MSOL, University of California, Los Angeles

Henry Samueli School of Engineering and Applied Science

Deep Learning for Prognostics and Health Management of Complex Engineering Systems

CEE-298, Summer 2022

Instructor: Prof. Enrique Lopez Droguett

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Course Description

This course offers a theoretical and hands-on introduction to Deep Learning for modeling, implementing, and deploying solutions for the Prognostics and Health Management of complex engineering systems such as structures and equipment. Given the rapid evolution of the artificial intelligence landscape, fueled by the global trend towards Industry 4.0, Deep Learning has become an inevitable part of reliability, predictive maintenance, safety, risk, and digital twin areas, as it encompasses the latest advances in artificial intelligence with important applications in assessing the health status of complex engineering systems using Big Machinery Data, i.e., massive and multidimensional data from multi-sensor networks, images, and text. During the course, students will be exposed to the theory behind Deep Learning techniques, understand how they work, build, and train models, and use them in equipment and structure health management and forecasting. Focus is placed on practice and problem-solving skills with case studies from fields such as Oil & Gas, Mining, Aviation, and Renewable Energy. By the end of the course, students are expected to be able to independently develop and run Deep Learning analysis. Grading is project-based (homework and final project).

Lecture (4 hrs.), outside study (8 hrs.). Prerequisites: permission of the department

Instructor

Prof. Enrique Lopez Droguett

email: eald@ucla.edu

Office Hours

Monday & Wednesday 2-3 PM or by appointment

Grading

Homework: 60%

Final Project: 40%

Grade Description

The course is not expected to be graded on a curve. Final grades will be assigned based on the total number of percentage points accumulated by the student. As a sample guide, letter grades will generally be assigned as follows: total percentage in the 90s: A+ and A-, 80s: B+ and B-, 70s- C+ and C-, 60s- D+ and D-, below 60s- F.

Programming Language and DataBruin

The use of Python and TensorFlow Keras is recommended, but the choice of the programming language is at the discretion of the student. Hands-on introduction to Python and TensorFlow Keras will be provided both in regular lectures and in discussion sessions. Students will also have access to DataBruin (https://databruin.com/): an open access and web-based graphical programming environment for preprocessing of multi-sensor monitoring data and developing deep learning solutions. DataBruin provides an implementation of data flow diagrams in an intuitive drag-and-drop manner that not only offers a fast prototyping and code-free platform by helping practitioners to focus on the concepts rather than the syntax, but also provides the opportunity to guide them toward error-free prototyping of Deep Learning-based Prognostics and Health Management models. DataBruin provides standardization on the structure of deep learning PHM projects by offering a comprehensive path from preparing datasets all through the predictions and necessary assessments, with the standard auto-generated Python code for each analysis step.

Homework Exercises

Homework will generally take the form of data analysis, fault regression or classification involving a practical case study with real field data. Typed reports presenting the results obtained are expected to be submitted, together with the input files/code used. Homework not received in this manner will receive: (a) negative points or (b) in case of repetitive action or exceptional cases will not be graded and the student will receive an incomplete for the assignment. Homework will be assigned as needed and will be due the following week on an assigned day for the entire duration of the course. No late homework will be accepted without the prior consent of the instructor. Submitted homework should be of an individual nature. If there is reason to believe that work has been copied or completed in collaboration with another student, university regulations will be followed regarding application and enforcement of punitive action including immediate failure of the homework or the course as warranted by the circumstances. Further measures may be applied at the discretion of the instructor and University Staff.

Final Project

Students are expected to develop an individual project on a topic of relevance under advisement by the instructor and submit a report compiling the results obtained.

Textbooks

There is no formal textbook. Readings will be posted as needed. The following texts will serve as useful references:

1. Aurélien Géron. *Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow: Concepts, Tools, and Techniques to Build Intelligent Systems*. O'Reilly Media, 2nd Edition, 2019.
2. Ian Goodfellow, Yoshua Bengio, Aaron Courville. *Deep Learning*. MIT Press, 2016.

Course Outline

- Deep Learning in Prognostics and Health Management:
    - Prognostics and Health Management (PHM)
    - Internet of Things and Big Machinery Data
    - Why Deep Learning?
- Machine Learning Basics
- Deep Neural Networks:
    - Gradient Based Learning
    - Multi-Layer Perceptron
    - Backpropagation
    - Vanishing and Exploding Gradients
    - Regularization
    - Optimization
- Data Preprocessing Pipeline in PHM
- Convolutional Neural Networks (CNNs):
    - The Visual Cortex
    - Convolutional Layer
    - Pooling Layer
    - 2D Convolutions
    - 1D Convolutions for Time Series
    - CNN Architectures for Classification and Regression in PHM
- Recurrent Neural Networks (RNNs):
    - Unrolling Computational Graphs
    - Basic RNNs Architectures
    - Long-Short-Term Memory Recurrent Networks (LSTMs) for PHM
    - Gated Recurrent Units (GRUs) for PHM
    - Bidirectional RNNs
    - Remaining Useful Life (RUL) Assessment
- Autoencoder Based Anomaly Detection:
    - Introduction
    - Various Autoencoders Architectures for PHM
    - Deep Autoencoders for PHM
- Physics-Informed Neural Networks in PHM
- Bayesian Neural Networks in PHM

Class Schedule

Tentative (subject to change):

Week	Topic
1	Deep Learning in Prognostics and Health Management (PHM) Machine Learning Basics
2	Deep Neural Networks Deep Neural Networks
3	Deep Neural Networks Data Preprocessing Pipeline in PHM
4	Data Preprocessing Pipeline in PHM Convolutional Neural Networks (CNNs)
5	Convolutional Neural Networks (CNNs) Convolutional Neural Networks (CNNs)
6	Recurrent Neural Networks (RNNs) Recurrent Neural Networks (RNNs)
7	Recurrent Neural Networks (RNNs) Autoencoder Based Anomaly Detection
8	Autoencoder Based Anomaly Detection Autoencoder Based Anomaly Detection
9	Physics-Informed Neural Networks in PHM Physics-Informed Neural Networks in PHM
10	Bayesian Neural Networks in PHM Bayesian Neural Networks in PHM
11	FINAL PROJECT

SUPPLEMENTAL INFORMATION FOR DISTANCE EDUCATION COURSE PROPOSALS

Course Title and Number: C&EE 298- Deep Learning for Prognostics and Health Management of Complex Engineering Systems

Instructional Modality Requested: Online

Instructor Submitting this Request: Enrique Lopez Droguett

Additional Instructors who may teach this course under the indicated modality: None

Please provide a brief response to each of the following questions about the requested instructional modality for this course.

(A) What is the academic rationale for delivering this course in the proposed instructional modality?

Provide students with access to computers in real time and be able to interact among them and with the instructor in real time, thus providing an appropriate setup to an active learning environment, which will be enforced by having students to read papers prior to class, and have a hands-on experience with the topics discussed in the course by performing in-class (synchronously) case studies development, implementation, and discussion with the instructor and with peers.

The pedagogical rationale for delivering the course in an online that utilizes active learning can be derived from papers published on the benefits of active learning in STEM, such as:

1. Active learning increases student performance in STEM fields (Freeman et al. 2014). Student outcomes for STEM courses offered using traditional lecturing were compared with those for the same courses offered using active learning. Student performance was found to increase by 0.47 standard deviations under active learning, and exam scores improved by about 6%. Students in traditional courses were 1.5 times more likely to fail compared with those in active learning courses.
2. Active learning narrows achievement gaps for underrepresented students in STEM fields (e.g., Theobold et al. 2020). Although active learning improves student performance across all demographic groups, those benefits are disproportionately high for URM students and students from low-income backgrounds. Active learning had an overall positive impact on exam scores for underrepresented students, and an even larger positive impact on course pass rates.

(B) What is the projected enrollment of the course?

35 to 45 students

(C) What percentage of the curriculum will be distance education if the course is approved for the proposed mode of delivery (i.e., <25%, 25-50% or >50%)?

100% distance education

(D) What opportunities will students have to interact synchronously with the instructor, TAs, and fellow students?

The course is planned to be 100% synchronous, thus students will interact directly with the instructor in real time during lectures. Moreover, office hours will be held via Zoom as wells in person. If a TA is available for this course, TA sessions will also be 100% synchronous.

How will students ask questions, exchange ideas and gauge their own progress relative to others?

Lectures will be delivered in real time via Zoom sessions. Thus, students will interact with the instructor synchronously. Also, the course is designed to focus on active learning, thus every single lecture will encompass content delivery and then development of case studies involving real data on complex engineering systems such as infrastructures and physical assets (e.g., turbines, compressors, pumps), which are going to be developed both individually and in small working groups (usually, no more than 3 students per group). These live and interactive sessions will provide students with opportunity to interact with the instructor, with colleagues as well as gauge their progress.

How will the course facilitate cohort building and interaction among students?

The lecture sessions will be held in real time where students will work on case studies involving fault diagnostics and prognostics of complex engineering systems (infrastructures and static and rotary physical assets such as valves, heat exchangers, pumps, and compressors) and dealing with real monitoring data (e.g., multi-sensor data, images, thermography). In these instances, students will work in small groups of no more than 3 individuals. Moreover, the course also requires students to develop a term project, which is designed to be developed through the course and in teams of up to 5 students.

(E) What technologies will be employed? How will you ensure that all students understand and have access to this technology, including students with disabilities? Please include a statement from the responsible campus organization, ensuring the availability of this technology or committing the resources to obtain it.

The course makes use of open-source tools and libraries (Python, TensorFlow, Keras, Jupyter Lab) as well as a software platform called BruinLearn, which is an open access set of applications designed and developed by my lab that allows students and practitioners to develop and deploy deep learning solutions in a visual manner, no coding required. In terms of hardware, it is only required a computer running Windows, MacOS or Linus, in addition to internet access. Besides personal computers, students can have access to the required technology by accessing computers in one of our own computer labs.

(E) How will the course ensure equal access to students with disabilities?

I am in the process of creating my website with accessibility in mind. Also, all of my videos have closed-captioning available, and the website itself meets the WAVE web accessibility evaluation standards.

(F) How does a distance learning version of this course fit into the curriculum or the student's overall program of study?

This course provides an interdisciplinary bridge among the different specialization areas in the Civil & Environmental Engineering graduate students as it offers a theoretical and hands-on introduction to Deep Learning for modeling, implementing, and deploying solutions for the Prognostics and Health Management of complex engineering systems such as structures and equipment.

(H) What role will TAs play? How will they receive the training necessary to deliver the course in the proposed format? How will the expected TA workload compare to existing norms for similar in-person courses?

There will be no TA in this course.

(I) How will students be evaluated? How will the proposed method(s) of evaluation be administered? What efforts will be made to ensure academic integrity among students?
Students are expected to develop an individual project on a topic of relevance under advisement by the instructor and submit a report compiling the results obtained. Moreover, students will also be evaluated based on their homework solutions. Homework will generally take the form of data analysis, fault regression or classification involving a practical case study with real field data.

(J) What form will the primary course offerings take? Will they be synchronous or prerecorded? If pre-recorded, will they be updated for each course offering?

Lectures will be synchronous, thus providing real time participation and interaction with students and among them. Also, lectures will be recorded (with closed caption) and make available to students).

Theobald, E. J., Hill, M. J., Tran, E., Agrawal, S., Arroyo, E. N., Behling, S., … Freeman, S. (2020). Active learning narrows achievement gaps for underrepresented students in undergraduate science, technology, engineering, and math. Proceedings of the National Academy of Sciences, 117(12), 6476–6483. doi:10.1073/pnas.1916903117

Freeman, S., Eddy, S. L., McDonough, M., Smith, M. K., Okoroafor, N., Jordt, H., & Wenderoth, M. P. (2014). Active learning increases student performance in science, engineering, and mathematics. Proceedings of the National Academy of Sciences, 111(23), 8410–8415. doi:10.1073/pnas.1319030111