

WWU DATA 571 (Machine Learning) Syllabus

Fall 2026

Last modified: 2026-10-28

Note

This is the Fall 2026 syllabus. Items marked **TBD** (to be determined) have not been set yet. The syllabus is subject to change; I will announce in class any change made after the first day of class.

Course Information

Number DATA 571¹

Name Machine Learning

Website *Machine Learning for Data Science* (lds)²

Term Fall 2026

Credits 4

Time Monday, Tuesday, Wednesday, and Friday, 12–1pm

Place Kaiser Borsari Hall 311

Office hours Monday, Wednesday, and Thursday, 4–5pm, in my office (CF 463) unless otherwise noted

Prerequisites Graduate status; MATH 204 (Elementary Linear Algebra)³ and MATH 341 (Probability and Statistical Inference)⁴; or instructor permission. MATH 224 (Multivariable Calculus and Geometry I)⁵ is recommended. The mathematics, probability, and statistics prerequisites are covered in the lab's open notes: *Math for Data Science* (mds)⁶, *Probability for Data Science* (pds)⁷, and *Statistics for Data Science* (sds)⁸.

CRNs (course reference numbers) TBD

Contact Information

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All other course correspondence goes through Canvas; see [Communication](#).

Course Description

Key machine learning theory, algorithms and experimentation techniques. Generalization, bias and variance. Classification, regression, and clustering. Linear models and nonlinear models, including neural networks.

¹https://catalog.wwu.edu/preview_course_nopop.php?catoid=23&coid=166998

²<https://morrison-lab.github.io/lds/>

³<https://morrison-lab.github.io/swc/course/MATH-204.html>

⁴<https://morrison-lab.github.io/swc/course/MATH-341.html>

⁵<https://morrison-lab.github.io/swc/course/MATH-224.html>

⁶<https://morrison-lab.github.io/mds/>

⁷<https://morrison-lab.github.io/pds/>

⁸<https://morrison-lab.github.io/sds/>

⁹<mailto:ezra.morrison@wwu.edu>

Ethical issues in machine learning.

Course Outcomes

On completion of DATA 571, students will demonstrate:

- A thorough understanding of classification, regression and clustering.
- An understanding of machine learning theory affecting model generalization.
- An understanding of key performance metrics.
- An understanding of ethical issues in machine learning.
- The ability to implement standard machine learning algorithms.
- The ability to conduct machine learning experiments, including training and tuning models, as well as evaluating and comparing model performance.
- A thorough understanding of one advanced topic in machine learning.
- An ability to write using the stylistic conventions of the machine learning subfield.

Textbooks and readings

There are no required textbooks for the course, but several books and notes are recommended:

- *Machine Learning for Data Science* (lds)¹⁰, the course notes for DATA 571.
- The lab's companion prerequisite notes:
 - *Math for Data Science* (mds), covering linear algebra, calculus, and vector calculus, available at <https://morrison-lab.github.io/mds/>.
 - *Probability for Data Science* (pds), covering probability theory, random variables, and distributions, available at <https://morrison-lab.github.io/pds/>.
 - *Statistics for Data Science* (sds), covering estimation, hypothesis testing, and inference, available at <https://morrison-lab.github.io/sds/>.
- *The Elements of Statistical Learning* (2nd ed.) [1], ISBN 0387848576. A PDF can be downloaded at no cost from the authors' webpage¹¹.
- *An Introduction to Statistical Learning* (2nd ed.) [2]. A PDF can be downloaded at no cost from the authors' webpage¹². The authors' video course using R is *Statistical Learning with R*¹³. The 2023 Python edition, *An Introduction to Statistical Learning with Applications in Python* (which adds Jonathan Taylor to James, Witten, Hastie, and Tibshirani), has its own course, *Statistical Learning with Python*¹⁴; its Python lab sessions are also collected on their own, as ISLP Python Labs¹⁵. The Data Science Learning Community¹⁶ has recorded book clubs that read the book chapter by chapter:
 - the R edition¹⁷ [3];
 - the Python edition¹⁸ [4].
- *Tidy Modeling with R*, by Max Kuhn and Julia Silge, teaches the tidymodels framework that the R code in this course's labs uses. It can be read at no cost at tmwr.org¹⁹. The Data Science Learning Community's book club recordings²⁰ [5] go through it chapter by chapter.
- *Deep Learning* [6]. The book can be viewed at no cost from the book's webpage²¹. For video lectures on deep learning, see Stanford's CS230, *Deep Learning*²² (Autumn 2025).
- *Pattern Classification* (2nd ed.) [7], ISBN 0471056693.
- *Machine Learning: A Probabilistic Perspective* [8], ISBN 0262018020.

¹⁰<https://morrison-lab.github.io/lds/>

¹¹<https://hastie.su.domains/ElemStatLearn/>

¹²<https://www.statlearning.com/>

¹³https://www.youtube.com/playlist?list=PLoROMvody4rOzrYsAxzQyHb8n_RWNuS1e

¹⁴<https://www.youtube.com/playlist?list=PLoROMvody4rPP6braWoRt5UCXYZ71GZIQ>

¹⁵<https://www.youtube.com/playlist?list=PLoROMvody4rNHU1-iPeDRH-J0cL-CrIda>

¹⁶<https://www.youtube.com/@dslcvids>

¹⁷<https://www.youtube.com/playlist?list=PL3x6DOfs2NGjlpKMiWsDcKL2nngwXROq>

¹⁸<https://www.youtube.com/playlist?list=PL3x6DOfs2NGgBSNh0UG87rrM-z5LiKLZp>

¹⁹<https://tmwr.org>

²⁰<https://www.youtube.com/playlist?list=PL3x6DOfs2NGgSt6vIGQWtLwZXS2Q7WZIE>

²¹<https://www.deeplearningbook.org/>

²²<https://www.youtube.com/playlist?list=PLoROMvody4rNRRGdS0rBbXOUGA0wjdh1X>

- *Probabilistic Machine Learning: An Introduction* [9], ISBN 9780262046824 and its sequel, *Probabilistic Machine Learning: Advanced Topics* [10], ISBN 9780262048439. Murphy rewrote his 2012 book as these two volumes, with the first covering foundations, classical methods and deep learning at the level of this course. The author offers free PDFs of both on the books' webpage²³.
- *A Course in Machine Learning* [11], a short first course in the subject. It can be read at no cost at ciml.info²⁴.
- *Pattern Recognition and Machine Learning* [12], ISBN 0387310738. The book can be viewed at no cost via the author²⁵.
- *Deep Learning: Foundations and Concepts* [13], ISBN 9783031454677, by Christopher Bishop and Hugh Bishop. A version to read online is free on the book's webpage²⁶.
- *Machine Learning* [14], ISBN 0070428077, a single-source introduction to the field. A PDF can be downloaded at no cost from the author's webpage²⁷.
- *Mathematics for Machine Learning* [15], on the mathematical foundations of the field: linear algebra, vector calculus, probability and optimization. The authors keep a PDF available at no cost on the book's webpage²⁸.
- *Patterns, Predictions, and Actions: Foundations of Machine Learning* [16]. The authors offer a PDF at no cost on the book's webpage²⁹.
- *Understanding Machine Learning: From Theory to Algorithms* [17], published by Cambridge University Press³⁰.
- *Foundations of Machine Learning* (2nd ed.) [18]. The book can be downloaded at no cost, as a PDF or in HTML, from the first author's webpage³¹.
- *Data Science and Machine Learning: Mathematical and Statistical Methods* [19], ISBN 9781138492530. The authors offer a PDF of the first edition free for educational use from the book's webpage³².
- *Hands-On Machine Learning with Scikit-Learn and TensorFlow* [20], ISBN 9781491962299.
- *Machine Learning with PyTorch and Scikit-Learn* [21], ISBN 9781801819312. Code examples and Jupyter notebooks are available from the book's GitHub repository³³.
- *Applied Machine Learning Using mlr3 in R* [22], ISBN 9781032507545. It teaches the practical workflow in R — fitting and evaluating models, tuning hyperparameters, and building pipelines — with the `mlr3` packages, and can be read at no cost on the book's webpage³⁴.
- *Learning From Data: A Short Course* [23]. More information is available from the book's webpage³⁵.
- The lecture notes for Stanford's CS229, *Machine Learning* [24], available at no cost from the course webpage³⁶. The course's lectures are on YouTube, both the Spring 2026 offering³⁷ and Andrew Ng's Autumn 2018 offering³⁸.
- For an optimization reference: *Convex Optimization* [25], ISBN 0521833787, available at no cost from the authors' website³⁹.

The class will not follow one book closely; use these books and notes as references.

Similar Courses

Other universities teach courses much like this one, and many post their materials at no cost. They are a good place to see a topic explained a second way. Each table starts with the courses that have both recorded

²³<https://probml.github.io/pml-book/>

²⁴<http://ciml.info/>

²⁵<https://www.microsoft.com/en-us/research/publication/pattern-recognition-machine-learning/>

²⁶<https://www.bishopbook.com/>

²⁷<https://www.cs.cmu.edu/~tom/mlbook.html>

²⁸<https://mml-book.com/>

²⁹<https://mlstory.org/>

³⁰<https://www.cambridge.org/core/books/understanding-machine-learning/3059695661405D25673058E43C8BE2A6>

³¹<https://cs.nyu.edu/~mohri/mlbook/>

³²<https://people.smp.uq.edu.au/DirkKroese/DSML/>

³³<https://github.com/rasbt/machine-learning-book>

³⁴<https://mlr3book.mlr-org.com/>

³⁵<https://amlbook.com/>

³⁶<https://cs229.stanford.edu/>

³⁷<https://www.youtube.com/playlist?list=PLaqpC4kq8Gpw>

³⁸<https://www.youtube.com/playlist?list=PLoROMvody4rMiGQp3WXShtMGgzqpfVfbU>

³⁹<https://web.stanford.edu/~boyd/cvxbook/>

lectures and written material, such as notes, slides or problem sets, and then lists the ones that have only one of the two. A dash means none is listed here.

Courses like this one

```
course_table("courses-like-this-one")
```

Course	Recorded lectures	Written material
Stanford's CS229, <i>Machine Learning</i>	Spring 2026 ⁴⁰ ; Andrew Ng ⁴¹ 's Autumn 2018 ⁴²	Lecture notes [24]
Stanford's <i>Statistical Learning</i> , taught by Hastie ⁴³ and Tibshirani ⁴⁴	R edition ⁴⁵ ; Python edition ⁴⁶ ; Python labs ⁴⁷	Its textbook, <i>An Introduction to Statistical Learning</i> [2], [26]; lab notebooks ⁴⁸
Stanford's EE104, <i>Introduction to Machine Learning</i> , taught by Lall ⁴⁹	YouTube ⁵⁰	A complete set of lecture notes ⁵¹
MIT's 6.036, <i>Introduction to Machine Learning</i> (Spring 2019) ⁵²	Open Learning Library ⁵⁵	Lecture notes, exercises, labs and homework ⁵⁶
Caltech's CS156, <i>Learning From Data</i> , taught by Abu-Mostafa ⁵⁷ from his book [23]	18 lectures ⁵⁸ , also on YouTube ⁵⁹	Slides ⁶⁰
The University of British Columbia's CPSC 340, <i>Machine Learning and Data Mining</i>	Gelbart's 2018 lectures ⁶¹	Schmidt's slides, 100 Lectures on Machine Learning ⁶²
Harvard's CS 1810 (formerly CS 181), <i>Machine Learning</i> (2026), taught by Alvarez-Melis ⁶³ and Du ⁶⁴	—	Syllabus ⁶⁵ ; free textbook of notes, <i>Undergraduate Fundamentals of Machine Learning</i> ⁶⁶ ; earlier years ⁶⁷ , including a recap of almost every lecture in 2022 ⁶⁸

⁴⁰<https://www.youtube.com/playlist?list=PLaqPC4kq8Gpw>

⁴¹<https://profiles.stanford.edu/andrew-ng>

⁴²<https://www.youtube.com/playlist?list=PLoROMvodv4rMiGQp3WXShMGzqpfVfbU>

⁴³<https://profiles.stanford.edu/trevor-hastie>

⁴⁴<https://profiles.stanford.edu/robert-tibshirani>

⁴⁵https://www.youtube.com/playlist?list=PLoROMvodv4rOzrYsAxzQyHb8n_RWNuS1e

⁴⁶<https://www.youtube.com/playlist?list=PLoROMvodv4rPP6braWoRt5UCXYZ71GZIQ>

⁴⁷<https://www.youtube.com/playlist?list=PLoROMvodv4rNHU1-iPeDRH-J0cL-CrIda>

⁴⁸https://github.com/intro-stat-learning/ISLP_labs

⁴⁹<https://lall.stanford.edu/>

⁵⁰https://www.youtube.com/playlist?list=PLoROMvodv4rN_Uy7_wmS051_q1d6akXmK

⁵¹<https://ee104.stanford.edu/>

⁵²Its materials are all usable without enrolling. The course is now numbered 6.390; its current webpage⁵³ has course notes⁵⁴ and lecture slides, and its recordings are open only to registered students.

⁵³<https://openlearninglibrary.mit.edu/courses/course-v1:MITx+6.036+1T2019/about>

⁵⁴<https://openlearninglibrary.mit.edu/courses/course-v1:MITx+6.036+1T2019/about>

⁵⁷<https://www.cms.caltech.edu/people/yaser>

⁵⁸<https://work.caltech.edu/telecourse>

⁵⁹<https://www.youtube.com/playlist?list=PLD63A284B7615313A>

⁶⁰<https://work.caltech.edu/telecourse>

⁶¹https://www.youtube.com/playlist?list=PLWmXHcz_53Q02ZLeAxigkiIJZFfCO6M-b

⁶²<https://www.cs.ubc.ca/~schmidtm/Courses/LecturesOnML/>

⁶³<https://dmelis.github.io/>

⁶⁴<https://yilundu.github.io/>

⁶⁵<https://harvard-ml-courses.github.io/cs181-web/>

⁶⁶<https://github.com/harvard-ml-courses/cs181-textbook/blob/master/Textbook.pdf>

⁶⁷<https://harvard-ml-courses.github.io/cs181-web/resources>

⁶⁸<https://harvard-ml-courses.github.io/cs181-web-2022/>

Course	Recorded lectures	Written material
Harvard's CS 109A, <i>Introduction to Data Science</i> (Fall 2021), taught by Protopapas and Pillai	—	A page for each lecture ⁶⁹ , most with slides, and the exercise notebooks
MIT's 6.867, <i>Machine Learning</i> (Fall 2006), a graduate course taught by Jaakkola ⁷⁰ , Singh and Mohammad	—	Lecture notes ⁷¹ for most lectures; assignments and exams on MIT OpenCourseWare ⁷²
The University of Washington's CSE 446/546, <i>Machine Learning</i> (Spring 2026), taught by Jaques ⁷³	—	Lecture slides ⁷⁴ [27], a textbooks page ⁷⁵ of free references and math refreshers, and the site of every earlier CSE 546 offering ⁷⁶
The University of Washington's CSE/STAT 416, <i>Introduction to Machine Learning</i> (Summer 2020), taught by Swamy	—	Lecture slides and Colab notebooks ⁷⁷ on regression, regularization, classification, clustering and neural networks
The University of Washington's STAT 535, <i>Foundations of Machine Learning</i> (Autumn 2021), taught by Meila ⁷⁸	—	Handouts ⁷⁹ on bias and variance, gradient descent, model selection, support vector machines and double descent; the follow-on STAT 548 handouts ⁸⁰ (Winter 2022) go further into theory
The University of Washington's CSE 312, <i>Foundations of Computing II</i> (Summer 2020), taught by Tsun	5MinuteAI's playlist ⁸¹ follows the course [28]	Materials and videos ⁸² on probability and statistics for computing
The University of Washington's CSE 547, <i>Machine Learning for Big Data</i>	—	A page for each offering ⁸³ , covering regularized linear models, matrix factorization, clustering, and sketching and hashing at scale
Stanford's STATS 202, <i>Data Mining and Analysis</i>	—	A full set of course notes ⁸⁴
Stanford's MS&E 226, <i>Fundamentals of Data Science</i>	—	Lecture notes ⁸⁵ with R Markdown notebooks
Stanford's CME 250, <i>Introduction to Machine Learning</i> , a short course	—	Slides ⁸⁶

⁶⁹<https://harvard-iacs.github.io/2021-CS109A/pages/materials.html>

⁷⁰<https://people.csail.mit.edu/tommi/>

⁷¹<https://ocw.mit.edu/courses/6-867-machine-learning-fall-2006/pages/lecture-notes/>

⁷²<https://ocw.mit.edu/courses/6-867-machine-learning-fall-2006/>

⁷³<https://courses.cs.washington.edu/courses/cse446/26sp/>

⁷⁴<https://courses.cs.washington.edu/courses/cse446/26sp/schedule/lectures/>

⁷⁵<https://courses.cs.washington.edu/courses/cse446/26sp/textbooks/>

⁷⁶<https://courses.cs.washington.edu/courses/cse546/>

⁷⁷<https://courses.cs.washington.edu/courses/cse416/20su/>

⁷⁸<https://sites.stat.washington.edu/mmp/>

⁷⁹<https://sites.stat.washington.edu/mmp/courses/535/fall21/handouts.html>

⁸⁰<https://sites.stat.washington.edu/mmp/courses/548/win22/handouts.html>

⁸¹<https://www.youtube.com/playlist?list=PLB45KifGiuHesi4PALNZSYZFhViVGQJK>

⁸²<https://courses.cs.washington.edu/courses/cse312/20su/>

⁸³<https://courses.cs.washington.edu/courses/cse547/>

⁸⁴<https://web.stanford.edu/class/stats202/>

⁸⁵https://web.stanford.edu/class/msande226/l_notes.html

⁸⁶<https://web.stanford.edu/class/cme250/>

Course	Recorded lectures	Written material
Stanford's CS129, <i>Applied Machine Learning</i>	None open to the public ⁸⁷	Handouts for each lecture ⁸⁸
The University of Edinburgh's <i>Machine Learning and Pattern Recognition</i> (MLPR)	—	Course notes ⁸⁹
Carnegie Mellon's 10-301/10-601, <i>Introduction to Machine Learning</i> (Spring 2026), taught by Virtue ⁹⁰ and Gormley ⁹¹	—	Slides ⁹²
NYU's DS-GA 1003, <i>Machine Learning</i> (Spring 2019), taught by Rosenberg	—	Slides ⁹³
UCLA's Biostat 212A, <i>Statistical Machine Learning A</i> , taught by Jin Zhou [29] ⁹⁴	—	Syllabus ⁹⁵ ; a slide deck for each topic ⁹⁶ , many with code in both R and Python; the decks' Quarto sources ⁹⁷
Cornell's CS4780, <i>Machine Learning for Intelligent Systems</i>	Weinberger ⁹⁸ 's lectures ⁹⁹ ; the course webpage ¹⁰⁰ is for the Spring 2024 offering	—
The University of Tübingen's <i>Statistical Machine Learning</i> (2020), taught by von Luxburg	YouTube ¹⁰¹ , in English	—
UC Berkeley's Stat 154, <i>Modern Statistical Prediction and Machine Learning</i> , taught by Sanchez (site ¹⁰² , GitHub ¹⁰³)	—	Course repository ¹⁰⁴ , and the primary textbook, Sanchez and Marzban's <i>All Models Are Wrong: Concepts of Statistical Learning</i> ¹⁰⁵ , a work in progress; neither states a license, so ask the authors before adapting

For hands-on practice with scikit-learn, Inria's scikit-learn MOOC¹⁰⁶ has notebooks and exercises that are free to use.

⁸⁷CS129's lecture videos are on Coursera, in a session open only to students enrolled in the course.

⁸⁸<https://web.stanford.edu/class/cs129/>

⁸⁹<https://mlpr.inf.ed.ac.uk/2024/>

⁹⁰<https://www.cs.cmu.edu/~pvirtue/>

⁹¹<https://www.cs.cmu.edu/~mgormley/>

⁹²<https://www.cs.cmu.edu/~mgormley/courses/10601/>

⁹³<https://davidrosenberg.github.io/ml2019/>

⁹⁴Biostat 212A uses the same *An Introduction to Statistical Learning* and *The Elements of Statistical Learning* texts as this course.

⁹⁵<https://ucla-biostat-212a.github.io/2026winter/syllabus/syllabus.html>

⁹⁶<https://ucla-biostat-212a.github.io/2026winter/schedule/schedule.html>

⁹⁷<https://github.com/ucla-biostat-212a>

⁹⁸<https://www.cs.cornell.edu/~kilian/>

⁹⁹<https://www.youtube.com/playlist?list=PLl8OIHZGYOQ7bkVbuRthEsaLr7bONzbXS>

¹⁰⁰<https://www.cs.cornell.edu/courses/cs4780/2024sp/>

¹⁰¹<https://www.youtube.com/playlist?list=PL05umP7R6ij2XCvrRzLokX6EoHWaGA2cC>

¹⁰²<https://www.gastonsanchez.com>

¹⁰³<https://github.com/gastonstat>

¹⁰⁴<https://github.com/gastonstat/stat154>

¹⁰⁵<https://allmodelsarewrong.github.io/>

⁵³<https://introml.mit.edu/>

⁵⁴<https://introml.mit.edu/notes/>

¹⁰⁶<https://github.com/INRIA/scikit-learn-mooc>

Related topics

These courses cover the math this course builds on, or topics that go further than it does.

```
course_table("related-topics")
```

Course	Recorded lectures	Written material
Stanford's CS109, <i>Probability for Computer Scientists</i> , taught by Piech	2022 lectures ¹⁰⁷	A course reader and the slides ¹⁰⁸
Stanford's EE263, <i>Matrix Methods</i> , on least squares and the singular value decomposition	Boyd ¹⁰⁹ 's 2008 lectures ¹¹⁰ , from when it was <i>Introduction to Linear Dynamical Systems</i>	Slides ¹¹¹
MIT's 18.065, <i>Matrix Methods in Data Analysis, Signal Processing, and Machine Learning</i> (Spring 2018), taught by Strang ¹¹²	YouTube ¹¹³	A reading list ¹¹⁴ keyed to his book <i>Linear Algebra and Learning from Data</i>
MIT's 18.06, <i>Linear Algebra</i> , taught by Strang ¹¹⁵	His lectures, recorded in 1999, on MIT OpenCourseWare ¹¹⁶	Assignments and exams, on the Spring 2010 course page ¹¹⁷
Stanford's EE364A, <i>Convex Optimization I</i> , taught by Boyd ¹¹⁸ from his book [25]	2023 lectures ¹¹⁹	Slides ¹²⁰
Stanford's CS224N, <i>Natural Language Processing with Deep Learning</i>	Spring 2024 lectures ¹²¹	Slides and notes ¹²²

¹⁰⁷https://www.youtube.com/playlist?list=PLoROMvodv4rOpr_A7B9SriE_iZmkanvUg

¹⁰⁸<https://web.stanford.edu/class/cs109/>

¹⁰⁹<https://web.stanford.edu/~boyd/>

¹¹⁰<https://www.youtube.com/playlist?list=PL06960BA52D0DB32B>

¹¹¹<https://ee263.stanford.edu/>

¹¹²<https://math.mit.edu/~gs/>

¹¹³<https://www.youtube.com/playlist?list=PLU14u3cNGP63oMNUHXqIUcrkS2PivhN3k>

¹¹⁴<https://ocw.mit.edu/courses/18-065-matrix-methods-in-data-analysis-signal-processing-and-machine-learning-spring-2018/>

¹¹⁵<https://math.mit.edu/~gs/>

¹¹⁶<https://ocw.mit.edu/courses/18-06-linear-algebra-spring-2010/>

¹¹⁷<https://ocw.mit.edu/courses/18-06-linear-algebra-spring-2010/>

¹¹⁸<https://web.stanford.edu/~boyd/>

¹¹⁹<https://www.youtube.com/playlist?list=PLoROMvodv4rMJqxxviPa4AmDCIvcbHi6h>

¹²⁰<https://web.stanford.edu/class/ee364a/>

¹²¹<https://www.youtube.com/playlist?list=PLoROMvodv4rOaMFbaqxPD0LWjDaRApP9D>

¹²²<https://web.stanford.edu/class/cs224n/>

Course	Recorded lectures	Written material
Stanford's CS231N, <i>Deep Learning for Computer Vision</i>	2025 lectures ¹²³	Slides and links to the course notes ¹²⁴
Stanford's CS224W, <i>Machine Learning with Graphs</i>	YouTube ¹²⁵	Slides ¹²⁶
Stanford's CS236, <i>Deep Generative Models</i>	2023 lectures ¹²⁷	Course notes ¹²⁸
Stanford's CS234, <i>Reinforcement Learning</i>	Spring 2024 lectures ¹²⁹	Slides ¹³⁰
Stanford's CS224R, <i>Deep Reinforcement Learning</i>	YouTube ¹³¹	Slides ¹³²
Stanford's CS330, <i>Deep Multi-Task and Meta Learning</i>	Autumn 2022 lectures ¹³³	Slides ¹³⁴
Stanford's CS224U, <i>Natural Language Understanding</i>	Spring 2021 lectures ¹³⁵	Slides and notebooks ¹³⁶
Stanford's CS336, <i>Language Modeling from Scratch</i>	Spring 2026 lectures ¹³⁷	Lecture materials and assignments ¹³⁸
Stanford's CME 295, <i>Transformers and Large Language Models</i>	Autumn 2025 lectures ¹³⁹	The course webpage ¹⁴⁰ , with a cheatsheet ¹⁴¹ and a syllabus ¹⁴² that lists each lecture's topics and links its slides and video as they are posted
UC Berkeley's CS285, <i>Deep Reinforcement Learning</i> , taught by Levine ¹⁴³	2023 lectures ¹⁴⁴	Slides ¹⁴⁵
Carnegie Mellon's 11-785, <i>Introduction to Deep Learning</i>	Spring 2026 lectures ¹⁴⁶	Slides ¹⁴⁷

¹²³<https://www.youtube.com/playlist?list=PLoROMvodv4rOmsNzYBMe0gJY2XS8AQg16>

¹²⁴<https://cs231n.stanford.edu/>

¹²⁵<https://www.youtube.com/playlist?list=PLoROMvodv4rPLKxIpqhjhPgDQy7imNkDn>

¹²⁶<https://web.stanford.edu/class/cs224w/>

¹²⁷<https://www.youtube.com/playlist?list=PLoROMvodv4rPOWA-omMM6STXaWW4FvJT8>

¹²⁸<https://deepgenerativemodels.github.io/notes/>

¹²⁹<https://www.youtube.com/playlist?list=PLoROMvodv4rN4wG6Nk6sNpTEbuOSosZdX>

¹³⁰<https://web.stanford.edu/class/cs234/>

¹³¹https://www.youtube.com/playlist?list=PLoROMvodv4rPwxEOONYRa_itZFdaKCylL

¹³²<https://cs224r.stanford.edu/>

¹³³<https://www.youtube.com/playlist?list=PLoROMvodv4rNjRoawgt72BBNwL2V7doGI>

¹³⁴<https://cs330.stanford.edu/>

¹³⁵https://www.youtube.com/playlist?list=PLoROMvodv4rPt5D0zs3YhbWSZA8Q_DyiJ

¹³⁶<https://web.stanford.edu/class/cs224u/>

¹³⁷<https://www.youtube.com/playlist?list=PLoROMvodv4rMqXOcazWaTUhq-yembLCV>

¹³⁸<https://cs336.stanford.edu/>

¹³⁹<https://www.youtube.com/playlist?list=PLoROMvodv4rOCXd21gf0CF4xr35yINeOy>

¹⁴⁰<https://cme295.stanford.edu/>

¹⁴¹<https://cme295.stanford.edu/cheatsheet/>

¹⁴²<https://cme295.stanford.edu/syllabus/>

¹⁴³<https://www2.eecs.berkeley.edu/Faculty/Homepages/svlevine.html>

¹⁴⁴https://www.youtube.com/playlist?list=PL_iWQOsE6TFVYGEGiAOMaOzzv41Jfm_Ps

¹⁴⁵<https://rail.eecs.berkeley.edu/deeprlcourse/>

¹⁴⁶<https://www.youtube.com/playlist?list=PLp-0K3kfddPwarejN0RmVerKwkwyvh3r>

¹⁴⁷<https://deeplearning.cs.cmu.edu/S26/index.html>

Course	Recorded lectures	Written material
MIT's 9.520, <i>Statistical Learning Theory and Applications</i> (Fall 2015), taught by Poggio ¹⁴⁸ and Rosasco ¹⁴⁹	YouTube ¹⁵⁰	Syllabus, slides for most classes, and a reading list ¹⁵¹
Harvard's AM207, <i>Stochastic Methods for Data Analysis, Inference and Optimization</i> , taught by Pan	A lecture video ¹⁵²	Lecture notes as Jupyter notebooks, and a summary of each lecture ¹⁵³
Stanford's STATS 191, <i>Introduction to Applied Statistics</i> , and its theory companion	—	Notebooks and lecture notes ¹⁵⁶ on applied regression and its statistical theory
STATS 306B, taught by Jonathan Taylor ¹⁵⁴ ¹⁵⁵	—	Scribed lecture notes ¹⁵⁸ ; the Autumn 2021 webpage ¹⁵⁹
Stanford's CS229M/STATS 214, <i>Machine Learning Theory</i> , taught by Ma ¹⁵⁷	—	Scribed notes for each lecture ¹⁶¹ , on estimation and hypothesis testing
Stanford's STATS 300A, <i>Theory of Statistics</i> , taught by Mackey ¹⁶⁰ (Fall 2015)	—	Slides for each lecture ¹⁶³ , on asymptotic statistics and concentration
Stanford's STATS 300B, <i>Theory of Statistics II</i> , taught by Duchi ¹⁶² (Winter 2021)	—	Student-written notes ¹⁶⁴ by Andrew Lin, on multiple testing, conformal inference and e-values
Stanford's STATS 300C, <i>Theory of Statistics III</i> , taught by Candès (Spring 2025)	—	Lecture notes by Dembo ¹⁶⁵ , a measure-theoretic treatment of probability
Stanford's STATS 310B, <i>Theory of Probability II</i>	—	

¹⁴⁸<https://mcgovern.mit.edu/profile/tomaso-poggio/>

¹⁴⁹<https://web.mit.edu/lrosasco/www/>

¹⁵⁰https://www.youtube.com/playlist?list=PLyGKBDfknk-iDj3FBd0Avr_dLbrU8VG73O

¹⁵¹<https://www.mit.edu/~9.520/fall15/>

¹⁵²<https://onefishy.github.io/am207/>

¹⁵³<https://onefishy.github.io/am207/>

¹⁵⁴<https://statistics.stanford.edu/people/jonathan-taylor>

¹⁵⁵Taylor is a co-author of *An Introduction to Statistical Learning's* Python edition [26].

¹⁵⁶<https://github.com/jonathan-taylor/stats-lecture-notes>

¹⁵⁷<https://ai.stanford.edu/~tengyuma/>

¹⁵⁸https://github.com/tengyuma/cs229m_notes/blob/main/master.pdf

¹⁵⁹<https://web.stanford.edu/class/stats214/>

¹⁶⁰<https://web.stanford.edu/~lmackey/>

¹⁶¹<https://web.stanford.edu/~lmackey/stats300a/>

¹⁶²<https://web.stanford.edu/~jduchi/>

¹⁶³<https://web.stanford.edu/class/stats300b/lectures.html>

¹⁶⁴<https://web.stanford.edu/~lindrew/stats300C.pdf>

¹⁶⁵https://web.stanford.edu/~montanar/TEACHING/Stat310B/NOTES/amir_notes.pdf

Course	Recorded lectures	Written material
Stanford's STATS 315A, <i>Modern Statistical Learning</i> , taught by Trippe (Winter 2026)	—	The syllabus ¹⁶⁶ , which reaches from regression and trees to deep learning and language models
Stanford's STATS 315B, <i>Modern Applied Statistics</i> , taught by Fox (Spring 2023)	—	The course webpage ¹⁶⁷ , on trees, deep learning, clustering and time series, with <i>Probabilistic Machine Learning</i> as a text
Stanford's STATS 200, <i>Introduction to Statistical Inference</i> , taught by Fan (Autumn 2016)	—	Lecture PDFs ¹⁶⁸ on testing, maximum likelihood, the bootstrap and regression
Stanford's STATS 305B, <i>Methods for Applied Statistics</i> , taught by Taylor ¹⁶⁹	—	Notes and slides ¹⁷⁰ on generalized linear models, loglinear models and survival analysis
Stanford's STATS 231/CS229T, <i>Statistical Learning Theory</i> , taught by Duchi (Spring 2017)	—	Slides ¹⁷¹ , with Liang's earlier course notes ¹⁷² , on uniform laws, optimization and online learning
Stanford's CS228, <i>Probabilistic Graphical Models</i>	—	Course notes ¹⁷³
Stanford's CS205L, <i>Continuous Mathematical Methods with an Emphasis on Machine Learning</i>	—	Slides ¹⁷⁴
Stanford's CS246, <i>Mining Massive Datasets</i>	—	Slides ¹⁷⁵ , with readings from the free book <i>Mining of Massive Datasets</i>
Stanford's CS329H, <i>Machine Learning from Human Preferences</i> , taught by Koyejo ¹⁷⁶	—	Its free textbook, <i>Machine Learning from Human Preferences</i> ¹⁷⁷ , linked from the course webpage ¹⁷⁸
Stanford's CS329S, <i>Machine Learning Systems Design</i> , taught by Huyen	—	Lecture notes and slides ¹⁷⁹

¹⁶⁶<https://web.stanford.edu/class/stats315a/syllabus.html>

¹⁶⁷<https://stanford-stats315b.github.io/spring2023/>

¹⁶⁸<https://web.stanford.edu/class/archive/stats/stats200/stats200.1172/lectures.html>

¹⁶⁹<https://statistics.stanford.edu/people/jonathan-taylor>

¹⁷⁰<https://web.stanford.edu/class/stats305b/>

¹⁷¹<https://web.stanford.edu/class/cs229t/2017/lectures.html>

¹⁷²<https://web.stanford.edu/class/cs229t/notes.pdf>

¹⁷³<https://ermongroup.github.io/cs228-notes/>

¹⁷⁴<https://web.stanford.edu/class/cs205l/>

¹⁷⁵<https://web.stanford.edu/class/cs246/>

¹⁷⁶<https://cs.stanford.edu/~sanmi/>

¹⁷⁷<https://mlhp.stanford.edu/>

¹⁷⁸<https://web.stanford.edu/class/cs329h/>

¹⁷⁹<https://stanford-cs329s.github.io/>

Course	Recorded lectures	Written material
Stanford's STATS 361, <i>Causal Inference</i> , taught by Wager ¹⁸⁰	—	His free draft textbook ¹⁸¹
Princeton's COS514, <i>Fundamentals of Deep Learning</i> (Fall 2025), taught by Arora ¹⁸²	—	A PDF for each lecture ¹⁸³ , and the draft book <i>Theory of Deep Learning</i>
University College London's COMP0090, <i>Introduction to Deep Learning</i> , taught by Hu	—	Jupyter notebooks ¹⁸⁴ that try out each idea with a small experiment
Carnegie Mellon's 36-708, <i>Statistical Methods for Machine Learning</i> , a more advanced, theory-heavy treatment taught by Wasserman ¹⁸⁵	—	Lecture notes ¹⁸⁶
UCLA's Biostat M257, <i>Statistical Computing</i> , taught by Hua Zhou ¹⁸⁷	—	The course webpage ¹⁸⁸ , on numerical linear algebra and optimization in Julia, the computational math behind this course's model-fitting methods
UCLA's Biostat 203B, <i>Introduction to Data Science</i> , taught by Hua Zhou ¹⁸⁹	—	The course webpage ¹⁹⁰ , on the data-engineering and reproducible-research tooling this course assumes, with a statistical-learning and tidymodels unit partway through
Stanford's CS230, <i>Deep Learning</i>	Autumn 2025 lectures ¹⁹¹ ; the course webpage ¹⁹² has the syllabus	—
Stanford's CS221, <i>Artificial Intelligence: Principles and Techniques</i>	Autumn 2025 lectures ¹⁹³ ; the course webpage ¹⁹⁴ is for the current offering	—

¹⁸⁰<https://web.stanford.edu/~swager/>

¹⁸¹https://web.stanford.edu/~swager/causal_inf_book.pdf

¹⁸²<https://www.cs.princeton.edu/~arora/>

¹⁸³<https://princetonuniversity.github.io/princeton-cos514-fall25.github.io/>

¹⁸⁴<https://github.com/YipengHu/COMP0090>

¹⁸⁵<https://www.stat.cmu.edu/~larry/>

¹⁸⁶<https://www.stat.cmu.edu/~larry/=sml/>

¹⁸⁷<https://hua-zhou.github.io/>

¹⁸⁸<https://ucla-biostat-257.github.io/2026spring/>

¹⁸⁹<https://hua-zhou.github.io/>

¹⁹⁰<https://ucla-biostat-203b.github.io/2026winter/>

¹⁹¹<https://www.youtube.com/playlist?list=PLoROMvodv4rNRRGdS0rBbXOUGA0wjdh1X>

¹⁹²<https://cs230.stanford.edu/>

¹⁹³https://www.youtube.com/playlist?list=PLoROMvodv4rMeDqwS1yFl3j3sR_-MQNEN

¹⁹⁴<https://cs221.stanford.edu/>

Course	Recorded lectures	Written material
MIT's 6.7960, <i>Deep Learning</i> (Fall 2024)	YouTube ¹⁹⁵ ; the syllabus is on MIT OpenCourseWare ¹⁹⁶	—
Harvard's Stat 110, <i>Probability</i> , the course gives as an example of the probability background it expects	YouTube ¹⁹⁷	—
UC Berkeley's Stat 210A, <i>Theoretical Statistics</i> , taught by Fithian ¹⁹⁸	—	Fall 2024 course site ¹⁹⁹ : course reader, handwritten notes, homework and old exams, licensed CC BY 4.0 ²⁰⁰ , so material can be adapted with attribution; also listed under Further reading in sds ²⁰¹
UC Berkeley's Stat 212A, <i>Topics in Selective Inference</i> (Fall 2015), taught by Fithian ²⁰²	—	Course page ²⁰³ : syllabus, references, homework with solutions; states no license, so ask before adapting; also listed under Further reading in sds ²⁰⁴
UC Berkeley's Data 8, <i>Foundations of Data Science</i> (taught by Fithian ²⁰⁵ in Spring 2019)	—	Spring 2026 course site ²⁰⁶ ; its public materials ²⁰⁷ (homework, labs, lectures) are licensed CC BY-NC 4.0, so they can be adapted with attribution and not commercially; its textbook <i>Computational and Inferential Thinking</i> ²⁰⁸ is CC BY-NC-ND 4.0, so link it and do not adapt it; the textbook is also listed under Further reading in sds ²⁰⁹
UC Berkeley's Stat 133, <i>Concepts in Computing with Data</i> , and Stat 151A, <i>Linear Modeling</i> , taught by Sanchez	—	Course repositories stat133 ²¹⁰ and stat151a ²¹¹ ; neither states a license, so ask before adapting
Sanchez's <i>PCA for Data Science</i>	—	Book ²¹² ; no license stated, so ask before adapting

¹⁹⁵<https://www.youtube.com/playlist?list=PLU14u3cNGP63URZnh5iqBzDTDYPUTQT-8>

¹⁹⁶<https://ocw.mit.edu/courses/6-7960-deep-learning-fall-2024/>

¹⁹⁷<https://www.youtube.com/playlist?list=PL2SOU6wwxB0uwwH80KTQ6ht66KWxbzTLo>

¹⁹⁸<https://www.stat.berkeley.edu/~wfithian/teaching.html>

¹⁹⁹<https://stat210a.berkeley.edu/fall-2024/>

²⁰⁰<https://stat210a.berkeley.edu/fall-2024/license.html>

²⁰¹<https://morrison-lab.github.io/sds/sufficiency.html#sec-sufficiency-reading>

²⁰²<https://www.stat.berkeley.edu/~wfithian/teaching.html>

²⁰³<https://www.stat.berkeley.edu/~wfithian/courses/stat212a/>

²⁰⁴<https://morrison-lab.github.io/sds/multiple-testing.html#sec-multiple-testing-reading>

²⁰⁵<https://www.stat.berkeley.edu/~wfithian/teaching.html>

²⁰⁶<https://www.data8.org/sp26/>

²⁰⁷<https://github.com/data-8/materials-sp26>

²⁰⁸<https://www.inferentialthinking.com/>

²⁰⁹<https://morrison-lab.github.io/sds/permutation-tests.html#sec-permutation-reading>

²¹⁰<https://github.com/gastonstat/stat133>

²¹¹<https://github.com/gastonstat/stat151a>

²¹²<https://pca4ds.github.io/>

Course	Recorded lectures	Written material
Sanchez's <i>R Ice Breaker</i> , <i>R Coding Basics</i> , <i>R Tidy Hurricanes</i> , <i>R Rolling Dice</i> , <i>R for Strings</i> and <i>R Web Technologies</i>	—	Short R books, each linked from his site ²¹³ , e.g. <i>R Coding Basics</i> ²¹⁴ ; each repository is licensed CC BY-NC-SA 4.0, so they can be adapted with attribution, not commercially, and under the same license
UC Davis's ECS 189G, <i>A Course on (Social) Fairness of Machine Learning Algorithms</i> (Spring 2023), taught by Matloff ²¹⁵	—	Course repository ²¹⁶ : a reading list running from the COMPAS investigation and Simpson's paradox to fairness measures and remedies; homework; quizzes; discussion-section R notebooks on the COMPAS and German credit data; and fair machine learning datasets [30]; licensed GPL-3.0 ²¹⁷ , so material can be adapted only if the adaptation is also released under GPL-3.0

Materials

I will distribute handouts, homework, and lab materials on Canvas. The lecture notes are on this site:

- The *Machine Learning for Data Science* (lds)²¹⁸ notes themselves, beginning at A First Model and Generalization and listed in full under **Notes** in the menu bar.
- Mathematical Prerequisites — links to the linear algebra, calculus, and matrix decompositions the notes assume.
- Probability — links to random variables, distributions, and expectations.
- Statistics — links to estimation, testing, and inference.
- The lab's open prerequisite and reference materials:
 - *Math for Data Science* (mds)²¹⁹
 - *Probability for Data Science* (pds)²²⁰
 - *Statistics for Data Science* (sds)²²¹

Course Agenda

The course calendar (**TBD**) gives the day-by-day agenda, including all deadlines.

Communication

Outbound. I will send official class announcements through Canvas Announcements. Please set Canvas to notify you of them right away, so you do not miss important information:

1. Open this course's notification settings²²² in Canvas.
2. In the **Announcement** row, click the icon in the **Email** column and choose **Notify immediately**, shown as a bell. A bell with a line through it means that notification is off. A calendar icon means you get a daily or weekly summary instead.
3. The other rows, such as **Due Date**, work the same way, so turn on any others you want to hear about.

²¹³<https://www.gastonsanchez.com>

²¹⁴<https://www.gastonsanchez.com/R-coding-basics/>

²¹⁵<https://heather.cs.ucdavis.edu/matloff.html>

²¹⁶<https://github.com/ucdavis/FairMLCourse>

²¹⁷<https://github.com/ucdavis/FairMLCourse/blob/main/LICENSE>

²¹⁸<https://morrison-lab.github.io/lds/>

²¹⁹<https://morrison-lab.github.io/mds/>

²²⁰<https://morrison-lab.github.io/pds/>

²²¹<https://morrison-lab.github.io/sds/>

²²²<https://www.instructure.com/courses/1906010?view=notifications>

In this example, **Announcement** is set to **Notify immediately**:

Course Activities	Email
Due Date Assignment due date change	
Grading Policies Course grading policy change	
Course Content Change to course content: • Page content • Quiz content • Assignment content	
Files New file added to your course	
Announcement New Announcement in your course	

Inbound. All course-related correspondence goes through Canvas. Nearly all questions or comments from you to me and/or the grader should be posted on the official class discussion forum, which is Canvas Discussions²²³. Anything that should not be posted there, such as a grading question or objection, goes in a Canvas message to me and the grader.

The only class-related matters that should not go through Canvas at all are those containing confidential information (e.g., information about your health). Communications containing confidential information should be sent to my WWU email address, which is the one exception to using Canvas.

Questions and Corrections

If something in the course materials seems wrong, ask. The course materials include the notes, handouts, assignments, and anything I say or show in class, including my slides. I will make mistakes, and so will the other authors of the materials.

Do not assume that you are the confused one when the material might be wrong. Richard Feynman²²⁴ told a room of science teachers that “science is the belief in the ignorance of experts” [31], and in this course I am (supposedly) one of the experts. Ask your question first, in class or outside it, and we can talk through your reasoning together. If you are right, we all learn something and I fix the material. If you are not, we can jointly find out where the confusion started.

Health Precautions

The health and safety of everyone in the class is a top priority. In short: if you are sick with something that could be communicable, let me know ahead of time and I will try to arrange a remote participation option, so you can stay home and not expose others needlessly. Please contact me if you have questions, concerns or suggestions.

²²³https://www.instructure.com/courses/1906010/discussion_topics

²²⁴https://en.wikipedia.org/wiki/Richard_Feynman

Software

You may complete assignments in Python, R, Julia, or MATLAB/Octave. Other languages are negotiable. One of the course outcomes is implementing standard algorithms yourself, so expect to write core methods from scratch before reaching for libraries such as scikit-learn (Python). For any software that comes pre-installed in the department labs (e.g. Python), please use the default installed version.

Student-Centered Teaching

Student-centered teaching methodologies, which prioritize student learning outcomes over instructor output (“more doing, less listening”), have been shown to be vastly more effective than traditional lectures. As Brian Hutchinson highlights from wearable-sensor studies of electrodermal activity [32] and his lecture presentation [33], traditional passive lectures produce low sympathetic nervous system arousal and attention—comparable to watching television and sleeping. Active problem-solving, formative assessment, and peer discussion elevate engagement and learning.

Furthermore, cognitive science shows that “the less effort it takes to learn something, the less durable that learning is” [34]. This course is intentionally challenging for the right reasons, backed by a growth mindset: talent and mathematical ability can be developed through focused effort, challenges expand your abilities, and mistakes are essential opportunities to grow. Research confirms that an instructor’s growth-mindset beliefs predict student achievement and motivation even after accounting for other faculty characteristics [35].

I incorporate several student-centered techniques into class sessions, with the goal of you learning more durably and effectively, including ABCD cards, collaborative pop quizzes, and “flipped” video lectures.

ABCD Cards

On the first day of class, I will give each student an ABCD card, which you will use to vote on answers to questions in class. They work like electronic clickers, but they are free and need no batteries. I use them because they allow both you and me to quickly assess how well you understand the material, so that I can adjust what I emphasize in class and you can adjust what you study out of class to improve learning outcomes. Please bring this card to class each day. If you lose your card at any point during the quarter, you need to print a new, landscape-mode color copy (PDF: **TBD**). There are also apps for this purpose you can download; just make sure you use one with the same color scheme as our physical cards.

Video Lectures

Some of the lectures in this class will be “flipped”, in particular during the first few weeks. In a flipped lecture, I pre-record the lecture presentation and make it available to you as an online video lecture, which you must watch before coming to class. During class there will be individual and small-group exercises, to give you an opportunity to refine your understanding of the topic and to immediately exercise the knowledge you obtained. There will not be any “re-lecture” of the content; class will proceed with the assumption that everyone has already watched the lecture. The video lectures are posted on Brian Hutchinson’s video lecture site²²⁵ [36]. The site requires a login, which enrolled students find in the course’s Canvas site.

Grading

Course grades are letter grades, based on:

Category	Weight
Five homework assignments (5% each)	25%
Five homework self-grades (1% each)	5%
Three midterm exams (10%, 30%, 30%)	70%
Final exam (optional)	replaces the midterm average, if higher

²²⁵https://facultyweb.cs.wvu.edu/~hutchib2/video_lectures/data371/

I will assign final letter grades based on the weighted average of assignment scores, by the standard scale:

Cumulative score	Letter grade
$90\% \leq x$	A range
$80\% \leq x < 90\%$	B range
$70\% \leq x < 80\%$	C range
$60\% \leq x < 70\%$	D range
$x < 60\%$	F

Homework

The course has five graded homework assignments, as well as additional ungraded exercises and readings. Each homework assignment is worth 5% of your final grade (25% cumulative). Due dates are on the course calendar.

Homework Grading

I will post solutions after each homework submission deadline. You are encouraged to self-grade your homework assignments using the posted solutions. Accurately self-grading each homework is 1% of your grade (5% cumulative). The grader and I will spot-check your self-grading, and you are encouraged to ask for help with self-grading during office hours.

Submit your self-graded homework solutions on Canvas one week after I post the solutions. Self-grading should include specific, detailed annotations on each sub-problem, marking:

- where you made mistakes;
- what your mistake was;
- what a correct answer would have been.

In other words, give yourself the feedback that you think an ideal grader would give. Handwritten self-grading annotations are acceptable.

Self-grading serves multiple purposes:

- it enables the grader and me to spend more time on office hours and course preparation;
- it motivates you to learn from your mistakes.

You are also welcome to opt out of self-grading, in whole or in part. If you do not complete your self-grading for an assignment by the corresponding deadline, we will assume that you want us to grade it for you, but we would be grateful for explicit notification when you decide not to self-grade, which might enable us to provide feedback sooner.

All questions and objections to grading must be submitted in writing, as a private Canvas message to both me and the grader (see [Communication](#)).

Exams

The course has three in-class midterm exams, tentatively scheduled for Friday, October 30, Friday, November 13 and Monday, November 23 (see the course calendar). Midterm 1 covers linear regression and generalization. Midterm 2 covers gradient descent, logistic regression and performance metrics. Midterm 3 covers the lectures that Midterms 1 and 2 do not, through Wednesday, November 18 (see the course calendar for the topics). There is also an in-person final exam during finals week, on Friday, December 11, 8–10am. If a midterm's date changes, I will announce the change at least two weeks before that exam is given.

- I will provide a standardized note sheet for each exam.
- Any calculator allowed for the SAT is allowed for the exams.
- Midterms 1, 2 and 3 are worth 10%, 30% and 30% of the course grade.
- I hold a review session before each exam: in class on Wednesday, October 28 before Midterm 1, in class on Tuesday, November 10 before Midterm 2, in class on the Friday before Midterm 3, and during finals week for the final.

The final exam is entirely optional. If your grade on the final is higher than the average of your three midterm grades, weighted 10 to 30 to 30, I will use your final grade to replace all three of your midterm grades. I intend the final exam as an extra chance to demonstrate your mastery of the course material, and it can only improve your grade. If you are satisfied with your grade prior to the final, you are welcome to skip it entirely; doing so will not affect your course grade.

Deadlines and Late Work Policy

Please refer to the course calendar for the most up-to-date deadlines. I accept no late work, except where the calendar gives a no-penalty window, as it does for Homework 1. If you miss a deadline or exam due to a medical emergency, please contact me as soon as possible to discuss arrangements. If you know in advance that you will be unable to take an exam at the scheduled time, let me know at least one week before the exam, and we may be able to reschedule it for an earlier day and time.

Submitting Your Work

You will develop and store homework code in Git version control repositories, which you can access in Linux using the command-line client. Specifically, we will use private GitHub repositories under a course GitHub organization (**TBD**). If you do not yet have a GitHub account, please create one. Develop your programs from start to finish under version control. Be sure to push your final version before the assignment deadline: I will pull the current default branch of the repository at the due time. For an introduction to Git and GitHub, see the Git and GitHub²²⁶ chapter of the *Principles of Scientific Computing* (psc)²²⁷ notes. You should also push your code before coming to office hours if you would like to receive feedback on it.

Program Guidelines

The grader and I will grade your programs on three criteria, in this order:

1. correctness;
2. clarity;
3. efficiency.

Correctness. A correct program always produces the correct output for a given input. Also, a correct program does not produce unintended side effects. The most effective way to ensure that your program is correct is to test, test, test. Test each component as you introduce it; once you are confident that a component works, you can use it in other routines. Try to break your program in testing, and if you succeed, locate the bug and fix it. The better you test your program, the more likely it is to be correct, and the more likely it is to be correct, the more likely you'll earn a good score. Most of your grade will depend on the correctness of your code.

Clarity. The easier it is to read and maintain your code, the easier it is to locate and remove bugs. Your program should be:

- well organized;
- appropriately commented;
- easy to maintain.

To have a well-organized program, design your program thoughtfully and modularly. Think before you code: writing code without a plan leads to hard-to-read code. If you write code without a plan and it works but is hard to read, check it into your version control repository and try to make it easier to read. If your cleaning introduces bugs, you can always revert to the original version. If you have two separate code blocks doing essentially the same thing, try to create one subroutine and call it from both places (copying and pasting code is a sign of a problem). The psc notes' R Code Style²²⁸ chapter gives the lab's conventions for R, and many of its principles apply in any language. The less code you have to maintain, the fewer chances to introduce bugs

²²⁶<https://morrison-lab.github.io/psc/chapters/github.html>

²²⁷<https://morrison-lab.github.io/psc/>

²²⁸<https://morrison-lab.github.io/psc/chapters/coding-style.html>

(and the less code to change when you find a bug). As for comments, please follow these simple guidelines proposed by Emeritus Professor Osborne:

- A comment at the top of the program states the program's purpose, the author, and date.
- Each subprocedure is accompanied by a comment that states its purpose, describes pre- and post-conditions, and mentions any exceptions raised.
- Within a procedure, precede code sections by a comment that says what the section does. This is usually one line long.
- Occasionally in tricky pieces of code, a comment to the right explains what the code does.
- For each major variable, a comment explains its purpose.
- Don't over-comment. Brief is best, but not so brief as to be cryptic.

Efficiency. Your programs should be asymptotically efficient. In practice, you would use highly optimized machine learning or linear algebra libraries, but our goal here is educational: I want you to understand the individual operations in our machine learning algorithms. This probably means your code will have a higher constant than it could have; this is okay.

Academic Honesty

As a future professional, your integrity is crucial. It is your responsibility to read and be familiar with the university's academic dishonesty policy, found in Appendix D of the Western Washington University Course Catalog.

- **Homework:** you may collaborate freely with your classmates, and you may use AI tools, such as ChatGPT or GitHub Copilot.
- **Exams:** in-class exams are solo. Work alone, without help from anyone else and without AI tools or other devices; the only aids allowed are the provided note sheet and a calculator, as described under [Exams](#).

Cheating on an exam will result in failing the course (grade of F), and I will file documentation of the incident with the university. All cases of academic dishonesty will be reported. When in doubt, ask the instructor.

Computer Labs

This class does not have a scheduled lab, but we may meet during our lecture hour in a lab on specific occasions for hands-on activities. Outside of those sessions, several computer labs are available to use. You should be able to use any of the department's open labs. Most of these labs have the Linux operating system with Git installed. The psc notes' Unix²²⁹ chapter covers the shell basics. In addition, a dedicated AI lab is coming soon to the department.

Student Access to AI and Cloud Computing

Beyond commercial paid services and the department's upcoming AI lab, several free options are available to enrolled students:

- Azure for Students²³⁰: Microsoft provides access to a collection of free cloud services and \$100 in credit for paid services. This benefit is renewable every 12 months for students who remain actively enrolled.
- Google Gemini²³¹: Google offers a one-year free subscription to students, as long as they activate it while an active student.

Writing to Think

When you are stuck in this course, try putting your question into words in writing. Write it in full sentences, with the numbers or code you used and what you have already tried.

²²⁹<https://morrison-lab.github.io/psc/chapters/unix.html>

²³⁰<https://azure.microsoft.com/en-us/free/students/>

²³¹<https://gemini.google/students/>

The habit pays off in two ways. A written question can be posted on the class discussion forum (or Stack Exchange, etc.) so I and others can help. Writing your thoughts down also helps clarify your question, and that sometimes answers it. In an interview on the *5 Minute Mentor* podcast, Leslie Lamport²³² says:

As someone said, “Writing is nature’s way of showing you how fuzzy your thinking is.” If you think you understand something, and don’t write down your ideas, you only think you’re thinking.

— Leslie Lamport [37]

Library Writing Resources

The Hachler Research & Writing Studio supports almost anything that involves words: group projects, essays, posters, podcasts, lab reports, applications, grad theses and more. You can work with them just like an open art studio or lab space, where you get work done with feedback along the way. Drop into the Studio on the second level of Haggard Hall or use their online chat to:

- stay focused and get things done;
- discuss ideas with someone;
- share something you’re making;
- ask for tips any time you have difficulty.

See <https://library.wvu.edu/rws> for details.

Student Conduct

I am committed to maintaining an inclusive, supportive, and professional environment in all academic settings, including lectures, labs, and course-related online spaces. I expect students to live up to the Association for Computing Machinery (ACM) Code of Ethics and Professional Conduct²³³, the ethical code adopted by nearly every software professional. A pattern of failing to follow the ACM Code of Ethics and Professional Conduct can negatively affect course grades, up to and including a failing grade for the course.

Course Materials

The instructor retains all rights to the course materials. Do not redistribute any content (including, but not limited to, lecture videos, assignments, and demos).

Disabilities

Reasonable accommodation for persons with documented disabilities should be established within the first week of class and arranged through Disability Resources for Students: telephone 360-650-3083; email drs@wvu.edu²³⁴; and on the web at Disability Resources²³⁵.

Student Services

Western encourages students to seek assistance and support at the onset of an illness, difficulty, or crisis.

- In the case of a medical concern or question, please contact the Health Center: 360-650-3400, or visit Student Health²³⁶.
- In the case of an emotional or psychological concern or question, please contact the Counseling Center: 360-650-3400, or visit Counseling Services²³⁷.

²³²https://en.wikipedia.org/wiki/Leslie_Lamport

²³³<https://www.acm.org/code-of-ethics>

²³⁴<mailto:drs@wvu.edu>

²³⁵<http://www.wvu.edu/disability/>

²³⁶<https://studenthealth.wvu.edu/>

²³⁷<https://counseling.wvu.edu/>

- In the case of a health and safety concern, please contact the University Police: 360-650-3555, or visit University Police²³⁸.
- In the case of a family or personal crisis or emergency, please contact the Dean of Students²³⁹.
- To seek confidential support related to sexual violence, please contact CASAS (360-650-3700), the Student Health Center, and/or the Counseling Center. To report sexual violence, please contact University Police, Bellingham Police, and/or the Title IX Coordinator in Western's Civil Rights and Title IX Compliance²⁴⁰ office (360-650-3307). Faculty are responsible employees who are required to report sex discrimination, including sexual violence that they learn about, to the Title IX Coordinator.

Career Advising

I am glad to meet with you to discuss your short-, medium-, and long-term career goals. Academic Advising & Career Readiness²⁴¹ is also available for help with academic planning or your career, such as finding jobs and internships or getting feedback on your resume.

Other Policies

Please read Syllabi@WWU²⁴² for additional, important policies.

Start-of-Quarter Survey

Please fill out the anonymous start-of-quarter survey²⁴³ before class on Friday, September 25. Every question is optional, and it should take 15 to 20 minutes. Its last page asks a few more optional questions, which need your name and so go in a Canvas message to me instead.

Anonymous Feedback

Unlike the start-of-quarter survey, the anonymous feedback form²⁴⁴ stays open all quarter, so you can use it at any time. Tell me what is working, what is not, and how I could improve the course. I read every response.

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²³⁸<http://www.wvu.edu/ps/police/index.shtml>

²³⁹<https://www.wvu.edu/dean-students>

²⁴⁰<https://crtc.wvu.edu/>

²⁴¹<https://aacr.wvu.edu/>

²⁴²<https://syllabi.wvu.edu/>

²⁴³https://docs.google.com/forms/d/e/1FAIpQLSeUEh3S0Hq_Azfem3axha0nkTEQyH1OjRpvoW3lbtJHrHS_Q/viewform

²⁴⁴<https://docs.google.com/forms/d/e/1FAIpQLScJoI2iwwfUXm8Suy7oCDvehnNawjmQ-Bxm2i-6LsiZN5FFrA/viewform>

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