School of Public Health
Syllabus and Course Information

UNIVERSITY OF MINNESOTA
Driven to Discover℠

PubH 7485 & 8485: Methods for Causal Inference
Fall 2018

Meeting Days:	Monday and Wednesdays
Meeting Time:	11:15 am – 12:30 pm
Meeting Place:	Moos 2-620
Credits:	3 credits

Instructor:	David Vock
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Office Hours:	Monday and Tuesday 2-3 pm

Course website: http://ay18.moodle.umn.edu

COURSE DESCRIPTION

Although most of statistical inference focuses on associational relationships among variables, in many biomedical and health sciences contexts the focus is on establishing the causal effect of an intervention or treatment. Drawing causal conclusions can be challenging, particularly in the context of observational data, as treatment assignment may be confounded. The first part of this course focuses on methods to establish the causal effect of a point exposure, i.e., situations in which treatment is given at a single point in time. Methods to estimate causal treatment effects will include outcome regression, propensity score methods (i.e., inverse weighting, matching), and doubly robust approaches.

The second half of the course focuses on estimating the effect of a series of treatment decisions during the course of a chronic disease such as cancer, substance abuse, mental health disorders, etc. Methods to estimate these time-varying treatments include marginal structural models estimated by inverse probability weighting, structural nested models estimated by G-estimation, and the (parametric) G-computation algorithm. We will then turn our attention to estimating the optimal treatment sequence for a given subject, i.e., how to determine "the right treatment, for the right patient, at the right time," using dynamic marginal structural models and methods derived from reinforcement learning (e.g., Q-learning, A-learning) and classification problems (outcome weighted learning, C-learning).

PubH 8485 is appropriate for Ph.D students in Biostatistics and Statistics. The homework and projects will focus more on the theoretical aspects of the methods to prepare students for methodological research in this area. PubH 7485 is appropriate for Masters students in Biostatistics and PhD students in other fields who wish to learn causal methods to apply them to topics in the health sciences.

This course uses the statistical software of R, a freely available statistical software package, to implement many of the methods we discuss. However, most of the methods discussed in this course can be implemented in any statistical software (e.g., SAS, Stata, SPSS, etc.) and students will be free to use any software for homework assignments.

COURSE PREREQUISITES

7485 students: This course requires you to have a background in regression (e.g., linear, logistic, models) at the level of PubH 7405-7406, PubH 6450-6451, PubH 7402, or equivalent. Additionally, some background in statistical theory at the level of Stat 5101-5102 or PubH 7401 is helpful but not strictly required. The following texts may be helpful for review.

- Devore and Beck's Modern Mathematical Statistics with Applications (Springer, 2nd ed., 2012).
- Diez, Barr, and Çetinkaya-Rundel's OpenIntro Statistics (https://www.openintro.org/stat/textbook.php?stat_book=os) ← Free to download. A gentle introduction.
- Gill Essential Mathematics for Political and Social Science Research (Cambridge University Press, 2006) ← Good review of mathematical concepts.
- Wackerly, Mendenhall, and Scheaffer's Mathematical Statistics with Applications (Cengage Learning, 7th ed., 2008).
- DeGroot and Schervish's Probability and Statistics (Pearson, 4th ed., 2012).

8485 students: This course requires you to have a background in regression (e.g., linear, logistic) at the level of PubH 7405-7406, statistical theory at the level of Stat 8101-8102.

COURSE GOALS AND OBJECTIVES

Upon completion of this course:

- Students will analyze various methods for inferring the effect of a point or time-varying exposure and evaluate each method's strengths and limitations.
- Students will precisely define a dynamic treatment regime and learn and compare different algorithms for inferring the optimal dynamic treatment regime.
- Students will understand the connection between methods for right-censored data, methods for missing data, and methods for causal inference.
- Students will develop skills needed to conduct research in biostatistical methods including writing and presenting technical material to a broad audience.

METHODS OF INSTRUCTION AND WORK EXPECTATIONS

Instruction: This course is not taught in the traditional lecture style. There will be frequent opportunities for you to work out examples and investigate concepts during class. Therefore, you should come prepared to actively participate in class. Additionally, because of the frequent use of R in class, you should try to bring a laptop to class, if possible. You can access the course content and assignments via the course's Moodle page.

Work Expectation:

Class Time and Preparation for Class You are expected to attend class, participate in class discussions, and complete the assigned homework, exam, and projects. You should read through the assigned reading prior to coming to class. I certainly do not expect you to be experts on the assigned reading before class, but you should have at least skimmed the material before class. Some of the class periods have several journal articles assigned. I will help guide you as to which articles should be read in detail and which may be skimmed. Reading the book or articles before class help create context to enable you better make sense of the new material during class.

Homework There will be approximately 6 homework assignments. These assignments are intended to keep you actively engaged with the material. For all students, you can expect the homework will ask you to apply the methods we have learned to real datasets. Students enrolled in 8485 will have additional problems which explore the theoretical aspects of the methods that we are studying.

In general, homework will be assigned biweekly and students will have **two weeks** to complete the assignment. Try to work through the assignments throughout the week (rather than waiting until near the due date) in order to receive feedback from the instructors and the TA. You can expect homework to be returned within a week of the due date. Each homework assignment contributes equally in the final grade.

Working together on homework assignments is permitted, even encouraged. Students that work together will turn in their assignments as a group. However, if you work as a group, be sure you understand all of the material on the homework as you will be assessed individually on the exams.

Literature Project Each student will be assigned a paper from either the statistics literature (8485 students) or a domain-area journal (e.g., epidemiology, health services research, etc. for 7485 students) to read and report on to the class. Students will give a short presentation, 10-15 minutes, and write a short paper summarizing the main points of the manuscript. Each of the assigned papers will be related to the content of this course; some manuscripts will be extensions of topics that are covered in the course while others go beyond the topics covered in class but should be easily understood by someone in this course. In both the paper and presentation, you are to summarize, in your own words, a high-level description of the main findings and results of the manuscript. The target audience for this assignment is someone with advanced training in causal inference (as in the students of this course) but that may not be familiar with this particular line of research. You should not attempt to reiterate all the mathematical development of the manuscript or show the derivations of proofs or theorems; there is simply not space or time to do that nor is that particularly helpful in capturing the main ideas of the manuscript. You should concentrate on giving the main results of the manuscript and discussing why these results are important

These presentations will be given throughout the semester so the due dates will vary by student.

***Final* Project** As a final project, students will either analyze a data set using some of the methods for causal inference that we discuss (7485 students) or conduct a small simulation study to study the theoretical properties of a method or an extension of a method discussed in this course (8485 students). The findings will be written-up in a short paper. More on this assignment will be given later. The project will be due at the time of the final exam for this course.

Late Policy Late assignments are not accepted unless approved in advance by the instructors or for a documented reason (such as illness).

Course Communication You must use your U of M email address! All course communications will be sent to your University of Minnesota email account. If you have not yet initiated your U of M email account, you will need to do so at: http://www.umn.edu/initiate.

COURSE TEXT AND READINGS

There are two **required** textbooks for the course:

- Hernán MA, Robins JM (2018). Causal Inference. Boca Raton: Chapman & Hall/CRC, forthcoming.
- Chakraborty B, Moodie EEM (2013). Statistical Methods for Dynamic Treatment Regimes: Reinforcement Learning, Causal Inference, and Personalized Medicine. New York: Springer.

The hard copy of these books are available through the University of Minnesota bookstore. However, a free PDF of the second text is available via the University of Minnesota Library website.

Additional readings (including the book chapters) are available from the University of Minnesota Libraries website.

Books

- Boos DD, Stefanski LA (2013). Essential Statistical Inference: Theory and Methods. New York: Springer.
- Tsiatis AA (2006). Semiparametric Theory and Missing Data. New York: Springer.

Journal Articles

Almirall, D., Ten Have, T. and Murphy, S.A. (2010) Structural Nested Mean Models for Assessing Time-Varying Effect Moderation. *Biometrics*, **66**, 131–139.

Almirall, D., Nahum-Shani, I., Sherwood, N.E. and Murphy, S.A. (2014) Introduction to SMART designs for the development of adaptive interventions: with application to weight loss research. *Translational behavioral medicine*, **4**, 260–274.

Cain, L.E., Robins, J.M., Lanoy, E., Logan, R., Costagliola, D. and Hernan, M.A. (2010) When to Start Treatment? A Systematic Approach to the Comparison of Dynamic Regimes Using Observational Data. *International Journal of Biostatistics*, **6**, 18.

Chevrier, J., Picciotto, S. and Eisen, E.A. (2012) A Comparison of Standard Methods With G-estimation of Accelerated Failure-time Models to Address The Healthy-worker Survivor Effect Application in a Cohort of Autoworkers Exposed to Metalworking Fluids. *Epidemiology*, **23**, 212–219.

Cole, S.R. and Hernan, M.A. (2008) Constructing inverse probability weights for marginal structural models. *American Journal of Epidemiology*, **168**, 656–664.

Daniel, R.M., Cousens, S.N., De Stavola, B.L., Kenward, M.G. and Sterne, J.A.C. (2013) Methods for dealing with time-dependent confounding. *Statistics in medicine*, **32**, 1584–1618.

Davidian, M., Tsiatis, A.A., Laber, E.B., Davidian, M., Tsiatis, A.A. and Laber, E.B. (2016) Optimal Dynamic Treatment Regimes. *Wiley StatsRef: Statistics Reference Online* pp. 1–7. John Wiley & Sons, Ltd, Chichester, UK.

Gruber, S., Logan, R.W., Jarrín, I., Monge, S. and Hernán, M.A. (2015) Ensemble learning of inverse probability weights for marginal structural modeling in large observational datasets. *Statistics in medicine*, **34**, 106–17.

Hernan, M.A., Brumback, B. and Robins, J.M. (2000) Marginal structural models to estimate the causal effect of zidovudine on the survival of HIV-positive men. *Epidemiology*, **11**, 561–570.

Hernan, M.A., Cole, S.R., Margolick, J., Cohen, M. and Robins, J.M. (2005) Structural accelerated failure time models for survival analysis in studies with time-varying treatments. *Pharmacoepidemiology and drug safety*, **14**, 477–491.

Joffe, M.M., Yang, W.P. and Feldman, H. (2011) G-Estimation and Artificial Censoring: Problems, Challenges, and Applications. *Biometrics*, no-no.

Lunceford, J.K. and Davidian, M. (2004) Stratification and weighting via the propensity score in estimation of causal treatment effects: a comparative study. *Statistics in Medicine*, **23**, 2937–2960.

Mark, S.D. and Robins, J.M. (1993) Estimating the Causal Effect of Smoking Cessation in the Presence of Confounding Factors using a Rank Preserving Structural Failure Time Model. *Statistics in medicine*, **12**, 1605–1628.

Murphy, S.A. (2005) An experimental design for the development of adaptive treatment strategies. *Statistics in medicine*, **24**, 1455–1481.

Nahum-Shani, I., Qian, M., Almirall, D., Pelham, W.E., Gnagy, B., Fabiano, G.A., et al. (2012a) Q-Learning: A Data Analysis Method for Constructing Adaptive Interventions. *Psychological methods*, **17**, 478–494.

Nahum-Shani, I., Qian, M., Almirall, D., Pelham, W.E., Gnagy, B., Fabiano, G.A., et al. (2012b) Experimental design and primary data analysis methods for comparing adaptive interventions. *Psychological methods*, **17**, 457–477.

Neugebauer, R. and van der Laan, M.J. (2006) G-computation estimation for causal inference with complex longitudinal data. *Computational Statistics & Data Analysis*, **51**, 1676–1697.

Orellana, L., Rotnitzky, A. and Robins, J.M. (2010) Dynamic Regime Marginal Structural Mean Models for Estimation of Optimal Dynamic Treatment Regimes, Part I: Main Content. *International Journal of Biostatistics*, **6**, 8.

Robins, J.M. Structural Nested Failure Time Models. *Encyclopedia of Biostatistics* p. John Wiley & Sons, Ltd.

Robins, J.M. (1999) Marginal structural models versus structural nested models as tools for causal inference. *Statistical Models in Epidemiology: The Environment and Clinical Trials* (eds M.E. Halloran), & D. Berry), pp. 95–134. Springer-Verlag, New York.

Robins, J.M., Hernan, M.A. and Brumback, B. (2000) Marginal structural models and causal inference in epidemiology. *Epidemiology*, **11**, 550–560.

Robins, J., Orellana, L. and Rotnitzky, A. (2008) Estimation and extrapolation of optimal treatment and testing strategies. *Statistics in medicine*, **27**, 4678–4721.

Schulte, P.J., Tsiatis, A.A., Laber, E.B. and Davidian, M. (2014) Q- and A-Learning Methods for Estimating Optimal Dynamic Treatment Regimes. *Statistical Science*, **29**, 640–661.

Shortreed, S.M. and Moodie, E.E.M. (2012) Estimating the optimal dynamic antipsychotic treatment regime: evidence from the sequential multiple-assignment randomized Clinical Antipsychotic Trials of Intervention and Effectiveness schizophrenia study. *Journal of the Royal Statistical Society Series C-Applied Statistics*, **61**, 577–599.

Snowden, J.M., Rose, S. and Mortimer, K.M. (2011) Implementation of G-computation on a simulated data set: demonstration of a causal inference technique. *American Journal of Epidemiology*, **173**, 731–738.

Stuart, E.A. (2010) Matching methods for causal inference: A review and a look forward. *Statistical science : a review journal of the Institute of Mathematical Statistics*, **25**, 1–21.

Taubman, S.L., Robins, J.M., Mittleman, M.A. and Hernan, M.A. (2009) Intervening on risk factors for coronary heart disease: an application of the parametric g-formula. *International journal of epidemiology*, **38**, 1599–1611.

Valeri, L. and VanderWeele, T.J. (2013) Mediation analysis allowing for exposure–mediator interactions and causal interpretation: Theoretical assumptions and implementation with SAS and SPSS macros. *Psychological Methods*, **18**, 137–150.

Westreich, D., Cole, S.R., Young, J.G., Palella, F., Tien, P.C., Kingsley, L., et al. (2012) The parametric g□formula to estimate the effect of highly active antiretroviral therapy on incident AIDS or death. *Statistics in medicine*, **31**, 2000–2009.

Wey, A., Vock, D.M., Connett, J. and Rudser, K. (2016) Estimating restricted mean treatment effects with stacked survival models. *Statistics in Medicine*, **35**, 3319–3332.

Zhang, B., Tsiatis, A.A., Laber, E.B. and Davidian, M. (2012) A Robust Method for Estimating Optimal Treatment Regimes. *Biometrics*, **68**, 1010–1018.

Zhang, B. and Zhang, M. (2015) C-learning: a New Classification Framework to Estimate Optimal Dynamic Treatment Regimes. *The University of Michigan Department of Biostatistics Working Paper Series*.

Zhao, Y., Zeng, D., Rush, A.J. and Kosorok, M.R. (2012) Estimating Individualized Treatment Rules Using Outcome Weighted Learning. *Journal of the American Statistical Association*, **107**, 1106–1118.

COURSE OUTLINE/WEEKLY SCHEDULE

In the following H&R refers to Hernan and Robbins (2018) and C&M refers to Chakraborty and Moodie (2013). All other readings are cited as authors (year) with full citations given above.

Date	Lecture Title & Topics	Textbook Readings	Assessment Due Dates
Sept. 5	**Introduction** • Potential Outcomes Framework • Common Causal Estimands	H&R Chapter 1	
Sept. 10	**Introduction** • Causal Estimators when Treatment is Randomized • Why simple estimators do not estimate causal effects with observational data • Causal Identifying Assumptions	H&R Chapters 2 &3	
Sept. 12	**Review of Theory** • M-estimators - Definition, Asymptotic Properties, and Sandwich Variance Estimators	Boos & Stefanski (2013) Chapter 7.1-7.4	
Sept. 17	**Review of Theory** • M-estimation for regression problems • Review of bootstrap	Boos & Stefanski (2013) Chapter 7.5 & Chapter 11.1-11.5	
Sept. 19	**Point Exposure Studies** • Introduction to Confounding • Need for Models for Causal Inference • Regression Estimators	H&R Chapters 7, 11 & 15.1	Homework 1 Assigned **(Due Oct. 3)**
Sept. 24	**Point Exposure Studies** • Inverse Probability of Treatment Weighted Estimators • Stabilized versus Unstabilized Weights	H&R Chapter 12.1 – 12.3	
Sept. 26	**Point Exposure Studies** • Doubly Robust Estimators & Augmented Inverse Probability Weighted Estimators	(Lunceford and Davidian, 2004) Tsiatis (2006) Chapters 9-10	
Oct. 1	**Point Exposure Studies** • Propensity Score Stratification • Propensity Score Matching • Other Matching Methods	H&R 15.2-15.4 (Stuart, 2010)	
Oct. 3	**Point Exposure Studies** • Instrumental Variable Methods	H&R Chapter 16	Homework 1 Due Homework 2 Assigned **(Due Oct.**

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Oct. 8	**Point Exposure Studies** • Causal Mediation	(Valeri and VanderWeele, 2013)	
Oct. 10	**Point Exposure Studies** • Connection of Causal Estimators to Methods for Missing and Right-Censored Data	H&R Chapter 12.6	
Oct. 15	**Time-Varying Exposures** • Notation • Identifying assumptions	H&R Chapter 19.1-19.4, 19.6, 20.2-20.6	
Oct. 17	**Time-Varying Exposures** • Inverse Probability of Treatment Weighted Estimators of Static Regimes • (Static) Marginal Structural Models	H&R 12.4-12.5 (Robins, 1999; Robins, Hernan and Brumback, 2000; Cole and Hernan, 2008)	Homework 2 Due Homework 3 Assigned **(Due Oct. 31)**
Oct. 22	**Time-Varying Exposures** • Doubly Robust and More Efficient IPW Estimators	Tsiatis (2006) Chapters 9-10	
Oct. 24	**Time-Varying Exposures** • G-computation Formula	H&R Chapter 13.1-13.3 (Neugebauer and van der Laan, 2006; Taubman et al., 2009; Snowden, Rose and Mortimer, 2011; Westreich et al., 2012)	
Oct. 29	**Time-Varying Exposures** • Structural Nested Mean Model estimated by G-estimation	H&R 14.1-14.3 (Robins, 1999; Almirall, Ten Have and Murphy, 2010)	
Oct. 31	**Causal Inference and Survival Analysis** • Marginal Structural Cox Models	H&R Chapter 17.1-17.4 (Hernan, Brumback and Robins, 2000)	Homework 3 Due Homework 4 Assigned **(Due Nov. 14)**
Nov. 5	**Causal Inference and Survival Analysis** • Structural Nested Accelerated Failure Time Models	H&R Chapter 17.6 (Robins; Mark and Robins, 1993; Hernan et al., 2005; Joffe, Yang and Feldman, 2011; Chevrier, Picciotto and Eisen, 2012)	
Nov. 7	**Dynamic Treatment Regimes** • Introduction and definition • Notation • Definition of "optimal" regime	C&M Chapter 1 (Davidian et al., 2016)	

Nov. 12	**Dynamic Treatment Regimes** • Sequential Multiple Assignment Randomized Trial (SMART) • Comparison of first and second-stage treatment options • Embedded DTRs and estimation of their outcomes	(Murphy, 2005; Nahum-Shani et al., 2012b; Almirall et al., 2014)	
Nov. 14	**Dynamic Treatment Regimes** • Inverse Probability of Treatment Weighted Estimators • Doubly Robust Estimators • (Dynamic) Marginal Structural Models	C&M 5.1 (Zhang et al., 2012)	Homework 4 Due Homework 5 Assigned **(Due Nov. 28)**
Nov. 19	**Optimal Dynamic Treatment Regimes** • Optimal Regime within a Class of Regimes Defined by Marginal Structural Model	C&M 5.2, 5.4, 5.5 (Robins, Orellana and Rotnitzky, 2008; Cain et al., 2010; Orellana, Rotnitzky and Robins, 2010; Shortreed and Moodie, 2012)	
Nov. 21	**Dynamic Treatment Regimes** • G-computation Algorithm **Introduction of Final Project**	C&M Chapter 6	
Nov. 26	**Optimal Dynamic Treatment Regimes** • Value and Quality Functions • Q-learning	C&M Chapter 3 (Nahum-Shani et al., 2012a)	
Nov. 28	**Optimal Dynamic Treatment Regimes** • A-learning	C&M Chapter 4 (Schulte et al., 2014)	Homework 5 Due Homework 6 Assigned **(Due Dec. 12)**
Dec. 3	**Optimal Dynamic Treatment Regimes** • Outcome Weighted Learning • C-learning	(Zhao et al., 2012; Zhang and Zhang, 2015)	

Dec. 5	**Ensemble Learning to Estimate Nuisance Functions**	(Gruber et al., 2015; Wey et al., 2016)	
Dec. 10	**Review and One-on-One Meetings for Final Project**	(Daniel et al., 2013)	
Dec. 12	**Review and One-on-One Meetings for Final Project**		Homework 6 Due **Remember: Final Project Due During University Final Period**

EVALUATION AND GRADING

A student's final grade will be calculated by weighting assessments (homework, exam, projects) as follows:

- Homework (40%)
- Literature Project (25%)
- Final Project (35%)

Academic Integrity Policy: I expect that students will complete the exam and final project **INDEPENDENTLY,** without assistance from any other people. If I have any reason to suspect that a student gave assistance on an exam to another student or received assistance on an exam from another student or a person outside the class, I will file a claim with the Office of Student Conduct and Academic Integrity.

A/F letter grade will be determined by total effort as follows:

A = 93-100%	(4.000) Represents achievement that is outstanding relative to the level necessary to meet course requirements.
A- = 90-92%	(3.667)
B+ = 87-89%	(3.333)
B = 83-86%	(3.000) Represents achievement that is significantly above the level necessary to meet course requirements.
B- = 80-82%	(2.667)
C+ = 77-79%	(2.333)
C = 73-76%	(2.000) Represents achievement that meets the minimum course requirements.
C- = 70-72%	(1.667)
D+ = 67-69%	(1.333)
D = 63-66%	(1.000) Represents achievement that is worthy of credit even though it fails to meet fully the course requirements.
F = 62% or less	Represents failure (or no credit) and signifies that the 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.
For those enrolled S/N, a letter grade of C or better must be achieved to receive an S.	

The instructor reserves the right to adjust the scale downward (so that it requires a lower percentage to achieve a certain letter grade) but never higher.

If you would like to switch grading options (e.g., A/F to S/N), it must be done within the first two weeks of the semester.

For additional information, please refer to:
http://policy.umn.edu/Policies/Education/Education/GRADINGTRANSCRIPTS.html.

Course Evaluation

The SPH will collect student course evaluations electronically using a software system called CoursEval: www.sph.umn.edu/courseval. The system will send email notifications to students when they can access and complete their course evaluations. Students who complete their course evaluations promptly will be able to access their final grades just as soon as the faculty member renders the grade in SPHGrades:

www.sph.umn.edu/grades. All students will have access to their final grades through OneStop two weeks after the last day of the semester regardless of whether they completed their course evaluation or not. Student feedback on course content and faculty teaching skills are an important means for improving our work. Please take the time to complete a course evaluation for each of the courses for which you are registered.

Incomplete Contracts

A grade of incomplete "I" shall be assigned at the discretion of the instructor when, due to extraordinary circumstances (e.g., documented illness or hospitalization, death in family, etc.), the student was prevented from completing the work of the course on time. The assignment of an "I" requires that a contract be initiated and completed by the student before the last official day of class, and signed by both the student and instructor. If an incomplete is deemed appropriate by the instructor, the student in consultation with the instructor, will specify the time and manner in which the student will complete course requirements. Extension for completion of the work will not exceed one year (or earlier if designated by the student's college). For more information and to initiate an incomplete contract, students should go to SPHGrades at: www.sph.umn.edu/grades.

University of Minnesota Uniform Grading and Transcript Policy

A link to the policy can be found at onestop.umn.edu.

OTHER COURSE INFORMATION AND POLICIES

Grade Option Change (if applicable):

For full-semester courses, students may change their grade option, if applicable, through the second week of the semester. Grade option change deadlines for other terms (i.e. summer and half-semester courses) can be found at onestop.umn.edu.

Course Withdrawal:

Students should refer to the Refund and Drop/Add Deadlines for the particular term at onestop.umn.edu for information and deadlines for withdrawing from a course. As a courtesy, students should notify their instructor and, if applicable, advisor of their intent to withdraw.

Students wishing to withdraw from a course after the noted final deadline for a particular term must contact the School of Public Health Office of Admissions and Student Resources at sph-ssc@umn.edu for further information.

Student Conduct Code:

The University seeks an environment that promotes academic achievement and integrity, that is protective of free inquiry, and that serves the educational mission of the University. Similarly, the University seeks a community that is free from violence, threats, and intimidation; that is respectful of the rights, opportunities, and welfare of students, faculty, staff, and guests of the University; and that does not threaten the physical or mental health or safety of members of the University community.

As a student at the University you are expected adhere to Board of Regents Policy: *Student Conduct Code*. To review the Student Conduct Code, please see: http://regents.umn.edu/sites/default/files/policies/Student_Conduct_Code.pdf.

Note that the conduct code specifically addresses disruptive classroom conduct, which means "engaging in behavior that substantially or repeatedly interrupts either the instructor's ability to teach or student learning. The classroom extends to any setting where a student is engaged in work toward academic credit or satisfaction of program-based requirements or related activities."

Use of Personal Electronic Devices in the Classroom:

Using personal electronic devices in the classroom setting can hinder instruction and learning, not only for the student using the device but also for other students in the class. To this end, the University establishes the right of each faculty member to determine if and how personal electronic devices are allowed to be used in the classroom. For complete information, please reference: http://policy.umn.edu/Policies/Education/Education/STUDENTRESP.html.

Scholastic Dishonesty:
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. (Student Conduct Code: http://regents.umn.edu/sites/default/files/policies/Student_Conduct_Code.pdf) If it is determined that a student has cheated, he or she may be given an "F" or an "N" for the course, and may face additional sanctions from the University. For additional information, please see: http://policy.umn.edu/Policies/Education/Education/INSTRUCTORRESP.html.

The Office for Student Conduct and Academic Integrity has compiled a useful list of Frequently Asked Questions pertaining to scholastic dishonesty: http://www1.umn.edu/oscai/integrity/student/index.html. If you have additional questions, please clarify with your instructor for the course. 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.

Makeup Work for Legitimate Absences:
Students will not be penalized for absence during the semester due to unavoidable or legitimate circumstances. Such circumstances include verified illness, participation in intercollegiate athletic events, subpoenas, jury duty, military service, bereavement, and religious observances. Such circumstances do not include voting in local, state, or national elections. For complete information, please see: http://policy.umn.edu/Policies/Education/Education/MAKEUPWORK.html.

Appropriate Student Use of Class Notes and Course Materials:
Taking notes is a means of recording information but more importantly of personally absorbing and integrating the educational experience. However, broadly disseminating class notes beyond the classroom community or accepting compensation for taking and distributing classroom notes undermines instructor interests in their intellectual work product while not substantially furthering instructor and student interests in effective learning. Such actions violate shared norms and standards of the academic community. For additional information, please see: http://policy.umn.edu/Policies/Education/Education/STUDENTRESP.html.

Sexual Harassment:
"Sexual harassment" means unwelcome sexual advances, requests for sexual favors, and/or other verbal or physical conduct of a sexual nature. Such conduct has the purpose or effect of unreasonably interfering with an individual's work or academic performance or creating an intimidating, hostile, or offensive working or academic environment in any University activity or program. Such behavior is not acceptable in the University setting. For additional information, please consult Board of Regents Policy: http://regents.umn.edu/sites/default/files/policies/SexHarassment.pdf

Equity, Diversity, Equal Opportunity, and Affirmative Action:
The University will provide equal access to and opportunity in its programs and facilities, without regard to race, color, creed, religion, national origin, gender, age, marital status, disability, public assistance status, veteran status, sexual orientation, gender identity, or gender expression. For more information, please consult Board of Regents Policy: http://regents.umn.edu/sites/default/files/policies/Equity_Diversity_EO_AA.pdf.

Disability Accommodations:
The University of Minnesota is committed to providing equitable access to learning opportunities for all students. The Disability Resource Center Student Services is the campus office that collaborates with students who have disabilities to provide and/or arrange reasonable accommodations.

If you have, or think you may have, a disability (e.g., mental health, attentional, learning, chronic health, sensory, or physical), please contact DRC at 612-626-1333 or drc@umn.edu to arrange a confidential discussion regarding equitable access and reasonable accommodations.

If you are registered with DS and have a current letter requesting reasonable accommodations, please contact your instructor as early in the semester as possible to discuss how the accommodations will be applied in the course.

For more information, please see the DS website, https://diversity.umn.edu/disability/.

Mental Health and Stress Management:
As a student you may experience a range of issues that can cause barriers to learning, such as strained relationships, increased anxiety, alcohol/drug problems, feeling down, difficulty concentrating and/or lack of motivation. These mental health concerns or stressful events may lead to diminished academic performance and may reduce your ability to participate in daily activities. University of Minnesota services are available to assist you. You can learn more about the broad range of confidential mental health services available on campus via the Student Mental Health Website: http://www.mentalhealth.umn.edu.

The Office of Student Affairs at the University of Minnesota:
The Office for Student Affairs provides services, programs, and facilities that advance student success, inspire students to make life-long positive contributions to society, promote an inclusive environment, and enrich the University of Minnesota community.

Units within the Office for Student Affairs include, the Aurora Center for Advocacy & Education, Boynton Health Service, Central Career Initiatives (CCE, CDes, CFANS), Leadership Education and Development – Undergraduate Programs (LEAD-UP), the Office for Fraternity and Sorority Life, the Office for Student Conduct and Academic Integrity, the Office for Student Engagement, the Parent Program, Recreational Sports, Student and Community Relations, the Student Conflict Resolution Center, the Student Parent HELP Center, Student Unions & Activities, University Counseling & Consulting Services, and University Student Legal Service.

For more information, please see the Office of Student Affairs at http://www.osa.umn.edu/index.html.

Academic Freedom and Responsibility, for courses that involve students in research

Academic freedom is a cornerstone of the University. Within the scope and content of the course as defined by the instructor, it includes the freedom to discuss relevant matters in the classroom and conduct relevant research. Along with this freedom comes responsibility. Students are encouraged to develop the capacity for critical judgment and to engage in a sustained and independent search for truth. Students are free to take reasoned exception to the views offered in any course of study and to reserve judgment about matters of opinion, but they are responsible for learning the content of any course of study for which they are enrolled.* When conducting research, pertinent institutional approvals must be obtained and the research must be consistent with University policies.

Reports of concerns about academic freedom are taken seriously, and there are individuals and offices available for help. Contact the instructor, the Department Chair, your adviser, the associate dean of the college, (Dr Kristin Anderson, SPH Dean of Student Affairs), or the Vice Provost for Faculty and Academic Affairs in the Office of the Provost.

** Language adapted from the American Association of University Professors "Joint Statement on Rights and Freedoms of Students".*

Student Academic Success Services (SASS): http://www.sass.umn.edu:

Students who wish to improve their academic performance may find assistance from Student Academic Support Services. While tutoring and advising are not offered, SASS provides resources such as individual consultations, workshops, and self-help materials.