[PADP 8440] Big Data and Artificial Intelligence in Public Administration and Policy

University of Georgia

Spring 2023

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Course Information

Office Hours: TuTh 2:30-3:30
Course Time and Day: Mondays, 7:10-9:55 PM
Location: Baldwin 101D.

Course Objectives

The big data revolution is transforming public policy and governance. The goal of this course is to provide an overview of some of the methods driving big data methodologies and to explore how these technologies are shaping and will shape the future of public policy and government with an eye towards the ethical dilemmas that these technologies raise. We begin the course with a discussion of some of the fundamental theories and applications of machine learning methods, which form the basis of big data and artificial intelligence technologies. We then move on to an in-depth discussion of the ethical and societal promises and perils that these technologies pose for decision making in government more broadly, focusing on the potential of these techniques to shape government and policy.

Attendance and Participation

The most important content from this class will come from the lectures and group assignments during lecture time. Because of this and the rather technical nature of this class, attendance and participation in class is extremely important. If you cannot attend a lecture you must present me with a valid excuse at least 24 hours prior to the start of class unless the situation you encountered was an emergency. Either way, absence requires explanation and documentation if you do not want want points taken off your final participation grade.

Grading and Requirements

- *Participation/discussion leader: 30%.*
- *Policy application paper presentation: 30%*
- *Seven (7) problem sets: 40% (may be resubmitted for full credit up to three (3) times)*

Discussion Leaders

Groups of students will be assigned the role of "discussion leaders." Discussion leaders will lead the class discussion for that week by reading the assigned content, preparing a 15-30 minute presentation summarizing the readings and will propose a series of 3-5 and discussion points to start off our discussion about the content. Every student MUST participate in a group as a discussion leader at least once. Discussion leader groups can have a maximum of 2 people and if you do not sign up for one week as a discussion leader you will be assigned to a week.

PLEASE SIGN UP TO BE A DISCUSSION LEADER AT LEAST TWICE WITH YOUR NAME AND THE READING FOR THAT WEEK THAT YOU WOULD LIKE TO DISCUSS. Here is the sign-up sheet:

TBD

Policy Application Paper Presentation

For the first part of the class, in groups of 2-3 you will be asked to give a 10 minute presentation to the class summarizing a paper. In your presentations you must:

- Briefly summarize the paper:
    - What questions is it asking?
    - What are its conclusions?
    - How did it arrive at those conclusions?
- Briefly describe how the method mentioned in the Course Schedule was used in the paper and what conclusions the author drew from this.

You can sign up for a Policy Application Paper Presentation Slot here: https://docs.google.com/spreadsheets/d/1EQdLKn14Bf-jNCICXu-1fDtbWg1oDnI24gS6aVMgPqk/edit?usp=sharing

Problem Sets

- There will be weekly problem sets for the course. These problem sets will either require coding exercises in **R** or short response exercises. The purpose of the problem sets is to reinforce concepts learned in class.

- **RESUBMISSION POLICY:** You may resubmit, for full credit, any problem set that you would like. You can resubmit problem sets up to a total of THREE (3) times.

**All problem sets are due by 7:00PM EST and are to be submitted via the ELC*

Required and Recommended Texts*

Gareth, James, Witten Daniela, Hastie Trevor, and Tibshirani Robert. 2021. *An introduction to statistical learning: with applications in R*. (2021). Springer.

- Available free online: https://hastie.su.domains/ISLR2/ISLRv2_website.pdf
- Also available on the ELC.
- Referred to as **GWT** in the syllabus.
- Additional resources: https://www.statlearning.com/resources-second-edition

Kearns, Michael, and Aaron Roth. *The Ethical Algorithm: The Science of Socially Aware Algorithm Design.* Oxford University Press, 2019.

Nwanganga, F., & Chapple, M. (2020). Practical machine learning in R. John Wiley & Sons.

- Available free from the UGA Library: Online Access
- Referred to as **NC** in the syllabus.

Course Calendar*

Week	**Date**	**Topic**	**Readings (NC)**	**Readings (GWT)**	**Policy Application Reading**	**HW Due**
Part I: A Hands on Introduction to Artificial Intelligence and Machine Learning						
1 NO CLASS	01/09	Machine Learning and Artificial Intelligence Fundamentals	Ch. 1: What is Machine Learning	Ch. 2.1-2.2: Statistical Learning	"The Evolving Role of Artificial Intelligence and Machine Learning in US Politics" Center for Strategic and International Studies (No assignment for this reading).	--
2 NO CLASS	01/16	Introduction to R and RStudio	Ch. 2: Introduction to R and RStudio Ch. 3: Managing Data	Ch. 2.3: Introduction to R		Chapter 1: Exercises 1, 2. (**NC**) Chapter 2.4: 2 (**GWT**)
3	01/23	Regression As Machine Learning I: Linear Regression	Ch. 4: Linear Regression	Ch. 3.1-3.2: Linear Regression		Chapter 2: Exercises 1-3 (**NC**) Chapter 2.4: 7, 8. **(GWT)**
4	01/30	Regression As Machine Learning II: Logistic Regression	Ch. 5: Logistic Regression	Ch. 4.1-4.2: Classification and Logistic Regression	Linear Regression: Bisgaard, M. (2019). How getting the facts right can fuel partisan-motivated reasoning. *American Journal of Political Science*, *63*(4), 824-839.	Chapter 4: Exercises 1, 3. (**NC**) Chapter 3.7: 3, 9. (**GWT**)
4	02/06	Supervised Machine	Ch. 6: k-nearest neighbors.	Ch. 4.4.4 and 4.7.5: Naive	Logistic Regression:	Chapter 5: Exercises 1 (**NC**)

		Learning I: k-Nearest Neighbors and Naive Bayes	Ch. 7: Naive Bayes.	Bayes Ch. 4.7.6: K Nearest Neighbors	Goldring, E., & Matthews, A. S. (2021). To purge or not to purge? An individual-level quantitative analysis of elite purges in dictatorships. *British Journal of Political Science*, 1-19.	Chapter 4.8: 6, 14 (a)-(c) (**GWT**)
5	02/13	Supervised Machine Learning II: Decision Trees and Random Forests	Chapter 8: Decision Trees	Chapter 8: Tree-Based Methods	<u>Naive Bayes</u>: Schub, R. (2022). Informing the Leader: Bureaucracies and International Crises. *American Political Science Review*, 1-17.	Chapter 6: Exercises 1,2. (**NC**) Chapter 7: Exercises 3 (**NC**) Chapter 4.8: 13 (a)-(d), (g)-(j), 14 (g)-(h). (**GWT**)
6	02/20	Evaluating Machine Learning Performance	Chapter 9: Evaluating Performance		<u>Random Forests</u>: Gohdes, A. R. (2020). Repression technology: Internet accessibility and state violence. *American Journal of Political Science*, *64*(3), 488-503.	Chapter 8: Exercise 1 (**NC**) Chapter 8.4: 7, 8 (a), (b), (e). (**GWT**)
7	02/27	Unsupervised Machine Learning with K-Means Clusteing	Chapter 12			Chapter 9: Exercises 1-3 (**NC**)
END Part I						
Week	**Date**	**Topic**	**Readings**			**Discussion Leaders**
Part 2: Big Data and AI: Political, Economic and Social Implications						
NO CLASS SPRING BREAK March 06-March 10						

8	03/ 13	AI in Government and Public Policy - Overview	Kim, S., Andersen, K. N., & Lee, J. (2022). Platform government in the era of smart technology. *Public Administration Review*, *82*(2), 362-368.* Kleinberg et. al. (2018). Human decisions and machine predictions. *The quarterly journal of economics*, *133*(1), 237-293. Valle-Cruz et. al (2019, June). A review of artificial intelligence in government and its potential from a public policy perspective. In *Proceedings of the 20th Annual International Conference on Digital Government Research*(pp. 91-99).*	TBA
9	03/ 20	Bureaucracy, AI and Automation Technologies	Coglianese and Lehr. 2017. "Regulating by Robot Administrative Decision Making in the Machine-Learning Era". Georgetown Law Journal. A case study of algorithm-assisted decision making in child maltreatment hotline screening decisions. *Alexandra Chouldechova, Diana Benavides-Prado, Oleksandr Fialko, Rhema Vaithianathan* ; PMLR 81:134-148 Movie: *The Minority Report.* You can watch this for free on Internet Archive: https://archive.org/details/MinorityReport*	TBA
10		Artificial Intelligence and Law	Loomis v. Wisconsin, Rejected Petition for Writ of Certiorari: https://www.scotusblog.com/wp-content/uploads/2017/05/16-6387-CVSG-Loomis-AC-Pet.pdf Surden, H. (2019). Artificial intelligence and law: An overview. Georgia State University Law Review, 35, 19-22. Chicago* Xu, Z. (2022). Human judges in the era of artificial intelligence: challenges and opportunities. *Applied Artificial Intelligence*, *36*(1), 2013652.	TBA
11	03/ 27	Economics of Artificial Intelligence	Ernst, E., Merola, R., & Samaan, D. (2019). Economics of artificial intelligence: Implications for the future of work. *IZA Journal of Labor Policy*, *9*(1). Lu, Y., & Zhou, Y. (2021). A review on the economics of artificial intelligence. *Journal of Economic Surveys*, *35*(4), 1045-1072.	TBA

12	04/03	Algorithmic Fairness - Overview	Kearns, Michael, and Aaron Roth. *The Ethical Algorithm: The Science of Socially Aware Algorithm Design.* Oxford University Press, 2019. pp 1-94 Cath, C., 2018. Governing artificial intelligence: ethical, legal and technical opportunities and challenges. https://royalsocietypublishing.org/doi/pdf/10.1098/rsta.2018.0080	TBA
13	04/10	Algorithmic Fairness and Counterfactuals	Kasirzadeh, A., & Smart, A. (2021, March). The use and misuse of counterfactuals in ethical machine learning. In *Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency* (pp. 228-236). Johnson, R. A., & Zhang, S. (2022, June). What is the Bureaucratic Counterfactual? Categorical versus Algorithmic Prioritization in US Social Policy. In 2022 ACM Conference on Fairness, Accountability, and Transparency (pp. 1671-1682).	TBA
14	04/17	Machine Learning, Fairness and Bias	*Angwin et al.* Machine Bias *Angwin & Larson.* *Bias in Criminal Risk Scores Is Mathematically Inevitable, Researchers Say* *Chouldechova.* *Fair Prediction with Disparate Impact: A study of bias in recidivism prediction instruments.* Kleinberg et al. Inherent Trade-Offs in the Fair Determination of Risk Scores	TBA
15	04/24	Machine learning, big data and ethics: the modern panopticon?	*Foucault. "Panopticism" in Discipline and Punishment. Pp 195-228* *Ohm & Peppet. What if Everything Reveals Everything?* *Kosinski, Stillwell, and Graepel. Private Traits and Attributes Are Predictable From Digital Records of Human Behavior* *Wu & Zhang. Automated Inference on Criminality using Face Images* *Wang & Kosinsky. Deep neural networks are more accurate than humans at detecting sexual orientation from facial images*	TBA

*I reserve the right to change the calendar to ensure that we spend enough time on each topic. If changes become necessary, they will be announced in class.

Statement about Students with Disabilities

Students with special needs that require accommodation should notify me and the Office for Disability Services in the first two weeks of the course so appropriate arrangements can be made. All information and documentation of special needs is confidential.

Statement about Plagiarism and Academic Dishonesty

Students are responsible for maintaining the highest standards of honesty and integrity in every phase of their academic careers. The penalties for academic dishonesty are severe and ignorance of the policy is not an acceptable defense. See also https://ovpi.uga.edu/academic-honesty.