Empirical Evaluation of Management Practices I

Predictions and Machine Learning

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Content

1. Introduction to Machine Learning

General definition

[Machine Learning is the] field of study that gives computers the ability to learn without being explicitly programmed.

- (Arthur Samuel, 1959)

More specific definition

A computer program is said to learn from experience E with respect to some task T and some performance measure P, if its performance on T, as measured by P, improves with experience E.

- (Tom Mitchell, 1997)

Types of Machine Learning

Supervised Learning:

The task of learning a function that maps the input(s) X to an output y based on example input-output pairs.

- Regression: The output is continuous or discrete and ordered.
  - Example: Predicting house prices based on house characteristics.
- Classification: The output is a discrete and unordered set.
  - Example: Classifying an email as spam or ham based on the use of certain words.

This is a "mini-course" on supervised learning with Python.

Unsupervised Learning:

We observe inputs but no output. We can seek to understand the relationship between the variables or the observations.

- For example, we might observe multiple characteristics for potential customers.
  - We can then try to cluster potential customers into groups based on these characteristics
- We might also try to project our inputs into a lower dimensional space.
  - This can be a beneficial pre-processing for supervised learning when dealing with high-dimensional data.

We will not deal with unsupervised learning in this course.

Terminology

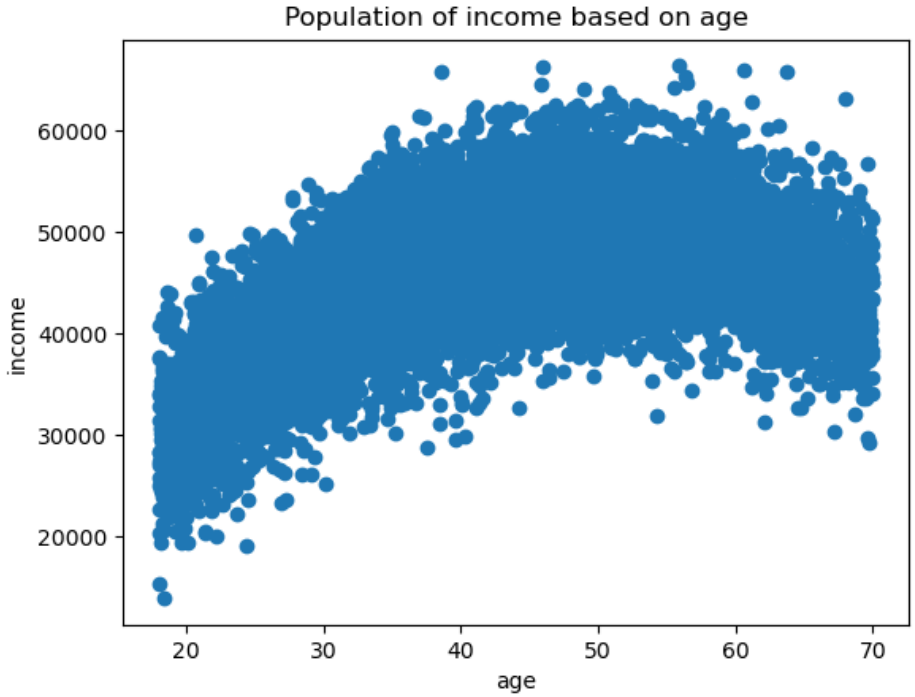
The terms used in the ML literature differs slightly from that used in Econometrics:

- Supervised learning $\rightarrow$ *Regression, classification, predicting* y_i *given* x_i*.*
- Features $\rightarrow$ x_i*, independent variables, explanatory variables, regressors, predictors.*
- Target $\rightarrow$ y_i*, dependent variable.*
- Training $\rightarrow$ *Estimating a model.*
- Testing $\rightarrow$ *Evaluating a model.*
- Training data $\rightarrow$ *The sample we use to train our model.*
- Test data $\rightarrow$ *The sample we use to test our model.*

2. Regression

Let us start with an example:

- Suppose our task is to predict income based on a person's age and that we had data on the whole population:



- What would be a "good" prediction here?

More formally

- Let X_i be a random vector (i.e. the vector of features).
- Let Y_i be a real variable (i.e. the response).
- We are interested in a function $f(X_i)$ which makes "good" prediction about Y_i.
- To know what a "good" prediction is, we require a loss function: $L(Y_i, f(X_i))$ which penalizes bad predictions
  - Common choice: Squared error – penalizes the quadratic distance:

$$L(Y_i, f(X_i)) = (Y_i - f(X_i))^2 \tag{1}$$

Recall from the lecture on Part 2:

CEF Prediction Property

Let $f(X_i)$ be any function of X_i. The conditional expectation function (CEF) solves:

$$E[Y_i|X_i] = \arg\min_{f(X_i)} E[(Y_i - f(X_i))^2] \tag{2}$$

- Thus, in terms of prediction, we can do no better than the CEF
- Also, recall:

CEF Decomposition Property

We can decompose Y_i such that

$$Y_i = E[Y_i|X_i] + \epsilon_i \tag{3}$$

Where:

1. ϵ_i is mean independent of X_i: $E[\epsilon_i|X_i] = 0$.
2. ϵ_i is uncorrelated with any function of X_i.

Thus, if we knew the population, calculating the CEF is usually not a difficult task:

We just predict the average income for people of the same age.

- In this case, we are dealing with simulated data with the following conditional expectation function:

$$f(income) = 2000 * age - 20 * age^2 \tag{4}$$