SYLLABUS & COURSE INFORMATION

SCHOOL OF PUBLIC HEALTH
UNIVERSITY OF MINNESOTA

PUBH 7485 & 8485, SECTION 001

Methods for Causal Inference
Fall 2019

COURSE & CONTACT INFORMATION

Credits: 3
Meeting Day(s): Monday and Wednesdays
Meeting Time: 11:15 am – 12:30 pm
Meeting Place: Moos 2-620

Instructor: David Vock
Email: vock@umn.edu
Office Phone: 612-625-1266
Fax: 612-626-0660
Office Hours: Friday, noon – 1:00 pm
Office Location: Mayo A452

TA: Ales Kotalik
Office Address: Mayo A446
Email: kotal004@umn.edu
Office Hours: Tuesday, 1:30 – 2:30 pm

TA: Evan Olawsky
Office Address: Mayo A446
Email: olaws004@umn.edu
Office Hours: Thursday, 10:00 – 11:00 am

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 website: https://sites.google.com/site/dmvock/courses-1/pubh-7485-8485-methods-for-causal-inference

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 & 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 webpage.

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.

Like other work in the course, all student to student communication is covered by the Student Conduct Code (https://z.umn.edu/studentconduct).

COURSE TEXT & READINGS

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

- Hernán MA, Robins JM (2019). 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

Date	Topic	Readings	Assessment Due Dates
Sept. 4	**Introduction** • Potential Outcomes Framework • Common Causal Estimands	H & R Chapter 1	
Sept. 9	**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. 11	**Review of Theory** • M-estimators - Definition, Asymptotic Properties, and Sandwich Variance Estimators	Boos & Stefanski (2013) Chapter 7.1-7.4	
Sept. 16	**Review of Theory** • M-estimation for regression problems • Review of bootstrap	Boos & Stefanski (2013) Chapter 7.5 & Chapter 11.1-11.5	
Sept. 18	**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. 2)**
Sept. 23	**Point Exposure Studies** • Inverse Probability of Treatment Weighted Estimators • Stabilized versus Unstabilized Weights	H&R Chapter 12.1 – 12.3	
Sept. 25	**Point Exposure Studies** • Doubly Robust Estimators & Augmented Inverse Probability Weighted Estimators	(Lunceford and Davidian, 2004) Tsiatis (2006) Chapters 9-10	
Sept. 30	**Point Exposure Studies** • Propensity Score Stratification • Propensity Score Matching • Other Matching Methods	H&R 15.2-15.4 (Stuart, 2010)	
Oct. 2	**Point Exposure Studies** • Instrumental Variable Methods	H&R Chapter 16	Homework 1 Due Homework 2 Assigned **(Due Oct. 16)**

Oct. 7	**Point Exposure Studies** • Causal Mediation	(Valeri and VanderWeele, 2013)	
Oct. 9	**Point Exposure Studies** • Connection of Causal Estimators to Methods for Missing and Right-Censored Data	H&R Chapter 12.6	
Oct. 14	**Time-Varying Exposures** • Notation • Identifying assumptions	H&R Chapter 19.1-19.4, 19.6, 20.2-20.6	
Oct. 16	**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. 30)**
Oct. 21	**Time-Varying Exposures** • Doubly Robust and More Efficient IPW Estimators	Tsiatis (2006) Chapters 9-10	
Oct. 22	**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. 28	**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. 30	**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. 13)**
Nov. 4	**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. 6	**Dynamic Treatment Regimes** • Introduction and definition • Notation • Definition of “optimal” regime	C&M Chapter 1 (Davidian et al., 2016)	
Nov. 11	**Dynamic Treatment Regimes** • Sequential Multiple Assignment Randomized Trial (SMART) • Comparison of first and second-stage treatment options	(Murphy, 2005; Nahum-Shani et al., 2012b; Almirall et al., 2014)	

	• Embedded DTRs and estimation of their outcomes		
Nov. 13	**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. 27)**
Nov. 18	**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. 20	**Dynamic Treatment Regimes** • G-computation Algorithm **Introduction of Final Project**	C&M Chapter 6	
Nov. 25	**Optimal Dynamic Treatment Regimes** • Value and Quality Functions • Q-learning	C&M Chapter 3 (Nahum-Shani et al., 2012a)	
Nov. 27	**Optimal Dynamic Treatment Regimes** • A-learning	C&M Chapter 4 (Schulte et al., 2014)	Homework 5 Due Homework 6 Assigned **(Due Dec. 11)**
Dec. 2	**Optimal Dynamic Treatment Regimes** • Outcome Weighted Learning • C-learning	(Zhao et al., 2012; Zhang and Zhang, 2015)	
Dec. 4	**Ensemble Learning to Estimate Nuisance Functions**	(Gruber et al., 2015; Wey et al., 2016)	
Dec. 9	**Review and One-on-One Meetings for Final Project**	(Daniel et al., 2013)	
Dec. 11	**Review and One-on-One Meetings for Final Project**		Homework 6 Due **Remember: Final Project Due During University Final Period**

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 website at www.sph.umn.edu/student-policies/. Students are expected to read and understand all policy information available at this link and are encouraged to make use of the resources available.

The University of Minnesota has official policies, including but not limited to the following:

- Grade definitions
- Scholastic dishonesty
- Makeup work for legitimate absences
- Student conduct code
- Sexual harassment, sexual assault, stalking and relationship violence
- Equity, diversity, equal employment opportunity, and affirmative action
- Disability services
- Academic freedom and responsibility

Resources available for students include:

- Confidential mental health services
- Disability accommodations
- Housing and financial instability resources
- Technology help
- Academic support

EVALUATION & 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.

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).

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.

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 (http://z.umn.edu/iuplagiarism).
Late Assignments	Late assignments are not accepted unless approved in advance by the instructors or for a documented reason (such as illness).
Attendance Requirements	
Extra Credit	