University of Oxford, Hilary term 2024, Syllabus for:
Foundations of machine learning

instructor	Maximilian Kasy
email	teachingmaxkasy@gmail.com
class time	Thursday 14:00-15:30 and Friday 11:30-13:00
webpage	https://maxkasy.github.io/home/ML_Oxford_2024/
canvas page	https://canvas.ox.ac.uk/courses/217519
location	Lecture Theatre, Manor Road Building

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, deep neural nets, and Transformer models for natural language processing. 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.

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

2 Assignments

Your grade for this class will be based on a portfolio of coding exercises (60% of grade), as well as a research proposal (40% of grade). Both of these are **due** on **29 March 2024**. And both have to be submitted in **pdf** format via **Inspera**. There will be no exam.

Coding portfolio The portfolio of coding exercises will be based on three problem sets. The problem sets focus on implementing some of the methods discussed in class in **R**, or in **Python** (the choice is yours). You will conduct simulation exercises to verify some of our theoretical results numerically. To help you learn these programming languages, if needed, I have compiled a list of resources here: https://maxkasy.github.io/home/computationlinks/.

I strongly encourage you to complete the problemsets early during the term, to avoid a time-crunch at the end of term, and to stay in sync with lectures. The suggested completion dates for the problemsets are 9 February, 23 February, and 8 March. Your coding portfolio has to satisfy the following conditions:

- For each of the 3 assignments, all results should be generated from a single script, running from start to end, producing all the output.
- Output and discussion of findings have to be integrated in a report generated in R-Markdown or Quarto (for R), or a Jupyter notebook (for Python).
- The findings need to be discussed in the context of the theoretical results that we derived in class.
- Figures and tables have to be clearly labeled and interpretable.
- You have to submit the pdf (and only the pdf) generated from your script. This pdf should contain, first, your discussion and overview of your code. The pdf should then show the source code used to generate your findings. This pdf should, finally, show the figures and tables generated by your code, joint with a discussion of your findings.

- Please make an effort to make this “human-readable” and do not include long lists of warnings, intermediate calculations, etc.

You are allowed, and in fact encouraged, to collaborate in small groups (of up to 4 students) for the coding assignments. You are allowed to share jointly written computer code with the classmates in your group. However, each one of you must write up your answers completely independently.

Research proposal The research 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. This corresponds to about 2500-3500 words. 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*, 101(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. (2016). Why experimenters might not always want to randomize, and what they could do instead. *Political Analysis*, 24(3):324–338.

Kasy, M. (2018). Optimal taxation and insurance using machine learning – sufficient statistics and beyond. *Journal of Public Economics*, 167.

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

Bartlett, P. L., Montanari, A., and Rakhlin, A. (2021). Deep learning: a statistical viewpoint. *arXiv preprint arXiv:2103.09177*

Large Language Models and Transformers

Jurafsky, D. and Martin, J. H. (2023). *Speech and Language Processing.* https://web.stanford.edu/ jurafsky/slp3/, chapters 9–11.

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

Hazan, E. (2016). Introduction to online convex optimization. *Foundations and Trends in Optimization*, 2(3-4):157–325.

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. (2023). Job search assistance for refugees in Jordan: An adaptive field experiment. *Journal of the European Economic Association (forthcoming).*

Cesa-Bianchi, N., Colomboni, R., and Kasy, M. (2023). Adaptive maximization of social welfare. *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.

☺Kasy, M. (2023b). The political economy of AI: Towards democratic control of the means of prediction. *Working Paper*.

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. (2023a). Algorithmic bias and racial inequality: A critical review. *Working Paper*.

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.