SPPH681A: CAUSAL INFERENCE IN PUBLIC HEALTH SCIENCES

INSTRUCTORS
Boris Sobolev, office hours: Wednesdays, 9 to 11am at VGH, or by appointment boris.sobolev@ubc.ca

PLACE AND TIME
1. Term 1, Weekly 3-hour class on Mondays, 2 to 5 pm, Room SPPH102
2. Term 1, Weekly 1-hour tutorial on Thursdays, 9 to 10 am, Room SPPH102

COURSE DESCRIPTION
Causal inference from observational data is a common task in the public health sciences. The goal of this 3-credit course is to develop knowledge, skills, and competence in causal inference methodology. The course offers in-depth coverage of methods developed over the past three decades. We will look at probabilistic causality, causal diagrams, counterfactuals, mediation analysis, and methods for evaluating treatment effects.

This course consists of 12 modules. In each module, you will find readings, tutorials, and videos that complement each other. The readings introduce the topic, the videos discuss ideas, and the tutorials help you put them into practice. I will also share a wealth of material that you can use both during and long after the course. The tutorials will use Stata; alternatively, you can apply your knowledge of R programming from previous courses. Additional tutorials will teach you how to create and analyze causal diagrams.

RATIONALE FOR TAKING THIS COURSE
This offering fulfills a recognized need for a graduate course that integrates concepts and practical skills in causal inference. Whether you are studying epidemiology, public health research, occupational health, or environmental health, you will benefit from the lectures, videos, tutorials, and readings in 681A! We will start by outlining the framework for causal reasoning. You will get a full exposition of causality and causal reasoning. Then you will learn about the conditions for classifying associations as causal. The course will then invite you to master causal reasoning by practical application to real data.

This course will be useful for those who analyze data from patient registries, routine medical records, hospital discharges, or research cohorts. After taking it, you will be able to create causal diagrams for your thesis projects, refine your research questions, find variables to adjust, detail your analysis plan, and attempt to estimate causal effects using data from your projects.

LEARNING OBJECTIVES
On completion of the course, students will be able to
(1) explain the causal inference framework;
(2) develop directed acyclic graphs and identify a minimal sufficient adjustment set;
(3) estimate total, direct and indirect treatment effects from observational data; and
(4) express causal queries through counterfactuals quantities.

PREREQUISITES
This 600-level course builds on the knowledge and skills acquired in SPPH500, SPPH503, and SPPH548. Working knowledge of statistical software is recommended.
COURSE STRUCTURE

The course combines lectures, discussions and tutorials, in-class and homework assignments, and relies on course reading materials and short video lectures.

EVALUATION OF LEARNING

Evaluation will be conducted using a combination of marks for 12 in-class assessments (maximum 24% of the total mark), six homework assignments (36%), and final homework assignment (40%).

In-class assignments

Each class involves assessment of the learning progress in class. The assessment tools will include a combination of multiple choice tests and short writing exercises covering the content from lectures, in-class discussions and required readings. The assessments provide an opportunity for students to evaluate their own progress through the course and help strengthen their understanding of core concepts and methods. Each test is worth 2 points (maximum 24 points for 12 tests).

Homework assignments

Bi-weekly homework assignments will involve various aspects of data analysis and preparing short reports. The quality of each report will be judged by clarity of presentation, suitability of methods, and interpretation of results. Each assignment is worth 6 points (maximum 36 points for 6 assignments).

A final homework assignment will involve data analysis and paper preparation. The paper should contain the following sections: Introduction, Methods, Results, Discussion, and References. Results should be presented in an organized fashion, such as in table or graphical formats. Computer outputs should be edited to eliminate irrelevant or redundant material. The quality of the report will be judged by the suitability of methods, correct computing, interpretation of results, and clarity of presentation (maximum 40 points).

PREPARATION

The student is expected to be prepared for topics discussed in class. Sufficient time should be allocated for reading of required and assigned texts, watching video lectures.

COURSE MATERIALS

Video lectures:

Course videos are available here http://tiny.cc/CWBsobor

Class road maps:

To help you navigate the course material, I have prepared road maps for each class. There you will find the learning objective for each class, suggested literature, brief summaries and YT chapters of each video: http://tiny.cc/CWBRM

Lecture slides and handouts of lab tutorials

Selected articles and book chapters:


Further readings:
# TENTATIVE COURSE SCHEDULE FOR 2022

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<tr>
<th>Date</th>
<th>Activity</th>
<th>Topic/Content/Learning objectives</th>
<th>Assessment</th>
<th>Videos</th>
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| Sep 12 | Class 1   | **Framework for drawing causal inference**  
- Treatment, outcome, summary measure, effect measure, effect size  
- Probabilistic causation  
- Independence and conditional probability  
- Spurious associations due to common cause, common effect  
**Learning objectives**  
- categorizing elements of the framework for drawing causal inferences  
- differentiating types of probabilities in describing associations  
- comparing the implications of common cause and common effect  | In-class assessment | C1V1: Framework  
http://tiny.cc/soboris1  
C1V2: Three probabilities  
http://tiny.cc/soboris2  
C1V3: Common cause and common effect  
http://tiny.cc/soboris3 | Pearce 2020  
Clarke 2019  
Berkson 1946 |
| Sep 19 | Class 2   | **Treatment effects and counterfactual reasoning**  
- Average treatment effect as difference in marginal means  
- Causal contrast: all treated vs all untreated  
- Holland’s problem  
- Potential outcomes of counterfactual treatment  
- Marginal means as weighted averages of expected outcomes  
**Learning objectives**  
- differentiating individual and average treatment effects  
- distinguishing marginal and conditional contrasts  
- interpreting potential outcomes of counterfactual treatment  | In-class assessment  
Homework 1 assignment  
Calculating marginal means  
(due 26/09/2022) | C2V1: Treatment effects  
http://tiny.cc/soboris4  
C2V2: Marginal and conditional contrasts  
http://tiny.cc/soboris5  
C2V3: Expected treatment outcomes  
http://tiny.cc/soboris6 | Maldonado 2002  
Hernan 2004 |
| Sep 26 | Class 3   | **Causal diagrams and directed acyclic graphs**  
- Basic elements of graphs: nodes and arrows  
- Exposure and outcome variables  
- Direct causes of exposure and direct causes of outcome  
- Pearl’s taxonomy of factors shown in a causal diagram  
- “Table 2 fallacy”  
- Common causes and colliders: causal and no-causal paths  
- Linking DAG to data: Markov assumption  
**Learning objectives**  
- presenting a network of dependencies graphically  
- constructing directed acyclic graphs  
- recognizing statistical relationships implied by a DAG  | In-class assessment  
Homework 1 due | C3V1: Dependency graph  
http://tiny.cc/soboris7  
C3V2: Causal diagrams  
http://tiny.cc/soboris8  
C3V3: Linking graphs to data  
http://tiny.cc/soboris9 | Digitale 2022  
Westreich 2013 |
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<tr>
<th>Oct 3</th>
<th>Class 4</th>
<th>Learning objectives</th>
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</thead>
</table>
|        | **Causal inference with DAGs** | - Identification of causal effect  
- Blocked and open paths  
- Conditioning to block paths  
- Causal paths  
- Non-causal open paths  
- Non-causal blocked paths  
- d-separation of nodes  
- Graphical identification criteria  

| In-class assessment | Homework 2 assignment | C4V1: Paths and associations  
http://tiny.cc/soboris10  
C4V2: Blocking non-causal paths  
http://tiny.cc/soboris11  
C4V3: Graphical criteria  
http://tiny.cc/soboris12A |

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<th>Oct 10</th>
<th>Class 5</th>
<th>Learning objectives</th>
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|        | **From identification to estimation** | - Back-door criterion for causal effect identification  
- Pre-intervention and post-intervention probabilities  
- Back-door adjustment for estimating treatment effects  
- Stratification on the back-door adjustment set  
- Minimal sufficient adjustment sets for conditioning  

| In-class assessment | Homework 2 is due | C5V1: The backdoor criterion  
http://tiny.cc/soboris13  
C5V2: Identifiable treatment effect  
http://tiny.cc/soboris14  
C5V3: The backdoor adjustment  
http://tiny.cc/soboris15 |

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<th>Oct 17</th>
<th>Class 6</th>
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|        | **Association and treatment effects revisited** | - Contrasting associations and treatment effects  
- Marginal and conditional risk differences  
- Stratification and averaging  
- Regression adjustment and averaging  
- Inverse treatment probability weighting  
- Causal odds ratios  

| In-class assessment | Homework 3 assignment | C6V1: How to find treatment effects  
http://tiny.cc/soboris16  
C6V2: Outcome models and averaging  
http://tiny.cc/soboris17  
C6V3: Treatment models in causal analysis  
http://tiny.cc/soboris18 |

**Williamson 2014**

**Elwert 2013**: 259-260, 258

**Vittinghoff 2012**:  
Chapter 9.3: 344-350  
Chapter 9.4: 352-360
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<th>Class 7</th>
<th>Estimating treatment effects: Stratification</th>
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<td>- The notion of strata and matching</td>
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<td>- Within-stratum estimates and averaging</td>
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<td>- Optimal number of strata</td>
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<td>- Marginal risk difference via stratification and averaging</td>
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<td>- Marginal odds ratio from stratification method</td>
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<td>Learning objectives</td>
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<td>- explaining the stratification and averaging method</td>
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<td>- constructing strata using conditioning variables</td>
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<td>- estimating treatment effects through stratification</td>
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<td>In-class assessment</td>
<td>Miettinen on stratification</td>
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<td>Homework 4 assignment</td>
<td>Estimate the risk difference using stratification</td>
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<td></td>
<td>C7V1:</td>
<td>How to make treatment groups comparable <a href="http://tiny.cc/soboris19">http://tiny.cc/soboris19</a></td>
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<tr>
<td></td>
<td>C7V2:</td>
<td>How to average strata effects <a href="http://tiny.cc/soboris20">http://tiny.cc/soboris20</a></td>
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<td>C7V3:</td>
<td>How conditioning variables define strata <a href="http://tiny.cc/soboris21">http://tiny.cc/soboris21</a></td>
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<tr>
<td></td>
<td>Vittinghoff 2012:</td>
<td>pp. 337,352,355-58</td>
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<td>Oct 31</td>
<td>Class 8</td>
<td>Estimating treatment effects: Treatment models</td>
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<td></td>
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<td>- Probability of being sampled in treatment group</td>
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<td>- Connection to Pearl’s formula</td>
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<td>- Inverse propensity score weighting method</td>
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<td>- Marginal risk difference and odds ratio with propensity scores</td>
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<td>- Treatment model using minimal adjustment sets</td>
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<tr>
<td>Learning objectives</td>
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<td>- constructing pseudo-samples using treatment probability</td>
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<td>- constructing propensity scores using treatment models</td>
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<td>Estimate the marginal probabilities, marginal risk difference and marginal odds ratio using IPW</td>
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<td>C8V1:</td>
<td>Groups comparability using treatment probability <a href="http://tiny.cc/soboris22">http://tiny.cc/soboris22</a></td>
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<td>C8V2:</td>
<td>Pseudo-samples <a href="http://tiny.cc/soboris23">http://tiny.cc/soboris23</a></td>
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<td>C8V3:</td>
<td>Inverse propensity weighting <a href="http://tiny.cc/soboris24">http://tiny.cc/soboris24</a></td>
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<td></td>
<td>Vittinghoff 2012:</td>
<td>pp. 337,352,355-58</td>
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<td>Nov 7</td>
<td>Class 9</td>
<td>Estimating treatment effects: Outcome models</td>
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<td>- Outcome model using minimal adjustment sets</td>
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<td>- Outcome model with treatment effect</td>
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<td>- Separate models for treatment groups</td>
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<td>- Calculating causal proportions and odds ratios with outcome models</td>
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<td>- Contrasting with inverse probability weighting</td>
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<td>Learning objectives</td>
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<td>- explaining the idea of covariate adjustment</td>
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<td>- contrasting the use of single model and separate models</td>
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<td>- estimating treatment effects via outcome models</td>
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<td>Contrasting IPW and POM methods</td>
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<td>Homework 5 is due</td>
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<td>Homework 6 assignment</td>
<td>Estimate the marginal probabilities, marginal risk difference and marginal odds ratio using POM</td>
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<td>C9V1:</td>
<td>Treatment effects via adjustment <a href="http://tiny.cc/soboris25">http://tiny.cc/soboris25</a></td>
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<td>C9V2:</td>
<td>Treatment effects via potential outcome means <a href="http://tiny.cc/soboris26">http://tiny.cc/soboris26</a></td>
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<td>C9V3:</td>
<td>Adjustment sets in causal analysis <a href="http://tiny.cc/soboris27">http://tiny.cc/soboris27</a></td>
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<tr>
<td></td>
<td>Vittinghoff 2012:</td>
<td>pp. 337,347-350</td>
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<td>Date</td>
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| Nov 14 | 10    | Probability of causation: Interpretation and Identification | - Causal queries that cannot be answered with data  
- Counterfactual interpretation of necessary and sufficient causes  
- Probability of necessity and probability of sufficiency  
- Identification of probability of necessity from observational data | The notion of necessary and sufficient causes  
Homework 6 is due                                                                 | C10V1: Counterfactual questions  
http://tiny.cc/soboris28  
C10V2: Pearl's (yet another) contribution  
http://tiny.cc/soboris29  
C10V3: Six counterfactuals and their meaning  
TianPearl2000, section 3.5 and Example 1 (section 4) |
| Nov 21 | 11    | Mediation analysis: Total and direct effects | - Basic mediation diagram  
- Contrasting total and direct effect  
- Natural direct effects  
- Confounded mediation diagrams  
- Sufficient conditions for identifying natural direct effects | In-class assessment                                                                 | C11V1: Effects in Mediation Analysis  
http://tiny.cc/soboris31  
C11V2: Direct and Indirect Effects  
http://tiny.cc/soboris32  
C11V3: Causal Mediation Formulas  
http://tiny.cc/soboris33 | Petersen2006  
Richiardi2013  
VanderWeele2013 |
| Nov 28 | 12    | Attributable proportion and counterfactual probabilities | - Attributable caseload and proportion  
- Attributable proportion and probability of disablement  
- Attributable proportion and probability of necessity  
- Pearl's formula for obtaining attributable proportions | In-class assessment  
Review of the final project  
(due 11/12/2021)                                                                 | C12V1: Observed and counterfactual risks  
http://tiny.cc/soboris34  
C12V2: Attributable proportions in causal analysis  
http://tiny.cc/soboris35  
C12V3: The probability of necessity in causal analysis  
http://tiny.cc/soboris36 | Suzuki 2012 |