Quelle recherche en education pour des labos d’informatique ?

P. Dillenbourg, EPFL
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)

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

Guillaume Zufferey, Patrick Jermann, Pierre Dillenbourg (EPFL)
$F(1,37) = 6.68, p < .05$
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”!

<table>
<thead>
<tr>
<th>Group</th>
<th>Collaboration quality</th>
<th>Manipulation discussion</th>
<th>Reflection discussion</th>
</tr>
</thead>
<tbody>
<tr>
<td>Group 6</td>
<td>1.4</td>
<td>2</td>
<td>0</td>
</tr>
<tr>
<td>Group 5</td>
<td>1.6</td>
<td>1.25</td>
<td>1.25</td>
</tr>
<tr>
<td>Group 8</td>
<td>1.4</td>
<td>1.25</td>
<td>1</td>
</tr>
<tr>
<td>Group 1</td>
<td>1.4</td>
<td>1.75</td>
<td>1.75</td>
</tr>
</tbody>
</table>
- Run a simulation of the current layout
- Ask the students to predict before running
PAUSE CLASS

CLASS

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

Sign. effect in understanding

Sign. effect in problem-solving

<table>
<thead>
<tr>
<th>Measures</th>
<th>Warehouse study's conditions</th>
<th>Evaluation of TinkerLamp 2.0 conditions</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Paper/pen</td>
<td>TinkerLamp 1.0</td>
</tr>
<tr>
<td>Understanding score</td>
<td>7.84(2.85)</td>
<td>7.43(2.82)</td>
</tr>
<tr>
<td>Problem-solving score</td>
<td>5.16(1.70)</td>
<td>5.15(1.78)</td>
</tr>
</tbody>
</table>
Augmented Reality for Training Carpenters (L. Lucignano)
Physics 101: Exercises Session

Problems are delicious
C’est pas parce que c’est de l’éducation que cela doit être chiant !
Modelling in Education

Bayesian Knowledge Tracing

Hidden State \( K_t \) \( \rightarrow \) \( K_{t+1} \)

Observable State \( B_t \) \( \rightarrow \) \( B_{t+1} \)

\[ p(K_{t+1} \mid B_{t+1}, K_t) \]

\[ p(K_t \mid B_t) \]
Temporally Coherent Clustering of Student Data

Severin Klingler  
Department of Computer Science  
ETH Zurich, Switzerland  
skneveling@inl.ethz.ch

Tanja Käser  
Department of Computer Science  
ETH Zurich, Switzerland  
kaesser@inl.ethz.ch

Markus Gross  
Department of Computer Science  
ETH Zurich, Switzerland  
grossm@inl.ethz.ch

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 evolve over time, resulting in temporally incoherent 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 effects 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 ITSs, 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 patterns 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 route recommendations [22], collaborative filtering tools [24], timetabulization [20], and clustering algorithms [5]. A variety of methods have been proposed to address the problem of clustering sequential data. For instance, Hidden Markov models (HMM) [3, 4]. Sequential pattern mining techniques have been contextualized using a variety of sequential models [34]. Others have employed unsupervised graph clustering using the predictions from a student model with additional constraints [26]. Clustering sequential data employing similarity measures on state sequences was used in [4, 6]. 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 counts [18].

While the previous work discussed above analyzes student clusters at a given point in time, a temporal analysis would allow to identify the interaction patterns change over time and how groups of similar students evolve. Temporal effects of cluster evolution have been analyzed in [15], based on statistical models. For instance, the evolution of the Markov model is sensitive to the data and may result in temporally incoherent clusters. Evolutionary clustering methods [7] address this problem by considering temporal dependencies over time steps. The temporal evolution increases the results of a cluster stability indicator and allows for a better analysis of student behavior, i.e., the student properties and interaction patterns over time. Recently, an evolutionary clustering approach [17] has been introduced that smooths the probability of students over time by using a clustering algorithm.

In this paper, we present a complete pipeline for evolutionary clustering that can be used as a black box by any ITS. We incorporate a variety of the AFFECT into our pipeline and demonstrate that temporal data has been successfully applied to a variety of applications such as route recommendations [22], collaborative filtering tools [24], timetabulization [20], and clustering algorithms [5]. A variety of methods have been proposed to address the problem of clustering sequential data. For instance, Hidden Markov models (HMM) [3, 4]. Sequential pattern mining techniques have been contextualized using a variety of sequential models [34]. Others have employed unsupervised graph clustering using the predictions from a student model with additional constraints [26]. Clustering sequential data employing similarity measures on state sequences was used in [4, 6]. 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 counts [18].
State = ?
Modelling Education

<table>
<thead>
<tr>
<th>Kernel</th>
<th>Features</th>
<th>Score</th>
<th>Cohen’s kappa</th>
</tr>
</thead>
<tbody>
<tr>
<td>RBF(c=1.31, g=0.0211)</td>
<td>Distance, Head travel norm., Num. still periods</td>
<td>61.86%</td>
<td>0.30</td>
</tr>
<tr>
<td>RBF(c=1.21, g=0.11)</td>
<td>Period, Row, Head travel norm., Mean duration still</td>
<td>61.72%</td>
<td>0.32</td>
</tr>
<tr>
<td>RBF(c=1.11, g=0.061)</td>
<td>Head travel norm., Mean duration still</td>
<td>60.42%</td>
<td>0.28</td>
</tr>
<tr>
<td>RBF(c=1.4, g=0.04)</td>
<td>Period, Distance, Row, Mean duration still</td>
<td>59.23%</td>
<td>0.30</td>
</tr>
</tbody>
</table>
Modelling Education

<table>
<thead>
<tr>
<th>Data source</th>
<th>Features</th>
<th>Best model</th>
<th>In-session perf.</th>
<th>Out-of-session perf.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Accuracy</td>
<td>κ</td>
</tr>
<tr>
<td>Eye-tracking only</td>
<td>All</td>
<td>Gradient Boosted T.</td>
<td>87.5%</td>
<td>0.75</td>
</tr>
<tr>
<td>EEG only</td>
<td>All</td>
<td>Gradient Boosted T.</td>
<td>55.1%</td>
<td>0.08</td>
</tr>
<tr>
<td>Accelerometer only</td>
<td>All</td>
<td>Gradient Boosted T.</td>
<td>67.6%</td>
<td>0.34</td>
</tr>
<tr>
<td>Audio only</td>
<td>All</td>
<td>Gradient Boosted T.</td>
<td>81.4%</td>
<td>0.62</td>
</tr>
<tr>
<td>Video only</td>
<td>All</td>
<td>Gradient Boosted T.</td>
<td>81.7%</td>
<td>0.63</td>
</tr>
<tr>
<td>All</td>
<td>All</td>
<td>Gradient Boosted T.</td>
<td>89.6%</td>
<td>0.81</td>
</tr>
<tr>
<td>Audio+video</td>
<td>All</td>
<td>Gradient Boosted T.</td>
<td>86.1%</td>
<td>0.72</td>
</tr>
<tr>
<td>All</td>
<td>Top 5</td>
<td>(SVM)</td>
<td>86.1%</td>
<td>0.72</td>
</tr>
<tr>
<td>All</td>
<td>Top 81</td>
<td>Gradient Boosted T.</td>
<td>90.6%</td>
<td>0.81</td>
</tr>
</tbody>
</table>
Modelling Education
Gaze Recurrence
DUET - Dual Eye-Tracking
Pair programming experiment

Low gaze recurrence

High gaze recurrence

Nüssli, Jermann & Mullins
Spatial Entropy of Gazes

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
<th>E</th>
</tr>
</thead>
<tbody>
<tr>
<td>t = 0</td>
<td>0.3</td>
<td>0.3</td>
<td>0.0</td>
<td>0.3</td>
<td>0.1</td>
</tr>
<tr>
<td>t = 1</td>
<td>0.2</td>
<td>0.2</td>
<td>0.2</td>
<td>0.2</td>
<td>0.2</td>
</tr>
<tr>
<td>t = 2</td>
<td>1.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
</tr>
</tbody>
</table>
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

Jean Piaget

Dillenbourg, EPFL, JSP 2016
Learning Analytics

Educational Design

Computational Modeling for Learning Sciences
EdTech Collider
Lundi 14 novembre, 10:19