

**Units:** 4

**Instructor:** Mohammad Reza Rajati, PhD  
PHE 412

[rajati@usc.edu](mailto:rajati@usc.edu) – Include INF 352 in subject

**Office Hours:** Wednesday 1:30 pm –3:00 pm

**Webpage:** [Personal Homepage at Intelligent Decision Analysis](#)

**Course Producer:** Zixuan Zhang

[zhangzix@usc.edu](mailto:zhangzix@usc.edu) – Include INF 352 in subject

**Office Hours:** TBD

**Lecture:** Tuesday, Thursday, 4:00 pm –5:50 pm in VKC 200

**Webpages:** [Piazza Class Page](#) for everything except grades  
and [USC Blackboard Class Page](#) for grades  
and [GitHub](#) for code submission

– All HWs, handouts, solutions will be posted in PDF format

**Prerequisite:** INF 250 and MATH 208.

**Other Requirements:** Computer programming skills.  
Using Python is mandatory.  
Students must know Python or must be willing to learn it.

**Tentative Grading:** Programming Assignments (Labs) 35%  
Problem Sets 15%  
Midterm Exam 20%  
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). You may post it anonymously if you wish. Often times, if one student has a question/comment, other also have a similar question/comment. Use e-mail with the professor, TA, graders only for issues that are specific to you individually (e.g., a scheduling issue or grade issue).

**Catalogue Description:** Foundational course focusing on the understanding, application, and evaluation of machine learning and data mining approaches in data intensive scenarios. .

**Course Description:** This is an introductory undergraduate course on Machine Learning and Data Mining with a focus on applications. The primary approach of instruction in this course is *Learning by Doing*. The focus of the course is to provide the students with basic understanding of Machine Learning and Data Mining algorithms and to make them use the algorithms to analyze massive data and convert them into information for decision-making.

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

- Broadly understand major algorithms used in machine learning.
- Understand supervised and unsupervised learning techniques.
- Understand regression methods.
- Understand resampling methods, including cross-validation and bootstrap.
- Understand decision trees, dimensionality reduction, regularization, clustering, and kernel methods.
- Understand feedforward neural networks and deep learning.
- Understand map reduce and its use in mining massive data.
- Understand methods for mining association rules.
- Understand how recommender systems work.

**Exam Dates:**

- **Midterm Exam:** Thursday March 12, 4:000-5:50 PM.
- **Final Exam:** Thursday, May 7, 4:30 PM- 6:30 PM as **set by the university**.

**Textbooks:**

- **Required Textbooks:**

1. Gareth James, Daniela Witten, Trevor Hastie, and Robert Tibshirani, *An Introduction to Statistical Learning with Applications in R*, Springer, 2013. (ISLR)  
Available at <http://faculty.marshall.usc.edu/gareth-james/ISL/ISLR%20Seventh%20Printing.pdf>

2. Jure Leskovec, Anand Rajaraman, and Jeffrey D. Ullman, *Mining Massive Data Sets*, 2<sup>nd</sup> Edition, Cambridge university Press, 2014. (MMDS)  
Available at <http://infolab.stanford.edu/~ullman/mmds/book.pdf>
3. Pang-Ning Tan, Michael Steinbach, Anuj Karpatne, and Vipin Kumar, *Introduction to Data Mining*, 2<sup>nd</sup> Edition, Pearson, 2014. (IDM)

• **Recommended Textbooks:**

1. *Applied Predictive Modeling*, 1<sup>st</sup> Edition  
**Authors:** Max Kuhn and Kjell Johnson; Springer; 2016. **ISBN-13:** 978-1-4614-6848-6
2. *Machine Learning: A Concise Introduction*, 1<sup>st</sup> Edition  
**Author:** Steven W. Knox; Wiley; 2018. **ISBN-13:** 978-1-119-43919-6
3. *The Elements of Statistical Learning: Data Mining, Inference, and Prediction*, 2<sup>nd</sup> Edition  
**Authors:** Trevor Hastie, Robert Tibshirani, and Jerome Friedman; Springer; 2008. (ESL) **ISBN-13:** 978-0387848570
4. *Machine Learning: An Algorithmic Perspective*, 2<sup>nd</sup> Edition  
**Author:** Stephen Marsland; CRC Press; 2014. **ISBN-13:** 978-1-4614-7137-0
5. *Deep Learning*, 1<sup>st</sup> Edition  
**Authors:** Ian Goodfellow, Yoshua Bengio, and Aaron Courville; MIT Press; 2016. (DL) **ISBN-13:** 978-0262035613
6. *Neural Networks and Learning Machines*, 3<sup>rd</sup> Edition  
**Author:** Simon Haykin; Pearson; 2008. **ISBN-13:** 978-0131471399
7. *Neural Networks and Deep Learning: A Textbook*, 1<sup>st</sup> Edition  
**Authors:** Charu Aggrawal; Springer; 2018. **ISBN-13:** 978-3319944623
8. *Introduction to Machine Learning*, 2<sup>nd</sup> Edition  
**Author:** Ethem Alpaydine; MIT Press; 2010. (AL) **ISBN-13:** 978-8120350786
9. *Machine Learning*, 1<sup>st</sup> Edition  
**Author:** Tom M. Mitchell; McGraw-Hill Education; 1997. **ISBN-13:** 978-0070428072

**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 grade in problem sets and your lowest grade in programming assignments (Labs) will be dropped from the final grade. Lab 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**

- Homework is assigned on an approximately weekly basis. A one-day grace period can be used for each homework with 10% penalty. *Absolutely no late homework will be accepted after the grace period. A late assignment results in a zero grade.*
- Homework solutions should be typed or *scanned* using scanners or mobile scanner applications like CamScan and uploaded (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 github as well.
- 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.
- 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 or family emergency, a signed letter from your manager or counselor or physician has to be submitted. This letter must include the contact of your physician or counselor or manager.
- Midterm and final exams will be closed book and notes. Calculators are allowed but computers and cell-phones or any devices that have internet capability are not allowed. One letter size cheat sheet (back and front) is allowed for the midterm. Two letter size cheat sheets (back and front) are allowed for the final.
- All exams are cumulative, with considerable emphasis on material presented since the last exam.

- **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

TUESDAY		THURSDAY	
Jan 14th	1	16th	2
<b>Introduction to Statistical Learning</b> (ISLR Chs.1,2, ESL Chs.1,2) Motivation: Big Data Supervised vs. Unsupervised Learning		<b>Introduction to Statistical Learning</b> (ISLR Chs.1,2, ESL Chs.1,2) Regression, Classification The Regression Function Nearest Neighbors	
21st	3	23rd	4
<b>Introduction to Statistical Learning</b> (ISLR Chs.1,2, ESL Chs.1,2) Model Assessment The Bias-Variance Trade-off No Free Lunch Theorem		<b>Linear Regression</b> (ISLR Ch.3, ESL Ch. 3) Estimating Coefficients Estimating the Accuracy of Coefficients	
28th	5	30th	6
<b>Linear Regression</b> (ISLR Ch.3, ESL Ch. 3) Variable Selection and Hypothesis Testing Multiple Regression Analysis of Variance and the F Test		<b>Linear Regression</b> (ISLR Ch.3, ESL Ch. 3) Stepwise Variable Selection Qualitative Variables	
Feb 4th	7	6th	8
<b>Classification</b> (ISLR Ch. 4, ESL Ch. 4) Multi-class and Multi-label Classification Logistic Regression Class Imbalance Hypothesis Testing and Variable Selection		<b>Classification</b> (ISLR Ch. 4, ESL Ch. 4) Subsampling and Upsampling SMOTE Multinomial Regression	
11th	9	13th	10
<b>Classification</b> (ISLR Ch. 4, ESL Ch. 4) Bayesian Linear Discriminant Analysis		<b>Classification</b> (ISLR Ch. 4, ESL Ch. 4) Measures for Evaluating Classifiers Quadratic Discriminant Analysis* Comparison with K-Nearest Neighbors The Naïve Bayes' Classifier Text Classification Feature Creation for Text Data Handling Missing Data	

TUESDAY		THURSDAY	
18th	11	20th	12
<b>Resampling Methods</b> (ISLR Ch. 5, ESL Ch. 7) Model Assessment Validation Set Approach Cross-Validation The Bias-Variance Trade-off for Cross-Validation Cross-Validation The Bootstrap Bootstrap Confidence Intervals		<b>Linear Model Selection and Regularization</b> (ISLR Ch.6, ESL Ch. 3) Subset Selection AIC, BIC, and Adjusted $R^2$ ) Shrinkage Methods Ridge Regression	
25th	13	27th	14
<b>Linear Model Selection and Regularization</b> (ISLR Ch.6, ESL Ch. 3) The LASSO Elastic Net Dimension Reduction Methods*		<b>Tree-based Methods</b> (ISLR Ch. 8, ESL Chs. 9, 10) Regression and Classification Trees	
Mar 3rd	15	5th	16
<b>Tree-based Methods</b> (ISLR Ch. 8, ESL Chs. 9, 10, 16) Bagging, Random Forests, and Boosting*		<b>Support Vector Machines</b> (ISLR Ch. 9, ESL Ch. 12) Maximal Margin Classifier Support Vector Classifiers	
10th	17	12th	18
<b>Support Vector Machines</b> (ISLR Ch. 9, ESL Ch. 12) The Kernel Trick L1 Regularized SVMs Multi-class and Multilabel Classification The Vapnik-Chervonenkis Dimension* Support Vector Regression		<b>Midterm</b>	
17th		19th	
Spring Recess		Spring Recess	
24th	19	26th	20
<b>Neural Networks and Deep Learning</b> (ESL Ch. 11, DL Ch. 6) The Perceptron Feedforward Neural Networks Feedforward Neural Networks Backpropagation and Gradient Descent Overfitting		<b>Neural Networks and Deep Learning</b> (DL Chs. 6, 7) Regularization Early Stopping and Dropout Convolutional Neural Networks*	

TUESDAY		THURSDAY	
31st <b>Unsupervised Learning</b> (ISLR Ch. 10, ESL Ch. 14) K-Means Clustering Hierarchical Clustering	<b>21</b>	Apr 2nd <b>Unsupervised Learning</b> (ISLR Ch. 10, ESL Ch. 14) Practical Issues in Clustering	<b>22</b>
7th <b>Unsupervised Learning</b> (ISLR Ch. 10, ESL Ch. 14) Principal Component Analysis* Anomaly Detection*	<b>23</b>	9th <b>Active and Semi-Supervised Learning</b> Semi-Supervised Learning Self-Training Co-Training Yarowsky Algorithm Refinements Active vs. Passive Learning Stream-Based vs. Pool-Based Active Learning Query Selection Strategies	<b>24</b>
14th <b>Introduction to Data Mining</b> (MMDS Ch. 1) Motivations Relationship with Machine Learning Summarization Bonferroni Correction	<b>25</b>	16th <b>Map Reduce and New Stack Software</b> (MMDS Ch. 2) Distributed Computing Distributed File Systems Map Reduce for Word Counting	<b>26</b>
21st <b>Frequent Itemsets and Association Rules</b> (MMDS Ch. 6, IDM Ch. 6) The Market-Basket Model Applications Association Rules High-Confidence Rules	<b>27</b>	23rd <b>Frequent Itemsets and Association Rules</b> (MMDS Ch. 6, IDM Ch. 7) Algorithms for Rule-Mining	<b>28</b>
28th <b>Recommendation Systems*</b> (MMDS Ch. 9) Content-Based Recommendation	<b>29</b>	30th <b>Recommendation Systems*</b> (MMDS Ch. 9) Collaborative Filtering	<b>30</b>

**Notes:**

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

**Statement on Academic Integrity:** USC seeks to maintain an optimal learning environment. General principles of academic honesty include the concept of respect for the intellectual property of others, the expectation that individual work will be submitted unless otherwise allowed by an instructor, and the obligations both to protect one's own academic work from misuse by others as well as to avoid using another's work as one's own. All students are expected to understand

and abide by these principles. SCampus, the Student Guidebook, contains the University Student Conduct Code (see University Governance, Section 11.00), while the recommended sanctions are located in Appendix A. See: <http://scampus.usc.edu>.

**Emergency Preparedness/Course Continuity in a Crisis** In case of a declared emergency if travel to campus is not feasible, USC executive leadership will announce an electronic way for instructors to teach students in their residence halls or homes using a combination of Blackboard, teleconferencing, and other technologies. See the university's site on Campus Safety and Emergency Preparedness: <http://preparedness.usc.edu>

**Statement for Students with Disabilities:** Any student requesting academic accommodations based on a disability is required to register with Disability Services and Programs (DSP) each semester. A letter of verification for approved accommodations can be obtained from DSP. Please be sure the letter is delivered to me (or to TA) as early in the semester as possible. DSP is located in STU 301 and is open 8:30 a.m.–5:00 p.m., Monday through Friday. Website: [http://sait.usc.edu/academicssupport/centerprograms/dsp/home\\_index.html](http://sait.usc.edu/academicssupport/centerprograms/dsp/home_index.html)

(213) 740-0776 (Phone), (213) 740-6948 (TDD only), (213) 740-8216 (FAX) [ability@usc.edu](mailto:ability@usc.edu).