

Course Information Public Policy Analytics: Cases and Issues 90-802

6 Unit Course August 2021

Instructor:

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Classes: 2.00 – 3.20 pm on Tuesdays and Thursdays

Zoom:

Student Zoom ID 7206827059

Student Zoom Link https://australia-cmu-edu.zoom.us/j/7206827059

Panopto Recording Link

https://cmu.au.panopto.com/Panopto/Pages/Sessions/List.aspx#folderID=%227136745a-

4366-43ba-b9d1-ad8d005d585c%22

Motivation for this course

The purpose of this course is to focus on the significant challenge of replicating the private sector's successful use of big data analysis and predictive analytics in the public sector.

The reason the challenge is so great is that governments' relationships with their citizens are far more complex than the relations companies have with their customers. And there are other complexities here – constraints on public sector resources, skills shortages and competing political agendas. Perhaps the most important variable is the growing demand from citizens to participate in the government decisions that affect them, both as individuals and as members of communities.

Yet the challenge needs to be met as the rewards for successful use of predictive analytics in the public sector are potentially so great. Already, we see signs of analytics being used by governments to add public value is areas such as suicide reduction; early identification of public health problems; traffic management; optimizing public infrastructure investment; and improving educational outcomes.

This course looks closely at some practical issues that have emerged so far with a view to equipping students with the background and skills needed to successfully deploy predictive analytics when their turn comes. To do that, the course looks closely at practical cases with important lessons. Most of the cases reveal application of solutions which are technically sound but which meet hurdles of accountability, transparency, legitimacy and citizen empowerment.

For instance, how can an algorithm used to identify children at risk of mistreatment be hailed as a success in Pennsylvania, called "useless" in New Zealand and be the subject of successful legal action by citizens in Scotland? Are data techniques applied to policing and the criminal justice systems prone to racial bias? What rights should citizens have over the dissemination and use of data collected on them by governments? What redress should citizens have when data anonymized by governments is re-identified?

These and other cases raise policy, ethical and management issues. In considering these issues, the course traverses the various levers available to governments such as legislation, administrative reform and participative democracy as well as the pitfalls. All of these matters will be considered in a classroom that places a premium on student participation. This is a very new area and the course will work best if we take the journey together. The ultimate aim is to develop sound understandings of the principles which public policy professionals using big data analytic techniques can apply to achieve successful outcomes for both governments and their citizens. Students completing this course will be able to: Learning objectives Understand the context and critical success factors for using predictive analytics successfully to address public policy problems and service delivery by governments Diagnose the impacts of ethical considerations and value judgements associated with the use of predictive risk modelling in public sector applications Evaluate governance regimes intended to deal with normative, ethical and democratic issues Understand the current debate over some contentious uses of PRM in specific areas such as child protection and sentencing and parole decisions in the criminal justice Identify practical opportunities for successful use of data analytics in government service delivery Course Materials For each lecture, the instructor will provide lectures notes and any class material relevant for the lecture in advance, including additional readings. The reading load for this course is significant. The assignment load has been kept moderate to ensure students have sufficient time to complete the readings. Accordingly, all students are expected to have completed all of

Evaluation Method

In each of the first three weeks students will be given a short list of questions to answer in written form by the following week. There will be three of these assignments, each worth 20% of the final grade. The word limit for each assignment will be 1,500 words. Where there are multiple questions, students are expected to allocate their own word number limits to each question to allow the overall limit to be met.

the readings. The second half of the class in each week will be devoted largely to class debate

In week four, students will be given a topic on the use of predictive risk modelling in the criminal just system This one will be longer, up to 3,000 words. It will count for 40%

A schedule for submitting assignments follows. It also indicates the dates for return of graded assignments to students. Late submissions will be penalized with a one grade deduction for each day it is received after the deadline i.e. from say, A to A-.

Each assignment will be assessed as follows:

Understanding of concepts: 40% Quality of argument: 40% Quality of writing: 20%

of these readings.

| Grading Scale | A+ 95% – 100 A 90% – 94. A– 85% – 89. Scores below 55% eq | 99 % B 75% – 99 % B– 70% – | - 79.99 % C 60° - 74.99 % C 55° | % –69.99 % % – 64.99 % % – 59.99 % |
|---------------------|--|-------------------------------|------------------------------------|--|
| Assessment schedule | | I.B. () | | |
| schedule | Assignment | Date posted | Due date | Return date |
| | 1: Policy Analytics and child protection | 29 October | 6 November | 13 November |
| | 2: Policy analytics | 5 November | 12 November | 19 November |
| | 3: Regulation | 12 November | 19 November | 26 November |
| | 4: PRM in the criminal justice system | 19 November | 3 December | 4 December |
| | Grades due | | | 7 December |
| Academic integrity | There is no tolerance for breaches of academic integrity in this course. Copying or paraphrasing the work of others without attribution will result in penalties, including the possibility of a failing grade. Carnegie Mellon University policy prescribes that, in any presentation, creative, artistic, or research, it is the ethical responsibility of each student to identify the conceptual sources of the work submitted. Failure to do so is dishonest and is the basis for a charge of cheating or plagiarism, which is subject to disciplinary action. Further information on the university's policies, including sanction to be applied for breacher of academic integrity can be found at: https://www.cmu.edu/policies/student-and-student-life/academic-integrity.html | | | |

Course Outline / **Readings**

Week 1: 18 October

Policy analytics and child protection

We begin with a case that has attracted enormous controversy. Vaithianathan's child protection algorithm has been used in at least three jurisdictions with little or no challenge to its predictive accuracy. Yet it has been rejected in two of those jurisdictions. We look closely at the causes of the failure and consider the lessons to be learnt for the application of a technique which appears sound but found troubled waters in its implementation.

Required reading:

Vaithianathan, R 2012 'Can administrative data be used to identify children at risk of adverse outcomes? Centre for Applied Research in Economics, University of Auckland. September

Other readings:

Katz I, Cortis N, Shlonsky, A and Mildon R 2016 'Modernising Child Protection in New Zealand: Learning for system reforms in other jurisdictions' Social Policy Evaluation and Research Unit. University of New South Wales. May

Putnam-Hornstein, E and Needell B 2011 'Predictors of child protective service contract between birth and age five: An examination of California's 2002 birth cohort'. Centre for Social Services Research, University of California at Berkeley

Scherz, C. 2011 'Protecting Children, Preserving Families: Moral Conflict and Actuarial Science in a Problem of Contemporary Governance' Political and Legal Anthropology Review. May pp. 33-50

Week 2: 25 October

Policy analytics

What is policy analytics? At one level, it is the use of analytic techniques using public data to describe, prescribe and predict for the betterment of service delivery by public agencies. However, there is another level at which the performance of these functions, particularly the use of predictive risk modelling, becomes more problematic. The fundamental problem is that the relationship between governments and their citizens is far more complex than that between companies and their customers. For governments, people are customers, clients, citizens and subjects. As citizens, they elect representatives and expect those representatives to be accountable to them for both outcomes and process virtue. This class examines how the potential of policy analytics for improving outcomes in policy development and in public sector service delivery. It then turns to a vital issue for governments – the tension between realizing the benefits of policy analytics while meeting the growing demands from citizens for greater involvement in government decisions which affect them.

Required reading

Daniell, K, Morton A and Insua D 2016 'Policy analysis and policy analytics' *Annals of Operations Research* 236:57-73

Other readings

Albaek, E 1995 'Between Knowledge and Power: Use of the Social Sciences in Public Policy Making. *Social Sciences* Vol.28 No. 1 pp 79-100

Australian Government Commonwealth Ombudsman 2017 Centrelink's automated debt raising and recovery system. April

Bozeman, Barry. "Public-value Failure: When Efficient Markets May Not Do". *Public Administration Review* 62.2 (2002): 145–161

Bryson J., Crosby B and Bloomberg L. 2014 'Public Value Governance: Moving Beyond Traditional Public Administration and the New Public Management' *Public Administration Review*, Vol. 74, Iss. 4, pp. 445–456.

Cleary, D 'Predictive Analytics in the Public Sector: Using Data Mining to Assist Better Target Selection for Audit' *Revenue Irish Tax and Customs, Ireland.* Self published. <u>dcleary@revenue.ie</u>

De Marchi, G, Lucertini, G and Tsoukias 2016 'From evidence-based policy making to policy analytics' *Annals of Operations Research* 236:15-38

Denhardt, R and Denhardt, J 2000 'The New Public Service: Serving Rather Than Steering'. *Public Administration Review*, Vol.60, No.6 Nov – Dec. pp. 549-559

Donaldson, D 2016 'Magnificent Seven: government data uses that actually work' *The Mandarin* 9/12/2016

https://www.themandarin.com.au/73449-data-that-works/?utm_source=The+Juice+-+combined+list&utm_campaign=b1691aa3b8-&utm_medium=email&utm_term=0_d98f7edac0b1691aa3b8-261389401

Fung, A and Wright, E 2003. Deepening Democracy. Verso. London. Ch. 4.

McKinsey Global Institute: 'Big Data: The Next Frontier for Innovation, Competition and Productivity'. 2011.

https://www.mckinsey.com/business-functions/digital-mckinsey/our-insights/big-data-the-next-frontier-for-innovation

Scharaschkin, A and McBride, T 2016 'Policy analytics and accountability mechanisms: judging the 'value for money' of policy implementation' *Annals of Operations Research* 236:36-56

Tsoukis, A et. al. 2013 'Policy analytics: an agenda for research and practice'. *European Journal of Decisions Processes*. Vol. 1 pp 115 - 134

Turner S. 2001 'What is the Problem with Experts?' Social Studies of Science 31:1 pp 123-149

Week 3: 1 November

Accountable algorithms

The need for governments to account to their citizens for the application of data analytics inevitable raises the issue of values. What values judgements are being made and embedded in the analytic tools? Who makes those judgements? Who should make them? How should they be made? The reality is that value judgements are an unavoidable part of all forms of analysis, including predictive analytics. Yet many people think of big data analytics as a truth factory in which the pesky distortion of values can be eliminated. Attempts to suppress values only service to make the explicit implicit to the dtriment of transparency and accountability. The task is not to try and exclude them but to have robust approaches for dealing with the ethical issues that stem from the injection of value judgements. To do that, we ask a seemingly simple question, what makes a policy algorithm ethical?

Required reading:

Eubanks, V 2017 Automating Inequality: How high tech tools profile, police and punish the poor. St. Martin's Press New York. Chapter 5 pp. 127-173

Valnathian's ethical statement at end of Valnathian article op. cit.

Other readings:

Anderson, R and Sharrock W 2013 'A brief comment on an extensive muddle' http://www.sharrockandanderson.co.uk/wp-content/uploads/2017/04/Ethical-Algorithms.pdf

Angwin J 2016 'Make Algorithms Accountable' The New York Times. 1 August

Angwin, J and Castaneda, L.1998' The Digital Divide' *US Black Engineer and Information Technology*, 08/1998, Volume 22, Issue 2

Baronies, R., & Goodman, E. P. (2017). 'Algorithmic transparency for the smart city.' https://scholar.google.com.au/scholar?hl=en&as_sdt=0%2C5&q=Robert+Brauneis+Smart+City&oq=R obert+Brauneis

Finkel, A 31/10/2019 'Harnessing the power of artificial intelligence to benefit all' Speech to Go8 Artificial Intelligence Collaboration and Commercialisation Summit. Melbourne https://www.chiefscientist.gov.au/news-and-media/harnessing-power-artificial-intelligence-benefit-all

Flores A, Bechtel Kristin and Lowenkamp, C. 2016 'False positives, false negatives, and false analyses: a rejoinder to "Machine bias: there's software' *Federal Probation*, 09/2016, Volume 80, Issue 2

Kraemer F, van Overveld K and Peterson M 2011. 'Is there an ethoics of algorithms?' *Ethics Information Technology* 13:251–260

O'Neil, C 2017 Weapons of Math Destruction: How Big Data Increases Inequality and Threatens Democracy Broadway Books. New York. Ch. 5 Civilian Casualties: Justice in the Age of Big Data

Sandvik C, Hamilton K, Karahalios K & Langbort, C 2016 'When the Algorithm Itself is Racist: Diagnosing Ethical Harm in the basic Components of Software' *International Journal of Communication* 10, 4972 - 4990e Algorithm

Sudden, H 2017 'Values Embedded in Legal Artificial Intelligence' https://papers.csmr.com/sol3/papers.cfm?abstract_id=2932333

Week 4: 8 November

Privacy and security

Privacy is a perennial issue for data analysts and for the people whose data they use. The problem is particularly acute for policy analytics as governments are expected to meet higher standards of trust than private companies. In this class, we consider the adequacy of the approaches taken by various governments to build that trust and the principles that need to be met. In particular, we compare the fragmented, light-handed regulation used in the US with the highly centralist approach used by the EU.

Required readings

Burton, T "Data Rights for All" The Mandarin 24 March 2017

'Stormy seas ahead as TfNSW loses critical Opal Card privacy case'

Other readings:

Angwin J 2014 'Dragnet Nation: A Quest for Privacy, Security and Freedom in a World of Relentless Surveillance' Chapter 1: Hacked, 12 Colo. Tech. L.J. 291

Australian Government AI ethics principles. 2019 https://www.industry.gov.au/data-and-publications/building-australias-artificial-intelligence-capability/ai-ethics-framework/ai-ethics-principles

Australian Government Productivity Commission Inquiry: Data Availability and Use Report Overview No. 82, 31 March 2017. http://www.pc.gov.au/inquiries/completed/data-access#report

Australian Media and Communications Authority. 2013. Privacy and Personal data: Emerging issues in media and communications

Citron D 2007 'Technological Due Process' Washington University Law Review Vol.85, pp.1249-1313

Cohen, J.2013 'What privacy is for' Harvard Law Review, May pp. 1904-1932

Dawson D and Schleiger E*, Horton J, McLaughlin J, Robinson C∞, Quezada G, Scowcroft J, and Hajkowicz S† (2019) Artificial Intelligence: Australia's Ethics Framework. Data61 CSIRO, Australia. https://consult.industry.gov.au/strategic-policy/artificial-intelligence-ethics-framework/supporting documents/ArtificialIntelligenceethicsframeworkdiscussionpaper.pdf

Dutta D and Bose I 2015 'Managing a Big Data project: the case of Ramco Cements Limited'. International Journal of Production Economics pp. 293-306

Dwork C, Hardty M, Pitassiz T, Reingold O, Zemel R November 30, 2011 'Fairness through Awareness' Microsoft Research https://arxiv.org/pdf/1104.3913.pdf

Fukami, C and McCubbrey, D 2001 'Colorado Benefits Management System: Seven Years of Failure' Communications of then Association for Information Systems. Vol.29 Article 5

Mossberg K, Tolbert C and MacNeal R Digital Citizenship: The Internet, Society and Participation MIT Press. Cambridge Massachusetts

Week 5: 15 November

PRM in the criminal justice system

The US criminal justice system has attracted more research than any other area of the use of predictive risk modelling by public agencies. This research has generated much debate about issues such as whether the AI performs better than judges; the purposes of incarceration; and human rights. The most intense debate has surrounded about allegations of racial bias embedded in algorithms used to assess prisoners for parole and for sentencing. In this class, we look at all of these issues and particularly at the most controversial case to arise to date – the use of the COMPAS algorithm for predicting the likelihood of offenders re-offending.

Required readings

Angwin J Larson J Mattu S Kirchner L 2016 'Machine Bias' ProPublica https://www.propublica.org/article/machine-bias-risk-assessments-in-criminal-sentencing

Angwin J Larson J Mattu S Kirchner L 2016 'How We Analyzed the COMPAS Recidivism Algorithm" ProPublica

https://www.propublica.org/article/how-we-analyzed-the-compas-recidivism-algorithm

Other readings

Chouldechova A 2017 'Fair Prediction with Disparate Impact: A Study of Bias in Recidivism Prediction Instruments' Big Data, June Vol.5(2), pp.153-163

Dieterich W, Mendoza C and Brennan T 2016 'COMPAS Risk Scales: Demonstrating Accuracy Equity and Predictive Parity Performance of the COMPAS Risk Scales in Broward County' July. Northpointe Inc. Research Department

http://go.volarisgroup.com/rs/430-MBX-989/images/ProPublica Commentary Final 070616.pdf

Flores, A Bechtel, K and Lowenchamp C 2016 'False Positives, False Negatives, and False Analyses: A Rejoinder to "Machine Bias: There's Software Used Across the Country to Predict Future Criminals. And It's Biased Against Blacks" *Federal Probation* Vol. 80, Iss. 2, Sept 38-46,66

Holder A 2014. Speech to National Association of Criminal Defense Lawyers 57th Annual Meeting. PA. August 1

 $\underline{https://www.justice.gov/opa/speech/attorney-general-eric-holder-speaks-national-association-criminal-defense-lawyers-57th}$

Kleinberg, Jon; Lakkaraju, Himabindu; Leskovec, Jure; Ludwig, Jens; Mullainathan, Sendhil 'Human Decisions and Machine Predictions' *The Quarterly Journal of Economics*, 2017, Vol. 133(1), pp.237-293

Sandvik C 2016 'When the Algorithm Itself is a Racist: Diagnosing Ethical Harm in the Basic Components of Software' International Journal of Communication 10 pp 4972 - 4990

Week 6: 21 November

Big data, analytics and process virtue

The use of policy analytics throws up challenges for democratic theory. For instance, we may need to adapt standards of transparency and accountability to meet the reality that many citizens will simply be unable to understand how some decisions are being made. In those circumstances, what specific rights of redress need to be provided and how do those rights differ from the ones available today? This requires us to consider models of technological due process. This class focusses on what such due process might look like and the competing views on the impact of such regulation for innovation.

Readings

European Union. 2016 Regulation 2016/679 of the European Parliament and of the Council on the protection of natural persons with regard to the processing of personal data and on the free movement of such data, and repealing Directive 95/46/EC (General Data Protection Regulation) https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=celex:32016R0679

Kim G-H, Trimi, S and Chung J-H 2014 'Bi-Data Applications in the Government Sector' Communications of the ACM. March. Vol.57, No.3 pp.78 – 85

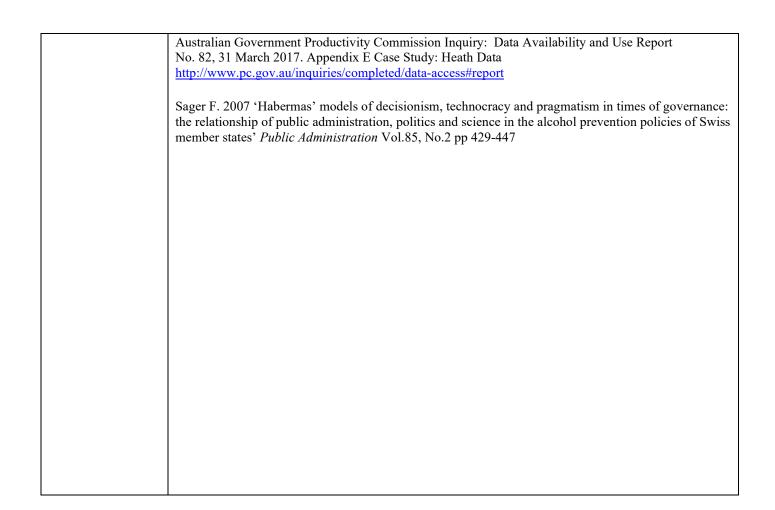
Week 7: 28 Novmber

If time permits: Special additional topic for policy analytics: public health care

Brennan A, Meier P, Purshouse ·R Rafia R, Meng Y and Hill-Macmanus D 2016 'Developing policy analytics for public health strategy and decisions—the Sheffield alcohol policy model framework' *Annals of Operations Research* 236:149-176

Dare T, 'Deceiving Third Parties' 2010 Journal of Primary Health Care Vol.2 No.1 March pp. 83-85

Ola O and Sedig K "The Challenge of Big Data in Public Health: An Opportunity for Visual Analytics" *Online Journal of Public Health Informatics* * ISSN 1947-2579 * http://ojphi.org * 5(3):e223, 2014



Course Policies & Expectations

Lectures:

Class participation is essential to the success of this course. The subjects dealt with in this course are very new and there is no established syllabus internationally for the topic as a whole. Therefore, we need to find our way through the various issues and this can only be achieved with the active involvement of each student.

This is post-graduate education so it should not be necessary to set rules regarding arriving on time, using mobile phones and other distractions. We are in this together so the expectation is that each student will behave in a way that adds to the achievements of the group as a whole.

Each class will be recorded and made available to students. No student may make their own recording of any classroom activity without the express written consent of the instructor. If a student believes that he/she has a special requirement, they should speak with me directly.

Academic Honesty and Integrity

All CMU students are expected to follow the ethical guidelines and adhere to the policies as defined in your Program's <u>Student Handbook</u> or in any other source describing such policies as they apply to students at Carnegie Mellon University. These policies and guidelines are available on the CMU web site.

Individual assignments must reflect individual effort. Sharing your assignments with any other student in any form (whether it is a paper document, an electronic document such like a MS Word document, or a document in any other format) is not permitted and will be considered cheating. Any "discussion" between students that results in a similar submission is also not allowed.

Any violations of academic integrity in this class will have the following consequences:

- (a) at the minimum, no credit for assignment in question <u>and</u> lowering final grade by one letter (e.g., from B to C);
- (b) in more serious offences, failing the class;
- (c) cases will be reported to the Dean's office