Research Seminar in Machine Learning and Policy (10-830/90-904)

Course Description

This research seminar is intended for Ph.D. students in Heinz College, the Machine Learning Department, and other university departments who wish to engage in cutting-edge research at the intersection of machine learning and public policy. Qualified master's students may also enroll with permission of the instructor; all students are expected to have some prior background in machine learning and/or artificial intelligence (10-601, 10-701, 90-866, or a similar course). The course has three main objectives: 1) to facilitate in-depth discussions of current research articles and essential topics in machine learning and policy, 2) to benefit the students' own ongoing research projects through presentations, critiques, and discussions, and 3) to encourage interdisciplinary research collaborations between students in Heinz, MLD, and other departments. We plan to achieve these goals through a discussion-based course format: students will present and discuss current research articles on selected topics in machine learning and policy, as well as giving presentations on their ongoing research projects and/or smaller-scale course projects in this domain.

Course Objectives

Upon completion of this course, the student will be able to:

- Illustrate the state of the field of machine learning and determine the directions the field is growing.
- Distinguish what machine learning can contribute to policy research and practice and what policy can contribute to machine learning.
- Determine if a policy application is, or is not, amenable to solution using machine learning methods, and which methods are most appropriate to apply.

These objectives will be assessed through students' course projects, topic presentations, and class participation.

Instructor

Daniel Neill (neill@cs.cmu.edu)
Office hours: Mondays 9:30-10:15am, Wednesdays noon-12:45pm
Hamburg Hall 2105B, x8-3885

Faculty assistant: Natalia Pascal (npascal@andrew.cmu.edu), Hamburg Hall 2112

Class Schedule

Mondays and Wednesdays, 10:30-11:50am, Hamburg Hall 1511

Grading and Due Dates

Class participation: 20%
Topic presentation 1: 20%
Topic presentation 2: 20%
Project proposal presentation (Wednesday, January 27th): 5%
Project proposal (due Wednesday, January 27th, at the beginning of class): 5%
Final presentation (Monday, February 29th): 5%
Final report (due Wednesday, March 2nd, at 11:59pm Eastern time): 25%

Each deliverable will be assigned a letter grade and corresponding numeric grade as follows: A+ = 100%, A = 95%, A- = 90%, B+ = 85%, B = 80%, B- = 75%, C+ = 70%, C = 65%, C- = 60%, F = 0%. Final numerical grades will be computed and rounded to the nearest letter grade (e.g., 97.5-100% A+, 92.5-97.5% A, etc.).
Class Participation

One major goal of this course is to have engaging and insightful group discussions about selected topics and research directions at the intersection of machine learning and public policy, and thus active participation by all students in these discussions is an essential component of the course. Students are expected to attend all class meetings, to read the assigned research articles in advance, and to contribute useful insights, comments, and questions to the discussions.

Topic Presentations

Ten of the fourteen course meetings will be devoted to discussion of specific topics (such as causal discovery, social networks, and the wisdom of crowds). Each student is expected to give a high quality, 20 minute PowerPoint presentation at two of these meetings. Goals of the presentation should be 1) to introduce the topic and provide essential background information, 2) to very briefly review the assigned readings and their relevance to the discussion, and 3) to facilitate the remainder of the discussion by posing questions for discussion, preliminary conclusions, and ideas to explore. For most of the topic discussions, we will have two student presenters: in this case, the students are responsible for coordinating their presentations to avoid unnecessary repetition and to explore different aspects or perspectives of the general topic under discussion.

*** PLEASE LIMIT YOUR PRESENTATION TO 20 MINUTES TO ALLOW SUFFICIENT TIME FOR DISCUSSION!!! ***

To ensure that presentations will be useful and relevant for the class, the presenter(s) should send the instructor a brief text outline of the main topics/points that their presentation will cover, and a proposed set of 2-3 electronically available research articles that the class should read, at least one week prior to the presentation. Failure to follow this timeline may adversely affect your topic presentation grade. The instructor will provide feedback and suggestions, and will post the articles on Blackboard so that the class can read them in advance of the presentation. The chosen research articles should present methods and approaches that are new (or not commonly known), that are likely to be of relevance to both ML and policy researchers, that cover a variety of perspectives, and that raise important issues for discussion.

An important thing to keep in mind is that you want to focus on papers and discussion topics with explicit connections to policy (these could be methodological connections, e.g. combining ML methods with or comparing to methods used in policy, or could be applications of ML to general or specific policy areas). But it's fine for some of the papers/topics to be more general as well. Some good ways to find relevant papers include looking through recent ML conference proceedings (KDD, ICML, AAAI, NIPS) or various journals (economics/econometrics, statistics, policy analysis, etc... I might be able to provide more specific recommendations depending on your topic of interest). Using Citeseer, Google Scholar, or just a Google search is also a good way to get started. Your main goals should be to get a general sense of the discussion topic (the current state of the art, and where the field is headed), and to find some specific papers and questions that will be interesting to discuss. Please note that your presentation should NOT simply describe your chosen papers, but should attempt to situate these in the larger context of the literature and the important advances and open problems related to the topic.

Course Projects

All students are expected to be involved in a research project relevant to machine learning and public policy, to make significant progress on this research over the duration of the course, and to produce a written document describing the project's background (including a description of previous work by the student and related work by others), methods, results, and conclusions. This final report should also include a brief description of how the progress of the work and the student's future research directions have been influenced by the semester's discussions. Students will also be expected to give two brief presentations of their work to the class (at the beginning of the course, describing their proposed work, and at the end of the course, describing their completed work), and to submit a short (1-2 page) proposal, thus providing opportunities for their work to benefit from feedback both from the instructor and from the
class. If desired, the course project can be part of the student's ongoing doctoral research (in which case the student's proposal should make it clear what specific aspect of this work will be addressed during the duration of the course), or can be a smaller-scale project specific to the course.

Note that the course project requirement can be waived for students auditing the course, but all students are expected to give two topic presentations and to be active participants in class discussions.

*** While we expect most projects to be done individually, students can also work in pairs with the instructor's permission. Permission to do so is much more likely to be granted if the two students have complementary skills and perspectives (e.g. ML methodology + expertise in the application domain of interest). Please talk to the instructor if you are interested in this possibility. ***

Syllabus (subject to change- please check back frequently!)

(M 1/11) The Big Picture
Introductions (be prepared to speak for 2-3 minutes each about your background and interests)
Discussion of the course syllabus (course structure, goals, topic presentations, course projects)
The current convergence of ML and public policy (research, curriculum, at CMU and elsewhere)
Preliminary discussion of the "big picture" (we will revisit many of these issues and questions at the end of the course)

(W 1/13) Quick Review of Core Machine Learning Concepts
This course assumes a knowledge of basic machine learning methods as a prerequisite. The instructor will provide a quick review of many of these core concepts, using slides from his "Large Scale Data Analysis for Policy" course. Please look over these slides before the lecture and come prepared to ask questions on any topics that may be unfamiliar. Topics to be covered include supervised learning (decision trees, k-nearest neighbor, naive Bayes), unsupervised learning (clustering, anomaly detection, anomalous pattern detection), graphical models (e.g. Bayesian networks), and other relevant ML paradigms (active learning, reinforcement learning, ...) We can spend as much, or as little, on any of these topics as needed: please let me know before class if there is something you would like us to discuss in detail.

(M 1/18) MLK DAY- NO CLASS / NO OFFICE HOURS!

(W 1/20) Discussion Topic 1: New Directions in Supervised Learning- Explanation and Visualization (Daniel)
Readings: Domingos (required), El-Arini et al. (required), Harle et al. (optional), Green (optional), Guyon and Elisseeff (optional)

Some possible questions for discussion: Perhaps the most common current application of machine learning methods to policy is the use of simple classification and regression techniques (e.g. decision trees) for prediction. In policy analysis, we typically wish not only to achieve high-accuracy predictions of the output variable, but also to determine which input variables have the greatest influence on our predictions. What are the tradeoffs between accuracy and interpretability in classification? How can we design classifiers so that the results are easily visualizable and understandable, but without losing (much) prediction accuracy? When is it preferable to use a more interpretable classifier (such as decision trees or naive Bayes) and how can the outputs of each classifier be interpreted? How are our interpretations affected by correlations between input variables? When can we draw conclusions about the causal relationships between the input and output variables? When is it better to use a less interpretable classifier (such as neural networks or support vector machines), or combine classifiers (e.g. through bagging or boosting) for higher accuracy? Can we improve the interpretability of such methods without sacrificing accuracy, or can we learn an interpretable model which closely matches the output of the less interpretable model? How can we perform dimensionality reduction and data visualization such that the low-dimensional classifier has high accuracy, but the projected dimensions are still interpretable?

(M 1/25) Discussion Topic 2: Graphical Models and Causality (Daniel)
Readings: Mahmood (required), Mwebaze et al. (required), Jensen et al. (optional), Spirtes (optional), Statnikov et al. (optional)
Some possible questions for discussion: How can we use Bayesian networks and other graphical models to understand the relationships between variables in policy domains? What recent innovations have made inference and learning of Bayesian networks efficient and scalable (e.g., new methods for structure learning; variational inference; context-specific independence)? How can we deduce causal relationships from observational data, experimental data, or from a combination of data and prior knowledge? What assumptions need to be made to interpret a Bayes Net causally? What role do latent (hidden) variables play in causal discovery, and how can we model them?

(W 1/27) Project Proposal Presentations
Each student will present a short PowerPoint presentation on their proposed course project, as well as turning in a short (1-2 page) proposal.

(M 2/1) Discussion Topic 3: Integrating Machine Learning and Economic Approaches to Causal Inference
Readings: Athey and Imbens (required), Sengupta (required), Angrist et al. (optional), Doyle (optional), Imbens and Lemieux (optional).

Some possible questions for discussion: How do the models, methods of analysis, and perspectives applied in typical social science, economics, and policy research compare to those developed by machine learning and data mining researchers? Is it possible to integrate ideas from these two fields to improve the quality of decision-making and policy analysis? More specifically, economists tend to think about causal inferences in very different ways than the graphical model-based approaches we previously discussed (natural experiments, instrumental variables, matching, etc.) Are there ways in which these approaches can be usefully integrated with machine learning methods to make policy-relevant causal inferences from massive data?

(W 2/3) Discussion Topic 4: Active Learning and User Interaction
Readings: Press (required), Yan et al. (required), Ambati et al. (optional), Donmez and Carbonell (optional), Ganti and Gray (optional), Vijayanarasimhan and Grauman (optional), Settles (optional).

Some possible questions for discussion: How can unlabeled data be used effectively to improve the accuracy of classification? Given a human user “in the loop” who can provide feedback to the system, how can active learning methods be used to choose the best points for the user to label? In what contexts and for what applications are active learning methods most useful for policy, and how can they best be applied? How can systems and interfaces be designed to incorporate ML methods in ways that maximize benefit to users in the public sector?

(M 2/8) Discussion Topic 5: Machine Learning for Policy Decision Support
Readings: Meyer et al. (required), Tulabandhula and Rudin (required), Duro et al. (optional), Merkert et al. (optional), Sleesman (optional).

Some possible questions for discussion: What are the various ways in which machine learning can be used by policy-makers to make better decisions? Some possible applications include counterfactual analysis, learning probabilistic and causal relationships between variables, determining optimal sequential decisions in a large and uncertain state-space, and modeling multi-person decision-making interactions. Are there ways in which the output of machine learning algorithms (models, predictions, recommended decisions, etc.) could be framed to facilitate understanding and adoption by policy-makers (e.g., interpretable classifiers)? Under what circumstances is it necessary to perform a causal analysis, or when is a purely predictive analysis sufficient?

(W 2/10) Discussion Topic 6: Social Network Analysis and Mining
Readings: Chen and Neill (required), McAuley and Leskovec (required), Banerjee et al. (optional), Cheng et al. (optional), Sarkar et al. (optional), Jackson (optional).

Some possible questions for discussion: What can machine learning tell us about the structure and organization of social networks (including, but not limited to, online social networks)? Which methods can be used most effectively to predict link formation, detect communities, and model the propagation of behavior through a network? How can we effectively detect or predict emerging patterns in an online social network such as Twitter, and how can these approaches be used for policy applications such as civil unrest prediction, disease surveillance, and human rights?

(M 2/15) Discussion Topic 7: ML for Politics and Law
Readings: Cleland-Huang et al. (required), Nickerson and Rogers (required), Aktolga et al. (optional), Ashley and Walker (optional), Kolar et al. (optional), Surden (optional).
Some possible questions for discussion: How can machine learning be used to understand or improve the political process? This could include targeted and efficient campaigning strategies (e.g. viral marketing, crowdsourcing, analyzing the factors underlying legislative or court decisions, etc. Text analysis (e.g., of legislative documents) and graph analysis (e.g., of the relationships and social structures impacting congressional votes on an issue) may be interesting to discuss here.

(W 2/17) Discussion Topic 8: ML for the Developing World
Readings: Ermon et al. (required), Waidyanatha et al. (required), Baba et al. (optional), McBride & Nichols (optional), Mwebaze et al. (optional).

Some possible questions for discussion: How can machine learning methods best be applied to improve the quality of life in developing countries (e.g. influencing international health and development policy, disease surveillance and other event monitoring systems). How can ML methods be adapted to account for poor quality and availability of data, and how can they be used to optimize limited resources (e.g. deciding which data to obtain)? What are the common features and challenges of development data, and which methodological approaches might be most useful for addressing these challenges?

(M 2/22) Discussion Topic 9: ML for Safety and Security
Readings: Roberts (required), Shakarian et al. (one required, one optional), Subrahmanian et al. (optional), Sun et al. (optional).

Some possible questions for discussion: What are the various ways in which machine learning can be used to keep our society safer and more secure? Applications include predictive policing, anti-terrorism, cybersecurity, customs monitoring, fighting human trafficking, civil unrest prediction, etc. What data sources are most useful for these applications, and what are the main challenges and potential solutions? How should machine learning algorithms be designed when data may be adversarial rather than produced by nature, and the adversary may adapt as the system learns?

(W 2/24) Discussion Topic 10: Deep Learning for Policy + The Big Picture, Revisited (Daniel)
Readings: Bengio et al. (required), Louizos et al. (optional), Woelfl (optional)

Some possible questions for discussion: Deep learning is an extremely popular machine learning technique useful for extracting latent structure in data and achieving state of the art performance on a variety of challenging tasks (image classification and understanding, speech recognition, etc.) What is deep learning, and what are the main advances that allow it to work effectively? What policy problems might benefit most from the use of deep learning? What are the main challenges (e.g., lack of interpretability and transparency) that impede its use in the public sector, and how might these be overcome?

(M 2/29) Project Presentations
Each student will give a short presentation on their course project. Final project reports are due Wednesday 3/2 at 11:59pm Eastern time.