The University of Connecticut **Spring 2021**
Dept. of ECE **KRP**

ECE 6141 : Neural Networks for Classification and Optimization

General Information

Instructor:

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Office Hours: Tuesday: 1 PM – 2 PM

Classes: Time: Tuesday, 6PM-9PM, Online https://uconn-cmr.webex.com/meet/krp02004

Text: Sergios Theodoridis, *Machine Learning*: *A Bayesian and Optimization Perspective*, Academic Press, 2020.
(Optional) C. M. Bishop, *Pattern Recognition and Machine Learning*, Springer, New York, 2006.
(Optional) Kevin P. Murphy, Machine Learning: A Probabilistic Perspective, MIT Press, 2012.

Objectives and Learning Outcomes:

Objective: The objective of this course is to provide students with a thorough understanding of the mathematical underpinnings of statistical machine learning, neural networks and graphical models, as well as the implementation and testing of various forms of machine learning models in software.

Learning Outcomes: By the end of this course, the students should be able to

a. Understand the differences among supervised, unsupervised, semi-supervised and reinforcement learning methods.
b. Visualize and pre-process the data for model building.
c. Understand the differences between generative and discriminative models.
d. Grasp the mathematical, statistical and optimization underpinnings of widely-used classification, regression and clustering (density estimation) methods.
e. Trade-off between bias and variance in data-driven modeling for classification, regression and clustering.
f. Understand the metrics to assess and compare the performance of classification, regression and clustering models.
g. Experiment with widely used learning algorithms for classification, regression and clustering.
h. Train, evaluate, validate and improve the accuracy of models learned from data.
i. Work in teams in (i) making presentations, (ii) applying the concepts and methods learned on a term project related to research or based on a real-world problem, and (iii) reporting on the project's outcomes.
j. Appreciate the wide applicability of machine learning methods to contemporary problems.

Assessment & Evaluation:

1. Homework Assignments to assess and evaluate outcomes (b, d, e, f, g, h). This constitutes 40% of the grade.
2. A Take Home Mid-term examination that assesses and evaluates outcomes (d, e, f, g, h). This comprises 25% of the grade.
3. Review paper presentation to assess and evaluate outcomes (a-j). This comprises 10% of the grade.
4. Term Project and Final Presentation to assess and evaluate outcomes (i, j). This constitutes 25% of the grade.

Additional Information:

- Starting with March 16 Lecture, each lecture will have two parts. Instructor will present course materials the first 2.5 hours, and the students will present reviews of recent journal publications in teams of 3 students in the remaining 0.5-hour.
- Paper reviews should be based on relevant and recent (2014 and up) journal articles from, e.g., Journal of Machine Learning Research, IEEE Trans. On Pattern Analysis and Machine Intelligence, Machine Learning (Journal), Neurocomputing, IEEE Trans. On Neural Networks, IEEE Trans. On Signal Processing, IEEE Trans. On Automatic Control IEEE Trans. On SMC, Pattern Recognition, Biological Cybernetics, Neural Computation, Statistical Science.
- Teams of three students work on Term projects relevant to machine learning topics. Topics related to research, or real-world problems are expected. Numerical implementation and testing are must.
- Term project proposals are due on March 16; project presentations will occur on Tuesday May 4 from 6 PM to 9 PM, and final reports are due on the same day.
- Any programming language is acceptable for Homework and Term Projects.

Course Outline

Lectures 1-2: **Introduction and Course Overview:**

- *Course Objectives*
- *What is Predictive Data Analytics?*
- *What is Machine Learning?*
- *Deep Learning and History of Neural Networks*
- *Getting to Know the Data: Data Visualization, Data Statistics, Data Scaling, Data Cleaning*
- *What kind of problems can be solved using Machine Learning?*
- *Basic Learning Tasks:* Density Estimation, Classification and Regression.
- *Generative versus Discriminative Learning*
- *Learning from Data:* MAP and ML Criteria, Likelihood-based Cost Functions, Canonical from of the Gradients of the Cost function, Optimization Algorithms
- *Graphical Models:* Naïve Bayes, Markov Chains, Hidden Markov Models, Factor Graphs, Markov Random Fields, Bayesian Networks

Lectures 3-5: **Statistical Inference and Probability Density Estimation**

- *Bayesian Hypothesis Testing:* Minimizing risk and probability of error, Decision rules for known distributions (Linear and Quadratic Discriminants, Logistic and Multinomial (Soft-max) Regression)
- *General Density Estimation:* Parametric methods, ML methods, Bayesian Inference, Sequential parameter estimation, Gaussian mixtures and the EM algorithm, Non-parametric methods
- *Performance Assessment of Decision Rules:* Confusion Matrix, Precision, Recall, Sensitivity, Specificity, Error Rates, Odds Ratio, Kappa, ROC)

- *Performance Assessment of Regression Models*: BIC, AIC, MDL and variants
- *Comparing Classification and Regression Models*

Lecture 6: **Decision-based Learning**

- *Classification as a Function Approximation Problem*
- *Approximating Posterior Probabilities*
- *Decision Based Learning*
- *Perceptron Convergence Theorem*
- *Optimal Learning Rate & Normalized Perceptron*
- *Extension to Multiple Classes*
- *Fuzzy Updates*
- *LVQ as a Perceptron Update*
- *Decision Trees (Method for constructing decision trees, Choosing Tests, Splitting Rules, Pruning Rules, Handling Missing Values, Extensions to Complex Tests, Boosted Decision Trees and Random forests)*

Lecture 7: **Regression-based Learning**

- *Linear and Nonlinear Regression Based Learning*: Least Squares (L2) Regression; Ridge Regression; L1 Regression; Combined L1 and L2 Regression
- *Nonlinear Optimization Techniques*
- *ADALINE (Adaptive Linear Element)*
- *Stochastic Convergence Analysis*
- *Support Vector Machines*
- *Kernel, Support Vector Machine (SVM) and Gaussian Process Regression*

Lectures 8-9: **Multi-layer Perceptrons and Deep Learning**

- *Multilayer Perceptrons:* Gradient Calculation via Back Propagation; Relationship to Calculus of Variations; Variants of the classic Back Propagation algorithm (Momentum term, Weight Decay, Quickprop, Learning Rate Adaptation, Incremental Gauss-Newton (Extended Kalman Filter))
- *MLP learning as an Optimization Problem:* Conjugate Gradient and Quasi-Newton Methods, Recursive Hessian Computation and Newton's Method, Levenberg-Marquardt Method.
- *MLP as Universal Function Approximator*
- *Practicalities:* type of nonlinearities, Initialization, batch versus recursive training, prior information
- *Managing Network Complexity:* Pruning Networks; Selecting the Number of Hidden Nodes; regularization; Incremental Network Construction
- *Deep Learning:* Need for Deep Architectures, Deep Convolutional Networks, Recurrent Neural Networks

Lecture 10: **Radial Basis Functions and Gaussian Processes**

- *RBF Networks and Training*
- *Regularization Theory*
- *Relation to Kernel Regression*
- *Gaussian Processes*
- *Relevance Vector Machine*

Lecture 11: **Unsupervised Learning and Feature Extraction**

- *Projection Methods:* SVD, Projection Pursuit, probabilistic PCA
- *More Clustering Algorithms:* Dirichlet process mixture models, Spectral clustering, Hierarchical Clustering
- *Independent Component Analysis*

- *Self-organizing Map (SOM)*
- *Feature Selection*: Bayesian variable selection, sparse linear models, Greedy search, Discretization of Numeric Features: Entropy, Error-based and Unsupervised
- *Connections to Deep Learning:* Autoencoders and Stacked autoencoders

Lectures 12-13: Graphical Models for Machine Learning

- *Graphical Models:* Markov Chains, HMMs, Hybrid Systems, Factor Graphs, Markov Random Fields and Bayesian Belief Networks
- *The Sum-product Algorithm, Variational Inference, Loopy Belief Propagation, Monte Carlo Methods ((Importance Sampling, Markov Chain Monte Carlo (MCMC) Methods, Gibbs Sampling, Contrastive Divergence)*
- *Graphical Model Learning*
- Connection to Deep Learning: Deep Directed Networks, Deep Boltzmann Machines, Deep Belief Networks, Auto-Regressive Networks

Lecture 14: Neuro-dynamic Programming (unlikely to get to this!)

- *Principle of Optimality and Dynamic Programming (DP) Recursion*
- *Cost-to-go Approximations in DP*
- *Approximation Architectures*
- *Simulation and Training*
- *Neuro-dynamic Programming:* Q-learning, Temporal Difference Methods
- *Rollout policies*

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