Neural Machine Learning II

COMP / ELEC / STAT 602, Fall 2021

Elective course, 3 credits (3 contact hours per week)

Course home page: http://www.ece.rice.edu/~erzsebet/NMLcourseII.html
(This website is also linked from the Canvas front page.)
Students are responsible for being familiar with this syllabus, and with the contents of both the above and the Canvas website and follow the postings as the course proceeds.
The information contained in the course syllabus, other than the absence policies, may be subject to change with reasonable advance notice as deemed appropriate by the instructor.

Instructor: Erzsébet Merényi
Class meets: TTH 4:00pm – 5:15pm, KCK 107 (planned as in-person, in-class instruction*)
Office/Phone: MXF 229, 713-348-3595 (email preferred except for urgency)
Office hours: by appointment
Assistant: N/A
email: erzsebet@rice.edu

As per Provost's announcement on Aug 19, 2021: remote instruction via Zoom will be in effect (at least) until Sep 3. The first class will be on Thu, Aug 26. Zoom link will be provided separately. Please check the course home page in Canvas and/or at the above link for details and further updates.

*Should Covid-19 circumstances force substantial changes in safety measures we may revert to remote instruction via Zoom.
While in class or visiting me in my office I expect everyone to strictly adhere to Rice University's mask requirements and other guidelines for minimizing the spread of the Covid-19 virus.

Short course description

Advanced topics in Artificial Neural Network theories, with a focus on learning high-dimensional complex manifolds with neural maps (Self-Organizing Maps and variants, Learning Vector Quantization variants, both unsupervised and supervised paradigms). Application to data mining, clustering, classification, dimension reduction, sparse representation. Comparison with "gold standards" on data of various complexities. Examples through image and signal processing, bioinformatics, brain mapping from fMRI, mining spectral image cubes for environmental mapping and astronomy problems. The course will be a mix of lectures and seminar style discussions with presentations and simulations by students, based on research articles. Strong coding skills in MATLAB, R, or C are assumed. Students can also have access to research software environment for simulation experiments.

Prerequisites

ELEC / COMP / STAT 502 Neural Machine Learning I., or equivalent, or instructor's permission. Further details can be found at the course web page, http://www.ece.rice.edu/~erzsebet/NMLcourseII.html under Prerequisites.

Sample Course Outline

1. Review part of COMP / ELEC / STAT 502, Neural Machine Learning I.

1.1. Review of prototype-based unsupervised learning of manifold structure with neural maps: Hebbian Learning, Self-Organizing Maps (SOM)
1.2. The basic Kohonen SOM; and basic Learning Vector Quantizers (LVQs)

2. Interpretation of Kohonen Maps for Extraction of Manifold Structure

2.1. Visualization of SOM knowledge – basics: U-matrix and variations, density map
2.2. Visualization of SOM knowledge – advanced: Connectivity Matrix and graph representation, underlying theories
2.3. Finding clusters: interpretation of the visualized knowledge, and structure extraction
2.4. Data compression and coding aspects, sparsity

3. Advanced Variants of Neural Maps and Measures of Mapping Quality

3.1. Kohonen vs Conscience SOM, neighborhood functions and metrics
3.2. Criteria of topology-preserving mapping; Measures of topology violation
3.3. Visualization and monitoring of violations, fixes
3.4. Neural Gas, Growing Self-Organizing Maps
3.5. Magnification in neural maps, and explicit control for different optimality criteria
3.6. Preferential discovery of small clusters with controlled magnification in SOMs
3.7. Distortion based and information based Self-Organizing Maps, density matching

4. Self-Organizing Maps for High-Dimensional and Complex Data

4.1. Issues related to high dimensionality and complexity of data spaces
4.2. Why and how some favorite traditional methods fail for complicated, high-dimensional data
4.3. How do SOMs deal with high-dimensional data; Applications, case studies
4.4. Comparison with classics (PCA, MDS variants, LLE-s, ISOMAP)

5. Unsupervised Learning as Support for Supervised Classification

5.1. Hybrid ANN architectures containing unsupervised and supervised learning components
5.2. Classification versus regression (parameter inference, learning underlying causes)
5.3. The use of unlabeled samples to boost performance of supervised learning (classification)

6. Evaluation of Clustering Quality and Classification Accuracy

6.1. Cluster validity indices: classics; and advanced ones, CONNindex
6.2. Evaluation of classification accuracy: sampling requirements, k-fold cross-validation, ROC curves, Kappa statistics, Wilcoxon signed ranks
6.3. Case studies

7. Intrinsic Dimensionality, Non-linear Dimensionality Reduction

7.1. Classics
7.2. Generalized Relevance Learning Vector Quantization
7.3. Neural ICA

8. Similarity Metrics for Learning, and Learning of Metrics

8.1. Feature spaces: homogeneous and inhomogeneous (mixed) feature vectors
8.2. Feature representation: homogeneous and inhomogeneous representations
8.3. Domain specificity in metric construction (e.g., divergences for functional data)

The exact course contents will be shaped to emphasize the interest of the participants.

Software: Simulations and exercises can be based on Matlab, R, or C programming, and / or using my group's research software environment

Course Materials

The course will be based on Lecture Notes, assigned papers from literature, scheduled as posted at the course web site http://www.ece.rice.edu/~erzsebet/NMLcourseII.html under Course Schedule. Copies of mandatory reading will be provided in class.
Further recommended background reading will include selected parts of the following books, available at www.amazon.com, or at the Fondren Library at Rice.

- Simon Haykin: Neural Networks. A Comprehensive Foundation. McMillan, New Jersey, 1999. (2nd Edition)
- Teuvo Kohonen: Self-organizing Maps (Springer Series in Information Sciences S.). Springer-Verlag, 2001 (3rd Edition, ISBN: 3540679219)

Objectives of the Course

1. Student understanding of concepts, and mastery, of neural manifold learning and data mining methods, and their applications to high-dimensional complex data.
2. Student mastery of neural computation, both theoretically and through software simulations.
3. Student competence in analyzing and critiquing articles from literature and communicating their own findings from neural computing exercises.

Detailed Course Schedule

A detailed schedule of class topics will come on-line in a timely manner at the course web site http://www.ece.rice.edu/~erzsebet/NMLcourseII.html under Course Schedule along with the schedule of reading, review (home work) and presentation assignments. The materials (such as lecture notes and assignments) indicated in the Course Schedule will be downloadable from Canvas or from other designated site.

Assignments, Grading Policies and Other Logistic Requirements

Grades will be made up of the following components, with approximate weights as shown:
75% - Performance in class (presentation and analysis of assigned articles, simulations)
15% - Mini Project
10% - Homework

1. Performance in class The instructor will give an introductory lecture for each major topic, after which students will take turns presenting and critiquing articles assigned by the instructor. Demonstration of thorough understanding of theories, rigorous presentation of algorithms, evaluation of scope, significance, applicability will be expected. Demonstrations or evaluations of capabilities of published algorithms or possible improvements will, in many cases, involve the presenter's own simulations. The presenter will be required to turn in their presentation and code (as applicable) and will receive feedback and grade points. Every student will be required to read all articles and expected to contribute to discussions

lead by the presenter. This occasionally will require everyone to run simple prescribed experiments to answer a specific question and to discuss and compare results through short informal presentations. Details of roles and requirements will be discussed in class.

2. Mini Project There will be a short (nominally 2-week) project on a focused topic chosen from the semester's material, as a conclusion of the semester. Projects will be evaluated based on a presentation or a report, or combination of the two, depending on circumstances. The exact schedule and requirements as well as suggested topics will be discussed in class well ahead of time. Students are encouraged to pursue topics aligning with their research (as applicable).

3. Homework Students will be required to run short simulations and discuss experiment results. There will be no other homework. Students are encouraged to collaborate with classmates but everyone will hand in their own experiment documentation and will be expected to understand their results.

3.1 Late Homework Policy Homework is due on the due date indicated in the Course Schedule. After the due date, but before the posted "late deadline" (the "accept until" date in Canvas), homework can be turned in for 50% credit.

Missed assignments If you must miss (or be late with) an assignment (homework, presentation) due to an extraordinary circumstance please notify me as much ahead of time as possible and make arrangements with me for completing the missed assignment. If, in extreme emergency, you are unable to provide advance notice, please let me know as soon as possible afterwards, and I will work with you on a solution accordingly.

Expectations Regarding Honor Code, Collaboration, and Citation

In preparing assignments (presentations, homeworks, project), students are encouraged to consult freely any material and anyone. However, each individual will write and turn in his or her own write-up or presentation, which they are expected to understand. In all work, students are expected to be scrupulous about proper citation of sources (where applicable), as required both as a matter of integrity and formally as a part of the Rice Honor Code.

Class Attendance and Absence Policy

Students are expected to attend all classes since 75% of the grade is composed of participation and performance in class. Students who must miss a class or assignment because of unavoidable circumstances should consult with the instructor well in advance so that alternative arrangements may be made.

University Disability Accommodation Policy

The University seeks to foster an environment of broad access and feasibly equal opportunity to education. The Office of Disability Support Services (DSS; Allen Center, Room 111; 713-348-584; adarice@rice.edu) supports and implements federal guidelines under the Rehabilitation Act of 1973 and the Americans with Disabilities Act. Students with documented disabilities requiring accommodation under Rice's established policies should consult DSS and the instructor; all such consultations and accommodations will be held confidential to the extent feasible.

Use of Machines during Class, and Class Etiquette

Cell phones must be turned off – or rendered silent – during class. If you need to take an urgent call, please set your phone to vibration and take the call outside the room. Laptops or other small devices may be used in class only for specific class purposes such as taking notes. If you have an urgent need to be online for other purposes during class time, feel free to do so **. . .** but outside the classroom. Should we need to do Zoom classes please have live camera presence in class if possible, or at least a static picture of you in Zoom, and be available for discussion. I will expect students to be punctual and to refrain from eating or other distractions during class.