

Prediction and machine learning

[EC524/424]






Winter 2021 Syllabus






<https://github.com/edrubin/EC524W21>

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	<u>Instructor</u>	<u>GE</u>
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	<u>Lecture</u>	<u>Lab</u>
	Tu. & Th., 2:15pm–3:45pm	Fr., 12:30p–1:30p
	Zoom (linked in Canvas) and/or MCK 240A	Zoom (linked in Canvas)
	Ed	Stephen Ed
	Our class: https://github.com/edrubin/EC524W21/	
	Last year: https://github.com/edrubin/EC524W20/	

Course summary

Description Following the first course on econometrics and causal inference in our sequence, EC524 turns to examining the **tools available and best practices for predicting outcomes**. Put simply, we are now focusing on \hat{y}_i rather than $\hat{\beta}$ from the model $y_i = \alpha + \beta x_i + \varepsilon_i$.

Learning statistical programming is inherent to practicing applied econometrics. Consequently, throughout this course we will also teach the statistical programming language R.

Objectives

1. **Distinguish** between settings that require **causal inference** vs. settings that want **prediction**.
2. Understand the main **themes and best practices** in modern **prediction** methods.
3. Develop **familiarity** with common machine-learning algorithms—and their strengths/weaknesses.
4. Build **intuition** for prediction—especially the bias-variance tradeoff.
5. Expand **R expertise**.

Prerequisites This course requires the previous course in our sequence—*i.e.*, Economics 423/523. I also assume you are comfortable in R.

Books

I know you are busy and reading for class is often difficult. However, **if you are actually here to learn, then read these books**.

Note Each book (except one of the recommended books) is available for **free online**. The physical copies are also very reasonably priced—I suggest you buy physical versions for books that you like.

Required books

1. [Introduction to Statistical Learning](#) *ISL*
2. [The Hundred-Page Machine Learning Book](#) *100ML*
3. [Data Visualization](#) *Data Viz*

Suggested books

1. [R for Data Science](#)
2. [Introduction to Data Science](#) (not available without purchase)
3. [The Elements of Statistical Learning](#) (*ESL*, the big brother of *ISL*)

Software and tools

- We will use the statistical programming language **R**.
- We will use **RStudio** to interact with R.

Learning R will require time and effort, but it is a powerful and versatile tool that is valued by many employers. Put in the requisite effort and time, and you will be rewarded.

Labs, assignments, projects, and exams

Attend the lab This course includes a lab, which is **integral to learning** the material in (and passing) this course. The lab includes both general econometrics instruction and computing resources necessary to complete the course and learn/master its topics.

Assignments

- You will submit **typed assignments via Canvas**.
- Assignments will typically be due on Thursday evenings.
- We will grade on a **complete/incomplete scale**. Low-quality work will be returned to be re-submitted as late.

Late submissions Students whose assignments are occasionally late will be penalized half a letter grade. Students whose assignments are frequently late will be penalized a full letter grade.

Group work Feel free to work together on the assignments. Unless explicitly stated, each student is required to write and submit independent answer sheets. This means that word-for-word copies will not be accepted and will be viewed as academic dishonesty. If you work with other students, you must list the students in your study group at the top of your assignment. If you fail to do so, you will receive a score of zero.

Project We will have one major project. Details coming.

Exams

- We will proctor an **in-class final on Tu., March 17, 2021 at 2:45pm** (likely online).
- A **take-home final exam will be due Tu., March 17, 2021 by 11:59pm**.

Recommendations

1. **Be kind.**
2. **Take responsibility** for your own education and try to **learn** as much as you can.
3. **Do your own work.**
4. Develop your **intuition**—e.g., why would method x work in one situation and fail in another?
5. **Learn R.** Struggle while you try—and use **Google** to figure things out.
6. Come to **office hours**.¹

Honesty and academic integrity

You must do your own work. Do not claim credit for any work other than your own. Cheating or plagiarizing of any sort on any component of this class will result in a failing grade for the term and a report of the offense to the university. Please acquaint yourself with the **Student Conduct Code**.

¹Two related articles from NPR on office hours: [College Students: How to Make Office Hours Less Scary](#) and [Uncovering A Huge Mystery Of College: Office Hours](#).

Accessibility

If you have a documented disability and anticipate needing accommodations in this course, please make arrangements with me during the first week of the term. Please request that the [Accessible Education Center](#) send me a letter verifying your disability.

Grading

Grades will be assigned as follows.²

<u>Grade</u>	<u>Assignments</u>	<u>Project</u>	<u>Final exam</u>
A	<i>Incomplete</i> on ≤ 1 assignment.	\geq <i>Professional</i>	$\geq 80\%$
B	<i>Incomplete</i> on ≤ 2 assignments.	\geq <i>Minor revision</i>	$\geq 70\%$
C	<i>Incomplete</i> on ≤ 3 assignments.	\geq <i>Moderate revision</i>	$\geq 60\%$
D	<i>Incomplete</i> on ≤ 4 assignments.	\geq <i>Major revision</i>	$\geq 50\%$

Recall that assignments are graded as *Complete* vs. *Incomplete*—the standard for *Complete* is much higher than simply submitting.

²Undergraduates are allowed to miss one additional assignment in the scheme.

Tentative, overly-ambitious, predicted outline

0. An introduction to prediction and statistical learning

1. What are we doing? **Readings** *ISL* Introduction, Ch1
2. Prediction vs. causal inference **Readings** *Prediction Policy Problems* by Kleinberg et al. (2015)
3. Modeling decisions and assessment **Readings** *ISL* Ch3

1. Exploratory data analysis

1. Building insights from graphics **Readings** *Data Viz* Preface, Ch1
2. ggplot2 **Readings** *Data Viz* Ch3

2. Supervised learning

1. An introduction to machine learning **Readings** *100ML* Preface, Ch1–Ch4; *ISL* 2.1–2.2
2. Resampling methods and other best practices **Readings** *100ML* Ch5; *ISL* Ch5
3. Why don't we stick with regression? **Readings** *ISL* Ch3
4. LASSO and Ridge regression **Readings** *ISL* 6.1–6.3, 6.6
5. Classification and logistic regression **Readings** *ISL* 4.1–4.3
6. Decision trees **Readings** *100ML* 3.3; *ISL* 8.1
7. Ensembles: Bagging, random forests, boosting **Readings** *ISL* 8.2–8.3 *100ML* 7.5 and Ch8
8. SVM **Readings** *100ML* 3.4; *ISL* 9.1–9.4
9. Neural nets **Readings** *100ML* 6
10. Additional topics **Readings** *100ML* Ch7 and Ch11

3. Unsupervised learning

1. Introduction to unsupervised learning **Readings** *100ML* Ch9; *ISL* 10.1
2. Principal components analysis **Readings** *ISL* 10.2; *100ML* 9.3
3. Nearest-neighbor matching, *K*-means, and hierarchical clustering **Readings** *100ML* Ch9; *ISL* 10.3

4. Extensions

1. Bias and fairness **Readings** *Hao (2019)*