The Predictive Paradigm

Big Data y Machine Learning para Economía Aplicada

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Agenda

1. About the Course

2. Machine learning is all about prediction

3. Prediction vs Causality

4. ML Tasks

5. Regression, Prediction and loss functions

6. Bias/Variance Decomposition

7. Prediction and linear regression

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¿Qué entendemos por Big Data y ML?

- ▶ ¿Que es Big Data?
  - ▶ Big n, es solo parte de la historia
  - ▶ Big también es big k, muchos covariates, a veces $n << k$
  - ▶ Vamos a entender Big también como datos que no surgen de fuentes tradicionales (cuentas nac., GEIH, etc)
    - ▶ Datos de la Web, Geográficos, etc.

- ▶ Machine Learning
  - ▶ Cambio de paradigma de estimación a predicción

Lenguajes

- Estadística y Econometría

- Inglés

- Código
    - Elijan el que quieran:
        - R, Python, o cualquier otro
        - no hay restricción
        - yo me basare en R
    - Github
    - Slack

- Aprender haciendo y mucha prueba y error!
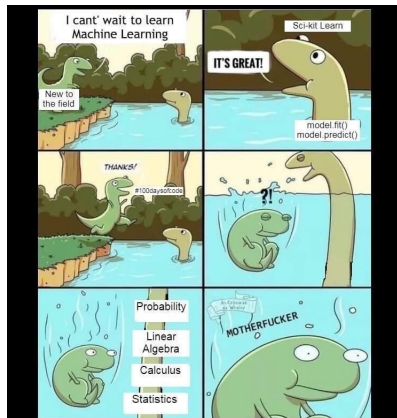
Materiales

1. Bloque Neón

2. Statistical Learning (FREE!!! (as beer, not speech))
   https://www.gnu.org/philosophy/free-sw.en.html

   ▶ James, G., Witten, D., Hastie, T., & Tibshirani, R. (2013). An introduction to statistical learning (ISLR)

   ▶ Hastie, T., Tibshirani, R., & Friedman, J. (2009). The elements of statistical learning: data mining, inference, and prediction

3. Libros de econometría

   ▶ Davidson, R., & MacKinnon, J. G. (2004). Econometric theory and methods

   ▶ Wooldridge, J. M. (2010). Econometric analysis of cross section and panel data.

   ▶ Hayashi, F. (2000). Econometrics

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Machine learning is all about prediction

▶ Machine learning is a branch of computer science and statistics, tasked with developing algorithms to predict outcomes y from observable variables x.

▶ The learning part comes from the fact that we don't specify how exactly the computer should predict y from x.

▶ This is left as an empirical problem that the computer can "learn".

▶ In general, this means that we abstract from the underlying model, the approach is pragmatic

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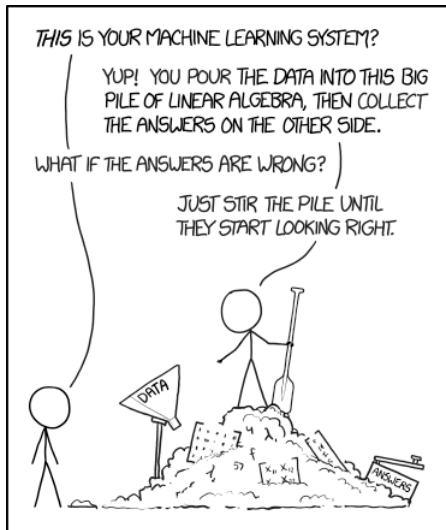
"Whatever works, works...."????

▶ In many applications, ML techniques can be successfully applied by data scientists with little knowledge of the problem domain.

▶ For example, the company Kaggle hosts prediction competitions (`www.kaggle.com/competitions`) in which a sponsor provides a data set, and contestants around the world can submit entries, often predicting successfully despite limited context about the problem.

"Whatever works, works...."????

▶ However, much less attention has been paid to the limitations of pure prediction methods.

▶ When ML applications are used "off the shelf" without understanding the underlying assumptions then the validity and usefulness of the conclusions can be compromised.

▶ A deeper question concerns whether a given problem can be solved using only techniques for prediction, or

▶ whether statistical approaches to estimating the causal effect of an intervention are required.

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Policy Prediction Problems

▶ Empirical policy research often focuses on causal inference.

▶ Since policy choices seem to depend on understanding the counterfactual— what happens with and without a policy—this tight link of causality and policy seems natural.

▶ While this link holds in many cases, there are also many policy applications where causal inference is not central, or even necessary.

The Causal Paradigm

$$y = f(X) + u \tag{1}$$

- ▶ Interest lies on inference

- ▶ "Correct" $f()$ to understand how y is affected by X

- ▶ Model: Theory, experiment

- ▶ Hypothesis testing (std. err., tests)

The Predictive Paradigm

$$y = f(X) + u \tag{2}$$

- ▶ Interest on predicting y

- ▶ "Correct" $f()$ to be able to predict (no inference!)

- ▶ Model? We treat $f()$ as a black box, and

- ▶ any approximation $\hat{f}()$ that yields a good prediction is good enough (*Whatever works, works.*).

Prediction vs. Causality

Prepare

► A loan officer wants to know the likelihood of an individual repaying a loan based on income, employment, and other characteristics.

Influence

► A mortgage lender wants to know if direct debit will increase loan repayments.

Prediction vs. Causality

Prepare

▶ A home seller wants to know what price homes with the characteristics of his or her home typically sell for.

Influence

▶ A home seller wants to know by how much installing new windows will raise the value of his or her home.

Prediction vs. Causality: Target

$$y = f(x) + \epsilon \tag{3}$$
$$y = \alpha + \beta x + \epsilon \tag{4}$$
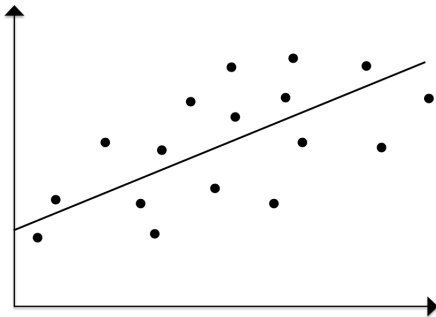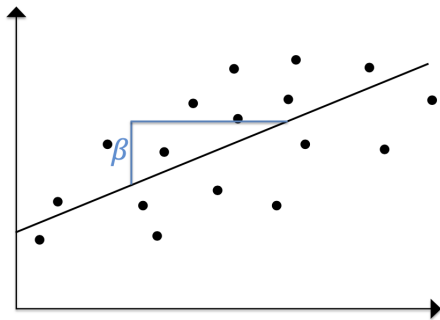
Prediction vs. Causality: Target

$$y = \underbrace{\alpha + \beta x}_{\hat{y}} + \epsilon \tag{5}$$
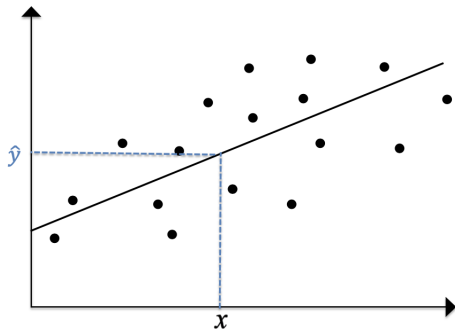
Prediction vs. Causality: Target

$$y = \alpha + \beta x + \epsilon \tag{6}$$

Prediction vs. Causality: The garden of the parallel paths?

- ▶ We've seen that prediction and causality
  - ▶ Answer different questions
  - ▶ Serve different purposes
  - ▶ Seek different targets

- ▶ Different strokes for different folks, or complementary tools in an applied economist's toolkit?
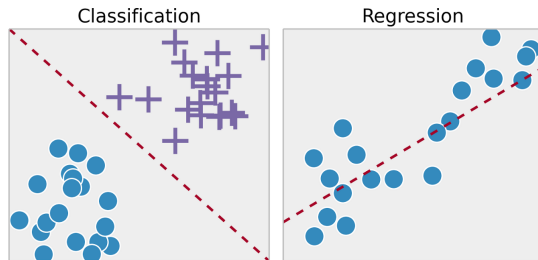
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ML branches

► ML tasks can (¿?) be divided into two main branches:

   1 Supervised Learning

ML branches

▶ Supervised Learning
   ▶ for each predictor x_i a 'response' is observed y_i.
   ▶ everything we have done in econometrics is supervised
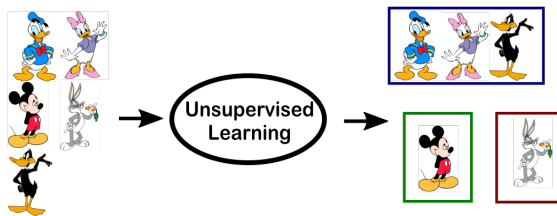

Source: shorturl.at/opqKT

ML branches

▶ ML tasks can (¿?) be divided into two main branches:

1. Supervised Learning

2. Unsupervised Learning

ML branches

▶ Unsupervised Learning
    ▶ observed x_i but no response.
    ▶ example: cluster analysis

Source: `shorturl.at/opqKT`

Agenda

Getting serious about prediction: Regression

$$y = f(X) + u \tag{7}$$

- ▶ Interest on predicting Y

- ▶ Model? We treat $f()$ as a black box, and any approximation $\hat{f}()$ that yields a good prediction is good enough (*"Whatever works, works..."*).

- ▶ How do we measure "what works"?

# Getting serious about prediction: Regression

$$y = f(X) + u \tag{7}$$

▶ Interest on predicting Y

▶ Model? We treat $f()$ as a black box, and any approximation $\hat{f}()$ that yields a good prediction is good enough (*"Whatever works, works..."*).

▶ How do we measure "what works"?

▶ Formal statistics can help figure out this: what is a good prediction.

Minimizing our losses

- ▶ Want our prediction to be "close" i.e. minimize the expected loss function

- ▶ Formally, a supervised learning algorithm takes as an input a loss function $L(\hat{y}, y)$ and searches for a function $\hat{f}$ within a function class $\mathcal{F}$ that has a low expected prediction loss

$$E_{(y,X)}[L(\hat{f}(X), y)] \tag{8}$$

on a new data point from the same distribution.
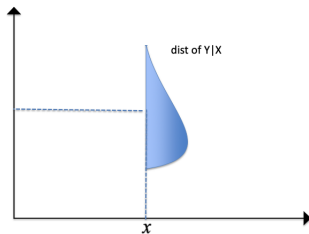
Minimizing our losses

▶ A very common loss function in a regression setting is the squared loss $L(d) = d^2$

▶ Under this loss function the expected prediction loss is the mean squared error (MSE)

▶ Can we find the function f^* within a function class $\mathcal{F}$ that has a low expected prediction loss?

Minimizing our losses

▶ By conditioning on X, it suffices to minimize the $MSE(f)$ point wise so

$$f(x) = argmin_{f^*} E_{y|X}[(y - f^*)^2 | X = x] \tag{9}$$

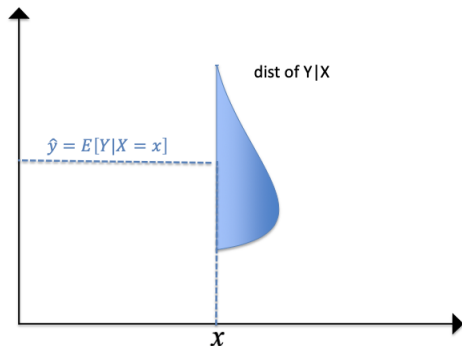▶ f^* a random variable and we can treat f^* as a constant (predictor)

$$min_m E(y - f^*)^2 = \int (y - f^*)^2 f(y) dy \tag{10}$$

▶ **Result**: The best prediction of y at any point $X = x$ is the conditional mean, when best is measured using a square error loss

Minimizing our losses

▶ **Result**: The best prediction of y at any point $X = x$ is the conditional mean, when best is measured using a square error loss

$$f^* = E[y|X = x] \tag{11}$$

Minimizing our losses

▶ Prediction problem solved if we knew $f^* = E[y|X = x]$

Minimizing our losses

▶ Prediction problem solved if we knew $f^* = E[y|X = x]$

▶ But we have to settle for an estimate: $\hat{f}(x)$

▶ The MSE of this

$$E(y - \hat{y})^2 = E(f(X) + u - \hat{f}(X))^2 \tag{12}$$

Reducible and irreducible error

$$E(y - \hat{y})^2 = \underbrace{[f(X) - \hat{f}(X)]^2}_{Reducible} + \underbrace{Var(u)}_{Irreducible} \tag{13}$$

▶ The focus the is on techniques for estimating f with the aim of minimizing the reducible error

▶ It is important to keep in mind that the irreducible error will always provide an upper bound on the accuracy of our prediction for y

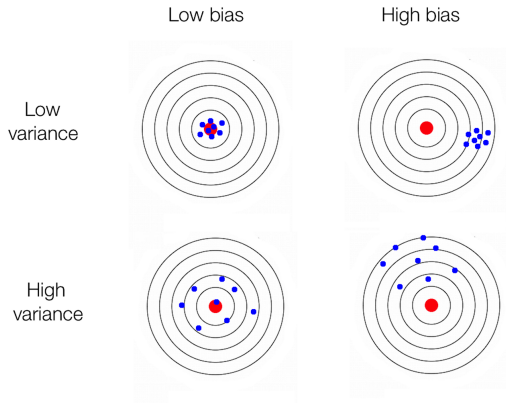▶ This bound is almost always unknown in practice

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Bias/Variance Decomposition

Recall that

- $Bias(\hat{f}(X)) = E(\hat{f}(X)) - f = E(\hat{f}(X) - f(X))$
- $Var(\hat{f}(X)) = E(\hat{f}(X) - E(\hat{f}(X)))^2$

Bias/Variance Decomposition

Source: https://tinyurl.com/y4lvjxpc
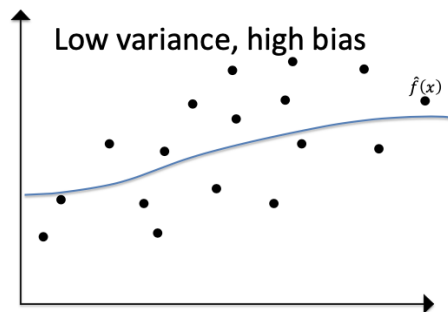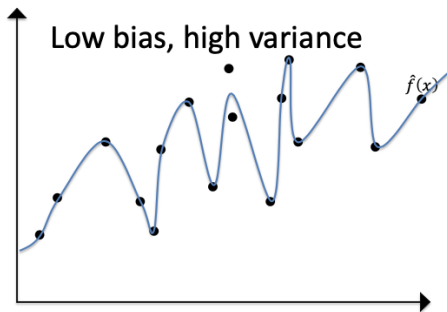
Bias/Variance Decomposition

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Result (very important!)

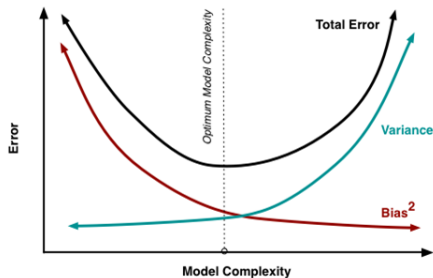$$EMSE = Bias^2(\hat{f}(X)) + V(\hat{f}(X)) + \underbrace{Var(u)}_{Irreducible} \qquad (14)$$

HW: Proof

Bias/Variance Decomposition

Low bias, high variance $\hat{f}(x)$

Low variance, high bias $\hat{f}(x)$

The Bias-Variance Trade-Off

$$EMSE = Bias^2(\hat{f}(X)) + V(\hat{f}(X)) + \underbrace{Var(u)}_{Irreducible} \tag{15}$$

Source: https://tinyurl.com/y4lvjxpc

▶ The best kept secret: tolerating some bias is possible to reduce $V(\hat{f}(X))$ and lower MSE

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Prediction and linear regression

▶ The goal is to predict *y* given another variables *X*.

▶ We assume that the link between *y* and *X* is given by the simple model:

$$y = f(X) + u \tag{16}$$

▶ we just learned that under a squared loss we need to approximate $E[y|X = x]$

Prediction and linear regression

▶ As economists we know that we can approximate $E[y|X = x]$ with a linear regression

$$f(X) = \beta_0 + \beta_1 X_1 + \cdots + \beta_p X_p \tag{17}$$

▶ The problem boils down to estimating βs

▶ We can estimate these using
   ▶ OLS
   ▶ MLE
   ▶ MM

photo from https://www.dailydot.com/parsec/batman-1966-labels-tumblr-twitter-vine/

Review

- ▶ This Week:
  - ▶ Machine Learning is all about prediction
  - ▶ ML targets something different than causal inference, they can complement each other
  - ▶ ML best kept secret: tolerating some bias is possible to reduce $V(\hat{f}(X))$ and lower MSE
- ▶ Next Week:
  - ▶ Linear Regression details