CSC 588 Machine Learning Theory

TuTh 9:30am - 10:45am, Gould-Simpson 701

Description of Course

This course provides an introduction to the theoretical aspects of machine learning. Students will learn how and when machine learning is possible/impossible as well as various algorithms with theoretical guarantees under minimal assumptions. Specifically, the course offers formulation of learning environments (e.g., stochastic and adversarial worlds with possibly limited feedback), fundamental limits of learning in these environments, various algorithms concerning sample efficiency, computational efficiency, and generality. Throughout, students will not only learn fundamental tools upholding the current understanding of machine learning systems in the research community but also develop skills of adapting these techniques to their own research needs such as developing new algorithms for large-scale, data-driven applications.

Course Prerequisites

Students must have strong familiarity with:

- Linear Algebra: linear space, basis, dimensions, linear transformations, matrices, eigenvalues and eigenvectors, positive definiteness of a matrix, matrix decompositions such as the SVD

- Multivariate Calculus: total derivative, gradient, linearity of the derivatives, (second-order) Taylor's expansion

- Basic probability theory: elementary events, definitions of probability, discrete and continuous random variables, distribution laws, (conditional) expectation, (conditional) independence, law of large numbers, central limit theorems

- Basic programming: fluency in at least one programming language (e.g. Matlab, Julia, Python, C, C++), using loops, lists, sorting, traversal in trees.

Instructor and Contact Information

Chicheng Zhang, GS 720, chichengz@cs.arizona.edu, https://zcc1307.github.io/

Office Hours: TBD Students are welcome to stop by the instructor's office during office hours, to discuss course-related issues such as homework questions, project ideas, etc.

Course Format and Teaching Methods

Lectures, individual written and programming assignments, scribe note taking assignments, a semester-long group project, in-class discussions.

Obtaining Help

- **Advising:** If you have questions about your academic progress this semester, or your chosen degree program, consider contacting your graduate program coordinator and faculty advisor. Your program coordinator, faculty advisor, and the Graduate Center can guide you toward university resources to help you succeed.**Computer Science students** are encouraged to email gradadvising@cs.arizona.edu for advising related questions.

- **Life challenges:** If you are experiencing unexpected barriers to your success in your courses, please note the Dean of Students Office is a central support resource for all students and may be helpful. The Dean of Students Office can be reached at 520-621-2057 or DOS-deanofstudents@email.arizona.edu.
- **Physical and mental-health challenges**: If you are facing physical or mental health challenges this semester, please note that Campus Health provides quality medical and mental health care. For medical appointments, call (520-621-9202. For After Hours care, call (520) 570-7898. For the Counseling & Psych Services (CAPS) 24/7 hotline, call (520) 621-3334.

Class Recordings

For lecture recordings, which are used at the discretion of the instructor, students must access content in D2L only. Students may not modify content or re-use content for any purpose other than personal educational reasons. All recordings are subject to government and university regulations. Therefore, students accessing unauthorized recordings or using them in a manner inconsistent with UArizona values and educational policies (Code of Academic Integrity and the Student Code of Conduct) are also subject to civil action.

Course Objectives

A successful student will be able to explain the key learning theory concepts and analyze the lower and upper bounds of various machine learning tasks:

- PAC learning model
- VC dimension, Rademacher complexity
- Sample complexity bounds for finite classes and linear functions
- Boosting
- Support vector machine
- PAC-Bayes bounds, stability bounds
- Online classification and mistake bounds
- Online convex optimization, follow the regularized leader, online mirror descent.
- Online-to-batch conversion
- Online learning with limited feedback (bandits)
- Online reinforcement learning

For a more fine-grained description of the learning objectives, see the week-by-week schedule and the description of the assignments below.
This course covers key topics that are both building blocks of advanced machine learning theory and also relevant in modern research. The students can directly adapt learned topics to their own research. Students are expected to dedicate a significant amount of time on understanding mathematical concepts and skills outside the classroom.

Expected Learning Outcomes

The expected learning outcomes of the course are:

- To identify the factors that affect the performance of learning algorithms, including label noise, approximation error, optimization error, generalization error
- To establish the concentration between training and test losses (i.e. going to zero in probability as sample size grows) by uniform convergence theory
- To explain how the complexity/size of the hypothesis class can affect an algorithm's generalization performance.
- To explain overfitting/underfitting in mathematical language, and use the theory of structural risk minimization to perform model selection
- To explain the role of margins in learning theory
- To explain the difference between follow the regularized leader and online mirror descent, and derive basic regret guarantees of the two types of algorithms
- To explain the connections between online optimization and offline optimization
- To derive generalization guarantees for online learning algorithms
- To analyze optimization errors of learning algorithms, such as boosting and SVM
- To use the "optimism in the face of uncertainty" principle to design algorithms with provable guarantees for sequential decision making with uncertainty

Absence and Class Participation Policy

The UA's policy concerning Class Attendance, Participation, and Administrative Drops is available at http://catalog.arizona.edu/policy/class-attendance-participation-and-administrative-drop

The UA policy regarding absences for any sincerely held religious belief, observance or practice will be accommodated where reasonable: http://policy.arizona.edu/human-resources/religious-accommodation-policy.

Absences pre-approved by the UA Dean of Students (or dean's designee) will be honored. See https://deanofstudents.arizona.edu/absences

Students are encouraged to see the Graduate Program Coordinator (GPC) if they have difficulty to obey the class participation and absence policy after the drop period (when a W will not appear on the transcript). The GPC will provide options and alternatives as appropriate for individual student situations.

Participating in the course and attending lectures and other course events are vital to the learning process. As such, attendance is required at all lectures. The instructor reserves the right to check attendance in any lecture, which may factor in the participation scores. Absences may affect a student's final course grade. If you anticipate being absent, are unexpectedly absent, or are unable to participate in class online activities, please contact me as soon as possible. To request a disability-related accommodation to this attendance policy, please contact the Disability Resource Center at (520) 621-3268 or drc-info@email.arizona.edu. If you are experiencing unexpected barriers to your success in your courses, the Dean of Students Office is a central support resource for all students and may be helpful. The Dean of Students Office is located in the Robert L. Nugent Building, room 100, or call 520-621-7057.

Illnesses and Emergencies

- If you feel sick, or may have been in contact with someone who is infectious, stay home. Except for seeking medical care, avoid contact with others and do not travel.
- Notify your instructor(s) if you will be missing up to one week of course meetings and/or

assignment deadlines.

- If you must miss the equivalent of more than one week of class and have an emergency, the Dean of Students is the proper office to contact (DOS-deanofstudents@email.arizona.edu). The Dean of Students considers the following as qualified emergencies: the birth of a child, mental health hospitalization, domestic violence matter, house fire, hospitalization for physical health (concussion/emergency surgery/coma/COVID-19 complications/ICU), death of immediate family, Title IX matters, etc.
- Please understand that there is no guarantee of an extension when you are absent from class and/or miss a deadline.

Statement on compliance with COVID-19 mitigation guidelines: As we enter the Spring semester, your and my health and safety remain the university's highest priority. To protect the health of everyone in this class, students are required to follow the university guidelines on COVID-19 mitigation. Please visit www.covid19.arizona.edu.

Makeup Policy for Students Who Register Late

If you register late for this class, contact me as soon as you do. You will be expected to submit all missed assignments within a week of your registration. It is your responsibility to catch up to the class content.

Course Communications

We will use D2L for communications and discussion.

Required Texts and Materials

There is no designated textbook for this course. Much of the course materials will be based on the following books (in order of appearance in class schedule):

Understanding machine learning: from theory to algorithms by Shai Shalev-Shwartz and Shai Ben-David,
A Modern Introduction to Online Learning by Francesco Orabona,
Bandit algorithms by Tor Lattimore and Csaba Szepesvari,
Reinforcement Learning: Theory and Algorithms by Alekh Agarwal, Nan Jiang, Sham Kakade, and Wen Sun.

Assignments: Schedule/Due Dates

There will be a total of six individual programming/written assignments paced at around one assignment every three weeks, skipping the week for the final presentation. Every homework is due in 2 weeks.

A1: Calibration homework (written + programming)

Students are asked to calculate probabilities, prove basic inequalities and conduct simple numerical simulations using their prerequisite knowledge of calculus, linear algebra, probability and programming.

A2: Concentration of measures, PAC learning, VC theory (written)

Students derive various forms of concentration inequalities and solve sample complexity on a

basic toy problem
Students develop simple algorithms that achieves PAC learning guarantees
Students compute VC dimensions of representative hypothesis classes

A3: Support vector machine, Boosting, Rademacher complexity (written + programming)
Students compute Rademacher complexities of representative function classes, and use it to assess the generalization performance of the learning algorithm
Students implement the AdaBoost algorithm and assess its training and generalization performance

A4: Regularization and stability, Online Convex Optimization (written + programming)

Students conduct basic stability analysis on learning algorithms, and use this to relate the algorithm's training performance to its generalization performance.
Students derive various generic forms of regret bound of the Follow-the-regularized-leader and Online-mirror-descent algorithms, compare their pros and cons, and perform numerical experiments.
Students analyze the performance of Perceptron and Winnow from an online convex optimization perspective.
Students prove regret bounds when the loss function is negative log likelihood of exponential family of distributions. Students discuss how online Newton step works on this case. Students compare it against the online regularized MLE empirically.

A5: Multi-armed bandits and linear bandits (written + programming)

Students implement epsilon-greedy, UCB, and EXP3 and compare their performance and induced variance and the tail distribution.
Students derive a generalized linear model version of OFUL.

Scheduled Topics/Activities

Week	Date	Description
1		
	1/13	Lecture: Introduction, motivation, course mechanics A1: Calibration Homework
2	1/18	Lecture: Basics: concentration of measure Objective: Explain the differences between sub-Gaussian, sub-exponential, light-tailed, heavy-tailed random variables. Derive the concentration inequalities using Markov's inequality / Chebyshev's inequality. Derive sample complexities to bound a random variable by a target constant.

	1/20	Lecture: The statistical learning / PAC learning framework Objectives: explain the key components of statistical learning framework. What is the inductive bias? Derive the generalization bound of finite hypothesis class under realizability assumption. A1 Due
3	1/25	Lecture: VC Theory (1) Objectives: develop the tools needed to guarantee generalization performance when learning from an infinite hypothesis set. Motivate the VC dimension as a notion of capacity of hypothesis classes. Compute the VC dimension for some exemplar hypothesis classes. State Sauer-Shelah lemma.
	1/27	Lecture: VC Theory (2) Objectives: explain the uniform convergence between the training loss and generalization loss, and motivate the issue of overfitting/model selection in machine learning. Prove Sauer-Shelah lemma, and state the uniform convergence theorem of VC classes. A1 graded A2: Concentration of measure, the PAC learning framework, VC Theory
4	2/01	Lecture: Rademacher complexity (1) Objectives: explain the notion of Rademacher complexity, and use this as a tool to prove the uniform convergence result. Give the proof of the uniform convergence theorem.
	2/03	Lecture: Support Vector Machine (1) Objectives: build geometric intuition of classification problems. Motivate the SVM optimization as the maximum margin hyperplane problem. Derive its primal form and dual form. Derive the stochastic gradient descent algorithm.
5	2/08	Lecture: Support Vector Machine (2); kernel methods, margin bounds Objectives: explain why Support Vector Machines has good generalization performance. State margin bounds, and use the Rademacher complexity of ramp loss and the contraction

		inequality to prove it.
	2/10	Lecture: Model Selection: Structural Risk Minimization Objectives: Revisit the model selection problem in machine learning from a theoretical perspective. Show that by structural risk minimization, one can find a classifier that best tradeoffs between expressiveness and generalization. A2 due
6	2/15	Lecture: Boosting (1) Objectives: motivate (distribution-free) weak learning as an important algorithmic primitive to machine learning. State the AdaBoost algorithm, and show that its training error decreases exponentially as a function of the number of iterations.
	2/17	Lecture: Boosting (2) Objectives: explain why AdaBoost has good generalization performance (it improves even if training error drops to zero) using large margin theory. Derive margin bounds for voting classifiers. A2 graded A3: Rademacher complexity, Support vector machines and Boosting
7	2/22	Lecture: Backgrounds on convex functions Objective: give an overview of convexity and how they are useful in machine learning. Definition of convex sets, separating hyperplane theorem, supporting hyperplane theorem, convex functions, subgradients, strong convexity, smoothness, fenchel duality, Fenchel-Young inequality)
	2/24	Lecture: Regularization and stability Objective: show regularization as a tool of controlling the capacity of model class. Show that adding regularization penalty is equivalent to certain constrained loss minimization problems.
8	3/01	Lecture: Regularization and stability Objective: show regularization as a tool of ensuring stability. Show that if an algorithm is stable, then it automatically generalizes. Show that ell_2 regularization over convex loss

		functions implies pointwise stability.
	3/03	Lecture: Online classification Objectives: understand the mistake bound model. Explain the difference between perceptron and winnow and prove the mistake bounds of them. What is Littlestone's dimension? Understand the second order perceptron algorithm, and how it is different from the standard perceptron. A3 due
9	3/08	Spring Recess
	3/10	Spring Recess
10	3/15	Lecture: Online Convex Optimization (OCO): Intro, online gradient descent, online-to-batch conversion Objectives: How does one state the guarantee of an OCO algorithm? Prove the online gradient descent regret bound. What is the fundamental role of the step sizes and what is the best step size? Understand why online-to-batch conversion works. **Project proposal due** A3 graded
	3/17	Lecture: Follow the regularized leader (FTRL) Objectives: Understand the key technique for proving FTRL. What is the key lemma for the proof and why is it important? Prove an adaptive stepsize version of FTRL.
11	3/22	Lecture: Online Mirror Descent (OMD) Objectives: When is OMD equivalent to FTRL? Understand the key difference from FTRL in the regret bound.
	3/24	Lecture: Online Convex Optimization for strongly-convex / exp-concave functions Objectives: Prove regret bounds of online gradient descent for strongly-convex functions. Prove regret bounds of online newton step for exp-concave functions. Understand how it can be instantiated for square loss. Understand the role of step sizes for these algorithms.

		A4: Regularization and stability, Online Convex Optimization
12	3/29	Lecture: Prediction with expert advice (1) Objectives: Understand the case of 0-1 loss and the role for randomization. Understand the Hedge algorithm.
	3/31	Lecture: Prediction with expert advice (2) Objectives: Understand the trick for competing with switching experts (the fixed share algorithm).
13	4/05	Lecture: Stochastic multi-armed bandits (1) Objectives: Understand the principle of "optimism in the face of uncertainty". Prove regret bound of the upper confidence bound algorithm. Prove the regret bound of Thompson sampling. **Project midterm report due**
	4/07	Lecture: Stochastic multi-armed bandits (2) Objectives: Understand the difference between regret minimization and pure exploration. What is the difference between the fixed confidence setting and the fixed budget setting? Prove the guarantees of the successive elimination algorithm and the successive reject algorithm. A4 due
14	4/12	Lecture: Adversarial multi-armed bandits Objectives: Understand the EXP3 algorithm. What is the key trick that overcomes the nature of limited feedback? How is it related to the weighted majority algorithm?
	4/14	Lecture: Stochastic linear bandits (1) Objectives: Understand how the side-information can improve the regret bound. Prove the regret bound of OFUL algorithm. Understand how it can be extended to linear Thompson sampling. A4 graded A5: Multi-armed bandits, linear bandits
15	4/19	Lecture: Stochastic linear bandits (2) Objectives: Understand the proof of self-normalized martingale inequality. Understand the SupLinRel algorithm and the need

		for independent samples.
	4/21	Lecture: Online reinforcement learning in Markov decision processes (1) Objective: understand the Markov decision process model and the meaning of PAC learning in this context. Understand the extra challenges of reinforcement learning compared to bandit problems. Present the UCB-VI algorithm and its intuition.
16	4/26	Lecture: Online reinforcement learning in Markov decision processes (2) Objective: Prove the online regret bound of the UCB-VI algorithm. Understand the simulation lemma and its usage in the proof. A5 due
	4/28	Project presentation I
17	5/03	Project presentation II **Project final report due** A5 graded
18		

Project

The course will have a project component, carried out by each student individually. The project can be of three types:

a. Literature survey. A maximum 4-page literature survey of >=3 papers on a learning theory research topic;
b. Implementation. Implement an algorithm in a recent learning theory paper with theoretical guarantees, and assess if / how the theoretical results align with the empirical results through numerical experiments;
c. Original research. Formulate a new learning theoretic problem and propose a solution

for it, or attack an existing open problem in the learning theory community.

See the course website for more details on the project. Throughout the course, students are highly encouraged to attend office hours of the instructor to discuss their project choice, project progress, etc.

Grading Scale and Policies

The instructing staff will grade your assignments and project on a scale from 0 to 100, with the following weights:

- Assignments: 40%
- Scribe notes: 10%
- Project: 50%
    - 10% proposal
    - 15% midterm progress
    - 10% presentation
    - 15% final report

The final grade in the course is determined by the better of a per-class grading curve and overall performance:

- 90% or better: A;
- 80% or better: B;
- 70% or better: C;
- 60% or better: D;
- below 60%: E.

Students in this class will be asked to take turns preparing scribe notes to be posted on the class website using LaTeX. Please submit your scribe notes in no later than one week of the lecture.

See the "scheduled topics / activities" section for the timeline and due dates of the assignments and project. Every homework is due in about 2 weeks, and will be returned to students before the next homework is due. Grading delays beyond promised return-by dates will be announced as soon as possible with an explanation for the delay.

As a general rule, each late day for homework submission will result in a deduction of 20% of the grade of the corresponding assignment (e.g., if a student submits their homework solution 3 days after the due date, and it gets a score of 12 (out of 15 points), the submission will receive (100%-3*20%) * 12 = 4.8 points (out of 15 points). Lateness is counted starting from the due time of the homework (e.g., if a homework is due on Sep 10 at 2pm, then submitting it on Sep 10 at 3pm counts as one late day.)

Department of Computer Science Grading Policy:

1. Instructors will explicitly promise when every assignment and exam will be graded and returned to students. These promised dates will appear in the syllabus, associated with the corresponding due dates and exam dates.
2. Graded homework will be returned before the next homework is due.
3. Exams will be returned "promptly", as defined by the instructor (and as promised in the syllabus).
4. Grading delays beyond promised return-by dates will be announced as soon as possible with an explanation for the delay.

Incomplete (I) or Withdrawal (W):

Requests for incomplete (I) or withdrawal (W) must be made in accordance with University policies, which are available at http://catalog.arizona.edu/policy/grades-and-grading-system#incomplete and http://catalog.arizona.edu/policy/grades-and-grading-system#Withdrawal respectively.

Dispute of Grade Policy: If you wish to dispute your grade for an assignment or project, you have two weeks after the grade has been turned in. In addition, even if only you dispute one portion of the grading for that unit, I reserve the right to revisit the entire unit (assignment or project).

Department of Computer Science Code of Conduct

The Department of Computer Science is committed to providing and maintaining a supportive educational environment for all. We strive to be welcoming and inclusive, respect privacy and confidentiality, behave respectfully and courteously, and practice intellectual honesty. Disruptive behaviors (such as physical or emotional harassment, dismissive attitudes, and abuse of department resources) will not be tolerated. The complete Code of Conduct is available on our department web site. We expect that you will adhere to this code, as well as the UA Student Code of Conduct, while you are a member of this class.

Classroom Behavior Policy

To foster a positive learning environment, students and instructors have a shared responsibility. We want a safe, welcoming, and inclusive environment where all of us feel comfortable with each other and where we can challenge ourselves to succeed. To that end, our focus is on the tasks at hand and not on extraneous activities (e.g., texting, chatting, reading a newspaper, making phone calls, web surfing, etc.).

Students are asked to refrain from disruptive conversations with people sitting around them during lecture. Students observed engaging in disruptive activity will be asked to cease this behavior. Those who continue to disrupt the class will be asked to leave lecture or discussion and may be reported to the Dean of Students.

Some learning styles are best served by using personal electronics, such as laptops and iPads. These devices can be distracting to other learners. Therefore, students who prefer to use electronic devices for note-taking during lecture should use one side of the classroom.

Threatening Behavior Policy

The UA Threatening Behavior by Students Policy prohibits threats of physical harm to any member of the University community, including to oneself. See http://policy.arizona.edu/education-and-student-affairs/threatening-behavior-students.

Notification of Objectionable Materials

This course will contain material of a mature nature, which may include explicit language, depictions of nudity, sexual situations, and/or violence. The instructor will provide advance notice when such materials will be used. Students are not automatically excused from interacting with such materials, but they are encouraged to speak with the instructor to voice concerns and to provide feedback.

Accessibility and Accommodations

At the University of Arizona, we strive to make learning experiences as accessible as possible. If you anticipate or experience barriers based on disability or pregnancy, please contact the Disability Resource Center (520-621-3268, https://drc.arizona.edu/) to establish reasonable accommodations.

Code of Academic Integrity

Students are encouraged to share intellectual views and discuss freely the principles and applications of course materials. However, graded work/exercises must be the product of independent effort unless otherwise instructed. Students are expected to adhere to the UA Code of Academic Integrity as described in the UA General Catalog. See http://deanofstudents.arizona.edu/academic-integrity/students/academic-integrity.

Uploading material from this course to a website other than D2L (or the class piazza) is strictly prohibited and will be considered a violation of the course policy and a violation of the code of academic integrity. Obtaining material associated with this course (or previous offerings of this course) on a site other than D2L (or the class piazza), such as Chegg, Course Hero, etc. or accessing these sites during a quiz or exam is a violation of the code of academic integrity. Any student determined to have uploaded or accessed material in an unauthorized manner will be reported to the Dean of Students for a Code of Academic Integrity violation, with a recommended sanction of a failing grade in the course.

The University Libraries have some excellent tips for avoiding plagiarism, available at https://new.library.arizona.edu/research/citing/plagiarism.

Selling class notes and/or other course materials to other students or to a third party for resale is not permitted without the instructor's express written consent. Violations to this and other course rules are subject to the Code of Academic Integrity and may result in course sanctions. Additionally, students who use D2L or UA e-mail to sell or buy these copyrighted materials are subject to Code of Conduct Violations for misuse of student e-mail addresses. This conduct may also constitute copyright infringement.

Nondiscrimination and Anti-harassment Policy

The University of Arizona is committed to creating and maintaining an environment free of discrimination. In support of this commitment, the University prohibits discrimination, including harassment and retaliation, based on a protected classification, including race, color, religion, sex, national origin, age, disability, veteran status, sexual orientation, gender identity, or genetic information. For more information, including how to report a concern, please see http://policy.arizona.edu/human-resources/nondiscrimination-and-anti-harassment-policy

Our classroom is a place where everyone is encouraged to express well-formed opinions and their reasons for those opinions. We also want to create a tolerant and open environment where such opinions can be expressed without resorting to bullying or discrimination of others.

Additional Resources for Students

UA Academic policies and procedures are available at http://catalog.arizona.edu/policies

Visit the UArizona COVID-19 page for regular updates.

Campus Health
http://www.health.arizona.edu/
Campus Health provides quality medical and mental health care services through virtual and in-person care. Voluntary, free, and convenient COVID-19 testing is available for students on Main Campus. COVID-19 vaccine is available for all students at Campus Health.
Phone: 520-621-9202

Counseling and Psych Services (CAPS)
https://health.arizona.edu/counseling-psych-services
CAPS provides mental health care, including short-term counseling services.
Phone: 520-621-3334

The Dean of Students Office's Student Assistance Program
http://deanofstudents.arizona.edu/student-assistance/students/student-assistance

Student Assistance helps students manage crises, life traumas, and other barriers that impede success. The staff addresses the needs of students who experience issues related to social adjustment, academic challenges, psychological health, physical health, victimization, and relationship issues, through a variety of interventions, referrals, and follow up services.
Email: DOS-deanofstudents@email.arizona.edu
Phone: 520-621-7057

Survivor Advocacy Program
https://survivoradvocacy.arizona.edu/
The Survivor Advocacy Program provides confidential support and advocacy services to student survivors of sexual and gender-based violence. The Program can also advise students about relevant non-UA resources available within the local community for support.
Email: survivoradvocacy@email.arizona.edu
Phone: 520-621-5767

Campus Pantry

Any student who has difficulty affording groceries or accessing sufficient food to eat every day, or who lacks a safe and stable place to live and believes this may affect their performance in the course, is urged to contact the Dean of Students for support. In addition, the University of Arizona Campus Pantry is open for students to receive supplemental groceries at no cost. Please see their website at: *campuspantry.arizona.edu* for open times.

Furthermore, please notify me if you are comfortable in doing so. This will enable me to provide any resources that I may possess.

Preferred Gender Pronoun

This course affirms people of all gender expressions and gender identities. If you prefer to be called a different name than what is on the class roster, please let me know. Feel free to correct instructors on your preferred gender pronoun. If you have any questions or concerns, please do not hesitate to contact me directly in class or via email (instructor email). If you wish to change your preferred name or pronoun in the UAccess system, please use the following guidelines:

Preferred name: University of Arizona students may choose to identify themselves within the University community using a preferred first name that differs from their official/legal name. A student's preferred name will appear instead of the person's official/legal first name in select University-related systems and documents, provided that the name is not being used for the purpose of misrepresentation. Students are able to update their preferred names in UAccess.

Pronouns: Students may designate pronouns they use to identify themselves. Instructors and staff are encouraged to use pronouns for people that they use for themselves as a sign of respect and inclusion. Students are able to update and edit their pronouns in UAccess.

More information on updating your preferred name and pronouns is available on the Office of the Registrar site at https://www.registrar.arizona.edu/.

Safety on Campus and in the Classroom

Familiarize yourself with the UA Critical Incident Response Team plans: https://cirt.arizona.edu/

Department of Computer Science Evacuation Plan for Gould-Simpson:
https://drive.google.com/file/d/1iR1IcGcV_BgbGnEFBzZ2-do0FbLC3cvo/view?usp=sharing

Also watch the video available at
https://ua-saem-aiss.narrasys.com/#/story/university-of-arizona-cert/active-shooter

Confidentiality of Student Records

http://www.registrar.arizona.edu/personal-information/family-educational-rights-and-privacy-act-1974-ferpa?topic=ferpa

Land Acknowledgement Statement

We respectfully acknowledge the University of Arizona is on the land and territories of Indigenous peoples. Today, Arizona is home to 22 federally recognized tribes, with Tucson being home to the O'odham and the Yaqui. Committed to diversity and inclusion, the University strives to build sustainable relationships with sovereign Native Nations and Indigenous communities through education offerings, partnerships, and community service.

Subject to Change Statement

Information contained in the course syllabus, other than the grade and absence policy, may be subject to change with advance notice, as deemed appropriate by the instructor.