Big Data in Spatial Economics

Lecture 2: Working with Big Data

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Lecture Plan

- Lecture 1: Overview of Current and Future Research
  1. Literature review
  2. A detailed example: Smartphone GPS data in Couture, Dingel, Green, and Handbury.
  3. How to find a big data research question.
  4. Ethics of big data

- Lecture 2: Working with Big Data
  1. Basic principles
  2. `Stata` for big data
  3. Alternatives to `Stata` for really big data (`SQL`, `Python`, `Julia`)
  4. Machine learning for high dimensional/complex data

Lecture 2: Objectives

- Learn some general principles of working with big data
  - E.g., Break down your big data into smaller chunks
- Learn how and when to use `Stata` with big data.
  - Some commands and packages are faster than others.
- Recognize when alternatives to `Stata` are desirable.
  - e.g., `SQL` to clean and assemble smartphone data
- Recognize when alternatives to our traditional econometric framework are desirable
  - e.g., Machine learning for imagine recognition

Working with Big Data: Basic Principles

1. Take time to organize your work flow
2. Store data efficiently (skinny & relational)
3. Break down big data into smaller chunks
4. Analyze data efficiently (use server & parallelize)
5. Test your code before running large data tasks
6. Run code efficiently (build tools)

Working with Big Data: Basic Principles

Take time to organize your work flow

- Gentzkow and Shapiro, *Code and Data for the Social Sciences. A Practitioner's Guide.*
  - Must read for empirical economists and their RAs.
  - Brings some best practices from data science and computer science to economics.

- https://github.com/jdingel/projecttemplate
  - Full research template that we use for smartphone project, from Jonathan Dingel.
  - Lots of links to sources to train yourself or your RA.
  - Focuses on tools we use (Bitbucket for version control, Asana for task management, etc.)

Working with Big Data: Basic Principles

Store data efficiently (skinny + relational)

- Keep data skinny:
  - Import only variables and observations needed
  - Use efficient data format (e.g., bytes instead of double for dummies.)
  - Clean before generating new variables.

- Keep a relational database:
  - Each dataset has a unique identifer.
  - E.g., smartphone relational database consists of:
    1. device dataset with unique device id
    2. place dataset with unique place id
    3. visit dataset relating device and place

Working with Big Data: Basic Principles

Break down your big data into smaller chunks

- Most important rule of big data.
  - High computation times are especially unproductive when code testing.
  - *Test your code on a small sample*.

- Choose a natural partition for the type of operations you are trying to do
  - Spatial data can often be broken down in smaller geographical units.
  - 200 city level estimations often faster than 1 national estimation.
  - Many statistical procedures are non linear in sample size.

Working with Big Data: Basic Principles

Analyze data efficiently (use server + parallelize)

- Your university likely has a server that is faster than your laptop.
- Some languages and commands are faster than others (more on that below.)
- Parallelize whenever possible
  - Bash scripts can automatically submit jobs when queues become available
  - Think carefully about the best dimension to split your code on for parallelizing
  - E.g., Your server has 5 nodes, run 40 city-level regressions on each $\rightarrow$ 5X faster.
  - Most universities have a limit on the amount of jobs you can run simultaneously
  - Check your university's documentation for example scripts to run parallel bash scripts.

Working with Big Data: Basic Principles

Test your code before running large data tasks:

- When working on servers it is best practice to know how much computing resources large data tasks will take up
- Likely you are sharing resources with your colleagues!
- Benchmark different approaches to the same problem against each other
- Check how your computational efficiency scales as data size increases

Working with Big Data: Basic Principles

Run code efficiently (build tools) *Special thanks to Jonathan Dingel for slide material*

- Research projects are collections of code executed in sequence to produce output.
  - Your code has a first step (download raw data) and a last step (generate paper PDF).
  - A "master" do file in `Stata` is a simple way to automate this.
  - If a project involves A through Z, master.do executes A, B, . . . , Y, Z in order.
- The "run everything" master is inefficient: if you edit Y, you only need to run Y and Z.
  - Do not run time-consuming data cleaning steps for every new estimation.
- Software build tools automate the choice of what to run.
  - Build tools use a dependency graph and information about file changes (e.g., timestamps) to produce output using (all and only) necessary steps.
  - In an appendix, we describe `Make`, the build tool that we use for the smartphone project.

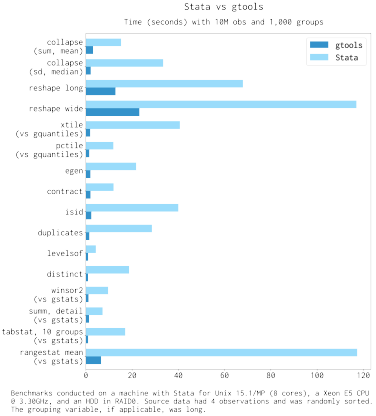
Working with Big Data in Stata

- Stata is the most common language in empirical economics
  - Good for co-authoring, all our co-authors know Stata
  - Stata has lots of built in commands for econometrics.
  - Stata MP on good server can handle big (not huge) data.

- Avoid computationally heavy commands on large datasets
  - Many popular commands in Stata are slow because they rely on underlying sort.
  - E.g., “collapse”, ”reshape”, ”sort” , and ”egen”
  - User-written Stata packages such as gtools offer faster alternatives

- Choose well-suited regression commands
  - ”reghdfe” by Sergio Correia, is often the best reg option
  - ”asclogit” for logit models

Gtools vs. Generic Stata Commands



Source: https://gtools.readthedocs.io/en/latest/

Alternatives to Stata

- `Stata` is not well-suited to perform certain tasks.
- `SQL` for cleaning and assembling *really* big data.
- `Python` for ArcGis or machine learning or scraping or anything you can't do in `Stata`.
- `Matlab` or `Julia` for coding estimators or structural models.
- Many other languages that we haven't used for our projects (e.g., `R` can do ArcGis, machine learning, estimation, etc.)

Working with *Really* Big Data: Data Cleaning and Assembling

Problem: Smartphone data has over a trillion raw visits.

- `Stata MP` on best current computer can take 10 to 20 Billion obs.
- Breaking down data is not enough.

Solution:

- `SQL` well-suited for data cleaning and assembling.
- `Python` offer similar options through Panda library.
- In smartphone project we use `SQL` to clean, merge and create estimation tables:
  - E.g., assign home location to each device
  - E.g., remove near simultaneous visits to same location
  - E.g., aggregate data at monthly level
- `SQL` has limitations, and cannot produce regressions or figures.
  - Need to export to another language for analysis.

Working with *Really* Big Data: Data Cleaning and Assembling

Caveat: Your university (likely) lacks the expertise to set up an efficent `SQL` warehouse.

- Cloud data warehouses like Snowflake and Amazon Redshift offer that service.
- Our smartphone data is on Snowflake.
  - Snowflake is a software-as-a-service (SaaS).
  - You pay for efficient storage and computing power ($>$\$40/hour)
  - Handles huge data with clever "partitioning" (break down big table into smaller chunks!)
  - Repeated operations that rely on similar structures become faster.

Case Study: SQL and Smartphone Data

- Lots of variation in speed across different types of operations
- Subsetting/aggregating operations are fast
- Join/merge operation also relatively fast
- Window functions - e.g., lags/leads, min/max in group, etc - are slow

Selected Queries on tables with 20 billion smartphone visits and 5 variables

SQL Operation	Stata Analog	Time to Run in SQL	Query
where	Keep if	23 sec	select * from visits_all where local_date = '2019-01-01'
group by	collapse	2 min 42 sec	select sum(*) as num_visits, local_date from visits_all group by local_date
join	joinby/merge	9 min 58 sec	select v1.device_key from visits_all as v1 inner join visits_all as v2 on v1.device_key = v2.device_key
lag/lead	xtset/tsset	35 min 13 sec	select lag(unix_time) over(partition by device_key order by unix_time) as lag_time from visits_all

Working with *Really* Big Data: Estimation

Problem: Discrete choice model has huge choice set of venues in large cities.

Possible Solution:

1. Break down data into smaller geography: Smallest reasonable unit (city) still too large.
2. Alternative programming language: `Stata`'s asclogit already a fast command.
3. Alternative estimation approach: Machine learning less familiar to econ audience.
4. Use discrete choice theory to reduce dimensionality: Worked well so far!
   - Venue FE estimation is particularly time-consuming
   - One solution is to exploit IIA and randomly drop venues.
   - Other solution is to derive venue FE analytically from utility max problem to concentrate them out (we coded this estimator in `Julia`.)

Machine Learning (ML) and Big Data

- Limited objective: Give you a sense of the kind of problems and data ML can help with.
- Many tools seen so far are useful when data is big in the sense of billions of observations.
- ML is useful when data is big in the sense of being complex and high dimensional.
  - E.g. Image recognition: Predict face from set of pixel .
  - E.g. Text analysis: Classsifying industry using 10-K fillings
  - E.g. Regression with tons of regressors, discrete choice with huge/rich choice sets.
- Slides drawn from: Mullainathan and Spiess, *Machine Learning: An Applied Econometric Approach*, Journal of Economic Perspective (2017)
- Slides also drawn from more technical: Athey and Imbens, *Machine Learning Methods Economists Should Know About*, March 2019

Machine Learning vs Traditional Econometrics

- Traditional Econometrics:
  - Write statistcal model relating variables as function of parameters.
  - Estimate best fit parameters using random data sample (e.g., minimize squared error.)
  - Focused on property of estimator (asymptotic), causality, and confidence intervals.
- Machine Learning:
  - Write an algorithm that predicts (or classify) x based on set of y.
  - Focus on out-of-sample performance and finding general features from complex patterns.
  - Less focused on property of estimator, causality, and confidence intervals.
    - Could hurt in econ journal.

Machine Learning: An Example of Application

- Example in Mullainathan and Spiess (2017): Predict house prices
- Can do it with OLS, such hedonic regressions are popular.
  - But what if 150 house characteristics (e.g, # bedroom), and 1000s of interactions?
  - High R^2 in OLS could just mean overfitting with poor out-of-sample performance.
- ML tools well-suited to find variable and interactions with predictive power.
  - LASSO: sometimes used in economics.
  - Regression tree, random forest, etc: rarely used in economics.
- Principal Component Analysis: not covered in MS2017 but often used by economists to reduce dimensionality and avoid overfitting.

Machine Learning vs Deep Learning.

- Image recognition is an exciting ML application for spatial economists:
  - Measure local poverty
  - Measure neighborhood characteristics
  - Identify slums
- Deep Learning (DL) tools (e.g., neural networks) more powerful than traditional ML, which matters for video, audio, and image recognition.
- Introductory DL text: Goodfellow, I., Y. Bengio, and A. Courville (2016). Deep Learning. MIT Press. http://www.deeplearningbook.org
- In the next slides, I reproduce two slides from Tsivanidis and Gechter (2019), that compare ML with DL in the context of identifying slums from pictures in Mumbai.

Approach 1: ML

Method 1: ML Approach

- Summary: Machine "learns" mapping between a representation of the data and the outcome
- Step 1: Extract N features $\{X_{1i}, X_{2i}, \ldots, X_{Ni}\}$ for each pixel i.
- Step 2: Estimate the function $Y_i = f(X_{1i}, X_{2i}, \ldots, X_{Ni})$ using your favorite method (e.g. Random Forest)
- Key characteristics: Researcher chooses representation of the data.

Example: Predicting whether an image contains a person or not

- Extract features predictive of being a person, e.g. arms, legs
- But may be difficult: arms and legs look different based on angle/light etc, may be hard to hand-pick best way to extract features...

Approach 2: Deep Convolutional Neural Network

Summary: Machine "learns"

1. Mapping between a representation of the data and the outcome, AND
2. Representation of the data itself

Method:

- Network is a number of layers consisting of many nodes
- A node within a layer applies convolutions (i.e matrix transformation) to inputs from the previous layers, and aggregates up using a non-linear transformation
- Researcher chooses: hyperparameters (e.g. number of layers), the machine "learns" the rest...

Example: Predicting whether an image contains a person or not

- Layer 1: Take raw image in, apply a convolution to isolate edges
- Layer 2: Take edges as inputs, apply a convolution to aggregate into contours
- Layer 3: Take contours as inputs, aggregate these into objects (arm, leg, etc)
- Output Layer: Predict whether image is person or not based on objects

Additional Reading

- Varian, *Big Data: New Tricks for Econometrics*, Journal of Economic Perspective, 2014
  - From chief economist at Google and author of popular micro text.
  - Google tools for manipulating big data, and an introduction to ML.

- Einav and Levin, *Economics in the Age of Big Data*, Science, 2014
  - Nice overview of recent advances in big data research in economics.

- https://tradediversion.net/2018/09/17/why-i-encourage-econ-phd-students-to-learn-julia/
  - Why Dingel thinks you should learn Julia.

Appendix: Build automation for research projects

- Guest slides from Jonathan Dingel.
- Your research code input-output structure is a directed graph (dependency graph).
- Software build tools automate compiling source code into executable binaries.
  - If you've installed Linux packages, you've likely used `Make`.
- Build tools use a dependency graph and information about file changes (e.g., timestamps) to produce output using (all and only) necessary steps.

Appendix: Build automation with Make

- Build automation is valuable for any non-trivial research project.
  - Build automation can be particularly valuable for big data.
  - E.g., To process data for 100 cities, we shouldn't manually track which cities are up-to-date and which need to run the latest code.
  - Define the dependencies and let the build tool track everything.
- `Make` is an old, widely used build tool.
  - Should be available on every Linux box by default (e.g., it's available in Census RDCs)
  - For Mac users, it's in OS X's developer tools.
- Other build tools: Gentzkow and Shapiro use SCons (`Python`-based).
- If all your code in `Stata` consider `project` by Robert Picard.

Appendix: Makefiles

A Makefile consists of a dependency graph and a recipe for each graph node.

- Define dependencies by writing a target before the colon and that target's prerequisites after the colon.
- The next line gives the recipe that translates those inputs into output. Make can execute any recipe you can write on the command line.

```
Y.tex: Y.do X.dta
   stata-se Y.do
Z.pdf: Y.tex
   pdflatex -jobname=Z Y.tex
```

- When you type `make`, it will run `Y.do` in `StataSE` only if `Y.tex` does not exist or if `Y.tex` is older than `Y.do` or `X.dta`.
- `Make` will compile `Z.pdf` if `Y.tex` has changed since you last compiled `Z.pdf`. Changes to `X.dta` or `Y.do` trigger this.