Course Syllabus for SIADS 680: Learning Analytics

Course Overview and Prerequisites

SAIDS 680 provides an overview of a key application domain for data scientists—education. In this course students will examine the application of data science as a means to better understand and improve learning. Specifically, students will think critically about the ways in which data scientists can support research and improvement in educational organizations of all types. Anchored in the fields of learning analytics (LA) and educational data mining (EDM), this course analyzes the unique opportunities and challenges associated with applying data science methods to data stemming from schools, universities, and a myriad of learning opportunities. The course will cover the history of learning analytics, typical data and methods used, the importance of measurement, and the implementation of learning analytics products.

The prerequisites for this course are fulfilled by having completed the coursework necessary to achieve Milestone II.

Instructor and Course Assistants

Instructors:
Dr. Andrew Krumm, Assistant Professor, Medical School, School of Information - aekrumm@umich.edu

Course Lecturers:

Dr. Nick Sheltrown - sheltro@umich.edu, Deepti Pandey - deeptip@umich.edu

How to Get Help

If you have questions concerning the degree program, encounter a technical issue with Coursera, or issues using Slack, please submit a report to the ticketing system at umsimadshelp@umich.edu.

If you have an issue specific to the Coursera environment, you can also begin a live chat session with Coursera Technical Support (24/7) or view Coursera troubleshooting guides. (you may be asked to log in to your Coursera account).

For questions regarding course content, refer to the **Communications Expectations** section below.

Course Communication Expectations

- Contacting instructor and course assistant: Course channel in Slack or email
- Slack and email response time: 24 - 48 hours
- Office hours via Zoom: Please use passcode **680** to join
    A. **Andrew**: Thursdays at 11 am (ET)
    B. **Deepti**: Tuesdays at 5 pm (ET)
    C. **Nick**: Wednesdays at 8 pm (ET)

Weekly Readings

Week 1: **Required**

Siemens, G. (2013). Learning analytics: The emergence of a discipline. *American Behavioral Scientist*, *57*(10), 1380-1400.

Baker, R. S., & Inventado, P. S. (2014). Educational data mining and learning analytics. In J. A. Larusson & B. White. (Eds.), *Learning Analytics from Research to Practice: Methods, Tools, and Approaches* (pp. 103-119). Berlin: Springer-Verlag.

Slade, S., & Prinsloo, P. (2013). Learning analytics: Ethical issues and dilemmas. *American Behavioral Scientist*, *57*(10), 1510-1529.

Optional

Kuzilek, J., Hlosta, M., Herrmannova, D., Zdrahal, Z., Vaclavek, J., & Wolff, A. (2015). OU Analyse: analysing at-risk students at The Open University. *Learning Analytics Review*, 1-16.

http://www.laceproject.eu/learning-analytics-review/analysing-at-risk-students-at-open- university/
Kuzilek, J., Hlosta, M., & Zdrahal, Z. (2017). Open University Learning Analytics Dataset. *Scientific Data, 4*, 170171.

Week 2: **Required**

Krumm, A. E., Means, B., & Bienkowksi, M. (2018). *Learning analytics goes to school: A collaborative approach to improving education*. New York: Routledge. Chapter 2: Data used in educational data-intensive research (pp. 17-37)

Clow, D. (2014, March). Data wranglers: human interpreters to help close the feedback loop. In *Proceedings of the Fourth International Conference on Learning Analytics and Knowledge* (pp. 49-53).

Waddington, R. J., Nam, S. J., Lonn, S., & Teasley, S. D. (2016). Improving early warning systems with categorized course resource usage. *Journal of Learning Analytics*, *3* (3), 263-290.

Optional

DiCerbo, K. E. (2017). Building the evidentiary argument in game-based assessment. Journal of Applied Testing Technology, 18(S1), 7-18.

Krumm, A. E., Means, B., & Bienkowksi, M. (2018). *Learning analytics goes to school: A collaborative approach to improving education.* New York: Routledge. Chapter 6: Supporting conditions for collaborative data-intensive improvement (pp. 108-134).

Week 3: **Required**

Niemi, Pea, Saxburg, & Clark (2018). Inferential foundations for learning analytics in the digital ocean. In: Niemi D., Pea R. D., Saxberg, B., Clark R. E. (eds) *Learning analytics in education* (pp. 1-48). Charlotte, NC: Information Age Publishing.

Vytasek J.M., Patzak A., Winne P.H. (2020) Analytics for Student Engagement. In: Virvou M., Alepis E., Tsihrintzis G., Jain L. (eds) *Machine Learning Paradigms: Advances in Learning Analytics (pp. 23–48)*. Springer International Publishing.

Rosé, C. P., McLaughlin, E. A., Liu, R., & Koedinger, K. R. (2019). Explanatory learner models: Why machine learning (alone) is not the answer. *British Journal of Educational Technology, 50*(6), 2943-2958.

Gardner, J., Brooks, C., & Baker, R. (2019). Evaluating the Fairness of Predictive Student Models Through Slicing Analysis. Proceedings of the 9th International Conference on Learning Analytics & Knowledge, 225–234.

Optional

Dowell, N. M., Lin, Y., Godfrey, A., & Brooks, C. (2020). Exploring the relationship between emergent sociocognitive roles, collaborative problem-solving skills and outcomes: A group communication analysis. *Journal of Learning Analytics, 7*(1), 38-57.

Dowell, N. M., Graesser, A. C., & Cai, Z. (2016). Language and discourse analysis with Coh-Metrix: Applications from educational material to learning environments at scale. *Journal of Learning Analytics, 3*(3), 72–95.

Krumm, A. E., Means, B., & Bienkowksi, M. (2018). *Learning analytics goes to school: A collaborative approach to improving education*. New York: Routledge. Chapter 7: Five phases of collaborative data-intensive improvement (pp. 135-155).

Week 4: **Required**

Cooper, M., Ferguson, R., & Wolff, A. (2016, April). What can analytics contribute to accessibility in e-learning systems and to disabled students' learning?. In *Proceedings of the sixth international conference on learning analytics & knowledge* (pp. 99-103).

Salehian Kia, F., Teasley, S. D., Hatala, M., Karabenick, S., & Kay, M. (2020). How patterns of students dashboard use are related to their achievement and self-regulatory engagement. *Proceedings of the 10th International Conference on Learning Analytics & Knowledge* (pp. 340-349). Frankfurt, Germany: ACM.

Connor, C. M. (2019). Using Technology and Assessment to Personalize Instruction: Preventing Reading Problems. *Prevention Science*, *20*(1), 89–99.

Optional

Chatti, M. A., Muslim, A., Guliani, M., & Guesmi, M. (2020). The LAVA Model: Learning Analytics Meets Visual Analytics. In: Ifenthaler D., Gibson D. (eds) Adoption of Data Analytics in Higher Education Learning and Teaching (pp. 71-93). Springer, Cham.

Learning Outcomes

- *Be able to describe the field of Learning Analytics and identify key technologies and settings for applying educational data science*
- *Understand ethical concerns associated with collecting, communicating, and taking action on educational data.*

- *Think critically about available data*
- *Be able to connect available data to learning context*
- *Be able to describe differences between prediction and inference*
- *Be able to identify opportunities for applying inferential modelling, predictive modelling, and unsupervised learning.*
- *Understand the role of latent constructs in educational measurement*
- *Be able to identify limitations of behavioral data and how it can be used*
- *Understand the importance of implementation supports*
- *Be able to develop a predictive model and understand implications of using a predictive model*

Course Schedule

- **This course begins on Monday, September 27 and ends on Sunday, October 24, 2021** (Ann Arbor, Michigan time - Eastern Time Zone).
- Instructors must submit final grades one week after the course ends. Therefore, any **late assignments** - subject to course reduction specified below or an instructor-approved extension - **cannot be accepted after 11:59 pm, Monday, November 1, 2021** (Ann Arbor, Michigan time - Eastern Time Zone).

Weekly Office Hours via Zoom (Ann Arbor, Michigan time):

Your instructors will hold weekly, synchronous office hours using the video-conferencing tool, Zoom. The schedule of office hours can be found by clicking on the **Live Events** link in the left-hand navigation menu. Additionally, all office hours will be recorded and archived so that you can retrieve them at a later date. Office hours are recorded and published in respective weeks.

There will be 3 office hours per week. Each instructor and the course assistant will lead one of these hours. Drs. Teasley & Krumm will answer questions about materials in the lectures and readings, and the course assistant will address questions and any issues with the course assignments.

Grading

Course Item	**Points**	**% of Final Grade**	**Due**
Week 1- Notebook Assignment: Exploratory Data Analysis	100	20%	Thursday, 10/7 at 11:59 pm Eastern Time
Week 1 - Reflection Questions	100	10%	Monday, 10/4 at 11:59 pm Eastern Time
Week 2 - Notebook Assignment: Building Prediction Models	100	20%	Thursday, 10/14 at 11:59 pm Eastern Time
Week 2 - Reflection Questions	100	10%	Monday, 10/11 at 11:59 pm Eastern Time
Week 3 - Notebook Assignment: Bias Metrics	100	20%	Thursday, 10/21 at 11:59 pm Eastern Time
Week 3 - Reflection Questions	100	10%	Monday, 10/18 at 11:59 pm Eastern Time
Week 4 - Reflection Questions	100	10%	Monday, 10/25 at 11:59 pm Eastern Time
Total	**800**	**100%**	

Note: All assignments must be submitted to earn credit for this course. (See late submission policy below.)

Reflection Scoring Checklist

1. **Are examples from readings, videos, and/or Jupyter notebook work used in responding to each prompt? (0-2 points)**
2. **Are examples effectively used to fully address each prompt? (0-2 points)**
3. **Are citations used in responding to each prompt? (0-2 points)**
4. **Does each response have between 150-200 words? (0-2 points)**
5. **Is the response free from spelling and grammar errors? (0-2 points)**

Letter Grades, Course Grades, and Late Submission Policy

Refer to the MADS Assignment Submission and Grading Policies section of the UMSI Student Handbook (access to Student Orientation course required).

For this course, the late submission policy is 15% reduction if assignment is turned in one day late, 30% reduction if two days late, 45% reduction if three days, and a zero (0) if four or more days late. (But remember, you must turn in all assignments to pass.)
The late penalty may be waived for personal circumstances beyond the student's control. You **must contact all three instructors via email** as soon as possible to discuss the terms for a late submission.

The grading scale for this course is as follows:

Letter Grade	Point % needed
A	93%
A-	90%
B+	87%
B	83%
B-	80%
C+	77%
C	73%
C-	70%
D+	67%
D	63%
D-	60%
F	0%

Academic Integrity/Code of Conduct

Refer to the Academic and Professional Integrity section of the UMSI Student Handbook. (access to Student Orientation course required).

Accommodations

Refer to the Accommodations for Students with Disabilities section of the UMSI Student Handbook (access to the Student Orientation course required). Use the Student Intake Form to begin the process of working with the University's Office of Services for Students with Disabilities.

Accessibility

Refer to the Screen reader configuration for Jupyter Notebook Content document to learn accessibility tips for Jupyter Notebooks.

Library Access

Refer to the U-M Library's information sheet on accessing library resources from off-campus. For more information regarding library support services, please refer to the U-M Library Resources section of the UMSI Student Handbook (access to the Student Orientation course required).

Student Mental Health

Refer to the University's Resources for Stress and Mental Health website for a listing of resources for students.

Student Services

Refer to the Introduction to UMSI Student Life section of the UMSI Student Handbook (access to the Student Orientation course required).

Technology Tips

- Recommended Technology
  - This program requires Jupyter Notebook for completion of problem sets and Adobe or other PDF viewer for reading articles.
- Working Offline
  - While the Coursera platform has an integrated Jupyter Notebook system, you can work offline on your own computer by installing Python 3.5+ and the Jupyter software packages, including pyspark. For more details, consult the Jupyter Notebook FAQ.