SYLLABUS & COURSE INFORMATION

SCHOOL OF PUBLIC HEALTH
UNIVERSITY OF MINNESOTA

PUBH 8475/STAT 8056

Advanced Topics on Machine Learning
Spring 2026

Credits: 3 credits
Modality and Meeting Day(s), Time, and Place:

- This class is **in-person**. It meets at 9:45am—11:00am on Mondays and Wednesdays at Mechanical Engineering 321.

Contact Information

Instructors

Name and title: Professor Wei Pan, PhD
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Office Hours: Monday and Wednesday, 11:00–11:30 a.m. (in the weeks taught by the instructor)
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Name and title: Professor Xiaotong Shen, PhD
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Office Hours: Monday and Wednesday, 11:00 a.m.–12:00 p.m. (in the weeks taught by the instructor)
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No Teaching Assistant(s)

Name:
Pronouns:
Campus Email:
Office Hours:
Office Location:

Course Details

Course Description

This course surveys emerging topics at the intersection of machine learning, data analytics, and big data. We will introduce statistical and computational techniques for both prediction and inference, with applications to business analytics, engineering, and biomedical research. Students should have prior exposure to basic machine learning and data mining (e.g., PubH 7475, STAT 8053, or an equivalent course). Topics include data exploration; optimization for learning; high-dimensional methods; deep learning (FNN, CNN, RNN/LSTM) and modern advances (Transformers, diffusion models); recommender systems; graphical models; text mining and language models; and causal machine learning. Topics include the following:

Data exploration and data science;
Optimization for machine learning;
High-dimensional analysis: prediction and inference;
Deep neural network learning: basics (FNN, CNN, RNN/LSTM); advanced topics (Transformers, Diffusion models, etc);
Recommender systems: personalized prediction;
Undirected and directed graphical models;
Unstructured data and text mining: Numerical embedding and language models;
Causal Machine Learning.

Course home pages: Pub 8475- http://www.biostat.umn.edu/~weip/course/dm/s26/home.html
Stat 8056- http://www.stat.umn.edu/~xshen/stat8056.htm

Please check regularly.

Course Goals and Objectives

By the end of the course, students will be able to:
• Apply state-of-the-art AI/ML techniques to real datasets and interpret results;
• Compare and critique alternative modeling approaches for prediction and inference;
• Read, present, and evaluate current research papers;
• Design and execute a project, including written and oral components.

Prerequisites

Pubh7475 or Stat8053 or a similar course, or permission of instructor; familiarity with programming in R or Python.

Land Acknowledgement

The School of Public Health at the University of Minnesota Twin Cities is built within the traditional homelands of the Dakota people. Minnesota comes from the Dakota name for this region, Mni Sóta Maḳoce, which loosely translates to the land where the waters reflect the skies.

It is important to acknowledge the peoples on whose land we live, learn, and work as we seek to improve and strengthen our relations with our tribal nations. We also acknowledge that words are not enough. We must ensure that our institution provides support, resources, and programs that increase access to all aspects of higher education for our American Indian students, staff, faculty, and community members.

Methods of Instruction and Work Expectations

Course Workload Expectations

This is a 3-credit course. The University expects that for each credit, you will spend a minimum of three hours per week attending class or comparable online activity, reading, studying, completing assignments, etc. over the course of a 15-week term. Thus, this course requires approximately 3 * 45 hours of effort spread over the course of the term in order to earn an average grade.

Class meetings (in person) are the primary mode of instruction and emphasize active learning through discussion, short exercises, and paper critiques. Students are expected to attend class, complete assigned readings, submit homework on time, and collaborate professionally on a team project if needed. Late submissions are not accepted without legitimate reasons or prior approval from the instructors.

Technology

You will use the following technology tools in this course. Please make yourself familiar with them.

- *Instructors' websites*
- **R and Python**

Learning Community

School of Public Health courses ask students to discuss frameworks, theory, policy, and more, often in the context of past and current events and policy debates. Many of our courses also ask students to work in teams or discussion groups. We do not come to our courses with identical backgrounds and experiences and building on what we already know about collaborating, listening, and engaging is critical to successful professional, academic, and scientific engagement with topics.

In this course, students are expected to engage with each other in respectful and thoughtful ways.

In group work, this can mean:
- Setting expectations with your groups about communication and response time during the first week of the semester (or as soon as groups are assigned) and contacting the TA or instructor if scheduling problems cannot be overcome.
- Setting clear deadlines and holding yourself and each other accountable.
- Determining the roles group members need to fulfill to successfully complete the project on time.
- Developing a rapport prior to beginning the project (what prior experience are you bringing to the project, what are your strengths as they apply to the project, what do you like to work on?)

In group discussion, this can mean:
- Respecting the identities and experiences of your classmates.
- Avoid broad statements and generalizations. Group discussions are another form of academic communication and responses to instructor questions in a group discussion are evaluated. Apply the same rigor to crafting discussion posts as you would for a paper.
- Consider your tone and language, especially when communicating in text format, as the lack of other cues can lead to misinterpretation.

Like other work in the course, all student to student communication is covered by the Student Conduct Code.

Use of AI

Students should consult their instructors if they are unsure what constitutes acceptable use.
Resources:
- GenAI Syllabus Statement Guidance from the Executive Vice President and Provost's website
- Worksheet for developing a GenAI course policy]

Course Text & Readings

Textbook

No textbook required. Slides and published research papers will be shared.

Journal Articles

Following is a list of suggested (optional) readings, which will be updated as the course progresses during the semester.

1. Introduction
1) McKinsey Global Institute, June 2011. Big data: The next frontier for innovation, competition, and productivity.
2) Donoho D (2015). 50 Years of Data Science. JCGS.
3) Breiman L (2001). Statistical Modeling: The Two Cultures (with comments and a rejoinder by the author). Statist. Sci. 16, iss. 3, 199-231.
4) Hand, D.J. (2006). Classifier Technology and the Illusion of Progress (with comments and a rejoinder by the author). Statist. Sci. 21, Iss. 1, 1-34.
5) Guha S, Hafen R, Xia, et al. (2012), Large complex data: divide and recombine (D&R) with RHIPE, Stat 1, 53-67.
6) Cleveland W.S. (2001, republished 2014), Data science: An action plan for expanding the technical areas of the field of statistics. Statistical Analysis and Data Mining 7, Iss. 6, 414-417

2. Optimization
1) Breiman L and Cutler A (1993). A Deterministic algorithm for global optimization. Mathematical Programming, 58, 179--1993.
2) Horst, R, and Thoai, NV (1999). DC programming: Overview. Journal of Optimization Theory and Application. 103, 1-43.
3) Chen,Y, Ye Y, and Wang M. (2018). Approximation hardness for a class of sparse optimization problems. Journal of Machine Learning Research, 20, 1-27.

3. High-dimensional Analysis

1) Fan J, Li R (2001). Variable selection via nonconcave penalized likelihood and its oracle properties. Journal of the American Statistical Association 96 (456), 1348-1360.
2) Zou H (2006), The Adaptive Lasso and Its Oracle Properties. JASA, 101, 418-1429.
3) Zou H, Hastie T (2005), Regularization and variable selection via the elastic net. Journal of the Royal Statistical Society: Series B, 67, 301-320.
4) Austin E, Pan W, Shen X. (2013). Penalized Regression and Risk Prediction in Genome-Wide Association Studies. Stat Anal Data Min. 6(4). doi: 10.1002/sam.11183.
5) Zhu Y, Shen X, Pan W (2013). Simultaneous grouping pursuit and feature selection over an undirected graph. JASA, 108, 713-725.
6) Kim S, Pan W, Shen X (2013). Network-based penalized regression with application to genomic data. Biometrics. 69(3), 582-593.
7) Friedman J, Hastie T, Hoefling H, Tibshirani R (2007). Pathwise Coordinate Optimization. The Annals of Applied Statistics, 2(1), 302–332.
8) Friedman J, Trevor H, and Tibshirani R(2010). Regularization Paths for Generalized Linear Models via Coordinate Descent. Journal of Statistical Software, 33(1), 1-22.
9) S. Boyd, N. Parikh, E. Chu, B. Peleato, and J. Eckstein (2011). Distributed optimization and statistical learning via the alternating direction method of multipliers. Foundations and Trends in Machine Learning, 3(1):1-122.
10) Shi C, Song R, Chen Z, Li R (2019). Linear hypothesis testing for high-dimensional generalized linear models. Ann Stat, 47(5), 2671-2703.
11) Zhu Y, Shen X, Pan W (2020). On High-Dimensional Constrained Maximum Likelihood Inference. JASA, 115(529), 217-230.
12) Dezeure R, Buhlmann P, Meier L and Meinshausen N (2015). High-Dimensional Inference: Confidence Intervals, p-Values, and R-Software hdi. Stat Sci, 30(4), 533-558.
13) Fan J, Lv J (2008). Sure, independence screening for ultrahigh-dimensional feature space. JRSS-B 70, 849-911.
14) Wu, C., Xu, G., Shen, X., and Pan, W. (2020). A regularization-based adaptive test for high-dimensional generalized linear models. Journal of Machine Learning Research. 21(128), 1-67.

4. Graphical Models

1) Mazumder, R and Hastie, T (2012). The graphical lasso: New insights and alternatives. Electronic Journal of Statistics, 6, 2125-2149.
2) Guo J, Levina E, Michailidis G, and Zhu J (2010). Joint estimation of multiple graphical models. Biometrika, 98, 1-15.
3) Yuan Y, Shen X, Pan W, and Wang Z (2019). Reconstruction of a directed acyclic Gaussian graph. Biometrika. 106, 109-125.

5. Network analysis

1) Neuman MEJ. Detecting community structure in networks.
2) Blondel VD, Guillaume J-L, Lambiotte R, Lefebvre E. (2008). Fast unfolding of communities in large networks. arXiv:0803.0476
3) Zhao Y, Levina E, Zhu J (2012). Consistency of community detection in networks under degree-corrected stochastic block models. Ann. Statist. Volume 40, Number 4 (2012), 2266-2292.
4) Fortunato, S (2010). Community detection in graphs. Physics Reports 486, 75-174.
5) Meunier, D, Lambiotte, R, and Bullmore,E (2010). Modular and hierarchically modular organization of the brain networks. Front. Neurosci., 4, 200.

6. Semi/self-supervised learning:

1) Ting Chen, Simon Kornblith, Mohammad Norouzi, Geoffrey Hinton (2020). A Simple Framework for Contrastive Learning of Visual Representations. ICMK 2020.
2) Liu, P., Fang, Y., Zhao R., et. al .(2021). Outcome-Guided Disease Subtyping for High-Dimensional Omics Data. arXiv:2007.11123
3) Wagstaff et al (2001). Constrained K-means Clustering with Background Knowledge.
4) Liu B, Shen X, and Pan W (2013). Semi-supervised spectral clustering with application to detect population stratification. Frontiers in Genetics. 4:215. doi:10.3389/fgene.2013.00215.
5) Wang J, Shen X, Pan W. (2009). On efficient large margin semisupervised learning: method and theory. Journal of Machine Learning Research. 10, 719-742.
6) Wang J, Shen X, and Pan W(2006). On transductive support vector machines. Contemp. Math., 43, 7-19.
7) Pan W, Shen X, Jiang A, and Hebbel RP (2006). Semi-supervised learning via a penalized mixture model with application to microarray sample classification. Bioinformatics, 22, 2388-2395.

7. Causal ML

1) Ishwaran H and Lu M (2019). Standard errors and confidence intervals for variable importance in random forest regression, classification, and survival. Stat Med. 38(4):558-582.
2) Lu M, Sadiq S, Feaster DJ, and Ishwaran H. (2018). Estimating Individual Treatment Effect in Observational Data Using Random Forest Methods. J Comput Graph Stat. 27(1), 209-219.
3) Vincent Dorie, Jennifer Hill, Uri Shalit, Marc Scott, and Dan Cervone. (2019). Automated versus Do-It-Yourself Methods for Causal Inference: Lessons Learned from a Data Analysis Competition. Statist Sci, 34, 43-68.
4) Li, C, Shen, X, and Pan, W.(2020). Likelihood inference for a large causal network. Journal of American Statistical Association. 113, 1--16.
5) Chen, L, Li, C, Shen, X, and Pan, W (2023). Discovery and Inference of a Causal Network with Hidden Confounding.

Journal of the American Statistical Association.

8.Deep Learning
1) LeCun et al (1998). Gradient-based learning applied to document recognition. Proc of IEEE. (Comment: Section I. p.5-7 most helpful to understand convolutional NNs.)
2) Krizhevsky A, Sutskever I, Hinton G. (2012). ImageNet Classification with Deep Convolutional Neural Networks. NeurIPS.
3) Zhou J and Troyanskaya OG (2015). Predicting effects of noncoding variants with a deep-learning-based sequence model. Nature Methods, 12, 931-934.
4) Silver et al. (2016). Mastering the game of Go with deep neural networks and tree search. Nature, 529, 484-489.
5) Xiao M, Shen X, Pan W. (2019). Application of deep convolutional neural networks in the classification of protein subcellular localization with microscopy images. Genetic Epi, 43(3), 330-341.
6) Zhuang Z, Shen X, Pan W. (2019). A simple convolutional neural network for the prediction of enhancer-promoter interactions with DNA sequence data. Bioinformatics, 35(17), 2899-2906.
7) Fan J, Ma C, Zhong Y. (2019). A Selective Overview of Deep Learning. arXiv:1904.05526.
8) Bernhard Schölkopf, Francesco Locatello, Stefan Bauer, Nan Rosemary Ke, Nal Kalchbrenner, Anirudh Goyal, Yoshua Bengio. (2021). Towards Causal Representation Learning. arXiv:2102.11107
9) Zech JR, Badgeley MA, Liu M, Costa AB, Titano JJ, Oermann EK (2018) Variable generalization performance of a deep learning model to detect pneumonia in chest radiographs: A cross-sectional study. PLoS Med 15(11): e1002683. doi:10.1371/journal.pmed.1002683.
10) Chaofan Chen, Oscar Li, Daniel Tao, Alina Barnett, Cynthia Rudin, Jonathan K. Su (2019). This Looks Like That: Deep Learning for Interpretable Image Recognition. Advances in Neural Information Processing Systems 32 (NeurIPS 2019).
11) Ramprasaath R. Selvaraju, Michael Cogswell, Abhishek Das, Ramakrishna Vedantam, Devi Parikh, Dhruv Batra. Grad-CAM: Visual Explanations from Deep Networks via Gradient-based Localization. International Journal of Computer Vision (IJCV) 2019.
12) Stephanie Clark, Rob J Hyndman, Dan Pagendam, Louise M Ryan. (2020). Modern strategies for time series regression. International Stat Rev, 88(S1), S179-S204.
13) Volodymyr Mnih et al. (2015). Human-level control through deep reinforcement learning. Nature, 518, 529-533.
14) Dai, B., Shen, X., and Pan, W. (2022). Significance tests of feature relevance for a black-box learner. IEEE Transactions on Neural Networks and Learning Systems.
15) Sohl-Dickstein, J., Weiss, E., Maheswaranathan, N., and Ganguli, S. (2015). Deep unsupervised learning using nonequilibrium thermodynamics. International Conference on Machine Learning. 2256--2265.
16) Kingma, D. P. and Dhariwal, P. (2018). Glow: Generative flow with invertible 1 by 1 convolutions. Advances in neural information processing systems, 31.
17) **Kotelnikov, A., Baranchuk, D., Rubachev, I., and Babenko, A. (2023).**TabDDPM: Modelling tabular data with diffusion models.*in Proceedings of the 40th International Conference on Machine Learning (ICML 2023).*
18) Tian, X., and Shen, X. (2025). *Conditional Data Synthesis Augmentation*. Journal of the American Statistical Association. Advance online publication. https://doi.org/10.1080/01621459.2025.2586772
19) Shen, X., Liu, Y., & Shen, R. (2023). *Boosting Data Analytics with Synthetic Volume Expansion*. Annals of Applied Statistics. To appear. (Discussion paper). arXiv:2310.17848.

9. Recommender systems
1) Bi, X., Qu, A., Wang, J., and Shen, X. (2017). A group-specific recommender system. Journal of American Statistical Association, 112, 1344-1353.
2) Dai, B., Wang, J, Shen, X., and Qu, P. (2020). Smooth neighborhood recommender systems. The Journal of Machine Learning Research. 20(16),1-2.
3) Mazumder, R., Hastie, T., and Tibshirani, R. (2010). Spectral regularization algorithms for learning large incomplete matrices. Journal of Machine Learning Research, 11, 2287-2322.

COURSE OUTLINE/WEEKLY (TENTATIVE) SCHEDULE

This course has specific deadlines. All coursework must be submitted via the course site before the date and time specified on the site. **Note: assignments are due by 11:59pm Central Time unless indicated otherwise.**

Week	Topic	Readings	Activities/Assignments

Week 1, Jan 19–23	Data exploration and data science (Shen)	Selected papers in Group 1.	Readings Note: MLK Jr. Day, Monday, Jan 19—no class; first meeting Wed Jan 21
Week 2, Jan 26–30	Optimization for machine learning (Shen)	Papers in Group 2	Readings
Week 3, Feb 2–6	High-dimensional analysis (Pan)	Selected papers in Group 3.	Assignment 1 Readings
Week 4, Feb 9-13	Undirected and directed graphical models (Pan)	Selected papers in Group 4	Readings
Week 5, Feb 16–20	Network analysis; Semi-supervised learning (Pan)	Selected papers in Groups 5& 6	Readings
Week 6, Feb 23–27	Causal ML (Pan)	Selected papers in Group 7	Readings
Week 7, Mar 2-6	Deep learning Basics: FNN, CNN (Pan)	Selected papers in Group 8	Assignment 2 Readings
Week of Mar 9–13	Spring Break (No Class)		
Week 8, Mar 16–20	Python tutorial: Deep Learning (Guest: Tian)	Selected papers in Group 8	Readings
Week 9, Mar 23–27	DL Basics: RNN, LSTM, AE, and Applications (Pan/Shen)	Selected papers in Group 8	Project proposal due Readings
Week 11, Mar 30–Apr 3	Natural Language Processing and models (Shen)	Selected papers in Group 8	Assignment 3 Readings
Week 12, Apr 6–10	DL Advanced: Diffusion Models, Normalizing Flows, Synthetic Data, and Applications (Shen)	Papers in Group 8	Readings
Week 13, Apr 13–17	Recommender systems (Shen)	Selected papers in Group 9	Readings
Week 14, Apr 20–24	Guest lecture or Student presentations		Readings
Week 15, Apr 27–May 1	Student presentations		Critiques
Week 16, May 4	Student presentations		Critiques Final project report and peer critiques due in class on Mon, May 4

EVALUATION & GRADING

Evaluation is based on class participation (10%), homework assignments (40%), and a final project (50%). There will be approximately three homework assignments. Each assignment involves applying and evaluating statistical learning methods and/or writing a reading report; some may include theoretical or computational components. The final project may be a case study, a comparative empirical or theoretical analysis, a method development/implementation, or an in-depth literature review. Team size is 1–2 students (collaboration strongly encouraged). A short project proposal is due by the end of Week 9. Team presentations will occur in the final 2–3 weeks of the semester. The ≤5-page written project report for the team (Introduction/Background, Methods, Results, and optional Discussion) is due in class on Monday, May 4, 2026 (the last day of instruction).

There are about 3 homework assignments. Each assignment involves applying and evaluating some statistical learning methods, and/or writing a reading report; the students may need to do some more theoretical or computational problems, and read and critique journal articles. For the final project, possible topics include a case study (i.e. analysis of a specific data set), an empirical

or theoretical comparison of a few statistical learning methods, or development/implementation and evaluation of a new/existing method (e.g. not covered or emphasized in class), or do an extensive literature review/survey on a topic. Your final project topic may be discussed with and approved by the instructor in advance. A project proposal will be due by Week 9. The project may be undertaken individually or by a team of 2 students. In the final 2-3 weeks, a presentation on each project will be given by its team members. A ≤ 5-page final project report for a whole team, including Introduction (or Background), Methods, Results, and possibly Discussion sections, is to be submitted during the last class session (on Monday, May 4, 2026). Each student is required to write a short critique on each presentation (not given on the same day as one's own) and submit it with the same deadline as that for the final project report.
No late homework or project reports will be accepted without legitimate reasons (e.g., documented illness) or prior instructor approval.

Grading Scale
The University uses plus and minus grading on a 4.000 cumulative grade point scale in accordance with the following, and you can expect the grade lines to be drawn as follows:

% In Class	Grade	GPA
93 - 100%	A	4.000
90 - 92%	A-	3.667
87 - 89%	B+	3.333
83 - 86%	B	3.000
80 - 82%	B-	2.667
77 - 79%	C+	2.333
73 - 76%	C	2.000
70 - 72%	C-	1.667
67 - 69%	D+	1.333
63 - 66%	D	1.000
< 62%	F	

- A = achievement that is outstanding relative to the level necessary to meet course requirements.
- B = achievement that is significantly above the level necessary to meet course requirements.
- C = achievement that meets the course requirements in every respect.
- D = achievement that is worthy of credit even though it fails to meet fully the course requirements.
- F = failure because work was either (1) completed but at a level of achievement that is not worthy of credit or (2) was not completed and there was no agreement between the instructor and the student that the student would be awarded an I (Incomplete).
- S = achievement that is satisfactory, which is equivalent to a C- or better
- N = achievement that is not satisfactory and signifies that the work was either 1) completed but at a level that is not worthy of credit, or 2) not completed and there was no agreement between the instructor and student that the student would receive an I (Incomplete).

Evaluation/Grading Policy	Evaluation/Grading Policy Description
Scholastic Dishonesty, Plagiarism, Cheating, etc.	You are expected to do your own academic work and cite sources as necessary. Failing to do so is scholastic dishonesty. Scholastic dishonesty means plagiarizing; cheating on assignments or examinations; engaging in unauthorized collaboration on academic work; taking, acquiring, or using test materials without faculty permission; submitting false or incomplete records of academic achievement; acting alone or in cooperation with another to falsify records or to obtain dishonestly grades, honors, awards, or professional endorsement; altering, forging, or misusing a University academic record; or fabricating or falsifying data, research procedures, or data analysis (As defined in the Student Conduct Code). For additional information, please see https://z.umn.edu/dishonesty The Office for Student Conduct and Academic Integrity has compiled a useful list of Frequently Asked Questions pertaining to scholastic dishonesty: https://z.umn.edu/integrity. If you have additional questions, please clarify with your instructor. Your instructor can respond to your specific questions regarding what would constitute scholastic dishonesty in the context of a particular class-e.g., whether collaboration on assignments is permitted, requirements, and methods for citing sources if electronic aids are permitted or prohibited during an exam. Indiana University offers a clear description of plagiarism and an online quiz to check your understanding (https://plagiarism.iu.edu/certificationTests/).
Late Assignments	Not accepted unless with a prior approval or a legitimate reason (e.g. illness)
Attendance Requirements	Yes
Makeup Work for Legitimate Reasons	If you experience an extraordinary event that prevents you from completing coursework on time and you would like to make arrangements to make up your work, contact your instructor within 24 hours of the missed deadline if an event could not have been anticipated and at least 48 hours prior if it is anticipated. University policy recognizes that there are a variety of legitimate circumstances in which students will miss coursework and that accommodations for makeup work will be made. This policy applies to all course requirements, including any final examination. Students are responsible for planning their schedules to avoid excessive conflicts with course requirements. 1. Instructors may not penalize students for absence during the academic term due to the following unavoidable or legitimate circumstances: illness, physical or mental, of the student or a student's dependent; medical conditions related to pregnancy; participation in intercollegiate athletic events; subpoenas; jury duty; military service; bereavement, including travel related to bereavement; religious observances; participation in formal University system governance, including the University Senate, Student Senate, and Board of Regents meetings, by students selected as representatives to those bodies; and activities sponsored by the University if identified by the senior academic officer for the campus or the officer's designee as the basis for excused absences. 2. Voting in a regional, state, or national election is not an unavoidable or legitimate absence. 3. Instructors are expected to accommodate students who wish to participate in party caucuses, pursuant to the Board of Regents resolution (see December 2005 Board of Regents Minutes, p 147.) 4. For circumstances not listed in (1), the instructor has primary responsibility to decide on a case-by-case basis if an absence is due to unavoidable or legitimate circumstances and grant a request for makeup work. Because this course is entirely online and all materials are available to students from the first day of the term, we expect students to plan accordingly if travel or access to the internet will cause them to miss a deadline. Note that our deadlines are generally set for 11:55 p.m. CST, so traveling to a different time zone will require additional planning. Further, circumstances that qualify for making up missed work will be handled by the instructor on a case-by-case basis; they will always be considered but not always granted. For complete information, view the U of M's policy on Makeup Work for Legitimate Absences (https://policy.umn.edu/education/makeupwork).
Extra Credit	Not available

SPH and University Policies & Resources

The School of Public Health maintains up-to-date information about resources available to students, as well as formal course policies, on our Course Policies website. Students are expected to read and understand all policy information available at this link and are encouraged to make use of the resources available.

For a quick reference, here are links to the University policies on that page:

- Administrative Policy: Grading and Transcripts: Crookston, Morris, Rochester, Twin Cities
- Board of Regents Policy: Student Conduct Code
- Administrative Policy: Teaching and Learning: Instructor and Unit Responsibilities (Crookston, Morris, Rochester, Twin Cities)
- Administrative Policy: Excused Absences and Makeup Work: Crookston, Morris, Rochester, Twin Cities
- Administrative Policy: Teaching and Learning: Student Responsibilities (Crookston, Morris, Rochester, Twin Cities)
- Administrative Policy: Sexual Harassment, Sexual Assault, Stalking and Relationship Violence.
- Board of Regents Policy: Diversity, Equity, Inclusion, and Equal Opportunity
- Administrative Policy: Discrimination
- Board of Regents Policy: Disability Resources
- Board of Regents Policy: Academic Freedom and Responsibility

CEPH COMPETENCIES

Competency	Learning Objectives	Assessment Strategies
Evidence-based Approaches to Public Health	Apply suitable quantitative methods to analyze public health data	Homework assignments, readings, and final project
Public Health & Health Care Systems	Discuss structural bias, social inequities, and health inequities	Class discussions, readings
Planning & Management to Promote Health	NA	
Policy in Public Health	NA	
Leadership	Apply negotiation and mediation skills to create a vision, empower others, and foster collaboration	The final project as a team
Communication	Effective scientific communication both in writing and through oral presentation	Class discussions; final course project (oral presentation and written report)
Interprofessional Practice	Perform effectively on interprofessional teams	Final project with a team of 1-2 members (ideally from different majors or with different expertise).

Key Spring 2026 University Dates (Twin Cities)

• First day of spring classes: Tuesday, January 20, 2026 (Monday, January 19 is Martin Luther King Jr. Day; University closed).
• Spring break: Monday, March 9 – Friday, March 13, 2026 (no classes).
• Last day of instruction: Monday, May 4, 2026.
• Study days: Tuesday–Wednesday, May 5–6, and Sunday, May 10, 2026.
• Final examinations: Thursday–Saturday, May 7–9, and Monday–Wednesday, May 11–13, 2026.