This Economist and Machine Learning

(De-mystifying the Un-mystical)

Tim Savage

Machine Learning (ML) Is Statistical Learning

- Machine learning is simply stochastic modeling.
- Linear regression came first and remains an indispensable ML tool.
- Econometrics is a sizeable corner of the ML room.
  - Focus is Identification and treatment effects.
- The array of problems amenable to data analysis has expanded greatly in the last decade or so.
  - For these problems, regression does not work well or at all.
  - The toolkit <u>had to be expanded</u> well beyond regression.
  - And it started with the use of the humble logit for spam.
- But economists have been at the table for decades.

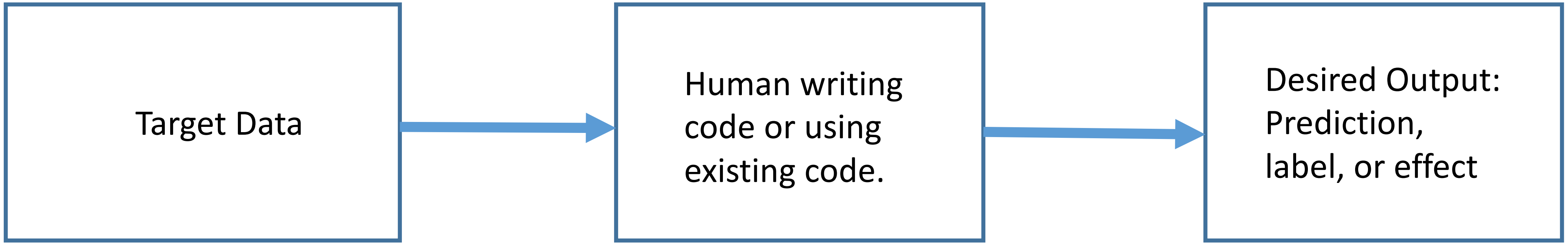
If It Can Be Digitized, It Can Be Analyzed

- We are awash in the digital exhaust of human behavior.
- The contours of the explosion are obvious.
  - Everything is saved because incremental cost is zero.
  - Low barriers to entry due to open source engines like R and Python.
  - Private sector sees potentially large returns to large-scale data mining (*e.g.*, recommendation systems for price discrimination).
  - Public policy-makers say they want “data-driven decision-making”.
- As we know from practice, ML tools work <u>very well</u> and are improving rapidly.

The Irrelevant

- Computer scientists have been remarkably successful at creating a mystique around the phrase “machine learning”.
  - Bagging.
  - Multilayered perceptron and deep learning.
- And yet, “I am a data scientist” is now akin to “I play sports”.
- ML is not artificial intelligence, but many computer scientists consider it to be a branch of artificial intelligence.
- I believe computer scientists have won the “language war”, which is irrelevant.
- Going forward, the phrases machine learning and data science will dominate in popular lexicon.

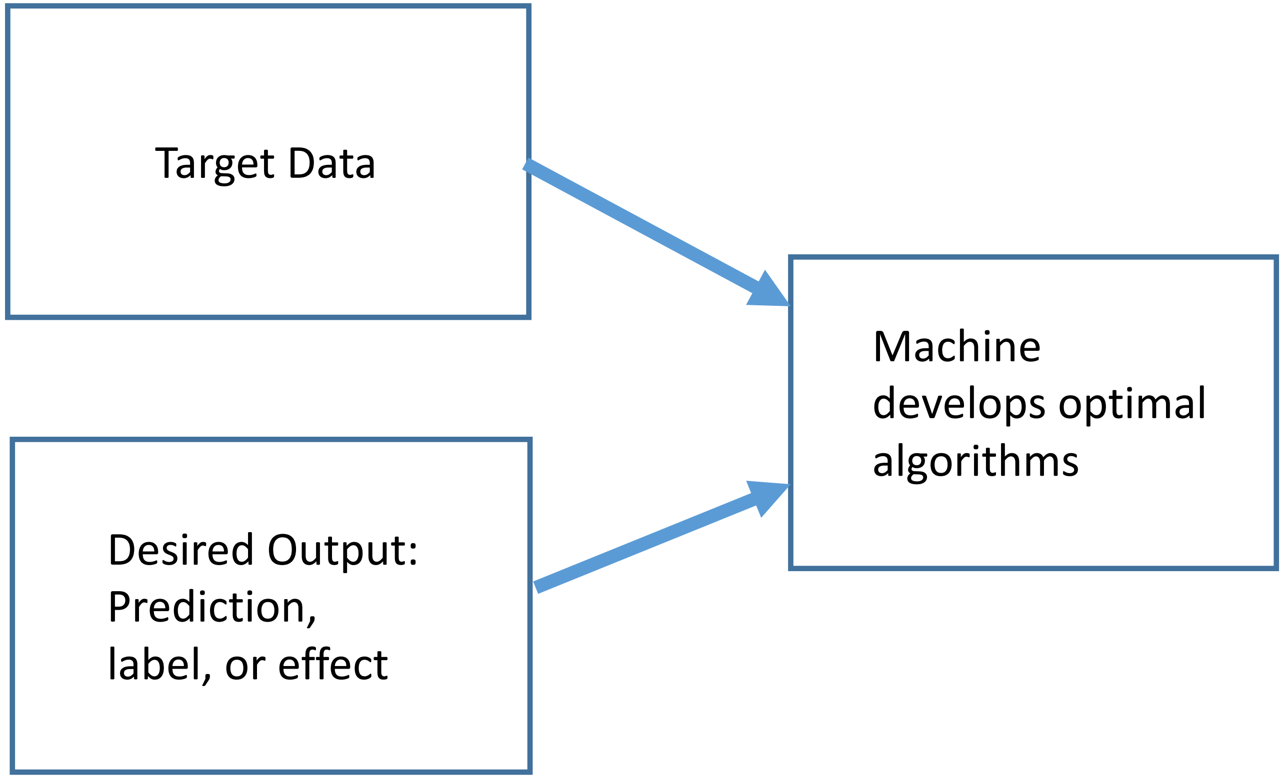
Traditional ML Paradigm



A Simple Example

- This unlabeled image from the internet contains a four-legged hairy animal.
- 83.56% of *similar* images from the internet are labeled “cat”.
- Therefore, this image should be labeled as “cat”.
- This process is entirely algorithmic.
- There is no artificial intelligence involved.
- This simple example covers more use cases than you would suspect, even if deep learning is involved.

Artificial Intelligence (AI) Paradigm



Every ML Algorithm Has Three Components

1. Representation
2. Evaluation
3. Optimization

- Computer scientists applying ML are typically focused on classification and prediction.
- Consider the problem of predicting an incoming email to be "spam" given its contents (that is, *conditional on its covariates*).

For Regression, It Is the Same

1. Representation: $y_t = \rho y_{t-1} + x_t' \beta + \epsilon_t + \theta \epsilon_{t-1}$
2. Evaluation: goodness of fit measures such as R^2 or MSE.
3. Optimization: $\min SSR(\beta) \rightarrow (X'X)^{-1} X' y$ or maximum likelihood

- It should be noted that many popular ML techniques, such as deep learning, do not have global optima, but they work very well in practice.
- Indeed, the ML mantra is often:
  - We have different tools for different problems.
  - How well do they work in practice?
  - How well do they scale (efficiency)?

Useful ML Terms (All Familiar)

- Features (independent variable, covariates, right-hand-side variables).
- Labels (dependent variable).
- Structured data (observation i at time t in a spreadsheet).
- Unstructured data (text).
- Training data.
- Test (or hold out) data.
- Supervised learning: $y = X\beta + \epsilon$.
  - Classification (classes of labels: red, blue, green).
  - Regression (continuous labels measuring some real world outcome).

Useful ML Terms (Mostly Familiar)

- Unsupervised learning: $y = f(x, \epsilon)$ or k-means clustering.
- Parallelization: why Google won the search engine war with distributed storage and distributed processing.
- UI: user interface, a type of HTML- or Java-based interface that allows users to interact with underlying hardware and software. (Jupyter notebook is an example.)
- API: application program interface, which assists analysts to input data from disparate sources, such as the Fed.
- IDE: integrated development environment, of which Jupyter notebook is a part.

Notable Shortcomings

- Terms one does not typically hear at ML conferences.
  - p-value.
  - Statistical significance.
- Any discussion of causation or of “treatment effects” in the Angrist-Imbens-Rubin sense of evaluating the impact of an intervention.
- Computer scientists do not typically see their regression functions as measures of partial derivative effects.
  - Prediction is forecasting: acid test is out of sample.
- While these may be very interesting policy questions, these are not common questions in a ML textbook:
  - What is the effect of raising the minimum wage on employment levels?
  - What is the effect of building a hospital in this village on health outcomes?

Economists Are Now Collaborating With Computer Scientists

- I presented a poster on treatment effects using big data and ML techniques at a recent ML conference.
- Susan Athey and Guido Imbens have some forthcoming papers on the use of ML in economics.
- DARPA's Next Generation Social Science (NGS2).
- As I point out to my friends who are computer scientists, economists have a long history of dealing with non-experimental data.
  - Heckman's inverse mills ratio as an omitted feature in regression to capture the selection effect.

Economists Were Already at the Table

- Long tradition of large-scale time-series modeling of markets and economies in macro and finance.
  - Hal White on penalized regression and the LASSO in the early 1990's.
  - George Tauchen and Ron Gallant on neural networks (now deep learning) in the mid-1990's.
  - More recent innovations in econometrics, however, have focused on natural experiments, RDD, and RCT.
- In my opinion, the use of a large suite of ML approaches will grow in econometrics (and I believe quite quickly).
  - I think we're stuck in the rut of RDD and RCT.

Let’s Do Some of This Stuff

Using the Jupyter IDE

Thank You