Educational Data Mining / Learning Analytics

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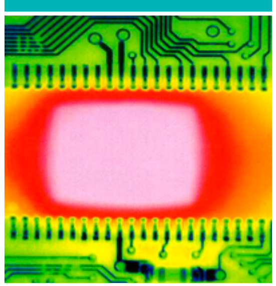

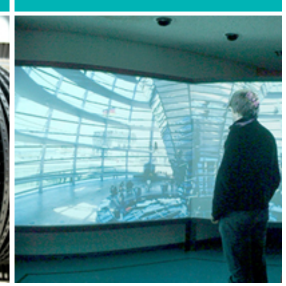

Outline

- About EDM and LA
- Methods and Tasks:
  - Prediction
  - Clustering
  - *Relationship Mining*
  - Distillation of Data for Human Judgment
  - *Discovery with Models*
- Current Trends
- Conclusions
- *List of References*

Educational Data Mining is an emerging discipline, concerned with developing methods for exploring the unique types of data that come from educational settings, and using those methods to better understand students, and the settings which they learn in. http://www.educationaldatamining.org/

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. https://tekri.athabascau.ca/analytics/

Both fields organized with annual conference, open access journal and society.

LAK 16

The 6th International

Learning Analytics & Knowledge Conference

University of Edinburgh, Edinburgh, UK, April 25-29, 2016

SOLAR SOCIETY for LEARNING ANALYTICS RESEARCH

acm In-Cooperation

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Methods and Tasks

- Methods (Baker & Yacef 2009) come mainly from data mining, machine learning, statistics, classical artificial intelligence, and increasingly from natural language processing.

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Prediction

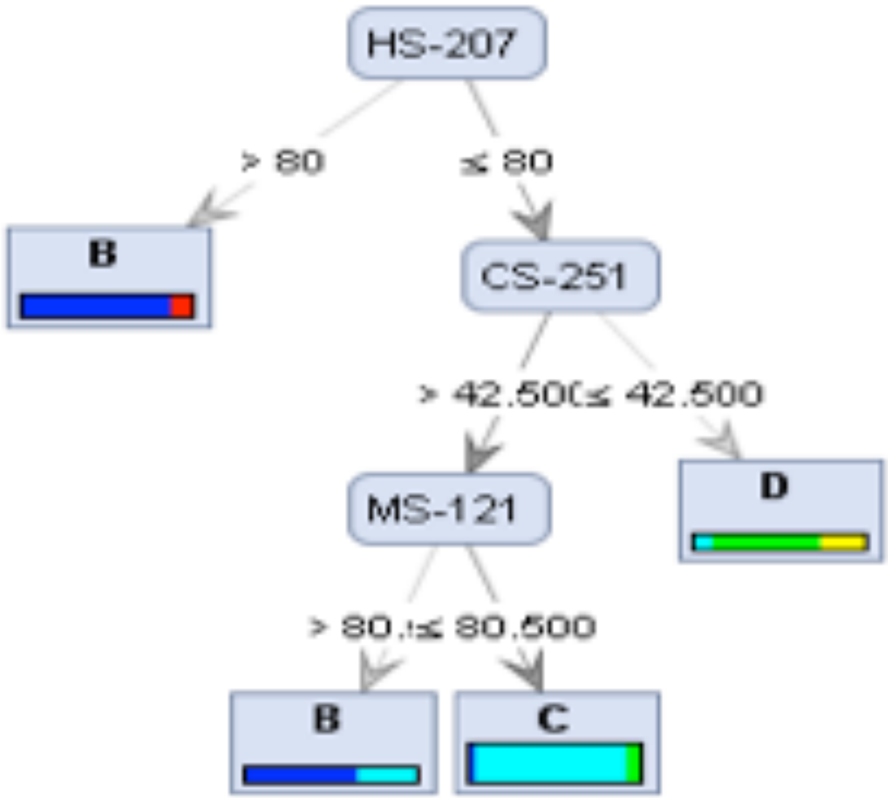
- Important task: predict performance.
- Different levels of granularity:
  - Drop-off (Wolff & al. 2013)
  - Pass/fail, mark in a degree (Zimmerman & al. 2015)
  - Pass/fail, mark in a course (Lopez & al. 2012)
  - Skill mastery in a tutoring system (Pardos & al. 2007).

Prediction: Mark in a degree

- Many works show that pass or fail, or even the interval of a mark in a degree or a course can be predicted with an accuracy of 70% or higher.
- No classifier that works best in all contexts (Huang & Fang, 2013).
- No set of features that work best in all contexts, though some works to predict the interval of the mark for a university degree suggest that including marks is essential (Golding & al. 2006, Zimmerman & al. 2015).

Prediction: Mark in a degree

- Example of classifier: Decision Tree (Asif & al. 2014).



Prediction: Mark in a degree

- Predict the interval of the degree mark: A, B, C, D or E (Asif & al. 2014).
- 4-years Bachelor Computing and Information Technology in a technical university of Pakistan.
- Competitive: selection on the marks in the High School Certificate (HSC) and entrance exam.
- **Conjecture**: academic records (no socio-economic feature) might be enough to predict the final mark with a reasonable accuracy: better than the baseline of predicting the majority interval C, 51.92%.

Prediction: Mark in a degree

Prediction: Mark in a degree

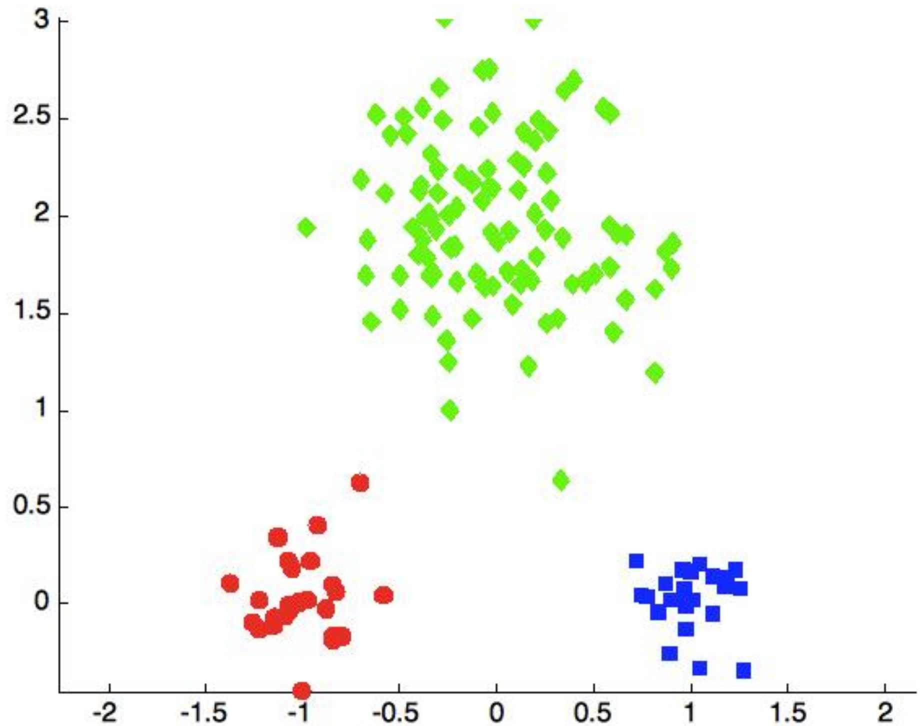
- **Which features?** HSC marks, marks of all modules from 1st and 2nd year and number of attempts.
- **Which classifiers?** Try all the well-known ones.
- **Validation:** one cohort as training set and the next cohort as test set (needs some stability in the curriculum) for generalization and pragmatic policy. *Different from other works which mostly use cross-validation.*
  - Cohort 1: 105 students graduated in 2012
  - Cohort 2: 104 students graduated in 2013

Prediction: Mark in a degree

Classifier	Accuracy / Kappa
Decision Tree with Gini Index	68.27% / 0.493
Decision Tree with Information Gain	69.23% / 0.498
Decision Tree with Accuracy	60.58% / 0.325
Rule Induction with Information Gain	55.77% / 0.352
1- Nearest Neighbors	**74.04% / 0.583**
Naives Bayes	**83.65% / 0.727**
Neural Networks	62.50% / 0.447
Random Forest with Gini Index	**71.15% / 0.543**
Random Forest with Information Gain	69.23% / 0.426
Random Forest with Accuracy	62.50% / 0.269

- Big variety of tasks.
- Variety of algorithms.
- Two works:
  - Clustering students to find out typical behaviours in a forum (Cobo & al. 2012)
  - Clustering utterances to find out speech acts or dialog acts (Ezen-Can & al. 2015).

Colors show an optimal clustering.



(Tan, Kumar & Steinbach, 2005)

Clustering: behaviours in forum

- **8 features: 4 for writing, 4 for reading:**
  - Number of initiated threads, number of reply posts, number of students replied, number of days with writing.
- **Hierarchical agglomerative clustering:**
  - All features calculated as ratio.
  - 2 clusterings: writing features and reading features.
  - Normalized Euclidean distance, complete link.
  - Adaptation of inconsistency criterion to isolate the best clusters.
  - Clusters from the 2 clusterings are combined.

Clustering: behaviours in forum

- Find known results: less students write than read.
- The smaller the reading, the higher the drop-off rate and fail rate.
- Results (Cobo & al. 2012)

Clustering: dialog acts

- When we talk, we do something (http://en.tintin.com/).

- Dialog acts:
  - Question: “What is an anonymous class?”.
  - Answer: “An anonymous class is a class without name.”.
  - Issue, problem: “this program does not compile”.
  - Statement: “this assignment is long”.
  - Reference: “An interesting video about Bubblesort.”.
  - Positive, negative acknowledgment: “Thanks, I got it”, “I am still confused”.
- Problem: **classify automatically sentences in forums or tutorial dialogs in dialog acts.**

Clustering: dialog acts

- Classical approach is supervised:
  - Annotate manually a large corpus (bottle neck).
  - Identify cues or features: punctuation, unigram, bigram, position of unigram in the sentence, preceding dialog act, etc. (Kim & al. 2010) .
  - Train a classifier. Support Vector Machine (Kim & al. 2010):
    - Positive_ack: F-Score 0.54 (9.20% of the sentences).
    - Questions: F-Score 0.95 (55.31% of the sentences).

- **Unsupervised approach** (Ezen-Can & al. 2015). Dialogues come from a computer mediated environment to tutor students on programming. Students recorded by Kinect cameras.
- Features to describe sentences:
  - **Lexical features**: unigram, word ordering, punctuation.
  - **Dialog-context features:** position in the dialog, length, author of previous message (tutor, student), etc..
  - **Task features:** task before the utterance (writing, compiling), status of most recent coding action, etc..
  - **Posture features:** head distance, torso distance.
  - **Gesture features:** one hand and two hands to head.

Clustering: dialog acts

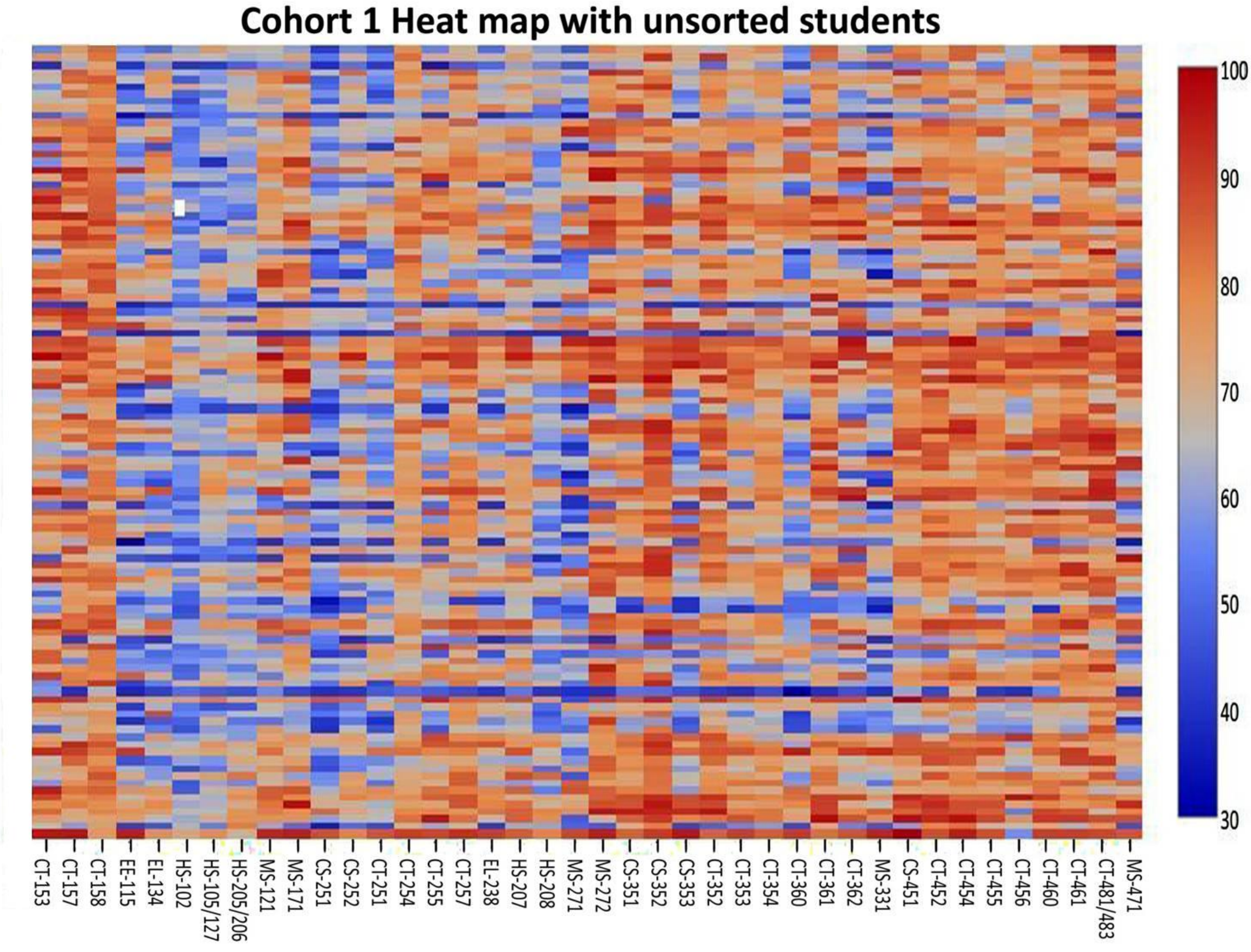
- K-Medoids algorithm with Bayesian Information Criterion (BIC) to infer the optimal number of clusters.
- Distance between utterances: cosine + longest common subsequence for lexical features.
- 7 clusterings according to the previous dialog act of tutors.
- The majority vote in each cluster gives the dialog act.
- A new utterance is predicted according to the cluster with the nearest center.
- Leave-on-Student-out validation: *67% average accuracy, 61% without posture and gesture features*.

Relationship Mining

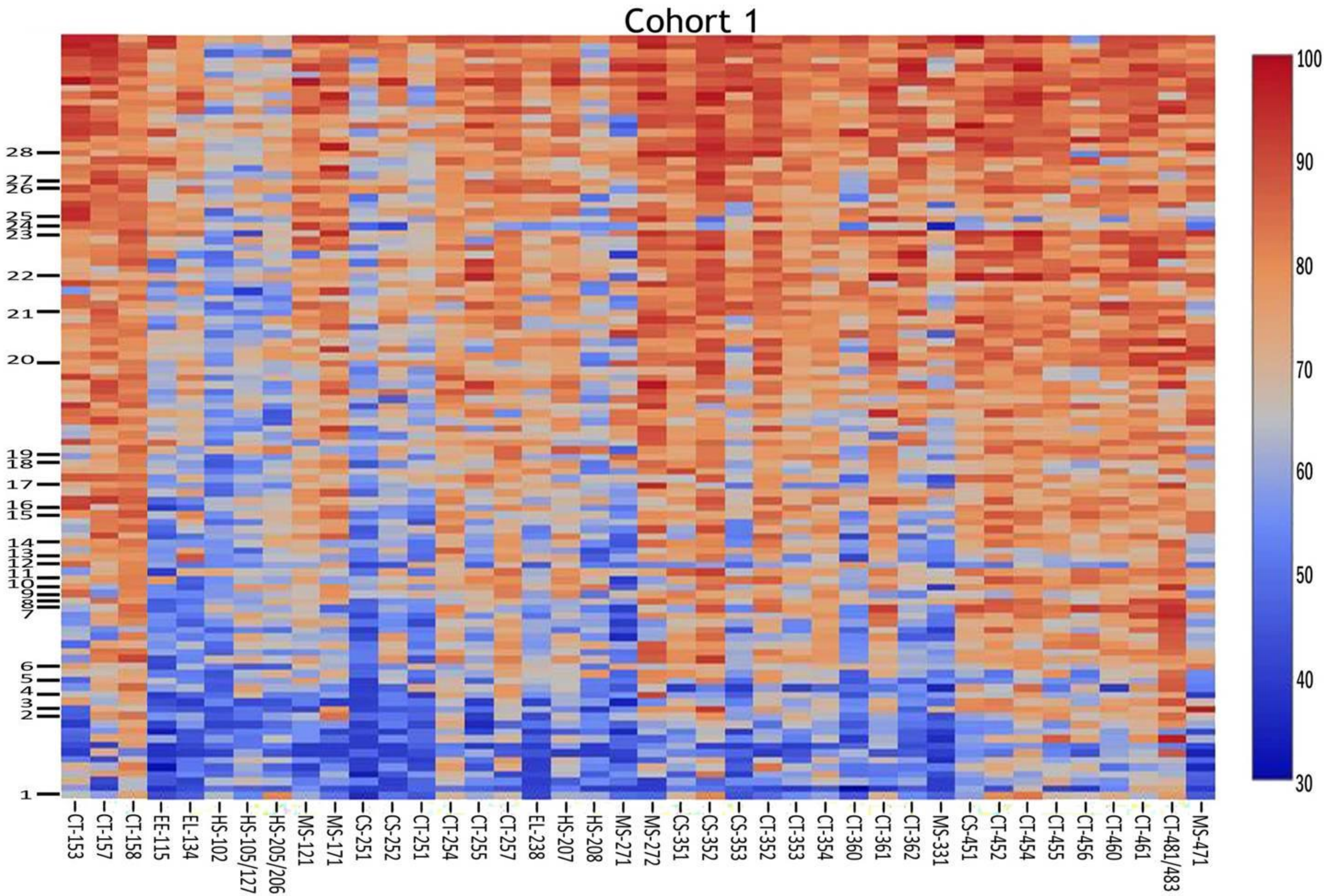
- Association rules mining: if students make mistake A, they also make mistake B (Merceron & Yacef 2005) .
- Correlation mining: negative correlation between gaming a tutoring system and post-test (Baker & al. 2004).

- Preliminary statistics.
- Visualizations. Here too data preparation is crucial.
  - LeMo project (Fortenbacher & al. 2013)

- Heatmap: marks of all students in all courses of a 4 years Bachelor degree, technical university :
  - First year courses on the left, then 2nd year courses, 3rd year courses and on the right 4th year courses.


Cohort 1 Heat map with unsorted students
100
90
80
70
60
50
40
30
CT-153
CT-157
CT-158
EE-115
EL-134
HS-102
HS-105/127
HS-205/206
MS-121
MS-171
CS-251
CS-252
CT-251
CT-254
CT-255
CT-257
EL-238
HS-207
HS-208
MS-271
MS-272
CS-351
CS-352
CS-353
CT-352
CT-353
CT-354
CT-360
CT-361
CT-362
MS-331
CS-451
CT-452
CT-454
CT-455
CT-456
CT-460
CT-461
CT-481/483
MS-471

- X-means clustering year wise (Asif et al. 2015):
  - Euclidean distance, Tool: Rapid Miner.
  - Gives 4 clusterings.
- Clusterings are combined.
- Heatmap shows now the groups of students with low marks, average marks and high marks, and give hints about courses that could act as detectors.



1- (60,52,54,65)	**2-** (60,52,66,65)	**3-** (60,52,66,77)	**4-** (60,62,54,65)	**5-** (60,62,66,65)	**6-** (60,62,66,77)	**7-** (60,62,66,85)
8- (60,62,75,77)	**9-** (60,73,66,65)	**10-** (60,73,66,77)	**11-** (60,73,75,77)	**12-** (71,52,54,65)	**13-** (71,62,66,65)	**14-** (71,62,66,77)
15-(71,62,66,85)	**16-**(71,62,75,77)	**17-** (71,73,66,77)	**18-** (71,73,75,65)	**19-** (71,73,75,77)	**20-** (71,73,75,85)	**21-** (71,73,83,77)
22- (71,73,83,85)	**23-** (78,62,66,65)	**24-** (78,73,75,65)	**25-** (78,73,75,77)	**26-** (78,73,75,85)	**27-** (78,73,83,77)	**28-** (78,73,83,85)

- Building on (Baker & al. 2004), (Baker & al. 2006) proposes a model for gaming the system. Features include:
  - Number of times a specific problem is wrong across all problems.
  - Probability that a student knows a skill.
  - Various times: time taken for the last 3 actions, 5 actions
  - Etc…
- Generalize to new lessons and new students.
- This detector is used with new data to discover more patters such as in (SanPedro & al. 2015): What happens to students who game the system?

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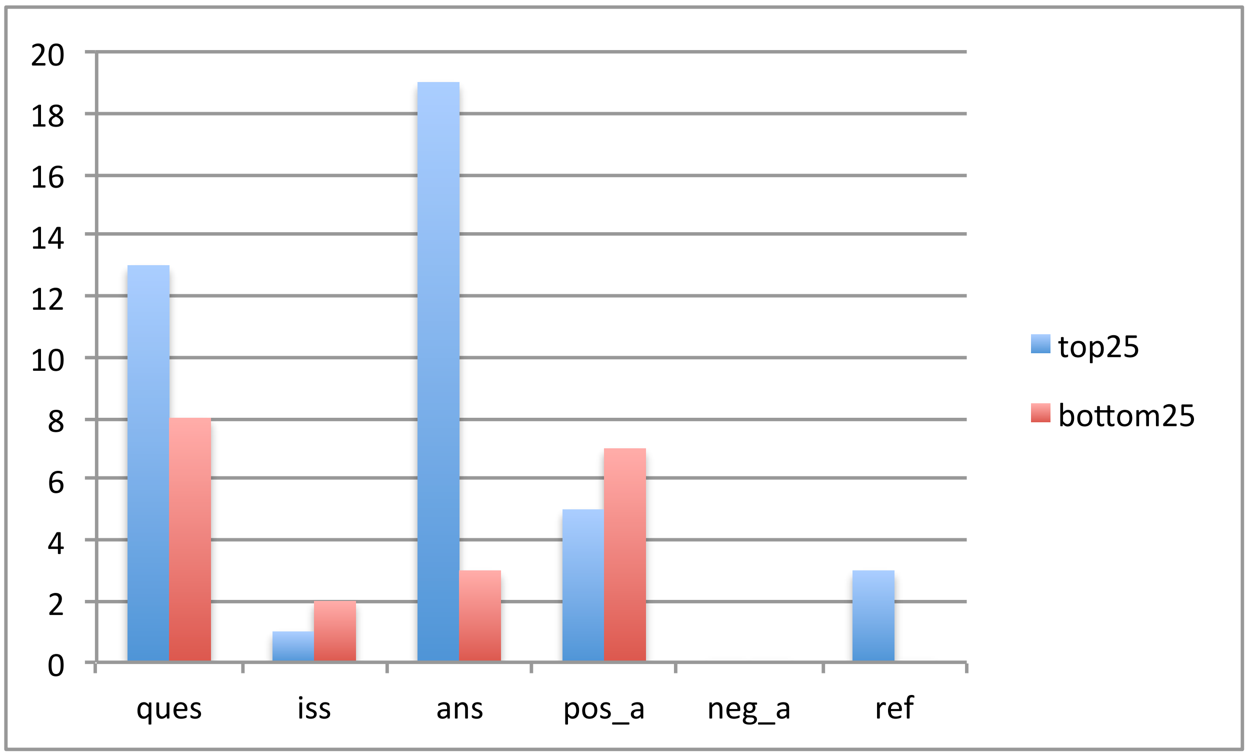
Current Trends

- Natural Language Processing: tutorial dialogues, essays, forums.
- Multimodal Analysis: data from the educational system + data from camera, from EEG etc.
- Multilevel Analysis: different levels of analysis with the data recorded by the system.

- **Relating level forum and performance level** (Merceron 2014) in a programming course of a LMS over 4 years:
  - Posts manually labelled with dialog acts: questions, issues, answers, references, positive and negative acknowledgments.
  - Hypothesis: questions and issues come preliminary from low achieving students.

After removing an outlier: high achieving students had more questions (and much more answers) than low achieving students.



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Conclusions

- Numerous approaches.
- Numerous tasks.
- Numerous findings.

- What is not a reality yet is the analysis of educational data on a *routine basis* to understand learning and teaching better and to improve them.

Conclusions

- Challenges:
  - Privacy: Opt-in. Limit the available data, hence the findings and validity of the results.
  - Generalizability: is a classifier to predict performance still valid 2 years later, or in another degree? Not sure. Most probably Data Scientists needed.

Comments? Ideas? Questions?

Thank you for your attention!

Data Science Group, Beuth University of Applied Science

https://projekt.beuth-hochschule.de/data-science/

References

- (Asif & al. 2014) Asif, R., Merceron, A. and Pathan, M. 2015. Predicting student academic performance at degree level: a case study. In International Journal of Intelligent Systems and Applications (IJSA), Vol. 7(1), 49-61. DOI: 10.5815/ijisa. 2015.01.05.
- (Asif & al. 2015) Asif, R., Merceron, A. and Pathan, M. 2015. Investigating Performance of Students: a Longitudinal Study. In LAK'15, March 16 - 20, 2015, Poughkeepsie, NY, USA. ACM, 108-112.
- (Baker & al. 2004) Baker, R.S.J.d., Corbett, A.T., Koedinger, K.R., and Wagner, A.Z. (2004). Off-task behavior in the cognitive tutor classroom: when students "game the system". In: Proceedings of SIGCHI conference on Human Factors in Computing Systems, 383-390. Vienna, Austria.
- (Baker & al. 2006) Baker, R.S.J.d., Corbett, A.T., Roll, I., and Koedinger, K.R. (2006). Developing a generalizable detector of when students game the system. User Modeling and User-Adapted Interaction, 18(3), 287-314.
- (Baker & Yacef 2009) Baker, R.S.J.D., Yacef, K. 2009. The State of Educational Data Mining in 2009: A Review and Future Visions", In *Journal of Educational Data Mining,* Vol. 1(1).

References

- (Cobo & al. 2012) Cobo, G., Garcia, D., Santamaria, E., Moran, J.A., Melenchon, J., Monzo, C. Using agglomerative hierarchical clustering to model learner participation profiles in online discussion forums. In (Dawson, S., Haythornthwaite, C. Hrsg.): Proceedings of the 2nd International Conference on Learning Analytics and Knowledge. (Vancouver, Canada, April 29 – May 2). ACM, 248-251.
- (Ezen-Can & al. 2015) Ezen-Can, A., Grafsgaard, J.F., Lester J.C., Boyer, K. E. (2015) Classifying Student Dialogue Acts with Multimodal Learning Analytics. In LAK'15, March 16 - 20, 2015, Poughkeepsie, NY, USA. ACM, 280-289
- (Fortenbacher & al. 2013) Fortenbacher, A.; Elkina, M.; Merceron, A.: The Learning Analytics Application LeMo – Rationals and First Results. In International Journal of Computing, Volume 12, Issue 3, 2013, ISSN 1727-6209, p. 226-234.
- (Golding & Donaldson 2006) P. Golding, O. Donaldson, "Predicting Academic Performance", Proceedings of 36th ASEE /IEEE Frontiers in Education Conference, 2006.

References

- (Huang & Fang 2013) Huang, S., Fang, N. (2013). Predicting student academic performance in an engineering dynamics course: A comparison of four types of predictive mathematical models, Computer and Education, 61, 133-145.
- (Kim & Kim 2010) Kim, J.; Li, J.; Kim. T. Towards Identifying Unresolved Discussions in Student Online Forums. In (Tetreault, J., Burstein, J., Leacock, C. Hrsg.): Proceedings of the NAACL HLT 5th Wokshop on Innovative Use of NLP for Building Educational Applications. (Los Angeles, CA, USA, June 2010). Association for Computational Linguistics, 84 -91.
- (Lopez & al. 2012) M. I. Lopez, R. Romero, V. Ventura, and J.M. Luna," Classification via clustering for predicting final marks starting from the student participation in Forums," In (Yacef, K., Zaïane, O., Hershkovitz, H., Yudelson, M., and Stamper, J. Hrsg.): Proceedings of the 5th International Conference on Educational Data Mining, Chania, Greece, June15-21, pp. 148-151, 2012.

References

- (Merceron & Yacef 2005) Merceron, A; Yacef, K. (2005). Educational Data Mining: a case study. In proceedings of Artificial Intelligence in Education (AIED2005) C.-K. Looi, G. McCalla, B. Bredeweg and J. Breuker Eds., 467-474, Amsterdam, The Netherlands.
- (Merceron 2014) Merceron, A. (2014). Connecting Analysis of Speech Acts nd Performance Analysis: a Initial Study. In Proceedings of the Workshop 3: Computational Approaches to Connecting Levels of Analysis in Networked Learning Communities, LAK 2014, Vol-1137
- (Pardos & al. 2007) Z. Pardos, N. Hefferman, B. Anderson, and C. Hefferman, "The effect of Model Granularity on Student Performance Prediction Using Bayesian Networks," Proceedings of the international Conference on User Modelling, Springer, Berlin, pp. 435-439, 2007

References

- (San Pedro & al. 2015) San Pedro, M.O., R. Baker, N. Heffernan, J. Ocumpaugh. (2015). What Happens to Students Who Game the System? . In LAK'15, March 16 - 20, 2015, Poughkeepsie, NY, USA. ACM, 36-40.
- (Tan, Kumach & Steinbach, 2005) Introduction to Data Mining, Addison Wesley, 2005.
- (Wolf & al. 2013) A. Wolff, Z. Zdrahal, A. Nikolov, and M. Pantucek, “Improving retention: predicting at-risk students by analysing clicking behaviour in a virtual learning environment,” Proceedings of the Third International Conference on Learning Analytics and Knowledge, pp. 145-149, 2013.
- (Zimmerman & al. 2015) J. Zimmermann, K. H. Brodersen, , H.R. Heiniman, J. M. Buhmann, “A Model-Based Approach to Predicting Graduate-Level Performance Using Indicators of Undergraduate-Level Performance”, Journal of Educational Data Mining*, Vol. 7 (3)*, 2015.