Exploring Technology to Support Collaboration and Reflection in Learning

Daniel Spikol
August 21, 2020
In my Talk

- The Context of Learning Analytics
- Exploring how technologies can augment learn
- Highlight interesting projects
- Risks and Opportunities of these new technologies
People should be provoked in their scientific, learning, analytic, creative, playing and personal activities and pursuit.

The ability to play is critical not only to being happy, but also to sustaining social relationships and being a creative, innovative person.

How do we design to provoke people to explore, play and learn together?
Learning LOGO turtle
Learning analytics is the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimising learning and the environments in which it occurs.
Problems with Learning Analytics

• Strong focus on online learning
• e.g. Click Stream data
• Learning at Scale (EDM and AIED)
• Generally at higher education
• Focused less on collaboration
Where Learning and Play happen

• How can we approach the human (complex and messy) learning from a Learning Analytics perspective?
• In the real-world humans communicate and leave traces across multiple modalities
• Measure, collect, analyse, and report to understand and improve
• Capture these learning traces from the real world
Modalities

• What we see
• What we hear
• How we move
• How we write
• How we blink
• Our pulse
• Brain activity?
• Our hormones?
• Future things?

Collaborative Technologies: Shadows and Lights
Shadows

• Performance only learning
• Panopticon Environment
• lockdown of learning (lack of creativity)
• lack of socio-cultural aspects of education
• role of teacher
• manipulation

https://www.theguardian.com/education/2020/aug/20/england-exams-row-timeline-was-oftal-warned-of-algorithm-bias

Students opposite Downing Street protesting against the downgrading of A-level results on 16 August. Photograph: Matthew Chattle/Rex/Shutterstock
Light

- Predictive understanding in specific contexts
- Personalization – adaptive feedback
- Social Recommendation systems
- Larger tools for societal reflection
How do we design Learning Analytics to support Collaboration?

Multimodal Learning Analytics
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
Projects

- **PELARS** - UCL Knowledge Lab & Internet of Things and People (IoTaP)
  - University College London and Malmö University
  - Mutlu Cukurova and Daniel Spikol - [https://www.ucl.ac.uk/ioe/departments-and-centres/centres/ucl-knowledge-lab](https://www.ucl.ac.uk/ioe/departments-and-centres/centres/ucl-knowledge-lab)

- **Round and Rectangular Tables for CPS** - Interactive & Distributed Technologies for Education (TIDE)
  - Universitat Pomeu Fabra
  - Milica Vujovic, Davina Leo-Hernandez, Patricia Santos - [https://www.upf.edu/web/tide](https://www.upf.edu/web/tide)

- **Multimodal Selfies** - Learning Analytics Research Network (LEARN)
  - New York University
  - Xavier Ochoa, Alyssa Wise, Yoav Bergner – [https://steinhardt.nyu.edu/learn](https://steinhardt.nyu.edu/learn)

- **BLINC** - Technological Innovations for Inclusive Learning & Teaching (TIILT)
  - Northwestern University
  - Marcelo Worsley, Kelia Human, Kit Martin- [https://tiilt.northwestern.edu/](https://tiilt.northwestern.edu/)

- **T(CA)^2** - University of Illinois at Urbana-Champaign
  - Theory-based Computational Analysis of Classroom Audiovisual Data
  - Stina Krist, Cynthia D'Angelo, Elisabeth Dyer, Nigel Bosch - [https://tca2.education.illinois.edu/](https://tca2.education.illinois.edu/)

- **SHARP** - Learning & Educational Technology Research Unit (LET)
  - Oulu University
  - Sanna Järvelä, Jonna Malmberg, Hanna, Järvenoja, Eetu Haataja - [https://www.oulu.fi/let/](https://www.oulu.fi/let/)

- **Multimodal Matrix** – Connected Intelligence Center
  - University of Technology Sydney & Monash University
  - Vanessa Escheverria, Roberto Martinez-Maldonado, and Simon Buckingham Shum - [https://cic.uts.edu.au/](https://cic.uts.edu.au/)
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 understanding 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?
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


Data Collected

<table>
<thead>
<tr>
<th>MMLA FEATURES (Independent)</th>
<th>Approach</th>
<th>How do these features affect the student outputs of collaboration patterns (Dependent)</th>
</tr>
</thead>
<tbody>
<tr>
<td>FLS - Number of faces looking at screen</td>
<td>1. Data Processing</td>
<td>ASQ - Artefact grade</td>
</tr>
<tr>
<td>DBF - Mean distance between faces</td>
<td>2. Clustering</td>
<td>CPS - Score IA, PE &amp; IPV</td>
</tr>
<tr>
<td>DBH - Mean distance between hands</td>
<td>3. Regression</td>
<td></td>
</tr>
<tr>
<td>HMS - Mean hand movement speed</td>
<td>4. Variable refinement</td>
<td></td>
</tr>
<tr>
<td>AUD - Mean audio level</td>
<td>5. Regression</td>
<td></td>
</tr>
<tr>
<td>HP - Mean hand positions</td>
<td>6. Deep Learning</td>
<td></td>
</tr>
<tr>
<td>ACA - Mean Arduino components activity</td>
<td></td>
<td></td>
</tr>
<tr>
<td>DEC - Number of connected Arduino components</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SB - Sentiment Buttons</td>
<td></td>
<td></td>
</tr>
<tr>
<td>PWR - Student Work Phases</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Visualizations
Designing Spaces
Round and Rectangular Tables for Collaborative Problem Solving UPF

• The current knowledge of the effects of the physical environment on learners’ behaviour in collaborative problem-solving tasks is underexplored.

• The research aims to critically examine the potential of multimodal learning analytics, using new data sets, in studying how the shapes of shared tables affect the learners’ behaviour when collaborating in terms of patterns of participation and indicators related to physical social interactions.

Multimodal Selfies NYU

- MultimodalSelfie, a personal recording device for students, capable of recording three data streams: video of the face, audio, and notes taken during the class session.

- The device is capable of collecting relatively noiseless high-quality data of the student during class while addressing privacy and ethical concerns.

BLINC - Northwestern

• Real-time multimodal learning analytics. We use ReSpeaker Core v2.0 microphone arrays to show educators what keywords have been said, a discussion timeline, direction of speech, and emotional tone indicators.

This research project builds on state-of-the-art computer vision and speech analytics methods tested on video data collected in STEM classrooms.

It does so within a computational grounded theory methodological framework, which leverages the interpretive power of grounded analytical approaches with the processing power of computational methods.
Self-regulation is an invisible demanding mental skill. Essentially it is a skill that individuals must acquire in order to function (socially, emotionally, cognitively).

They target trigger regulation moments in collaboration by analyzing input from various multimodal sources (i.e., 360° video, log data, heart rate, skin conductivity, self-report) making invisible mental cognitive, motivational, and emotional learning processes.

Multimodal Matrix

• An approach to unravel the complexity of multimodal data by organising it into meaningful layers that explain critical insights to teachers and students.

• The approach is illustrated through the design of two data storytelling prototypes in the context of nursing simulation.

The trouble with hype-

• There is no one algorithm to rule them all*
• Math cannot predict for the future anything it hasn’t seen before*
• Math cannot read your mind*
• Creating and Supporting creative/constructive collaboration is difficult

Next Steps

• Nudge devices – not so smart that foster Social and Reflective skills
• Supporting Group contexts – Collaborative Learning
• Exploring how to support Fast and Slow thinking
• Playful Collaborative Learning
Thought Propositions

• The moral of this story is to make technology less smart, put the focus on the people
• Technology should be used to augment social interaction and collaboration to provoke people into playing and learning together.
• Providing space for mistakes = learning, and developing resilience
• Using social context offers ways to create reflection
Play and Learning happen, design or no design. And yet there are few more urgent tasks than to design social infrastructure that foster play and learning...”


Thanks!

Daniel Spikol, PhD. - Associate Professor
Malmo University, Faculty of Technology and Society
Department of Computer Science & Media Technology
Internet of Things and People Research Center
http://iotap.mah.se/
daniel.spikol@mau.se
http://spikol.io/

Check out the PELARS Project:
http://www.pelars-project.eu/