "spaces": 4, "JSON": "4 characters selected", "Spaces": 4}

```

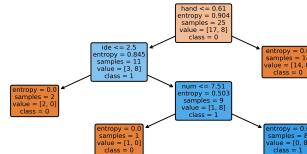
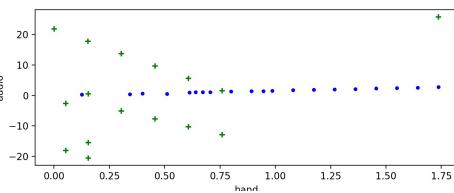


From 26K rows to 53
rows for human-learning

- 6 Minute Windows = 53 rows (60 Mins)
 - Also data set at 27 rows after 30 minutes

ML classification and Regression

- Decission Tree Ensemble
- Support Vector Machines
- Naïve Bayes Algorithm



	Actual Status	Predicted Status
30	1	1
34	1	1
28	1	1
3	0	0
19	0	0
17	0	0
21	1	1
23	1	1
29	1	0
26	1	1
27	1	1

Classification Report:

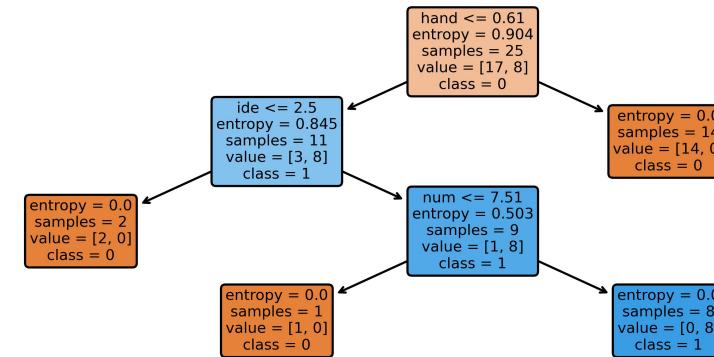
A Classification report is used to measure the quality of predictions from a classification algorithm.

```
[11]
print(classification_report(y_test, y_pred))
with open('sample_data/Example2.txt', 'a') as testwritefile:
    testwritefile.write("-----\n")
    testwritefile.write(classification_report(y_test, y_pred))

precision    recall  f1-score   support
          0       0.75    1.00    0.86      3
          1       1.00    0.88    0.93     11
   accuracy                           0.91     11
  macro avg       0.88    0.94    0.90     11
weighted avg       0.93    0.91    0.91     11
```

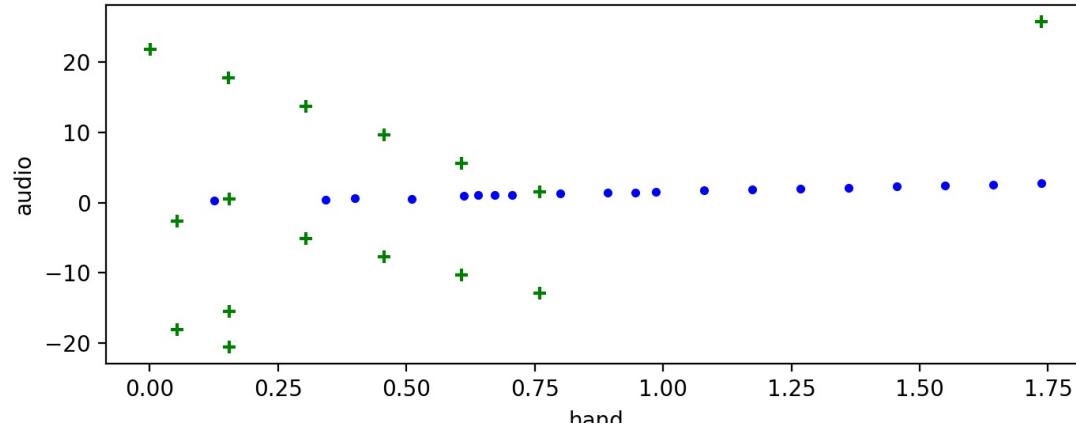
Decission Trees

- A decision tree is a flowchart-like tree structure where an internal node represents feature(or attribute), the branch represents a decision rule, and each leaf node represents the outcome. The topmost node in a decision tree is known as the root node. It learns to partition on the basis of the attribute value. It partitions the tree in recursively manner call recursive partitioning. This flowchart-like structure helps you in decision making. It's visualization like a flowchart diagram which easily mimics the human level thinking. That is why decision trees are easy to understand and interpret.



Support Vector Machines

- Support Vector Machines is considered to be a classification approach, it but can be employed in both types of classification and regression problems. It can easily handle multiple continuous and categorical variables. SVM constructs a hyperplane in multidimensional space to separate different classes. SVM generates optimal hyperplane in an iterative manner, which is used to minimize an error. The core idea of SVM is to find a maximum marginal hyperplane(MMH) that best divides the dataset into classes.



Naïve Bayes

- Naive Bayes is a supervised learning classification. It is a probabilistic classifier based on Bayes theorem. The name naive stems from the fact that classifier assumes that pairs of features are independent, thus significantly simplifying the model parameters are training requirements. This simplifies the computation that's why it is called as 'naive'. This is also called as class independence.

	Actual Status	Predicted Status
30	1	1
34	1	1
28	1	1
3	0	0
19	0	0
17	0	0
21	1	1
23	1	1
29	1	0
26	1	1
27	1	1

Classification Report:

A Classification report is used to measure the quality of predictions from a classification algorithm.

```
[11]
print(classification_report(y_test, y_pred))
with open('sample_data/Example2.txt', 'a') as testwritefile:
    testwritefile.write("----- D\n")
    testwritefile.write(classification_report(y_test, y_pred))
```

	precision	recall	f1-score	support
0	0.75	1.00	0.86	3
1	1.00	0.88	0.93	8
accuracy			0.91	11
macro avg	0.88	0.94	0.90	11
weighted avg	0.93	0.91	0.91	11

Links

- <https://github.com/spikol/mmla>