Introduction to Data Science for Public Policy

Class 1: Overview

Thomas Monk

t.d.monk@lse.ac.uk

with thanks to

Frank Muci, LSE; Dr. Melissa Sands, LSE; Dr. Eric Potash, Harris School of Public Policy & Fabian H. C. Raters, Georg-August-Universität Göttingen

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- Let me know as we progress what you'd like to see more of, or something you've seen elsewhere, and I'll try and get this included.

Data Science in Public Policy

- We saw a huge variety of applications of data to causal questions in PP455.
- This course is going to differ in two key ways:
  1. Causality is not going to be our focus. We will care about ingesting and manipulating data, with other meaningful applications, rather than being hung up on identification.
  2. The datasets we will use, and will be able to use, will be bigger.
- There's more to data than causal inference...

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Although the lines between these can be quite blurred, and often one type of inference depends on the conclusions of another.

Predictive/descriptive inference example: Gentzkow (2019)

This paper measures trends in the partisanship of congressional speech in the US House of Representatives and the Senate. The paper is mathematically complex and dense, but delivers an interesting conclusion (non-causally) based on a large quantity of data.

- **Definition.** Partisanship is defined as the ease with which an observer could infer a congressperson's party from a single utterance.
- **Data.** All congressional speech from 1873 to 2016. 508,352 unique phrases spoken a total of 287 million times by 7732 unique speakers.
- **Output**. A partisanship score for each session of congress. When the words (vectors) spoken by Democrats and Republicans are similar, there is low polarisation in Congress. When these vectors are far from each other, the parties speak differently and we say that partisanship is high.

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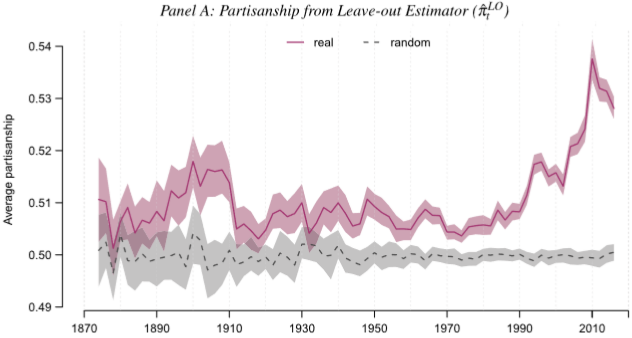

Polarisation in the US congress was roughly stable until the early 1990s.

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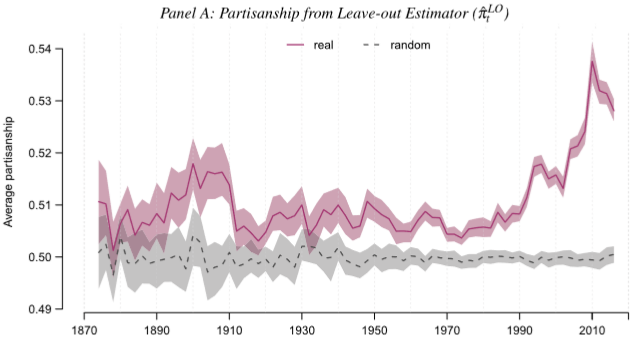

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Session 110 (2007–2008)						Session 114 (2015–2016)					
Republican	#R	#D	Democratic	#R	#D	Republican	#R	#D	Democratic	#R	#D
tax increas	87	20	dog coalit	0	90	american peopl	327	205	homeland secur	96	205
natur gas	77	20	war iraq	18	78	al qaeda	50	7	climat chang	23	94
reserv balanc	147	105	african american	6	62	men women	123	83	gun violenc	3	74
rais tax	44	10	american peopl	230	278	side aisl	133	93	african american	11	71
american energi	34	3	oil compani	20	65	human traffick	60	26	vote right	2	62
illeg immigr	34	7	civil war	17	45	colleagu support	123	89	public health	24	83
side aisl	132	106	troop iraq	11	39	religi freedom	34	4	depart homeland	48	93
continent shelf	33	8	children health	17	42	taxpay dollar	47	19	plan parenthood	66	104
outer continent	32	8	nobid contract	0	24	mental health	59	32	afford care	40	77
tax rate	26	4	middl class	15	39	radic islam	22	0	puerto rico	42	79

We have an insight into the most polarising phrases of each Congressional session.

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The best way for us to do that is to learn this **actively** - which we'll spend the rest of the course doing.

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  3. Mata. For complex software, Stata forces you to write in a language called Mata. It's fast, but based around matrices and relatively complex for general purpose tasks.

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- Academics and practitioners have preferences over languages for a variety of reasons.
- One of the main factors is the 'level' of the programming language.

Lowest level programming language: ASM

```
          global    _start

          section   .text
_start:   mov       rax, 1                  ; system call for write
          mov       rdi, 1                  ; file handle 1 is stdout
          mov       rsi, message            ; address of string to output
          mov       rdx, 13                 ; number of bytes
          syscall                           ; invoke operating system to do the write
          mov       rax, 60                 ; system call for exit
          xor       rdi, rdi                ; exit code 0
          syscall                           ; invoke operating system to exit

          section   .data
message:  db        Hello, World, 10        ; note the newline at the end
```

Here we are directly interacting with the processor of the computer, instructing the CPU in the only language it understands.

Lowest level programming language: C

```
#include <stdio.h>
int main() {
   printf("Hello, World!");
   return 0;
}
```

The number of lines we have to write has dropped significantly!

What do we think could be happening in the background?

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What do we think could be happening in the background? A program called a **compiler** is translating the more human readable code into a language the computer actually understands.

Higher level programming language: Fortran

```
program hello
  print *, 'Hello, World!'
end program hello
```

We come closer to a more human readable code base.

Higher level programming language: Fortran

```
C This program computes the equilibrium of the stochastic-beta economy in
C "Income and Wealth Heterogeneity in the Macroeconomy" (co-authored with
C Per Krusell of the University of Rochester).
      implicit real*8 (a-h,o-z)

      parameter (nkpts=132,durug=1.5D+00,nmupts=4,
     *           delta=0.025D+00,alpha=0.36D+00,unempg=0.04D+00,
     *           mxloop=12,sfac=0.25D+00,hfix=0.3271D+00,
     *           durgd=8.0D+00,unempb=0.1D+00,kgrid=278,
     *           xkbor=-2.4D+00,mgrid=30,
     *           durbd=8.0D+00,zgood=1.01D+00,zbad=0.99D+00,
     *           npbhat=2,durub=2.5D+00,ntop=9,
     *           xkglow=xkbor,xkghgh=25.0D+00,nlzpts=201,
     *           nbetas=3,nzpts=2,nrspts=132)

      common/cpr/pr(4,4),prbeta(nbetas,nbetas),prob(nbetas)
      common/cgrid/xkgpts(kgrid),xmgpts(mgrid)
      common/clzpts/xlzpts(nlzpts),xlzdat(nlzpts)
      common/cbetas/betas(nbetas)
      common/ctop/toppct(ntop)
      common/ccoef/coefk(kgrid-1,mgrid-1,4,nbetas,4),
```

But things can still get complex.

High level programming language: Python

```python
print("Hello, World!")
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- So is Python slow?

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High level programming language: Python

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- So is Python slow? No, as we'll be interfacing with pieces of code that are written in C. Python is our gateway to that code.

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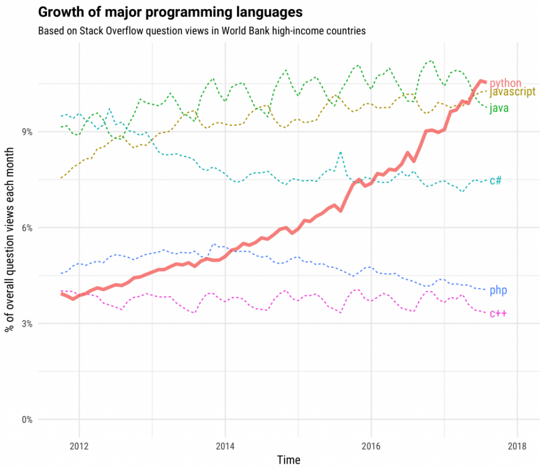
- **Idiosyncratic preference**. I prefer Python to R, so you'll learn Python.

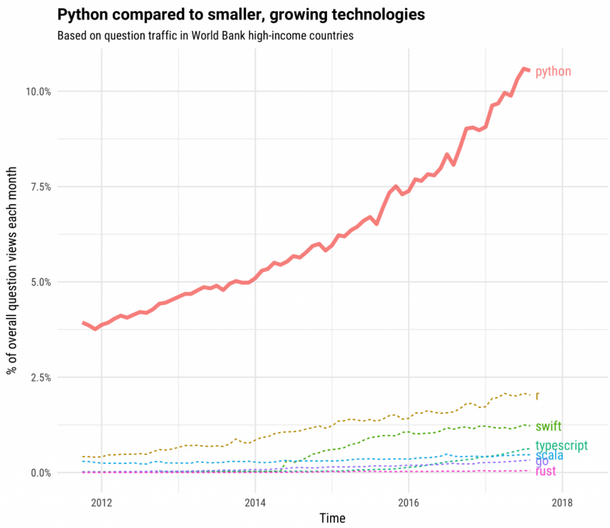
Global preference

Python has become extremely popular.



Global preference

The world prefers Python to R - this makes our life a lot easier.



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- In fact, learning how to use Python will give you a fundamental understanding of **programming thinking** - you'll even notice that learning Stata over the last year will have made this easier.
- The aim of course course is to teach you language agnostic concepts, that you can apply over your career. We happen to be understand these concepts through the lens of Python.

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Lets take ourselves to the point that we can actually run the example I've shown above!

We're going to spend the rest of the class installing **Anaconda** - the instructions are on these webpages depending on your OS. I'll walk you through.

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1. Install the Anaconda distribution (anaconda.com). Anaconda brings together a number of data science tools into one complete package.
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3. Open JupyterLab - this will be our main workspace in using Python.

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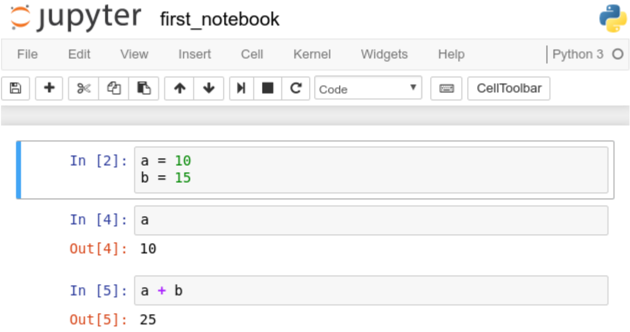

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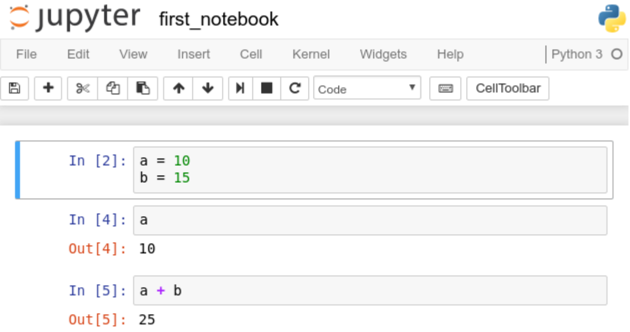

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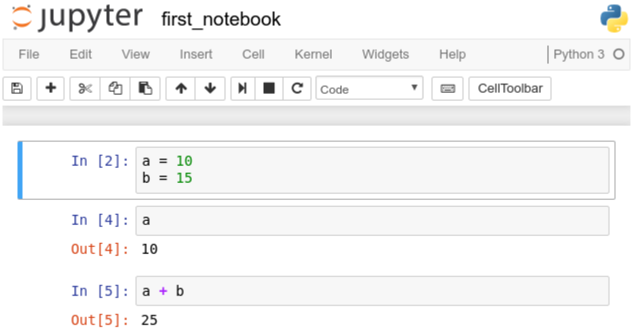

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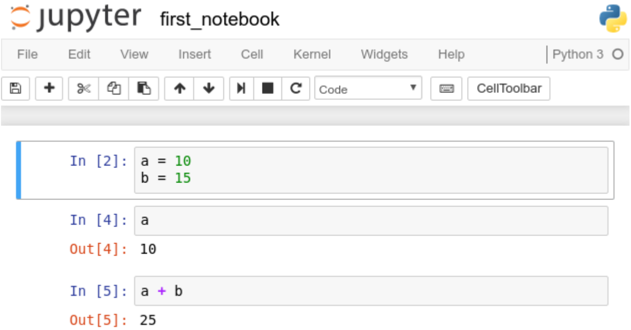

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