PLSC 40601

Week 1: Course orientation, potential outcomes framework.

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Spring 2024

Housekeeping

Housekeeping

- Sign up for papers/discussion

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- Fork and create a PR for the repo

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- https://bookdown.org/halflearned/ml-ci-tutorial/

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- $Y_i(0), \ldots, Y_i(K)$ are *potential* outcomes; typically, we only get to see an individual outcome under one version of treatment.
- **Fundamental problem of causal inference**: we can't see counterfactual potential outcomes for a given unit *at the same time*.
- How do we move from what we observe to what we would like, ideally, to measure?

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  - If we're dealing with a **finite population**, we can think about identifying a target quantity about that population, as if we were to repeat the procedure through we observed data about that population, averaging *across repetitions*, we could approximate the true quantity to arbitrary precision.

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  - We can consider parameters to be **point identified** or **interval identified**.

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- In econometrics, this is often expressed in terms of the "switching" equation.

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- But once we impose that $Y_i(W_i)$ is well defined, this is largely already implied.

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- This does get us identification:

$$\mathrm{E}\left[Y_i | W_i = 1\right] = \mathrm{E}\left[Y_i(1)\right]$$

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- In particular, if you don't have identification, fancy estimating procedures **will not save you**.

Causal inference as a missing data problem

Units	Covariates X_i	Treatment W_i	$Y_i(1)$	$Y_i(0)$	Observed Y_i
1	1	1	1	?	1
2	0	0	?	0	0
3	1	1	0	?	0
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
N	0	0	?	0	0

Machine learning.

What is machine learning?

> *…we define machine learning as a set of methods that can automatically detect patterns in data, and then use the uncovered patterns to predict future data, or to perform other kinds of decision making under uncertainty (such as planning how to collect more data!).*

Murphy (2012)

What is machine learning?

Arthur Samuel, an early American leader in the field of computer gaming and artificial intelligence, coined the term “Machine Learning ” in 1959 while at IBM. He defined machine learning as “the field of study that gives computers the ability to learn without being explicitly programmed” [1] . Other sources also attribute the definition of machine learning to Arthur Samuel [2] .

Learn more:

1. geeksforgeeks.org
2. nzfaruqui.com
3. geeksforgeeks.org

+3 more

What is machine learning?

1 Answer

Sorted by: Highest score (default)

9

The exact quote exists in neither the 1959 paper nor the 1967 paper (second version).

These are the closest quotes from the 1959 paper:

> A computer can be programmed so that it will learn to play a better game of checkers than can be played by the person who wrote the program.

And

> Programming computers to learn from experience should eventually eliminate the need for much of this detailed programming effort.

Also, Wiki page of Arthur Samuel states that:

> He coined the term "machine learning" in 1959

and references the 1959 paper.

Either the quote is created as a gist of Arthur Samuel's 1959 paper, or it is said but not written by him. In my opinion, the former is more probable, since it is not even remotely mentioned in the 1967 paper.

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edited Mar 7, 2019 at 17:06

answered Mar 7, 2019 at 16:56

Esmailian

8,967 • 2 • 30 • 46

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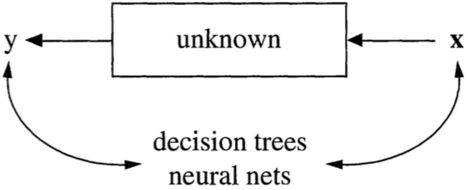
What is machine learning?

The Algorithmic Modeling Culture

The analysis in this culture considers the inside of the box complex and unknown. Their approach is to find a function $f(\mathbf{x})$—an algorithm that operates on $\mathbf{x}$ to predict the responses $\mathbf{y}$. Their black box looks like this:



Model validation. Measured by predictive accuracy.
Estimated culture population. 2% of statisticians, many in other fields.

Breiman (2001)

What is machine learning?

The traditional approach in econometrics ... is to specify a target, an estimand, that is a functional of a joint distribution of the data.

⋮

In contrast, in the ML literature, the focus is typically on developing algorithms ... The goal for the algorithms is typically to make predictions about some variables given others or to classify units on the basis of limited information, for example, to classify handwritten digits on the basis of pixel values.

Athey and Imbens (2019)

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In the context of this class:

- A culture/perspective, of a research community that has developed a set of tools to tackle some common objectives, which will inform how we think about framing what our research problems are, and how we go about addressing these problems.

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- Prediction for the next observation

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  - Given some data $(Y_1, \mathrm{X}_1), \ldots, (Y_N, \mathrm{X}_N)$, and potentially X_{N+1}, formulate a method to predict $\hat{Y}_{N+1}$, to minimize

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  - Do we think the mean is not linear in covariates, and we would like to allow it to take a flexible form?

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- What should we do next?

What are we actually asking from the data, and where can we find connections between machine learning and causal inference?

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ML in CI

- Many of the tools we use for estimating conditional means can be used for estimating conditional average treatment effects; but may need to account for optimizing for τ rather than $\mu(\cdot)$ in e.g., parameter selection.

ML in CI

- In particular, this form of the estimator will come back when we read Chernozhukov et al. (2018); Schuler and Rose (2017):

$$= \mathrm{E}\left[\frac{(Y_i - \mu(1, X_i))\, W_i}{e(X_i)} - \frac{(Y_i - \mu(0, X_i))\,(1 - W_i)}{1 - e(X_i)}\right] + \mathrm{E}\left[\mu(1, X_i) - \mu(0, X_i)\right]$$

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  - $\rightarrow$ "nuisance" parameters

- We can use cross-fitting and orthogonalization to get estimates of $\mu(w, x)$ and $e(x)$ that will result in an estimator that has really nice properties: **double robustness**.

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    - (if time: discuss applications)

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References I

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