USC Viterbi School of Engineering

EE 559: Machine Learning I: Supervised Methods (Spring 2025)

Units:	4
Instructor:	Mohammad Reza Rajati, PhD
Office Location:	GCS 302-B
	rajati@usc.edu – Include EE 559 in subject
Office Hours:	Right after the lecture, by appointment
TA(s):	TBD
	@usc.edu – Include EE 559 in subject
Office Hours:	TBA
Office Location:	TBA
Course Producer(s):	TBD
	tbd@usc.edu – Include EE 559 in subject
Lecture(s):	Tuesday, Thursday 12:00 noon - 1:50 pm, OHE 122
Discussion(s):	Friday, 11:00-11:50 am, OHE 122
Webpages:	Piazza Class Page for everything except grades
	and USC Brightspace Class Page for grades
	and GitHub for code submission
	– All HWs, handouts, solutions will be posted in PDF format.
	– *Student has the responsibility to stay current with webpage material*
Prerequisites:	No formal pre-requisites.
	Prior courses in multivariable calculus, linear algebra, and probability.
	– This course is a prerequisite to EE 660.
Corequisites:	EE 503, EE 510
Other Requirements:	Basic computer skills (e.g., plotting, Python, Matlab, R, etc.).
	–**Note:** Students need to be familiar with Python programming
	or be willing to learn Python.
Tentative Grading:	Assignments 45%
	Midterm Exam 25%
	Final Exam 30%
	Participation on Piazza* 5%

Letter Grade Distribution:

$\geq$ 93.00	A	73.00 - 76.99	C
90.00 - 92.99	A-	70.00 - 72.99	C-
87.00 - 89.99	B+	67.00 - 69.99	D+
83.00 - 86.99	B	63.00 - 66.99	D
80.00 - 82.99	B-	60.00 - 62.99	D-
77.00 - 79.99	C+	$\leq$ 59.99	F

Disclaimer: Although the instructor does not expect this syllabus to drastically change, he reserves every right to change this syllabus any time in the semester.

Note on e-mail vs. Piazza: If you have a question about the material or logistics of the class and wish to ask it electronically, please post it on the piazza page (not e-mail). Often times, if one student has a question/comment, other also have a similar question/comment. Use private Piazza posts with the professor, TA, graders only for issues that are specific to your individually (e.g., a scheduling issue or grade issue). Minimize the use of email to the course staff and only use it when *absolutely necessary.*

Catalogue Description: Distribution-free and probabilistic methods for supervised classification and regression; learning algorithms; optimization techniques; feature-space transformations; parametric and nonparametric methods; Bayes decision theory; artificial neural networks.

Course Objectives: Upon successful completion of this course a student will

- Broadly understand major algorithms used in supervised machine learning.
- Understand the difference between supervised and unsupervised learning techniques.
- Understand regression techniques.
- Understand resampling methods, including cross-validation and bootstrap.
- Understand methods of evaluation of classifiers and regression models.
- Understand statistical and distribution-free pattern recognition techniques.
- Understand density estimation techniques
- Understand kernel methods for regression and classification.
- Understand dimensionality reduction, feature creation, and regularization.
- Understand unsupervised learning methods that serve as pre-processing for supervised methods.
- Understand feedforward neural networks and deep learning.

Exam Dates:

- **Midterm Exam (in-person):** Thursday, March 13, 12:00 Noon- 1:50 PM
- **Final Exam:** Wednesday, May 14, 2:00-4:00 PM as set by the university.

  Important Note: Please make absolutely sure that you can make the above dates. No make-up exams can be offered for *any reason* whatsoever. Moreover, no online exam will be offered to on-campus students for *any reason.* If a student misses Midterm 1 due to a valid reason (e.g., documented medical or family emergency), the grade of Midterm 2 will be considered as the grade of Midterm 1. If a student misses Midterm 2 due to a valid reason, they will receive a grade of IN (Incomplete) and they must take the exam in the next semester with the students of that semester. Unexcused absence in an exam warrants a grade of zero.

Textbooks:

- **Required Textbooks:**

  1. *The Elements of Statistical Learning*, 2nd Edition
     Authors: Trevor Hastie, Robert Tibshirani, and Jerome Friedman; Springer, 2009. **ISBN-13:** 978-0-387-84857-0
  2. Gareth James, Daniela Witten, Trevor Hastie, and Robert Tibshirani, *An Introduction to Statistical Learning with Applications in R*, Springer, 2021. (ISLR)
     Available at https://web.stanford.edu/~hastie/ISLRv2_website.pdf

- **Recommended Textbooks:**

  1. Gareth James, Daniela Witten, Trevor Hastie, and Robert Tibshirani, *An Introduction to Statistical Learning with Applications in Python*, Springer, 2023.
  2. *Pattern Classification*, 2nd Edition
     Authors: Richard O. Duda, Peter E. Hart, and David G. Stork; Wiley, 2001. **ISBN-13:** 978-81-265-1116-7
  3. *Applied Predictive Modeling*, 1st Edition
     Authors: Max Kuhn and Kjell Johnson; Springer; 2016. **ISBN-13:** 978-1-4614-6848-6
  4. *Machine Learning: An Algorithmic Perspective*, 2nd Edition
     Author: Stephen Marsland; CRC Press; 2014. **ISBN-13:** 978-1-4614-7137-0
  5. *Pattern Recognition and Machine Learning*, 1st Edition
     Author: Christopher Bishop; Springer; 2006. **ISBN-13:** 978-0-387-31073-2
  6. *Pattern Recognition*, 1st Edition
     Author: Sergio Theodoridis; Academic Press; 2009. **ISBN-13:** 978-1-597492720
  7. *Computer Age Statistical Inference: Algorithms, Evidence, and Data Science*, 1st Edition
     Authors: Bradley Efron and Trevor Hastie; Cambridge University Press, 2016. **ISBN-13:** 978-1107149892
  8. *Deep Learning*, 1st Edition
     Authors: Ian Goodfellow and Yoshua Bengio; Springer, 2009. **ISBN-13:** 978-0-262-03561-3
  9. *Neural Networks and Learning Machines*, 3rd Edition
     Author: Simon Haykin; Pearson; 2008. **ISBN-13:** 978-0131471399

Grading Policies:

- The letter grade distribution table guarantees the *minimum* grade each student will receive based on their final score. When appropriate, relative performance measures will be used to assign the final grade, at the discretion of the instructor.
  – Final grades are non-negotiable and are assigned at the discretion of the instructor. If you cannot accept this condition, you should not enroll in this course.

- Your lowest homework grade and half of your second lowest homework grade will be dropped from the final grade. For example, if you received 90, 85, 10, 95, 65, 80, 100 your homework score will be $\frac{0.5\times65+80+85+90+95+100}{5.5} = 87.72$ instead of $\frac{10+65+80+85+90+95+100}{7} = 75$. This policy makes up for missing assignments because of heavy workload, sickness, etc. Remember that if you miss an assignment because of heavy workload in other courses and then miss another one because of sickness, only the second assignment's grade will be completely dropped from your score. Be aware of this when you decide not to submit an assignment, because later you may become sick.
- Homework 0 will not be graded.
- *Participation on Piazza has up to 5% extra credit, which is granted on a competitive basis *at the discretion of the instructor.*

- **Homework Policy**
  - The project of this course is integrated into the assignments. Assignments include theoretical problems as well as application of the algorithms to real-world data.
  - Homework is assigned on an approximately weekly basis. A three-day grace period can be used for each homework with 10% penalty per day. *Absolutely no late homework will be accepted after the grace period. A late assignment results in a zero grade.*
  - Late Days: No late homework will be accepted after the three day grace period. One second after the deadline is considered late. However, students are allowed to use *six* late days for homework for any reason (including sickness, family emergencies, overwhelming workload, exams, etc) *without incurring the 10% penalty.* Beyond that, no individual extension will be granted to anyone for any reason whatsoever.

    Example: A student can submit six assignments, one day late each, without any penalty. Or three assignments, two days late each, without penalty, or two assignments three days late each. A student cannot use four late days for one assignment, and two late days for another assignment. An assignment submitted four days late will receive a zero grade, although its grade will be dropped as the lowest homework grade, according to the above grading policies.
  - Use your six late days strategically and only if you absolutely need them. Always remember that later in the semester, you might become sick or have heavy workload in other courses and might need to use your late days.
  - Assignments are *project-style*; therefore, *we do not provide solutions to the assignments.* This is a firm rule.
  - Poor internet connection, failing to upload properly, or similar issues are **NOT** acceptable reasons for late submissions. If you want to make sure that you do not have such problems, submit homework *eight* hours earlier than the deadline. Please do not ask the instructor to make individual exceptions.
  - Homework solutions should be typed or *scanned* using scanners or mobile scanner applications like CamScanner and uploaded on the course website (photos taken by cell-phone cameras and in formats other than pdf will NOT be accepted). Programs and simulation results have to be uploaded on the course website as well, preferably in Jupyter Notebooks.

  - Students are encouraged to discuss homework problems with one another, but each student must do their own work and submit individual solutions written/ coded in their own hand. Copying the solutions or submitting identical homework sets is written evidence of cheating. The penalty ranges from F on the homework or exam, to an F in the course, to recommended expulsion. One important (but not exclusive) instance of cheating is having access to other students' solutions. Claims of " being inspired" by other students' codes, or using them as "sample code" are not acceptable. Asking questions from your peers and exchanging tips about coding are highly encouraged and should not be confused with outright cheating.
  - Posting the homework assignments and their solutions to online forums or sharing them with other students is strictly prohibited and infringes the copyright of the instructor. Instances will be reported to USC officials as academic dishonesty for disciplinary action.

- **Exam Policy**
  - **Make-up Exams:** No make-up exams will be given. If you cannot make the above dates due to a class schedule conflict or personal matter, you must drop the class. In the case of a required business trip or a medical emergency, a signed letter from your manager or physician has to be submitted. This letter must include the contact of your physician or manager.
  - An excused absence supported by documents in the midterm can be made up by using the final's grade in lieu of the first midterm. An excused absence in the final results in an IN (incomplete) grade.
  - Midterms and final exams will be closed book and notes. Calculators are allowed depending on the exam. No computers and cell-phones or any devices that have internet capability will be allowed. One letter size cheat sheet (back and front) is allowed for the midterms. Two letter size cheat sheets (back and front) are allowed for the final.
  - All exams are cumulative, with an emphasis on material presented since the last exam.
  - For several reasons, including unauthorized circulation of previous exams, we DO NOT provide exam solutions. This is a firm rule.
  - For several reasons, including the difficult logistics of dealing with a large class, we may not be able to hold a regrading session for the exams. Please make sure that you understand this rule when you take this course.

- **Attendance:**
  - Students are required to attend all the lectures and discussion sessions and actively participate in class discussions. Use of cellphones and laptops is prohibited in the classroom. If you need your electronic devices to take notes, you should discuss with the instructor at the beginning of the semester.

Important Notes:

- Textbooks are secondary to the lecture notes and homework assignments.
- Handouts and course material will be distributed.
- Please use your USC email to register on Piazza and to contact the instructor and TAs.

Tentative Course Outline[1]

Tuesday	Thursday
Jan 14th **1** **Introduction to Statistical Learning** Motivation: Big Data Supervised vs. Unsupervised Learning	16th **2** **Introduction to Statistical Learning** Regression, Classification The Regression Function Nearest Neighbors
21st **3** **Introduction to Statistical Learning** Model Assessment The Bias-Variance Trade-off No Free Lunch Theorem	23rd **4** **Linear Regression** Estimating Coefficients Estimating the Accuracy of Coefficients Variable Selection and Hypothesis Testing
28th **5** **Linear Regression** The Gauss-Markov Theorem Multiple Regression Analysis of Variance and The F-test Qualitative Variables	30th **6** **Linear Regression** Pseudo-Inverse Learning and Linear Regression
Feb 4th **7** **Classification** Some Simple Classification Problems The Bias-Variance Trade-off Overfitting Multi-Class and Multi-Label Classification Class Imbalance SMOTE Confusion Matrices and Hypothesis Testing Accuracy Other Metrics Receiver Operational Curve (ROC) Remedies for Class Imbalance	6th **8** **Resampling Methods** Model Assessment Validation Set Approach Cross-Validation The Bias-Variance Trade-off for Cross Validation The Bootstrap Bagging Classifiers Bootstrap Confidence Intervals*
11th **9** **Bayesian Decision Theory** Maximum Likelihood and Maximum A Posteriori Decisions Minimum Risk Decision Rule Minimum Error Rate Decision*	13th **10** **Bayesian Decision Theory** Discriminant Functions and Decision Surfaces Linear Discriminant Analysis Quadratic Discriminant Analysis* Conditional Independence Assumption

[1]Special Thanks to Prof. Keith Jenkins for his assistance in designing the syllabus.

Tuesday	Thursday
18th **11** **Parameter Estimation for Classification** Maximum Likelihood Estimation Maximum A Posteriori Estimation Naïve Bayes' Classifier Feature Creation for Text Data TF-IDF features	20th **12** **Parameter Estimation for Classification** Data Imputation Logistic Regression Multinomial Regression Generative and Discriminative Models Comparison with K-Nearest Neighbors Bayesian Estimation* Expectation Maximization*
25th **13** **(Linear) Model Selection, Regularization, and Feature Creation** Subset Selection Shrinkage Methods	27th **14** **(Linear) Model Selection, Regularization, and Feature Creation** Dimension Reduction Methods and Principal Component Analysis (PCA) Fisher's Linear Discriminant Analysis
Mar 4th **15** **Non-parametric Methods and Density Estimation** Histograms Parzen Windows K-Nearest Neighborhood Method for Density Estimation Kernel Density Estimation	6th **16** **Discriminant Functions** Linear Discriminants and Decision Surfaces Multi-Class and Multi-Label Problems One vs. One and One vs. All Classification Perceptrons
11th **17** **Discriminant Functions** Minimizing Perceptron Criterion Minimum Squared Error Learning Pseudo-Inverse Learning Gradient Descent Formulation Widrow-Hoff Algorithm Generalized Linear Discriminants	13th **18** **Midterm Exam**
18th Spring Recess	20th Spring Recess
25th **19** **Optimization for Discriminative Models** Lagrange Constrained Optimization **Support Vector Machines** Maximal Margin Classifier Support Vector Classifiers	27th **20** **Support Vector Machines** Support Vector Machines The Kernel Trick Mercer's Kernels and Mercer's Theorem

Tuesday	Thursday
Apr 1st **21** **Support Vector Machines** L1 Regularized SVMs Multi-class and Multilabel Classification Using SVMs The Vapnik-Chervonenkis Dimension Multi-Label Classification Metrics for Assessing Multi-Label Problems **Support Vector Regression**	3rd **22** **Radial Basis Function Neural Networks*** Training RBF Networks and Function Approximation Relationship with Least Squares, Pseudo-Inverse Learning, and Linear Regression
8th **23** **Radial Basis Function Neural Networks*** Relationship with Kernel Methods, and Kernel Linear Regression	10th **24** **Neural Networks and Deep Learning** Feedforward Neural Networks and Perceptrons Representation of Feedforward Neural networks The Universal Approximation Theorem*
15th **25** **Optimization for Discriminative Models** Gradient Descent (Batch, Sequential, Stochastic, Mini-batch) Newton and Quasi-Newton Methods* Conjugate Gradient* The Levenberg-Marquardt Algorithm* Nelder-Mead Algorithm* Broyden-Fletcher-Goldfarb-Shanno (BFGS) Algorithm*	17th **26** **Neural Networks and Deep Learning** Backpropagation and Gradient Descent Overfitting Regularization Early Stopping and Dropout
22nd **27** **Neural Networks and Deep Learning** Autoencoders and Deep Feedforward Neural Networks* Convolutional Neural Networks* Adversarial Training*	24th **28** **Unsupervised Learning*** K-Means Clustering Hierarchical Clustering Unsupervised Learning as Pre-Processing for Supervised Learning Training RBF Networks via Clustering

Tuesday	Thursday
29th **29** **Active and Semi-Supervised Learning*** Semi-Supervised Learning Self-Training Co-Training Yarowsky Algorithm Refinements Active vs. Passive Learning Stream-Based vs. Pool-Based Active Learning Query Selection Strategies	May 1st **30** **Guest Lecture or Fuzzy Systems***

Notes:

- Items marked by * will be covered only if time permits.

Homework and Exam Due Dates

Friday	
Jan 17th -	1
24th -	2
31st **Homework 0 Due (not graded, moved to Tuesday May 28)**	3
Feb 7th **Homework 1 Due**	4
14th -	5
21st **Homework 2 Due**	6
28th -	7
Mar 7th **Homework 3 Due**	8
14th -	9
21st Spring Recess	
28th **Homework 4 Due**	10
Apr 4th -	11

Friday	
11th **Homework 5 Due**	**12**
18th **-**	**13**
25th **Homework 6 Due**	**14**
$\boxed{\text{May 2nd}}$ **Homework 7 Due**	**15**

Statement on Academic Conduct and Support Systems

Academic Conduct:

Plagiarism – presenting someone else's ideas as your own, either verbatim or recast in your own words – is a serious academic offense with serious consequences. Please familiarize yourself with the discussion of plagiarism in SCampus in Part B, Section 11, "Behavior Violating University Standards" policy.usc.edu/scampus-part-b. Other forms of academic dishonesty are equally unacceptable. See additional information in SCampus and university policies on Research and Scholarship Misconduct.

Using Generative AI and Large Language Models:

Use of AI and specifically Large Language Models (LLMs) is allowed. However, it is only allowed as a tool to assist in learning. That is to say, that you may use AI models such as ChatGPT or Claude 2 to help understand the assignments, to ask generic questions about programming and to generate code samples that could be of use to explain how certain programming constructs work. Submitting assignments completely generated by AI is strictly prohibited and when discovered will be awarded 0 points for the assignment. We will be utilizing additional software to check for code generated by an AI. You must also specify which part of each assignment was done using help from AI.

Students and Disability Accommodations:

USC welcomes students with disabilities into all of the University's educational programs. The Office of Student Accessibility Services (OSAS) is responsible for the determination of appropriate accommodations for students who encounter disability-related barriers. Once a student has completed the OSAS process (registration, initial appointment, and submitted documentation) and accommodations are determined to be reasonable and appropriate, a Letter of Accommodation (LOA) will be available to generate for each course. The LOA must be given to each course instructor by the student and followed up with a discussion. This should be done as early in the semester as possible as accommodations are not retroactive. More information can be found at osas.usc.edu. You may contact OSAS at (213) 740-0776 or via email at osasfrontdesk@usc.edu.

Support Systems:

Counseling and Mental Health - (213) 740-9355 – 24/7 on call
studenthealth.usc.edu/counseling
Free and confidential mental health treatment for students, including short-term psychotherapy, group counseling, stress fitness workshops, and crisis intervention.

National Suicide Prevention Lifeline - 1 (800) 273-8255 – 24/7 on call
suicidepreventionlifeline.org
Free and confidential emotional support to people in suicidal crisis or emotional distress 24 hours a day, 7 days a week.

Relationship and Sexual Violence Prevention Services (RSVP) - (213) 740-9355(WELL), press "0" after hours – 24/7 on call
studenthealth.usc.edu/sexual-assault
Free and confidential therapy services, workshops, and training for situations related to gender-based harm.

Office for Equity, Equal Opportunity, and Title IX (EEO-TIX) - (213) 740-5086
eeotix.usc.edu
Information about how to get help or help someone affected by harassment or discrimination, rights of protected classes, reporting options, and additional resources for students, faculty, staff, visitors, and applicants.

Reporting Incidents of Bias or Harassment - (213) 740-5086 or (213) 821-8298
usc-advocate.symplicity.com/care_report
Avenue to report incidents of bias, hate crimes, and microaggressions to the Office for Equity, Equal Opportunity, and Title for appropriate investigation, supportive measures, and response.

The Office of Student Accessibility Services (OSAS) - (213) 740-0776
osas.usc.edu
OSAS ensures equal access for students with disabilities through providing academic accommodations and auxiliary aids in accordance with federal laws and university policy.

USC Campus Support and Intervention - (213) 821-4710
campussupport.usc.edu
Assists students and families in resolving complex personal, financial, and academic issues adversely affecting their success as a student.

Diversity, Equity and Inclusion - (213) 740-2101
diversity.usc.edu
Information on events, programs and training, the Provost's Diversity and Inclusion Council, Diversity Liaisons for each academic school, chronology, participation, and various resources for students.

USC Emergency - UPC: (213) 740-4321, HSC: (323) 442-1000 – 24/7 on call
dps.usc.edu,emergency.usc.edu
Emergency assistance and avenue to report a crime. Latest updates regarding safety, including ways in which instruction will be continued if an officially declared emergency makes travel to campus infeasible.

USC Department of Public Safety - UPC: (213) 740-6000, HSC: (323) 442-120 – 24/7 on call
dps.usc.edu Non-emergency assistance or information.

Office of the Ombuds - (213) 821-9556 (UPC) / (323-442-0382 (HSC)
ombuds.usc.edu
A safe and confidential place to share your USC-related issues with a University Ombuds who will work with you to explore options or paths to manage your concern.

Occupational Therapy Faculty Practice - (323) 442-3340 or otfp@med.usc.edu
chan.usc.edu/otfp
Confidential Lifestyle Redesign services for USC students to support health promoting habits and routines that enhance quality of life and academic performance.