Oxford University, Hilary term 2022, Syllabus for:
Foundations of machine learning

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1 Overview and Objectives

The goal of this course is to provide you with solid **theoretical foundations in machine learning**. This will allow you to

1. become critical consumers of machine learning research, including an understanding when new methods might or might not be useful for empirical work in economics,

2. develop your own research agenda around importing ideas from machine learning into economic and econometric theory, and

3. speak to the machine learning literature, contributing ideas from economics.

We begin by introducing some **foundations**. The class starts with a review of statistical decision theory, which provides the conceptual framework for the rest of the course. We next introduce probably approximately correct learning theory for classification and prediction. We then consider regularization and data-driven choice of tuning parameters. We will discuss the canonical normal means model. In this model, we will motivate shrinkage estimators in different ways, and will prove the famous result that shrinkage estimators can uniformly dominate conventional estimators.

We will then apply these general ideas and discuss several methods for **supervised machine learning**, that is, prediction. We will discuss Gaussian process regressions, random forests, and deep neural nets. In this context, we will also consider numerical methods used for training neural nets, such as stochastic gradient descent. We finish this part of class by discussing double/debiased machine learning, a framework for constructing estimators that use supervised learning estimators as an input.

The next part of class will cover different frameworks for **online and adaptive learning**. We will start with the adversarial online learning setting, where no probabilistic assumptions about data generation are made at all. We will next consider multi-armed bandits, and review some theoretical results providing performance guarantees (regret bounds) for algorithms used for learning in bandit settings. We will then turn to a generalization of bandit problems, Markov decision problems, and will discuss reinforcement learning approaches for solving these.

The class will conclude with a discussion of **ethics** and the **social impact** of artificial intelligence. We will, in particular, review debates surrounding fairness and discrimination, as well as differential privacy.

2 Assignments

Your grade for this class will be based on three problem sets (20% of grade each), as well as a research proposal (40% of grade). All of these have to be submitted via Canvas. There will be no exam.

If you need any special accommodations for physical or medical reasons, please send me an email.

Problem sets There will be three longer problem sets. The problem sets will focus on implementing some of the methods discussed in class in R, and conducting simulation exercises, verifying some of our theoretical results numerically.

Your solutions will have to satisfy the following conditions:

1. The code has to run from start to end on the grader's machine, producing all the output.
2. Output and discussion of findings have to be integrated in a report generated in R-Markdown.
3. Figures and tables have to be clearly labeled and interpretable.
4. The findings need to be discussed in the context of the theoretical results that we derived in class.

Research proposal You are asked to submit a research proposal at the end of the course. The proposal has to be based on one of the areas of machine learning covered in class. Proposals might fall in one of several domains, including

(i) applications of machine learning in empirical economics,

(ii) econometric theory drawing on ideas from machine learning, and

(iii) machine learning theory, drawing on ideas from economics.

Your research proposals have to satisfy the following conditions:

1. They cannot be identical with the topic of the MPhil thesis that you might be writing concurrently.
2. The proposals have to indicate clearly whether your contribution is of type (i), (ii), or (iii), as described above.
3. The proposals have to be between 7 and 10 pages, 12pt font, 1.5 linespacing, margins of 3cm, A4. Code and references do not count to this page limit.
4. The proposals cannot consist exclusively of a summary of literature; they have to propose new research.

3 References

Required readings are marked by ☺.

3.1 Foundations

Review of decision theory

☺Robert, C. (2007). *The Bayesian choice: from decision-theoretic foundations to computational implementation.* Springer Verlag, chapter 2.

Probably approximately correct learning theory

☺Shalev-Shwartz, S. and Ben-David, S. (2014). *Understanding machine learning: From theory to algorithms.* Cambridge University Press, chapters 2 to 6.

Shrinkage in the normal means model

Wasserman, L. (2006). *All of nonparametric statistics.* Springer Science & Business Media, chapter 7.

☺Stigler, S. M. (1990). The 1988 Neyman memorial lecture: a Galtonian perspective on shrinkage estimators. *Statistical Science*, pages 147–155.

☺Morris, C. N. (1983). Parametric empirical Bayes inference: Theory and applications. *Journal of the American Statistical Association*, 78(381):pp. 47–55.

Stein, C. M. (1981). Estimation of the mean of a multivariate normal distribution. *The Annals of Statistics*, 9(6):1135–1151.

van der Vaart, A. W. (2000). *Asymptotic statistics.* Cambridge University Press, chapter 7.

Hansen, B. E. (2016). Efficient shrinkage in parametric models. *Journal of Econometrics*, 190(1):115–132.

Abadie, A. and Kasy, M. (2019). Choosing among regularized estimators in empirical economics - the risk of machine learning. *Review of Economics and Statistics*, CI(5).

Fessler, P. and Kasy, M. (2019). How to Use Economic Theory to Improve Estimators: Shrinking Toward Theoretical Restrictions. *The Review of Economics and Statistics*, 101(4):681–698.

3.2 Supervised learning

Gaussian process priors, reproducing kernel Hilbert spaces, and Splines

☺Williams, C. and Rasmussen, C. (2006). *Gaussian processes for machine learning.* MIT Press, chapters 2 and 7.

Wahba, G. (1990). *Spline models for observational data*, volume 59. Society for Industrial Mathematics, chapter 1.

Kasy, M. (2016b). Why experimenters might not always want to randomize, and what they could do instead. *Political Analysis*, 24(3):324–338.

Kasy, M. (2019). Optimal taxation and insurance using machine learning – sufficient statistics and beyond. *Journal of Public Economics.*

Regression trees and random forests

☺Friedman, J., Hastie, T., and Tibshirani, R. (2001). *The elements of statistical learning*, volume 1. Springer series in statistics Springer, Berlin, chapters 8 and 9.

Athey, S. and Imbens, G. (2016). Recursive partitioning for heterogeneous causal effects. *Proceedings of the National Academy of Sciences*, 113(27):7353–7360.

Deep neural nets

☺Goodfellow, I., Bengio, Y., and Courville, A. (2016). *Deep learning.* MIT Press, chapters 6-8.

Bottou, L., Curtis, F. E., and Nocedal, J. (2018). Optimization methods for large-scale machine learning. *SIAM Review*, 60(2):223–311

Double/debiased machine learning

Chernozhukov, V., Chetverikov, D., Demirer, M., Duflo, E., Hansen, C., Newey, W., and Robins, J. (2018). Double/debiased machine learning for treatment and structural parameters. *The Econometrics Journal*, 21(1):C1–C68.

3.3 Online learning and active learning

Online learning

☺Cesa-Bianchi, N. and Lugosi, G. (2006). *Prediction, learning, and games.* Cambridge University Press, chapter 2.

Lewi, Y., Kaplan, H., and Mansour, Y. (2020). Thompson sampling for adversarial bit prediction. In *Algorithmic Learning Theory*, pages 518–553. PMLR

Bandit problems

Bubeck, S. and Cesa-Bianchi, N. (2012). Regret Analysis of Stochastic and Nonstochastic Multi-armed Bandit Problems. *Foundations and Trends® in Machine Learning*, 5(1):1–122.

☺Russo, D. J., Roy, B. V., Kazerouni, A., Osband, I., and Wen, Z. (2018). A Tutorial on Thompson Sampling. *Foundations and Trends® in Machine Learning*, 11(1):1–96.

Weber, R. et al. (1992). On the Gittins index for multiarmed bandits. *The Annals of Applied Probability*, 2(4):1024–1033.

☺Kasy, M. and Sautmann, A. (2021). Adaptive treatment assignment in experiments for policy choice. *Econometrica*, 89(1):113–132.

Wager, S. and Xu, K. (2021). Diffusion asymptotics for sequential experiments. *arXiv preprint arXiv:2101.09855.*

Caria, S., Gordon, G., Kasy, M., Osman, S., Quinn, S., and Teytelboym, A. (2020). Job search assistance for refugees in Jordan: An adaptive field experiment. *Working Paper.*

Reinforcement learning

Sutton, R. S. and Barto, A. G. (2018). *Reinforcement learning: An introduction.* MIT press.

François-Lavet, V., Henderson, P., Islam, R., Bellemare, M. G., and Pineau, J. (2018). An introduction to deep reinforcement learning. *Foundations and Trends® in Machine Learning*, 11(3-4):219–354.

3.4 Ethics and machine learning

☺Kearns, M. and Roth, A. (2019). *The Ethical Algorithm: The Science of Socially Aware Algorithm Design.* Oxford University Press.

Fairness

Pessach, D. and Shmueli, E. (2020). Algorithmic fairness. *arXiv preprint arXiv:2001.09784*

Kasy, M. and Abebe, R. (2021). Fairness, equality, and power in algorithmic decision making. *ACM Conference on Fairness, Accountability, and Transparency.*

Kasy, M. (2016a). Empirical research on economic inequality. `http://inequalityresearch.net/`

Roemer, J. E. (1998). *Theories of distributive justice.* Harvard University Press, Cambridge.

Differential privacy

Dwork, C. and Roth, A. (2014). The algorithmic foundations of differential privacy. *Foundations and Trends® in Theoretical Computer Science*, 9(3–4):211–407.