Statistics & Decisions

September 30, 2019

1 Project Planning and Decisions

1.1 Recall Project Nature and Goals

- Select linked research paper(s) for review, reanalysis, critique; create new examples (code of course), explore simple versions of more complicated models/problems.
- Deliverables include pre-project proposal and short in-class presentation of topic/area and basic questions, then final individual report and short in-class summary presentations.
- Goals are to introduce an area of analysis related to course topics, models and methods, and students engage with a published paper, or papers, on topics in that area. This will build your experience with developing and applying modelling ideas, developing code, critiquing modelling and decision analysis studies, and expanding into new areas related to the course topics. It will also engage you in collaborating with the other students on your project team– sharing ideas and learning together on a new topic outside of class as well as during in-class working sessions and brief presentations.

  While papers for review will be complete published works on a topic, the projects will necessarily focus on extracting smaller elements, with each student aiming to develop mastery over the technical as well as substantive aspects.

  This can involve some or all of the following:

  (i) basic derivations (presumably in all cases), (ii) evaluation and summary of findings in examples/applications in the paper, (ii) redevelopment/modification of models or code, (iv) new coding to replicate an example, or to apply the model/methods to new data (if you source new data), (v) critique of approach/results, (vi) link to other published papers as necessary.

1.2 Logistics and Timetable (also see web page Schedule)

- By **Wednesday 9th October**, email MW your 1st, 2nd and 3rd topic preference. MW will then assign teams: 3 students per team ("vertically integrated" as possible).
- Teams will start working collaboratively as soon as assigned, and decide on which aspects of the paper(s) to focus on– together and then also individually– and learn from each other as you explore the paper/topics.
- **Tuesday 19th November**: each team gives a short overview of the project area and goals, and progress to date. Each student will say something about different aspects of the project: teams are responsible for deciding who goes first and who speaks to what specific aspect. These are very short and succinct introductions of the project to the rest of the class. And 1 slide each, no more!. Each team will have 10 minutes for each of the 3 team members to say a few words, with 5 minutes for Q&A from the class.
- The following 2 classes, **Thursday 21st November** and **Tuesday 26th November**, will be in-class working sessions on projects, with MW and TAs as well as all the other students in the class to interact with. Teams will already be well advanced on their study, and these formal working classes will help focus late-stage "within-team" collaborations with opportunity for feedback from others.
- **Thursday 5th December**: final summary presentations/progress reports to class, in format as for the Tuesday 19th November preliminary presentations. And 2 slides each, no more!
- **Friday 6th December** (before 11:59pm): pdf of final individual reports emailed to MW and TAs.

Notes:

- The Matlab Statistics & Machine Learning toolbox has utilities for classification, mixture modelling, optimization, and others that are relevant to some of the project topics. It will be up to the project team to explore and exploit, if they want to. The same is true of the Optimization toolbox, the Financial Modelling and Statistical Analysis (e.g., both of these toolboxes have functions for a range of quadratic optimization problems in contexts of portfolio decisions, one project area), and others. There are also tons of resources available at the Mathworks "user contribution" code site– just google a specific topic and add "Matlab" to the search terms and you will much. The same general comments apply to R code, of course.
- If you use PowerPoint and want to include equations/maths (as is most likely) I recommend installing the IguanaTex plugin– trivial to install and use to embed LaTeX in slides (MW can demo....). You can find it, along with other LaTeX links and resources, at the department's resource page on LaTeX here.

1.3 Project Reports

Your final project reports will be written individually, of course. This will be no more than 8 pages (LaTeX 11pt fonts) and be a complete but *very* succinct summary of the paper/topic you and your team have explored. Each student will speak to their own work on the project and must be explicit about what they contributed. Brevity is needed, but you should aim to contact the following:

1. The topic and problem area.
2. Main modelling and/or decision analysis approaches and goals, and connections with topics of the course.
3. Main results/findings of the published paper(s).
4. Questions and uncertainties/criticisms about the topic arising from your work on the project.
5. Any new mathematical/statistical developments you engaged in.
6. Any new coding and/or data analysis you engaged in.
7. Relevant references (publications or web-based) for background, data, etc. you explored.

2 Projects/Topics/Papers

A. Medical Decision Analysis

Applications of Bayesian decision analysis in clinical diagnostic settings, with the use of formal statistical models/inference combined with utility assessments. Very central in recent and current developments in national policy settings in many countries, related to both personalized decisions for care and national-level questions about ensuring evidence-based medicine is really based on proper use of evidence/data.

Primary papers:

- A primer on Bayesian decision analysis with an application to a personalized kidney transplant decision, R. Neapolitan *et al* (2016) *Transplantation* 100: 489–496.
- Bayesian decision analysis for choosing between diagnostic/prognostic prediction procedures, J. Kornak and Y. Lu (2011) Statistics and Its Interface 4: 27–36.

Secondary paper: Evidence-based medicine as Bayesian decision-making, D.A. Ashby and A.F.M. Smith (2000) *Statistics in Medicine* 19: 3291–3305.

Technical: Links course examples of diagnostic testing, in terms of tests based on statistical thresholds and on expected utility evaluations. Who's utilities to evaluate? Where to get probabilities? Also involves evaluations of testing characteristics (sensitivity/specificity, ROC curves), and practical assessment. No multivariate distribution theory or linear algebra. Will require review and synthesis of ideas, approaches, methods and challenges identified. Perhaps some coding/derivations to explore comparisons with published examples.

Two possible projects based on either one of the two primary papers noted above. The secondary paper is non-technical, general and relevant to both of the others (written by two leading statisticians in UK) and gives general context and interesting supporting perspectives at a non-technical level. Also see more on medical decisions in the two secondary linked papers on the monitoring topic in Project B/B1 below.

B. Sequential Monitoring for Anomaly Detection/Early Warning Decisions

Sequential analysis of incoming data in a statistical model, or set of models, allows on-line/real-time monitoring to assess for potential changes, "anomalies", or causes for concern related to an interest in "early warnings". Use of Bayesian decision analysis, based on Bayes' factors and/or diagnostic probabilities, has been and is more and more important in such areas. Historical methods for monitoring univariate data arriving over time (univariate time series or simply random samples observed over time) based on Bayes' factors require extension to more modern, complicated multivariate and network settings (think cyber-security). Several teams may select different projects in this area.

B1. Sequential Monitoring for Change Detection Decisions in Medical Settings

Primary papers:

- Mathematical and statistical aids to evaluate data from renal patients, M.S. Knapp *et al* (1983), *Kidney International* 24: 474–486.
- Monitoring kidney transplant patients, A.F.M. Smith *et al* (1983), *The Statistician (now: Journal of the Royal Statistical Society, Series D)*, 32: 46–54

Technical: Role of decision-focused monitoring of probabilities in specific medical decision contexts. Understand calibration of testing characteristics (sensitivity/specificity, ROC curves), and practical assessment. Link to newer areas of application and potential alternative (more easily implemented?) methods based on Bayes' factor monitoring (e.g. B2 below).

B2. Sequential Monitoring for Anomaly Detection in Multivariate Settings

Primary papers: Bayesian model monitoring, M. West (1996), and just Section 5 and examples of Scalable Bayesian modeling, monitoring and analysis of dynamic network flow data, X. Chen *et al* (2018) *Journal of the American Statistical Association*, 113: 519–533.

Secondary paper: Recent and related to current/emerging challenges in cyber-security: Large-scale automated forecasting for network safety and security monitoring, R. Naveiro, S. Rodriguez and D. Rios Insua (2019) *Applied Stochastic Models in Business and Industry*, doi: 10.1002/asmb.2436

Technical: Understand theory and ideas behind Bayes' factor-based model monitoring, explore how it might extend and apply to more challenging, multivariate problems involving multivariate time series such as flows on networks (discrete count time series). Explore (synthetic data) in examples with two or more related measurements (e.g., bivariate normal or Poisson), with new coding for examples. Understand calibration of Bayes' factors in non-normal (e.g., Poisson, negative binomial, etc).

C. Decisions in A/B Testing and Design

Decision analysis for statistical design– choosing experiments to target information gain (e.g., in A/B testing, optimization of uncertain functions, etc) has for many years been central in industrial R&D, and in recent years this has mushroomed in the IT industries. R&D groups at Yahoo pioneered basic statistical decision analysis in A/B testing, and that has since evolved right across the spectrum: Amazon, Apple, Facebook, Google, LinkedIn (most notably), Microsoft, etc etc. *Search terms: A/B testing, recommender systems, web-based ranking problems*. A recent paper from a senior leader (at Amazon) is worth exploring (at least in part) for potential entrée to this area at a conceptual as well as technical statistical level.

Primary paper: Bayesian A/B testing, J.F. Geweke (2019), *Advances in Econometrics 40*, J. Tobias and I. Jeliazkov (eds.), chapter 6, pp 111–140 (in press), with references therein.

Technical: Understanding and redevelopment of derivations modelling aspects as well as core applied relevance of the approaches. Fairly standard manipulation of Bayesian models, mostly not involving advanced distribution or linear algebra. Understand setting and contexts, and perhaps link to A/B testing in the IT industry through search. Coding and evaluation on synthetic data to explore/understand and verify (at a general level) examples in the paper.

D. Foundational Aspects: Subjective Probability, Utility and Group Decisions

Some foundational aspects arise in areas such as group decision analysis– specifically, in questions of the role of subjective probability and utility.

We are a group of directors of a start-up with differing opinions about whether to agree to a contract or VC initiative. We each have our own opinions about the potential Good/Bad outcome if we contract, represented by our predictive probabilities. We agree on the potential Gains/Losses, but each value them differently. Can the group act rationally in making a decision on the contract? Links to modelling economic securities markets.

Primary paper: Bayesian aggregation, M. West (1984) *Journal of the Royal Statistical Society (Series A)* 147: 600-607. And references therein.

Secondary paper: Representing aggregate belief through the competitive equilibrium of a securities market, D.M. Pennock and M.P. Wellman (1997) Proceedings Proceedings of the 13th Conference on Uncertainty in Artificial Intelligence, 392-400.

Technical: Utility and probability derivations, calculus, no linear algebra or multivariate distribution theory. New coding from scratch for examples.

E. Classification and Design Decisions for Variable Prioritization in Mixture Models

Primary paper: Discriminative variable subsets in Bayesian classification with mixture models, with application in flow cytometry studies, L. Lin, C. Chan and M. West (2016) *Biostatistics* 17: 40–53.

Data arise from a mix of populations where measurements on multiple features may relate to an outcome of interest. For example, multiple genomic biomarkers have possible predictive value in indicating/predicting extent of progression and nature of a condition such as a cancer. Beyond the basic use of mixtures for classification, decision analysis questions arise when the goals are design focused: e.g., figure out which biomarkers “best discriminate” one sub-population from the others, to feed into decisions about future design and experimentation (which variables to measure modulo specific study goals), as well as cost-effectiveness (how few variables to measure for best discrimination in the face of technical/economic costs with many variables?)

Technical: Understand derivations of operating characteristics in using classification probabilities in mixtures, including true/false positive/negative classification rates and their technical development in Gaussian mixtures; associated development of metrics to prioritize which variables– in a multivariate Gaussian mixture– discriminate sub-populations. Coding and evaluation on simple GMMs with synthetic or real data.

F. Decision Analysis in Multivariate, Multi-Period Sales Forecasting

Commercial and business forecasting is increasing complex and challenging in larger companies (think IT majors, financial institutions, etc), and increasingly large-scale data and information flows are making it increasingly statistical (think internet sales forecasting for supply chain decisions). The use of goal-specific scores of forecasting accuracy– context-specific as well as probabilistic for forecast model evaluation and comparison– rely on essential probability modelling and decision theory.

Primary paper: Bayesian forecasting of many count-valued time series, L.R. Berry and M. West (2019), *Journal of Business and Economic Statistics* doi: 10.1080/07350015.2019.1604372.

Secondary paper: MW notes on new families of loss functions arising in commercial applications with non-negative count outcomes.

Project will explore a range of specific, multivariate loss functions in studies of optimal forecasting for (a) multiple time periods ahead, with (b) several (or many) discrete non-negative integer count time series to be forecast. Explore synthetic time series (simulate) from collections of related Poisson or other distributions, define and evaluate forecast risk functions, define and evaluate implied optimal pointy forecasts, compare across different loss functions. Learn about probability forecast scoring/utility functions for raw statistical forecast assessment as well as decisions. Challenges include how to evaluate optimal point forecasts when the predictive distributions are not available analytically, but when you have direct Monte Carlo simulations from them.

Technical: Calculus, coding, some aspects of multivariate distribution theory (recall Example 2 of our "get started homework" at the start of semester). New coding from scratch for examples, use of simulation and learning about/applying *importance sampling* (Section 6.4 of course notes) for Monte Carlo evaluations and optimization of "complicated" multi-variate risk functions.

G. Portfolio Decision Analysis in Financial Forecasting

A canonical setting for Bayesian decision analysis. Explore basics of constrained optimization of multivariate mean-variance portfolios in a Bayesian decision analysis framework– the foundation of modern portfolio theory since H.M. Markowitz (1959, republished in 1991) *Portfolio Selection: Efficient Diversification of Investments*, Wiley.

G1. Portfolio Decision Analysis in Financial Forecasting

Later in class we will discuss (with class notes) essentials of the formulation and quadratic optimization, as well as practicalities. A fundamental need is for forecast information– mean vectors and variance matrices– of financial assets, so much of the literature is based more heavily on improving forecasting models rather than the decision analysis; so in the first two papers, skip the models (as much as you like) but get a good sense of what they deliver and how it is used: these two papers cover just some basics and mastery of these sections– with some additional coding and exploration of examples– will define a project.

Primary papers:

- Bayesian dynamic factor models and portfolio allocation, O. Aguilar and M. West (2000), *Journal of Business and Economic Statistics* 18:338–357; Sections 4.3 and 4.4.
- Dynamic dependence networks: Financial time series forecasting & portfolio decisions (with discussion), Z. Zhao, M. Xie and M. West (2016), *Applied Stochastic Models in Business and Industry 32: 311–339; Sections 5 and 6.5*.

G1. Portfolio Decision Analysis in Financial Forecasting – Warning: More advanced –

For more advanced students, recent research-connected developments that address realistic problems of multi-period optimization with practically relevant constraints on portfolio utility functions. There is much here well beyond the scope of STA 623 (and it is not for students in STA 340) but it is noted here for broader connections with this area of applied Bayesian decision analysis. Distillation of the ideas and approach, and understanding of the extensions of portfolio decision analysis coupled with optimization techniques for optimal decisions, could form a more advanced project.

Primary paper: Bayesian emulation for multi-step optimization in decision problems, K. Irie and M. West (2016), *Bayesian Analysis* 14:137–160.

Technical: Understanding of new classes of loss/utility functions customized to multi-step forecasting, computational challenges in defining resulting optimization of risk functions; manipulation of multi-parameter optimization; use of customized EM algorithms, and more. Coding for exploration and examples.