

Big Data for Public Policy Analysis

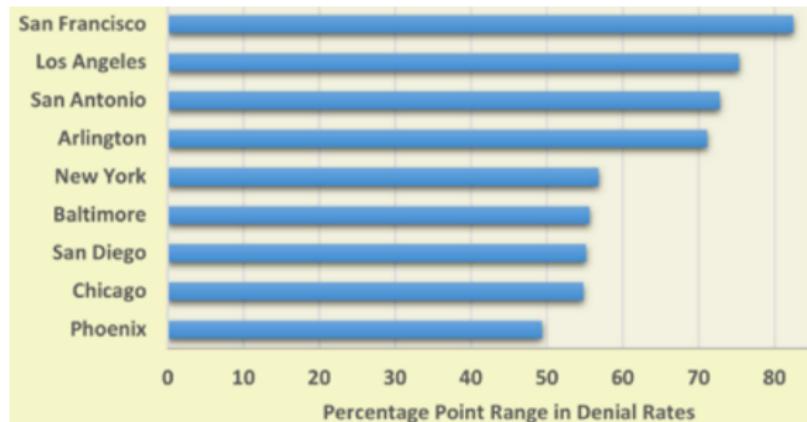
Instructors: Elliott Ash and Malka Guillot

1. Course Overview and Introduction

(Big) Data can diagnose policy problems.

(Big) Data can diagnose (and hopefully help solve) policy problems.

U.S. Asylum Courts: Disparities in Grant Rates



- In San Francisco, one judge grants 90.6% of asylum requests, while another judge grants just 2.9%!

Jailing Decisions Before/After Lunch Breaks

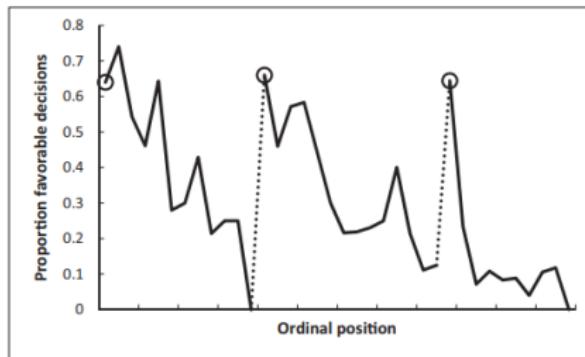
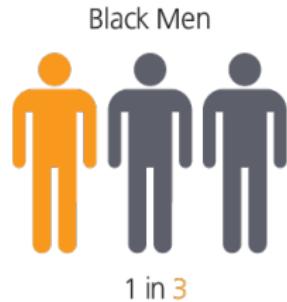
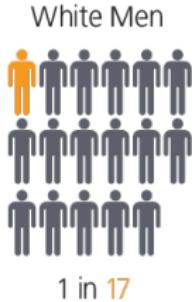


Fig. 1. Proportion of rulings in favor of the prisoners by ordinal position. Circled points indicate the first decision in each of the three decision sessions; tick marks on x axis denote every third case; dotted line denotes food break. Because unequal session lengths resulted in a low number of cases for some of the later ordinal positions, the graph is based on the first 95% of the data from each session.

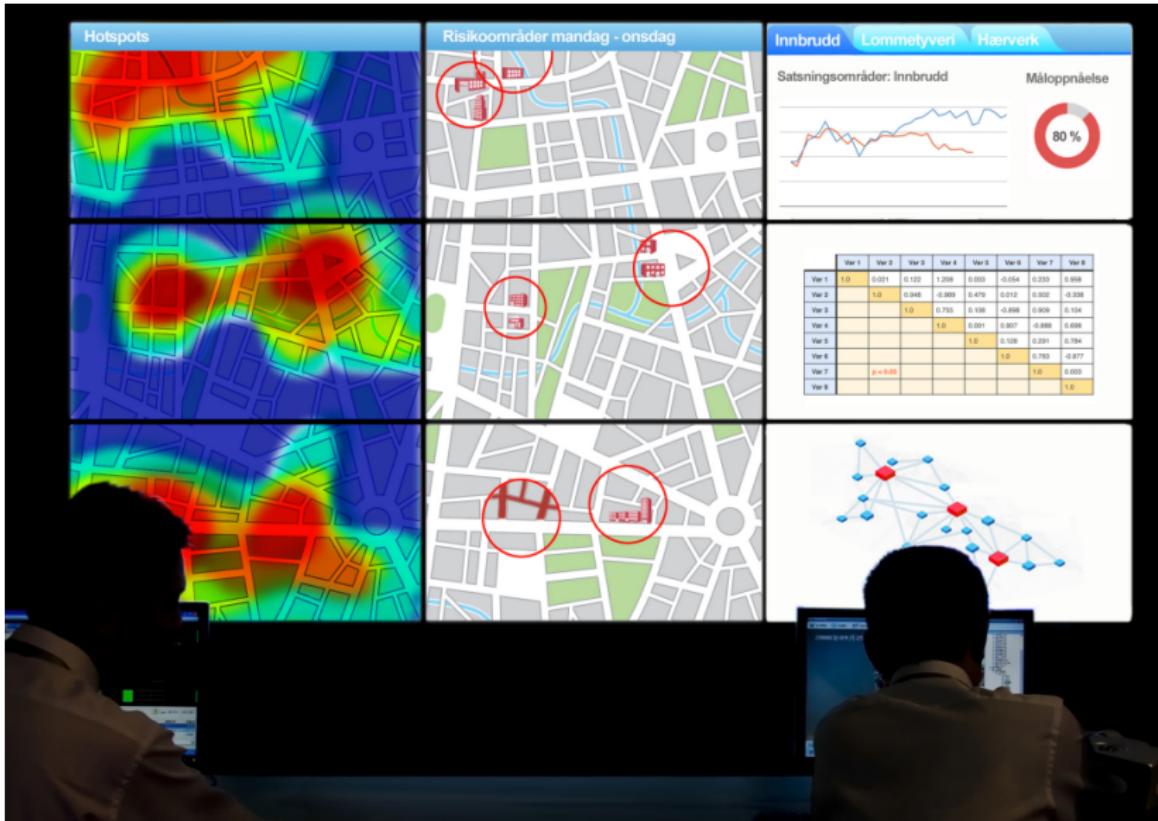
Source: Danziger et al, PNAS 2011, Israel judges deciding on parole.

Lifetime Likelihood of Imprisonment of U.S. Residents Born in 2001



Source: The Sentencing Project.

Predictive Policing



(Big) Data can cause (or magnify) problems.

Predictive policing poses discrimination risk, thinktank warns

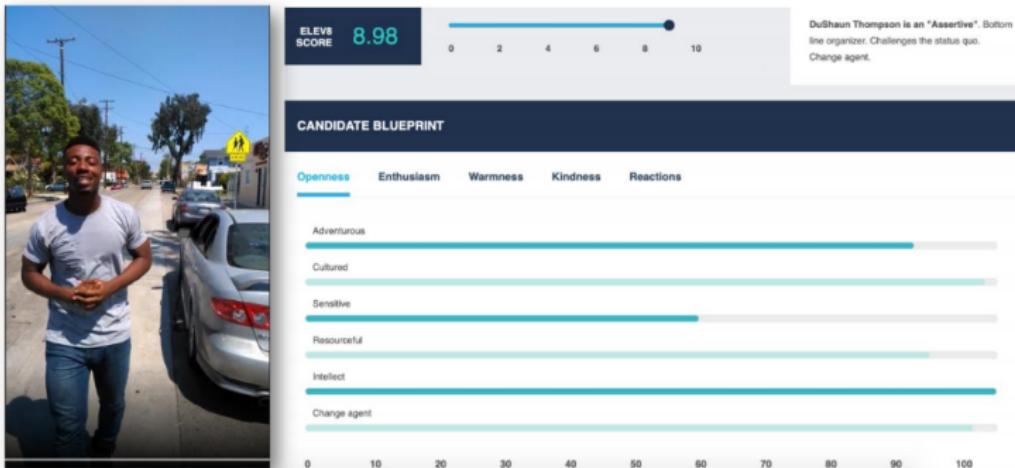
Machine-learning algorithms could replicate or amplify bias on race, sexuality and age



▲ One officer said human biases including more stop and searches of black men were likely to be introduced into algorithm data sets. Photograph: Carl Court/Getty Images

problematic: proprietary algorithms

Assessing personality & job suitability from 30-second video



Source: Narayanan slides.

...

OPENAI'S NEW MULTITALANTED AI WRITES, TRANSLATES, AND SLANDERS

A step forward in AI text-generation that also spells trouble

By James Vincent | Feb 14, 2019, 12:00pm EST

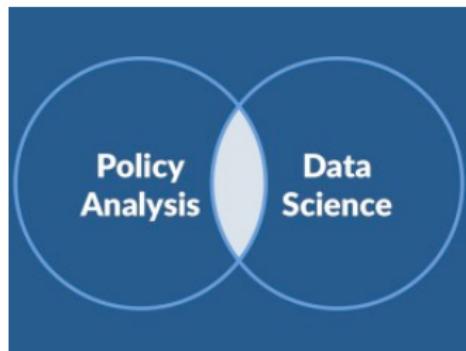
Howard, co-founder of Fast.AI agrees. "I've been trying to warn people about this for a while," he says. "We have the technology to totally fill Twitter, email, and the web up with reasonable-sounding, context-appropriate prose, which would drown out all other speech and be impossible to filter."

<https://transformer.huggingface.co/doc/distil-gpt2>

Fake news, content generation. Transformers can generate appropriately sounding text.

Welcome

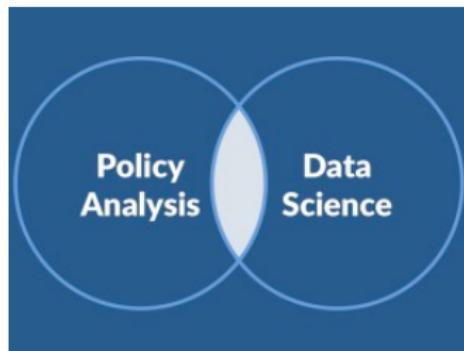
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- Goals:
 - Equip the standard machine learning toolkit.

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- Goals:
 - Equip the standard machine learning toolkit.
 - Put it to work on a real-world policy project.

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- What are the technical constraints of using large data sources?

Outline

1. Class Organization and Logistics
2. Motivations
3. Project Management

Lecture Times

- Tuesdays, 1:15pm-3pm
 - Location: UNO B11
- Office hours:
 - After lecture, or by appointment (ashe@ethz.ch & guillotm@ethz.ch).

Online Course Materials

- Course Syllabus:
 - https://docs.google.com/document/d/1rjo0jNQtEyML0m_PU2kK1UdUzWE942V7eaXqryCyjQQ/edit?ts=5dd7cc31
- GitHub Repo with Course Materials:
 - https://github.com/elliottash/big_data_policy_2020

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Daniela Witten
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Robert Tibshirani

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with Applications in R

Springer

Programming Languages

- The instructors are most familiar with Python, which is ideal for machine learning and text data.
 - We recommend Anaconda Distribution:
continuum.io/downloads
 - You are welcome to use R instead.

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- See `R-stata-cookbook-for-python.ipynb` for an intro to pandas, plotting and writing R code in python

Three Problem Sets

- Implement major methods in data collection, machine learning and text analysis from class.

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- See due dates on syllabus.
 1. Predicting firm stock price using Twitter data
 2. Crime re-arrest problem
 3. ML / Econometrics Problem

Course Project

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 - Can be done individually or in groups of 2.
 - In consultation with project advisors, form a research design using methods learned in the course.

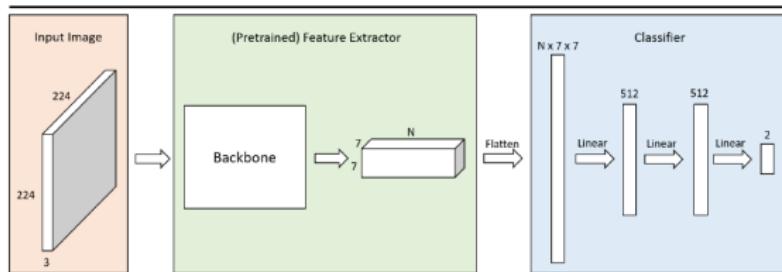
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- Deliverables: See syllabus

Example Spring 2019 Project

Dominik Borer: Predicting Candidate Party from Political Television Ads

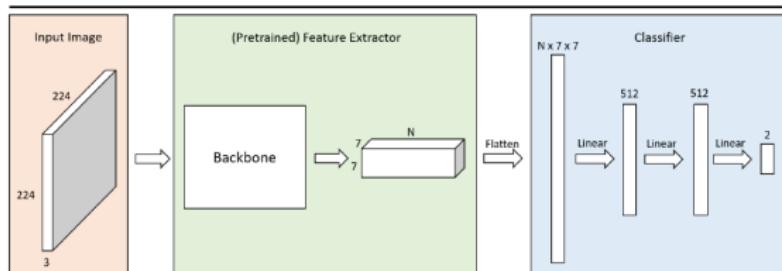
Figure 3: Overview of Model Architecture



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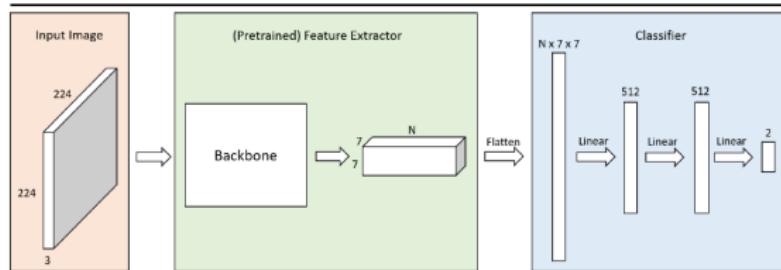
Panel C. Confusion matrix for test set

	Predicted Democratic	Predicted Republican
Actual Democratic	44.88% (793)	7.98% (141)
Actual Republican	15.73% (278)	31.41% (555)

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Panel A: News Show Images with Highest Democrat Slant



Panel B: News Show Images with Highest Republican Slant



Other Spring 2019 Projects

- One of the groups began building a legal research application for Swiss lawyers:
 - feature-rich legal search engine.
 - MSWord plugin that suggests cite references as you type.
 - Already partnered with Homberger law firm to test it out.

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 - Already partnered with Homberger law firm to test it out.
- Another group partnered with a local company to build out their environmental-regulation analytics
 - won an Innosuisse grant.

New Project Ideas

- We have a list of potential project ideas, will share with interested students.

Spirit of the class

- Learning
 - by doing
 - how to learn (i.e. asking your favorite search engine)
- Collaboration (group project...)
- Don't expect us to answer all questions

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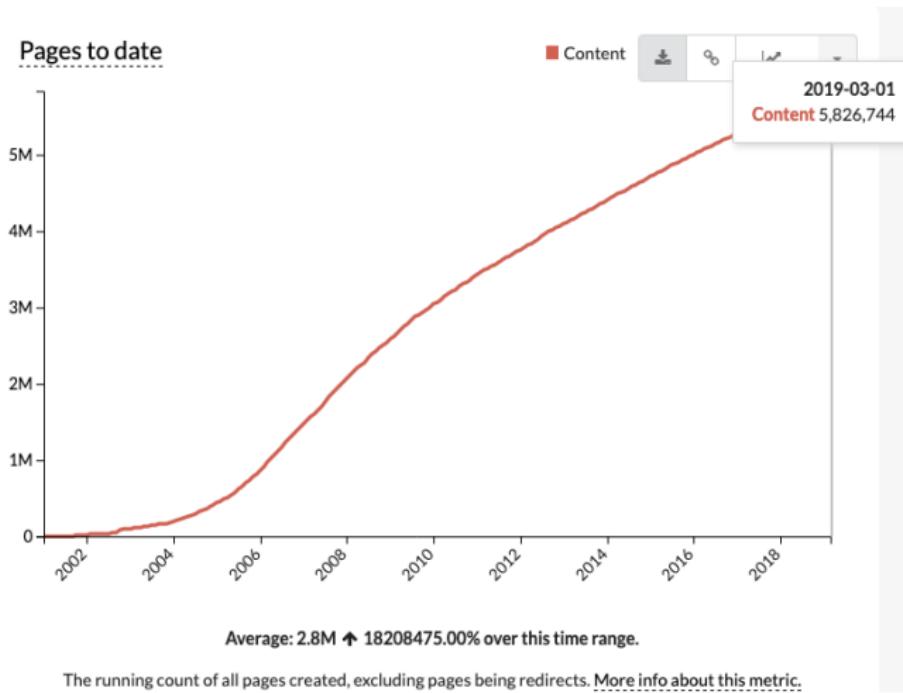
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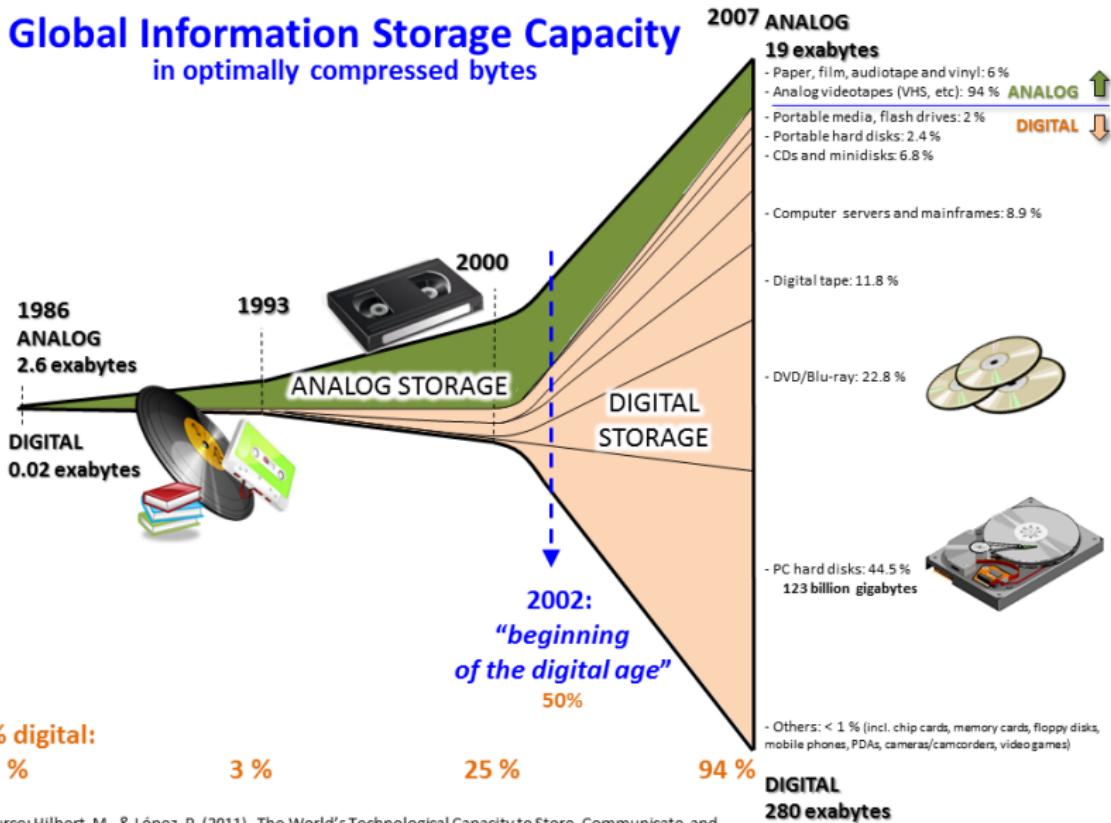
New possibilities: exciting!

of Wikipedia Pages, 2001-2019



Global Information Storage Capacity

in optimally compressed bytes



% digital:

1 %

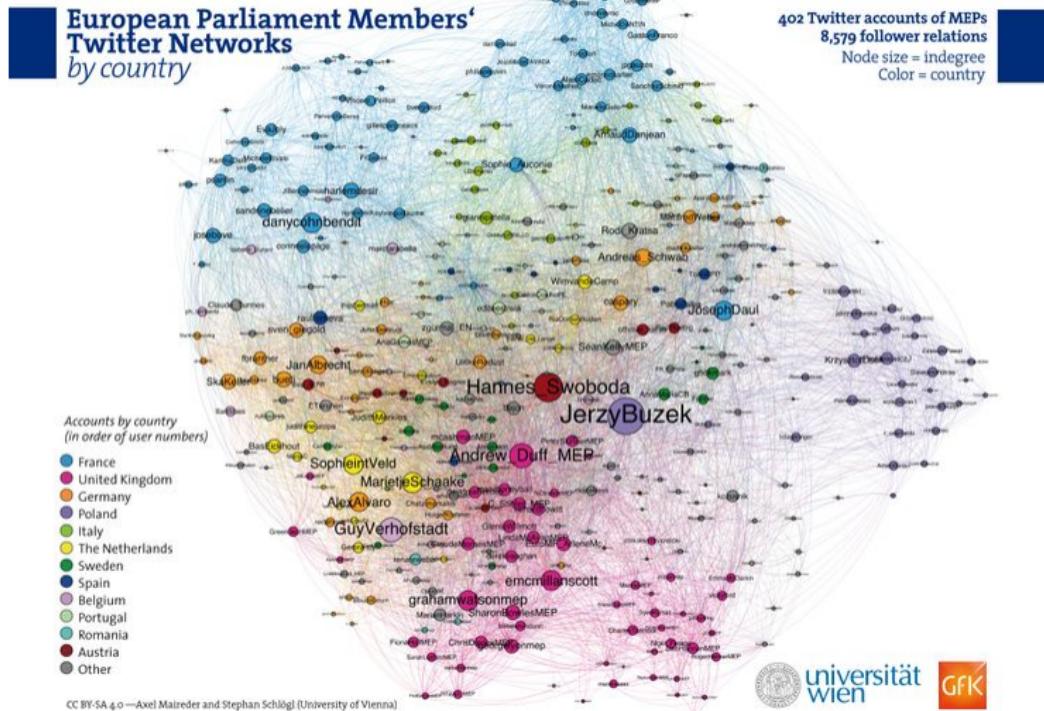
3 %

25 %

94 %

Source: Hilbert, M., & López, P. (2011). The World's Technological Capacity to Store, Communicate, and Compute Information. *Science*, 332(6025), 60–65. <http://www.martinhilbert.net/WorldInfoCapacity.html>

New Data, New Possibilities



CC BY-SA 4.0 —Axel Maireder and Stephan Schlägl (University of Vienna)

What is Big Data?

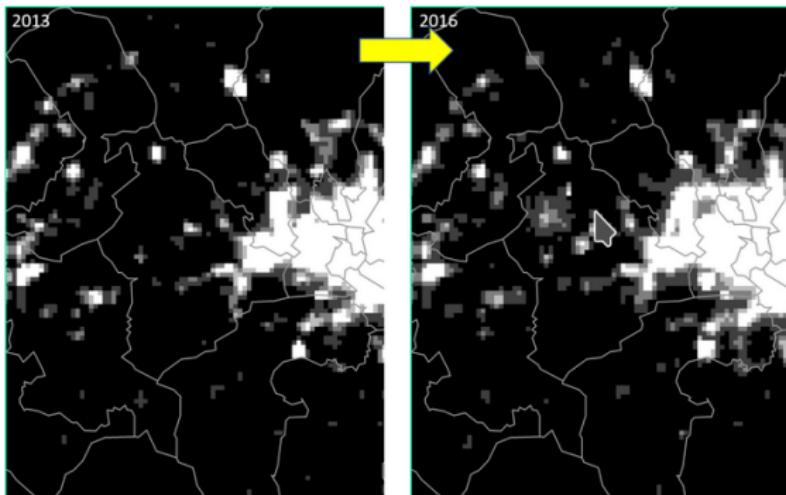
- Volume of data
- Format:
 - Structured
 - Unstructured
- Ready made vs. custommades

⇒ data will be even more important for policy making analyses

New Tools and Methods

- Data collection (eg. APIs, webscraping)
- Analysis (e.g. text analysis, machine learning)
- Visualization (e.g, maps, social networks, web apps)

New Measurements



FYR Macedonia: changes in nighttime light intensity

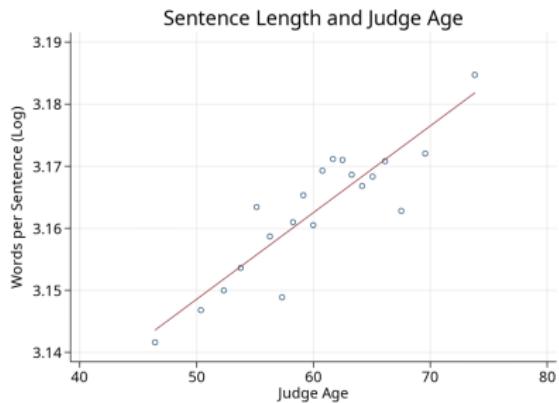
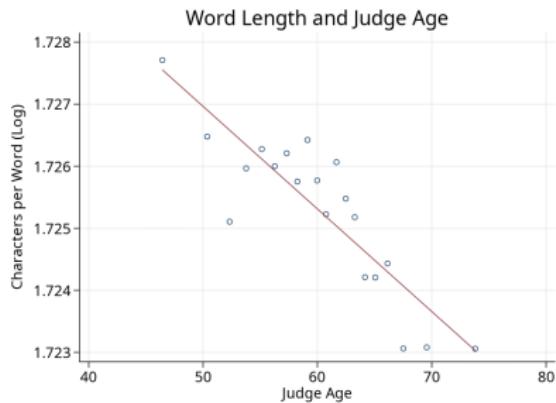
Source: World Bank.

New Measurements

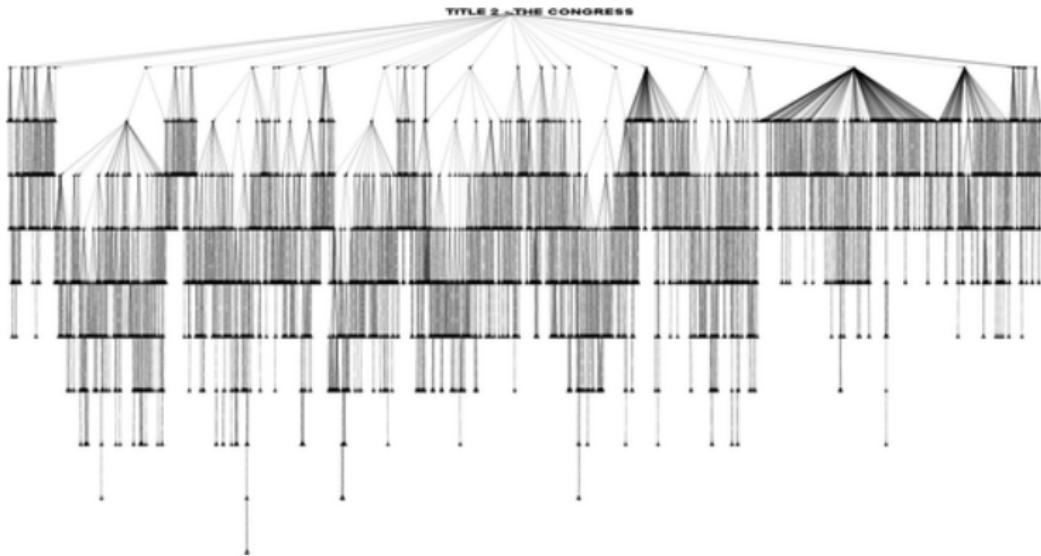


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Judge Age and Writing Style

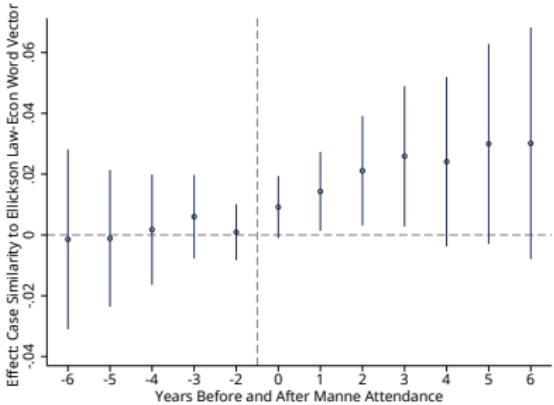


Ash and MacLeod (2020)



- The U.S. Code consists of 49 titles, which can be further subdivided into subtitle, chapter, subchapter, part, subpart, section, subsection, paragraph, subparagraph, clause, and subclause (Katz and Bommarito 2014)

Impact of Economics Training on Economics Language



After attendance, Economics Trained Judges increase use of a selection of terms related to law and economics (Ash, Chen, and Naidu 2019)

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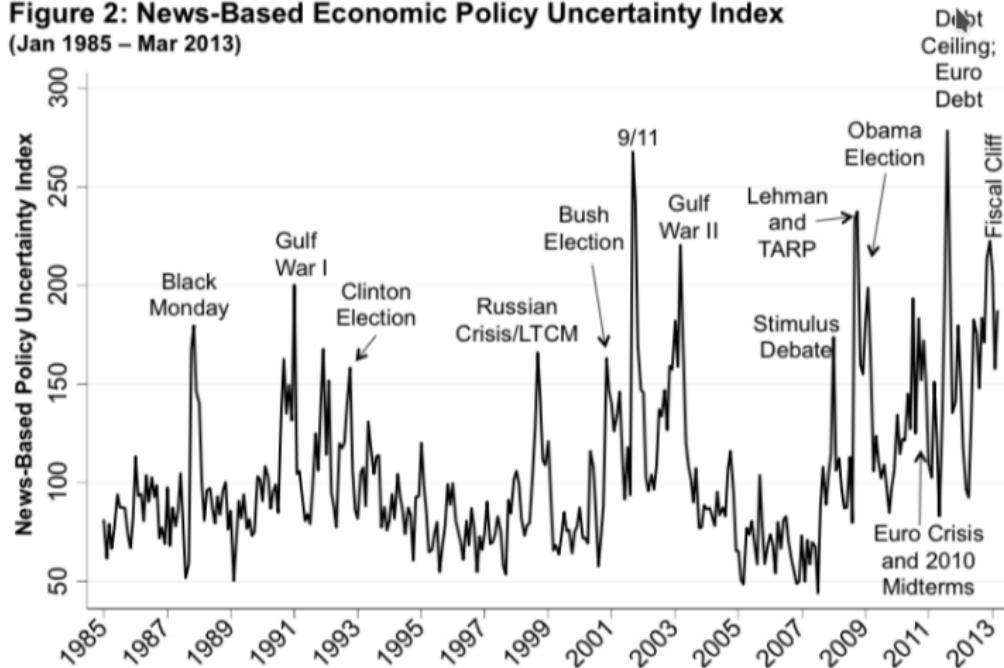
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- Normalize resulting article counts by total newspaper articles that month.

Measuring uncertainty in macroeconomy

Figure 2: News-Based Economic Policy Uncertainty Index
(Jan 1985 – Mar 2013)



Predicting U.S. Asylum Court Decisions

		Predicted	
		Denied	Granted
True	Denied	195,223	65,798
	Granted	73,269	104,406

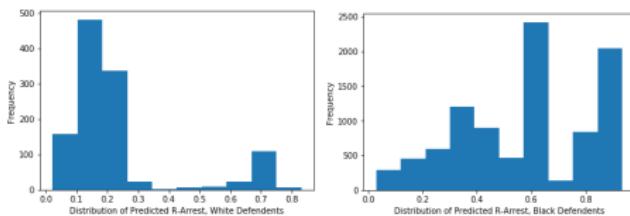
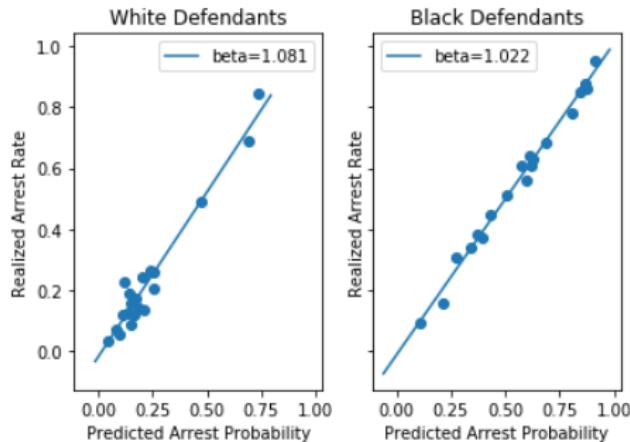
Accuracy = 68.3%, F1 = 0.60

- Prediction App (Beta):

<https://floating-lake-11821.herokuapp.com/>

Predicting Re-Arrest, New Orleans Prosecutor Office

Amaranto, Ash, Chen, Ren, and Roper (2018)



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 - But algorithms can also be used to detect systematic bias, to understand it – and therefore to help reduce it.

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- Other models/approaches improve interpretability:
 - Random Forests provide feature importance ranking.
 - LIME and related tools can help interpret any model (Ribeiro et al 2016). LIME ~ local model explanation

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- but $h(\cdot)$ does not provide a counterfactual prediction – that is, how the outcome would change if x 's were exogenously shifted.

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4. Empirical analysis
 - Produce statistics or predictions with the trained model.
 - **Solve the problem / Answer the research question.**

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Writing Good Code

Three commandments:

1. Comments

- Don't write documentation you will not maintain.
- Code should be self-documenting.

2. Reuse functions (no copy & paste) → **automation**

- Automate everything that can be automated
- Write a single script that executes all code from beginning to end

3. Use **version control** (no doc_final_v2.py)

- Store code and data under version control.
- Run the whole directory before checking it back in.

More on Project Management

- Naming
- PEP8
- Directories' organization
 - Separate directories by function.
 - Separate files into inputs and outputs.
 - Make directories portable.

Homework for next time

- install anaconda and packages
 - sklearn, gensim, xgboost
- run jupyter notebook
 - Play with the R-stata-cookbook-for-python notebook (on the github page of the class)
- register in the twitter API
 - For installation guidelines, see this (paragraph “An Example with Twitter’s API)