EEE511: Artificial Neural Computation

1) please use the email address of si@asu.edu for all 511 related communications
2) please use an informative subject line in emails such as "EEE511, question about xyz"
3) please use file name convention for all submissions: Team#_LastName_KeyWords
4) each team member is required to upload a TEAM (identical) report

INSTRUCTOR:
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Professor
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IMPORTANT LINKS:
Google sheets:
https://docs.google.com/spreadsheets/d/1HHAgyb0PD_QladCK6mFLF83zunihr_S0vGNm4JJW1_k/edit?usp=sharing

Zoom link:
https://asu.zoom.us/j/81346963424

OFFICE HOURS (via zoom):
M W 7:30pm-8:45pm

PREREQUISITES:
Signals and systems, random signal analysis, linear algebra, or instructor approval

REFERENCE MATERIALS (recommended reading):
Jennie Si's notes
Selected papers
Selected books, chapters/sections from the LIST
Andrew Ng's lectures: https://www.youtube.com/playlist?list=PLLssT5z_DsK-h9vYZkQkYNWcItqhlRJLN
Alexander Ihler's lectures: https://www.youtube.com/watch?v=qPhMX0vb6D8&list=PLaXDtXvwY-oDvedS3f4HW0b4KxqpJ_imw
Complete statistical theory of learning (Vladimir Vapnik):
https://www.youtube.com/watch?v=Ow25mjFjSmg&list=PLrAXtmErZgOeiKm4sgNOknGvNjby9efdf
Deep Learning State of the Art (2020):
https://www.youtube.com/watch?v=0VH1Lim8gL8&list=PLrAXtmErZgOeiKm4sgNOknGvNjby9efdf
David Silver: AlphaGo, AlphaZero, and Deep Reinforcement Learning:
https://www.youtube.com/watch?v=uPUEq8d73JI

COURSE DESCRIPTION

The course aims at providing students a solid foundation on machine learning and a knowledge of the latest and greatest developments in machine learning. Student will learn several important skills to effectively solve machine learning problems by learning how to prepare data, how to determine the impact of features, how to select models and learning algorithms, and finally and importantly, how to diagnose a learning process.

The course will provide a comprehensive and insightful coverage of key concepts of machine learning which include loss/cost function, local gradient, information/gradient flow, probabilistic inference, deep networks, convolution, recurrence, and more.

The course will entail hands-on experience based on state-of-the-art tools. Students' work will have firsthand experience with important platforms such as Kaggle.com, ROS, PyTorch, TensorFlow, Keras, Google Colab, and more. Students will have opportunities to directly experience and appreciate significant machine learning applications including natural language processing, imaging captioning, object detection, automatic language translation, automatic driving assistance, sequential decision making, and machine learning applications in many important fields such as medicine, sports, financial markets, and more.

In summary, the goal of the course is for students to 1) acquire comprehensive knowledge and gain insights on the basic theory and fundamental principles underneath some of the major learning frameworks, 2) understand what algorithms to use for a given problem, and 3) have hands on experience in solving some important classes of machine learning problems. The course aims at providing a coherent overview of the field, giving student an ability to identify and digest deeper knowledge in a specific subfield of interest. Most importantly, the course aims at giving students the ability to apply an appropriate type of machine learning model and/or machine learning algorithm to solve a significant machine learning application problem.

As the field of machine learning develops and progresses rapidly, this course will respond in a timely manner to incorporate state-of-the-art methods, models, and applications as soon as they become available.

COURSE TOPICS

- Module 1 (Introduction). Machine learning, (deep) neural networks, history and development, significant applications, opportunities. Requirements of semester long team project.
- Module 2 (Generalized linear models). Simple perception, least mean square adaptive algorithm by Widrow and Hoff, Wiener filter (optimal linear filter), univariate/multivariate linear regression, logistic regression, sum of squared errors, least squares, (stochastic) gradient descent, log likelihood, maximum likelihood, and last but not least, relationships among all these models.
- Module 3 (Multilayer feedforward neural networks). From single neuron to multilayer, nonlinear neural networks, activation functions, local gradient, details and insight of backpropagation, generalization of backpropagation, universal approximation theorem, universal approximation for deep neural networks (ReLU, width vs. depth).
- Module 4 (Regularization, bias-variance trade off, model selection). Under fitting, over fitting, Tikhonov regularization, learning algorithms with regularization under different error cost, weight decay, training-validation-test, how to build neural network (nonlinear regression) models, practical approaches to application, diagnosis of learning, support vector machines.
- Module 5 (Deep learning). Deep NN architectures, what drives deep learning progress? why it works, applications (natural language processing, computer vision, drug discovery, financial engineering, customer management, self-driving car, robotics…). Convolutional neural networks (CNN), CNN architectures, how CNN works, applications, complexity problem, regularization (pruning, sparsity, dropout, data augmentation…), training CNN (hyperparameters for filtering, pooling, …), deep recurrent neural networks (RNN), hidden states, dynamics of RNN, unfolding in time, truncated BP, long short-term memory, gated recurrent units.

- Module 6 (Unsupervised learning). Clustering, data mining, representation, K-means, cost function, complexity issue, hierarchical agglomerative clustering, DBSCAN, mean-shift, model-based clustering such as Gaussian mixture models, expectation-maximization (EM), maximum likelihood estimates.
- Module 7 (Supplementary materials). Support vector machines, principal component analysis, optimization techniques, introduction to reinforcement learning.

COURSE POLICY - GENERAL

- Use Canvas to turn in your work and retrieve your grades. When submitting your work, make sure to create a single pdf file to include all materials unless otherwise specified (For example, evaluation forms. Follow instructions in the assignment). To include a video, insert the link to the file in the pdf while upload the video to an accessible location (if the video is not accessible, we cannot consider it for credit).
- Each team member is required to submit a team report for each team assignment using the above file name convention.
- Once teams are formed, keep using the same team# and member# throughout the semester.

COURSE POLICY - LATE OR MISSED ASSIGNMENTS

- No late submissions are accepted in general except for special cases with special arrangements. Notify the instructor as early as possible, **BEFORE** an assignment due time for justifiable reasons of late submission.
- A 1% deduction will be given for every 2 minutes of late submission. It accrues up to 15% for the assignment (or 30 minutes late submission). A late submission by 3 days will receive up to 50% credit, but after that, there will be 0 credit for that assignment.
- Follow the appropriate University policies to request an accommodation for religious practices or to accommodate a missed assignment due to University-sanctioned activities.

GRADING GUIDELINES (subject to adjustment by the instructor)

Individual assignments (including quizzes) – 20%
Midterm (~late Oct/ early Nov) –12%
Team assignments – 18%
Final project (team) – 50%
A: >93.3; A-: [90, 93.3); B+: [86.7-90), B: [83.3-86.7), B-: [80-83.3); C's: 70's; D's: 60's; E: below 60.
A+: above 98, for individual students who complete the final project using option 2.

PLEASE NOTE – grades in canvas are for individual assignments, not weighted by the percentages shown above. Therefore, the total can be above 100 points. Please don't expect your final letter grades correspond with the total points in canvas.

ACADEMIC INTEGRITY

- Plagiarism is not tolerated. Take note of Academic Integrity Policy at ASU. Respect copyright law and other regulations. Offenses will result in serious consequences.
- During exams/quizzes in class, all backpacks must be placed in the front of the room. All cell phones (including smart watches and all other communication devices) must be in the backpack or if you do

not have a backpack, the cell phone must be face down, powered off, on the table near the podium. Any violation of this policy will result in a zero on the exam/quiz.

- A lack of contribution to teamwork (evaluated by team contribution form) will result in a lower score than what contributing teammates receive.

COPYRIGHTED MATERIALS

- Students must refrain from uploading to any course shell, discussion board, or website used by the course instructor or other course forum, material that is not the student's original work, unless the students first comply with all applicable copyright laws; faculty members reserve the right to delete materials on the grounds of suspected copyright infringement.
- Use color blue to highlight any copied materials from openly available references and provide a clear citation to the reference(s) and make a clear mention in your writing.