SYS 6014 Decision Analysis

Instructor: Arthur Small

University of Virginia, Spring 2020

Class meetings: MW 09:30-10:45 a.m. in 171 MSB, or online via Collab/Panopto recordings

Office Hours: MW 10:45 a.m.-12:00 noon, 101 Olsson Hall; and Mon 4-6 p.m. online via Zoom

Web Resources:

- Collab class site, for basic course information: https://collab.its.virginia.edu
- Github class site, for posting and sharing code: https://github.com/UVA-Engineering-Decision-Analysis
- Piazza forum, for collaborative discussion: https://piazza.com/class/k3r77mlugj53je, or via Collab
- Panopto, for recordings of class sessions: https://uva.hosted.panopto.com, or via Collab
- Zoom, for online office hours: https://virginia.zoom.us/my/arthursmalliii

Teaching Assistant: Nazanin Moradinasab, nm4wu@virginia.edu

- Ms. Moradinasab is in charge of all mechanics involving web resources. She should be the first point-of-contact for any related technical support questions.

Course Description

This course is designed to teach and train students how to build decision models - tools for generating data-driven recommendations to inform actions. The course will introduce students to statistical decision theory as a rigorous framework for integrating prediction with optimization. Examples will be drawn from diverse domains including environmental management, health care, energy, and finance.

In addition to learning theory, each student will undertake a semester-long project to build a working decision model. Ideally, this project will relate closely to the student's own dissertation research, professional practice, or other domain application that interests them. For example, if the student is developing a machine learning application for their research, a good project might involve using the predictions generated by their model as inputs to a decision tool. My hope is that these projects could form the basis for subsequent research papers, dissertation chapters, or other professional work products, for interested students.

The course design is motivated by an observation: even practitioners who are sophisticated about inferential or predictive methods frequently lack skills and instincts for how to use predictive models effectively in decision contexts. A central issue concerns the appropriate handling of *uncertainty*. When the values of relevant state variables are uncertain, and when the costs and benefits of actions depend on those state variables through nonlinear functions (as they often do), then the relationship between "what is known" and "what should be done" can be quite subtle.

With this perspective in mind, the course will be organized around four major themes:

- The need to formulate each decision model carefully in terms of the *objectives* of the intended users;
- The value of predictive models - including those based on regression techniques, machine learning, physics-based forecasting systems, and other methods - as tools for *reducing uncertainty* about the values of relevant state variables;
- The quantification of residual uncertainties as *probability distributions over relevant state variables*, conditional on the available data; and
- The use of statistical decision theory as a framework for deriving optimal decision rules.

For the most part, the course will not dive deeply into particular techniques for creating predictive tools. It is expected that those explorations will happen in other courses, e.g., in statistical methods or machine learning. One important exception: the course will cover inferential methods of Bayesian statistics. These methods are well suited to generation of probabilistic predictions, and are typically given scant coverage in introductory statistics courses.

Other topics will include: generating probability distributions from predictive models; methods for evaluating forecasting models, including those that generate probabilistic forecasts; different types of objective functions and loss functions for quantifying decision outcomes; techniques for evaluating the performance and value-add of decision models; the relationship between frequentist measures of model performance (e.g., statistical significance) and performance-based measures; the value of information, including the value of expending resources to improve model performance; and the elicitation of knowledge from domain experts and intended end-users.

Additional topics may be covered depending on time and student interest. These may include: multi-period decision problems, including techniques for intertemporal optimization such as dynamic programming, for cases in which choices affect payoffs in subsequent periods; multi-criteria decision analysis; model selection criteria; model averaging; portfolio management; and the use of weather forecasts in decision-making.

Prerequisites

Students should have taken at least one rigorous intermediate course in probability and statistics. They should be comfortable with the representation of uncertain information in the form of probability distributions, with conditional probabilities, and with other such foundational concepts.

In addition, to carry out the decision tool project, the student should be able to code, in some general-purpose language. They don't have to learn a new language for the course: any language the student wishes to work in (R, Python, Java, C++, Matlab,. . .) is probably fine. That said, the instructor works primarily in R, and will tend to use R when discussing code examples.

Expectations

Each student will be expected to prepare and deliver to the class one short presentation on one of the theoretical topics covered in the syllabus. In addition, each student will make a final presentation on their decision tool project. Students will be evaluated based on their performance in these presentations and on their final project, on occasional short quizzes; and on their contributions inside and outside of class towards helping other students.

Readings

The following references are strongly recommended.

- Berger, James O. Statistical Decision Theory and Bayesian Analysis, 2nd ed. Springer, 1993. ISBN: 978-0387960982.
- Hoff, Peter D. A First Course in Bayesian Statistical Methods. Springer, 2009. ISBN: 978-0387922997.

Both books are on order at the UVA bookstore. Alternative editions, including cheaper paperback or e-editions, are fine. The Berger book is a classic reference. The Hoff book includes guides to implementation in R. Other readings will be drawn from various published articles.

Additional readings including relevant articles will be provided as the course progresses.

Course Objectives

1. Students will learn the foundations of statistical decision theory and Bayesian analysis, as a framework for understanding decision models.
2. Students will gain the experience of building a working decision model, and will learn how to evaluate its performance.
3. Students will learn the concepts and practice of *reproducible research*, in the course of preparing a research paper.
4. Students will gain experience in making presentations.

Grading Policy

- **10%** of your grade will be determined by quizzes designed to test your understanding of the theoretical concepts introduced in class.
- **10%** of your grade will be determined by your performance in one in-class presentation, on a theoretical topic to be determined in consultation with the instructor.
- **10%** of your grade will be determined by your contributiions to assist other students. These contributions can come through class participation, by making useful contributions in online forums (Github, Piazza), or through other means that add value to the group experience.
- **70%** of your grade will be determined by your performance on your final project, including an in-class presentation and a final paper.

The Project: Build a working decision tool

The central goal of the course is for you to create a working decision tool, and to write a paper describing its purpose, construction, and performance. Additional details about the decision tool project will be provided separately.

Attendance Policy

> *Showing up is 80 percent of life* – Woody Allen, via Marshall Brickman

Missing class may on occassion be unavoidable. However, regular attendance is very much in your pedagogic interest.

Communications protocols, including emails and office hours

I prefer to avoide using email to communicate with students about class matters. For substantive questions about course materials and concepts, please use class time, Piazza, office hours, or meetings by appointment. Please use email only for brief clarifying questions, or to set up appointments. Please direct questions about course technical mechanics to Ms. Moradinasab.

Academic Dishonesty Policy

Don't cheat. Don't plagiarize. Don't present someone else's work as your own.

Disabilities Policy

Together with the University of Virginia, I am committed to assuring that all students have the full opportunity to benefit from the course regardless of their disability status. If you have a disability that may require accommodations, please see the instructor early in the semester to work out appropriate arrangements.

Course Outline

The course will be structured primarily as a *workshop*: the ultimate goal is to help you to create a new piece of potentially publishable research. Our workflow will, therefore, be subject to revision, according to my judgement of how best to use our time to help you with your research.

The course outline is divided into two major sections. First, we will introduce the theoretical framework of statistical decision theory and Bayesian analysis, with examples. In the later part of the semester, we will focus on workshoping your projects in progress.

Important: class readings are subject to change, contingent on mitigating circumstances and the progress we make as a class. Students are encouraged to attend lectures and check the course website for updates.

Course Introduction

Theory

Introduction

A simple example. Theme: data-driven decision-making. Humans make billions of decisions every day. Many are not optimal. Many are based on unexamined replication of whatever procedures were used historically. Sub-optimal decisions create waste. Explosion of access to data, analytic tools, computing power opens new opportunities for decisions to be more data driven.

The general form of the problems we'll take up: There is a decision-maker who must choose one option from a menu of options. The decision-maker has objectives. These objectives can be quantified in the form of an objective function (equivalently, a loss function). The payoffs to different choices depend on the values of certain state variables. The decision-maker is in general uncertain about the values of the relevant state variables. When feasible, the information the decision-maker has can be expressed in the form of probability distributions over the relevant state variables. Typically, options are available to apply analytic methods to data to reduce these uncertainties. Many, many problems correspond to this general form. More examples:

Note, though, that the way the problem is presented may hide that it shares the above structure. The outline of topics for this course is structured to provide insight into these concepts, and guidance for the construction of usable computational decision models

Readings: Berger 1.1-1.3, Hoff Ch. 1

Formalism for statistical decision models

The payoff to a decision depends on the value of some unobserved parameter θ, which could be a vector. We have some system for generating a probability distribution $\pi(\theta)$ over θ. In Bayesian approaches, the probability distribution $\pi(\theta)$ used is the posterior distribution of θ given the observed data: $\pi(\theta|y)$. Other approaches exist for creating probability distributions over states.

Objective functions, loss functions

- Loss functions that depend only on the magnitude of estimation error: MSE, MAE
- Asymmetric loss functions
- Measuring units of value
- Utility functions: ranking alternative bundles of goods
- Risk: risk estimation, risk appetites

Readings: Berger Ch. 2

Relationships between frequentist statistical estimation procedures and loss functions

Hypothesis testing; p-testing; tests of statistical significance. Statistical significance is not the same as practical significance. There is nothing sacred about the 95% confidence threshold. What matters for decision-making: the decision-maker's degree of reasoned belief in the values of relevant state variables. Generally, it does not matter whether or not the variable is statistically significant, or whether a given hypothesis test is passed or failed. These test results are irrelevant to the decision. Strictly irrelevant.

Bayesian approaches

Example: A highly accurate test for a rare disease. 2 states, 2 possible actions (2 X 2). ("When you hear hooves, think horses, not zebras.") Even if the test is positive, it is still most likely a false positive.

Predictive Modeling: Estimation, Forecasting, Nowcasting

Introduction: The Big Picture.

"Many roads to the same destination": Many analytic techniques are available. The common goal: probability distributions over relevant state variables. Typically this means: conditional probabilities, given the How to choose a predictive modeling approach. Which predictive modeling approach you use will depend on many things: the specifics of the prediction problem, the data you have or can gain access to; your own skills; how much time, budget, expert assistance you have available; whether the problem is important enough to bother getting fancy; whether someone else has already created a good-enough model that you can just use, or use with light modification. How much value does your predictive model add?

Machine learning:

Classification. Confusion matrices: Converting to conditional probabilities. Q: Should classification algorithms be designed to be conservative or "risk averse", allowing more false positives in order to avoid false negatives when the consequences of a false negative are severe? Ans: No! Separate the analysis from the decision. Job of the analysis is to provide the best possible information, not to prejudge how the information will be used. (Will return to this question when we take up scoring rules.)

Estimation, Forecasting, Nowcasting

Examples. The goal for us: probability distributions over relevant state variables. Some predictive modeling tools may produce scores that are not easy to interpret in terms of probabilities. These must be handled with specific care. #### A tour of forecasting and estimation models and methods Linear regression models. Time series forecasting models. Various machine learning models. Models that incorporate structural knowledge. Numerical weather prediction models. Physics-based models of engineered structures and systems. Hybrids/combinations: Example: "Cloud Hunter" forecasting model.

Bayesian Estimation

Forecast Evaluation

Forecasting Evaluation I: Deterministic Forecasts

Example: US AID Famine forecast US Terrorism Alerting System: "The threat level has been raised to 'Orange' ".

Forecasting Evaluation II: Probabilistic Forecasts

Example: IRI climate prediction system Observation: Scoring rules Strictly proper scoring rules Optimization Single-period optimization Dynamic optimization Dynamic programming Option-exercise models Optimal stopping rules Clinical trials Voting audits Optimization with an intelligent adversary: game theory

Pre-posterior analysis and the value of information

Paying for sharper estimates: is it worth it? When?

Other topics

Multi-period decision problems. Multi-period forecasting. Multi-period optimization. Dynamic programming. Option-exercise models. Systems with lagged response to actions. Multi-criteria decision models.

Often decisions involve or require accepting trade-offs between multiple competing goods or benefits.

Working with users and clients

Strongly recommend: At the start of a project, take the time to understand how decisions are made currently. If decisions are sub-optimal, try to understand why. Bring an attitude of respect: if they've been doing this for a while, there's almost certainly knowledge and valuable experience encoded into the existing processes. Strive to work on big, important decision challenges. Experts don't want to trust your 'black box' decision tool. Often find: they enjoy getting confirmation of the decision they were inclined to make anyway, but balk when recommendations conflict with their own expert judgement. Often will start "bargaining", or pointing out limitations in the formal modeling approach, the factors the model fails to take into account, etc.

Student Projects

In the later part of the semester, we will focus on interactive work with students on projects.