

Machine Learning: Applications in Empirical Microeconomics

BeNA Short Course, September 4–6, 2019

Jann Spiess*

Assistant Professor of Operations, Information & Technology

Stanford Graduate School of Business

jspiess@stanford.edu

Preliminary Syllabus

July 12, 2019

1 Overview of class purpose and content

Machine learning has created many engineering breakthroughs from real-time voice recognition to automatic categorization (and in some cases production) of news stories. What is particularly tantalizing though is that machine learning is, at its heart, an empirical tool. It takes as input large data sets and produces outputs such as a functions that relate one variable to others. The language is different: estimators are called algorithms; outcome variables are called labels; and so on. But at their core they are econometric tools: they find empirical relationships in data. Given the similarity to tools we know, it is tempting to ask whether it is merely old (econometric) wine in a new (machine learning) bottle.

In this course, we will argue that it is not. Far from it, we will discuss how these tools can powerfully improve and expand on the kind of empirical work we tend to do. At the same time, we will discuss their limitations and how they fit into the “econometric toolbox”. At a high level, this class will address these three questions:

1. How does machine learning work? There are textbooks to teach you how to implement machine learning. In fact, existing statistical packages make it trivial to do this in practice. But what makes them work? What statistical guarantees do they provide? In a way, machine learning is too easy to implement. By gaining a basic understanding of its econometric underpinnings, it can be used more accurately.

*Based on work with Sendhil Mullainathan.

2. What can machine learning tools do that our current toolbox cannot? Or put more positively, where does it fit in the toolbox of an applied economist? This class will give a sense of how it relates to the other existing tools, specifically causal inference and basic regression.
3. Where and how can machine learning be implemented to generate new research output in empirical microeconomics, specifically labor, health, and education? New computational tricks, statistical advances, and novel data sources allow us to improve answers to old questions as well as ask new questions.

We will cover standard machine learning techniques with a focus on supervised learning (such as regularized regression and methods based on decision trees). We will then discuss recent papers that use these methods, and attempt to implement some of these methods ourselves.

Unlike the BSE “Applied Econometric Approach” course, this class will focus less on econometric underpinnings and more on applications of machine learning in applied microeconomics, such as labor, health, and education. The two classes overlap significantly and are not designed to be taken together.

1.1 Target audience and prerequisites

The course is aimed at graduate students looking to deepen and expand their research toolset, specifically those who want to apply machine learning in their own empirical research in fields such as labor, health, and education. Students should have some basic graduate training in econometrics.

There will be examples and small exercises in the statistical programming language R. While we will not be able to teach R, knowledge of the specific language is not essential, but some familiarity with statistical programming (such as in Stata, Matlab, or Python) is helpful.

1.2 Limitations

Given time limitations and the availability of numerous resources on machine learning, we will not cover:

- The computational aspects of the underlying methods. There are some important innovations that have made these techniques computationally feasible. We will not discuss these, as there are computer science courses better equipped to cover them.
- The nitty-gritty of how to use these tools. The technical mechanics of implementation, whether it be programming languages or learning to use APIs, will not be covered in detail. We will instead focus on the conceptual aspects of applying available implementations in economics.

- In-depth econometric results and guarantees. The focus of this course will be on applications and not on the mathematical underpinnings of these methods.

Given the time constraints of the course, even for many other topics that are covered in the class we will only be able to give a high-level conceptual understanding as well as pointers to more detailed material.

1.3 General references

There is no required reading or unified textbook for the course. Some references will be given for specific topics. The class is largely following the framing and structure from Mullainathan and Spiess (2017). Helpful textbooks with background on machine learning are:

- Hastie, T., Friedman, J., and Tibshirani, R. (2001). *The Elements of Statistical Learning Data Mining, Inference, and Prediction*. Springer. Available online as a pdf download.
- Murphy, K. P. (2012). *Machine Learning: A Probabilistic Perspective*. MIT Press.
- Bishop, C. M. (2006). *Pattern Recognition and Machine Learning*. Springer.

2 Preliminary structure of the class

- 1. The rise of machine learning.** Where do recent breakthroughs in machine intelligence come from? How is machine learning (ML) different from classical artificial intelligence? What is the relationship to statistics?

- Breiman, L. (2001). Statistical modeling: The two cultures. *Statistical Science*, 16(3):199–231.
- Athey, S. (2018). The impact of machine learning on economics. In *The Economics of Artificial Intelligence: An agenda*. University of Chicago Press.

- 2. The secret sauce of ML.** What allows machine learning to predict well in very high-dimensional data? What are common features of supervised machine-learning algorithms? How are they implemented and how can we choose the right algorithms and parameters for the prediction task at hand?

- James, W. and Stein, C. (1961). Estimation with quadratic loss. In *Proceedings of the Fourth Berkeley Symposium on Mathematical Statistics and Probability, Volume 1: Contributions to the Theory of Statistics*. The Regents of the University of California.
- Tibshirani, R. (1996). Regression shrinkage and selection via the lasso. *Journal of the Royal Statistical Society: Series B (Methodological)*, 58(1):267–288.

- 3. Prediction (\hat{y}) vs estimation ($\hat{\beta}$).** How does ML relate to standard regression analysis in econometrics? Which guarantees do we need and obtain? What are the limits of interpreting parameters coming out of ML?
- Zhao, P. and Yu, B. (2006). On model selection consistency of lasso. *The Journal of Machine Learning Research*, 7:2541–2563.
 - Mullainathan, S. and Spiess, J. (2017). Machine learning: An applied econometric approach. *Journal of Economic Perspectives*, 31(2):87–106.
- 4. Uses of ML in empirical work.** Given that machine learning provides high-quality predictions but we often care about (causal) estimation in applied econometric work, how can we adapt techniques and insights from machine learning in a program-evaluation context?
- (a) Prediction policy problems: where prediction solutions directly solve the problem
 - Kleinberg, J., Ludwig, J., Mullainathan, S., and Obermeyer, Z. (2015). Prediction policy problems. *American Economic Review*, 105(5):491–95.
 - (b) Prediction in the service of estimation: where prediction techniques can enhance causal inference
 - Athey, S. and Imbens, G. (2016). Recursive partitioning for heterogeneous causal effects. *Proceedings of the National Academy of Sciences*, 113(27):7353–7360.
 - Athey, S., Tibshirani, J., and Wager, S. (2019). Generalized random forests. *The Annals of Statistics*, 47(2):1148–1178.
 - 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.
 - Belloni, A., Chen, D., Chernozhukov, V., and Hansen, C. (2012). Sparse models and methods for optimal instruments with an application to eminent domain. *Econometrica*, 80(6):2369–2429.
 - (c) Predictability as the question of interest: where properties of a prediction solution provide tests for theories
 - Kleinberg, J., Liang, A., and Mullainathan, S. (2017b). The theory is predictive, but is it complete? An application to human perception of randomness. In *Proceedings of the 2017 ACM Conference on Economics and Computation*, pages 125–126. ACM.
 - Gagnon-Bartsch, J. and Shem-Tov, Y. (2019). The classification permutation test: A flexible approach to testing for covariate imbalance. *Annals of Applied Statistics*.
 - (d) New data: where prediction solutions allow us to use new data sources to construct variables for further analysis

- Donaldson, D. and Storeygard, A. (2016). The view from above: Applications of satellite data in economics. *Journal of Economic Perspectives*, 30(4):171–98.
- Blumenstock, J., Cadamuro, G., and On, R. (2015). Predicting poverty and wealth from mobile phone metadata. *Science*, 350(6264):1073–1076.

5. Applications of ML in empirical microeconomics. Where have methods been used in the recent literature in applied microeconomics, specifically labor and public economics?

- Bansak, K., Ferwerda, J., Hainmueller, J., Dillon, A., Hangartner, D., Lawrence, D., and Weinstein, J. (2018). Improving refugee integration through data-driven algorithmic assignment. *Science*, 359(6373):325–329.
- Kleinberg, J., Lakkaraju, H., Leskovec, J., Ludwig, J., and Mullainathan, S. (2017a). Human decisions and machine predictions. *The Quarterly Journal of Economics*, 133(1):237–293.
- Enke, B. (2018). Moral values and voting. Technical report, National Bureau of Economic Research.

6. Implementation of machine-learning methods in applied micro. How can out-of-the-box ML solutions be implemented in applied research? Which computational innovations and econometric results are readily available?

- Varian, H. R. (2014). Big data: New tricks for econometrics. *Journal of Economic Perspectives*, 28(2):3–28.

7. Implications of the availability of machine learning. How would we expect labor markets to change when these techniques become more and more available? Who wins, who loses?

- Agrawal, A., Gans, J., and Goldfarb, A. (2018). *Prediction machines: the simple economics of artificial intelligence*. Harvard Business Press.