An Introduction to Machine Learning for Social Scientists

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What is machine learning? What is AI?

- **Machine learning (ML):** Allowing computers to learn for themselves without explicitly being programmed
  - **USPS:** Computer to read handwriting on envelopes
  - **Google:** AlphaGo, computer that defeated world champion Go player
  - **Apple/Amazon/Microsoft:** Siri, Alexa, Cortana voice assistants
- **Artificial intelligence (AI):** Constructing machines (robots, computers) to think and act like human beings
- **ML is a subset of AI**
ML in the social sciences

- A branch of statistics devoted to accurate prediction
- Maximize both in- and out-of-sample prediction
- Systematically combine estimation and model selection
- Computational techniques for stats on very large data sets
- Becoming more popular in “big data” era
- These slides based in part on Varian (2014)
Suppose you want to predict mortgage loan default (0/1 outcome).

You have a large number (over 5,000) of relevant \textit{variables}.

What would you do?

There are better methods of prediction than logit:

- Help you determine which of the 5,000 variables are most important.
- Automatically detect interactions among variables.
- Do a better job of predicting out-of-sample than logit.
Overfitting: estimating a model that performs well in-sample but poorly out-of-sample

Example: Suppose you have cross-sectional data for a continuous outcome across $n$ individuals

One way to predict earnings is to use OLS and estimate $n$ dummy variable coefficients (no constant)

$R^2 = 1$, indicating perfect in-sample fit

But if I gave you a separate sample of this data with $m$ different individuals, how would you predict the outcome? Which dummy coefficients would you assign to the new individuals?
Solution to overfitting

1. Penalizing parameter complexity (Adjusted $R^2$, AIC, BIC)
2. Testing a variety of models out-of-sample
3. Using cross-validation to find the best level of penalty
How cross-validation works

Typical steps used to cross-validate and test predictions:

1. Randomly divide up your data into three parts: training set (60%), cross-validation set (20%), and test set (20%)
2. Estimate your model parameters in the training set
3. Compute the prediction error in both the cross-validation and test sets
4. Repeat this for various levels of penalty
5. Pick the penalty level that minimizes error in the cross-validation set
   - Test set should only be used for out-of-sample prediction; some people lump test/CV together
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Commonly used machine learning algorithms

- **Continuous dependent variable:**
  - Ordinary least squares
  - Regression trees / random forests
  - Penalized regression (LASSO, Ridge, Elastic net)
  - Nearest neighbor
  - Support vector machine (SVM)
  - Neural network
  - Naive Bayes

- **Categorical dependent variable:**
  - Logistic regression
  - All others above
Ensemble prediction

- Often times, you will obtain better prediction by averaging across models (e.g. forests vs. trees; Bajari et al. (2015))
- e.g. obtain predictions from Penalized logistic regression, classification tree, and support vector machine
- Create a meta-prediction by regressing (in the cross-validation set) the outcome on the predictions from each model
- The meta-prediction will usually perform better in the test set than any single prediction
- But it’s harder to back out the decision rule from meta-predictions
Software to estimate ML models

- R and Python are the home of machine learning development
- Growing community in Julia
- Matlab has a ML toolbox, but lacks customizability
- Limited availability in Stata
Unsupervised learning

- Up to now, we’ve only discussed *supervised* learning
- *Unsupervised* learning → no dependent variable
- Used primarily to reduce large datasets
- e.g. detect partitions in data (*k*-means clustering, EM algorithm)
- Reduce dimensionality of data (PCA)
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Limitations of machine learning

- Machine learning is all about *prediction* (i.e. correlation)
- But social science is primarily motivated by *causality* (i.e. prediction in a counterfactual environment)
- Attempts currently being made to re-frame machine learning in terms of causal inference (Varian, 2014; Athey and Imbens, 2015; Bajari et al., 2015)
- Or to detect groups of unobserved heterogeneity using unsupervised ML (Bonhomme, Lamadon, and Manresa, 2017)
- These are (currently) largely application-specific
When should I use machine learning?

- If you are mainly interested in prediction
- If you have an intermediate step of your model estimation that requires making predictions
- If you need to compress a prohibitively large data set

