Macroeconomic Analysis with Machine Learning and Big Data

Lecture 1: Introduction

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July 2, 2019

Outline

Motivation of This Course

Big Data: New Way to Learn Economics?

The radical plan to change how Harvard teaches economics

Raj Chetty has an idea for introducing students to econ that could transform the field — and society.

By Dylan Matthews | @dylanmatt | dylan@vox.com | Updated May 22, 2019, 8:07am EDT

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The Highlight BY Vox

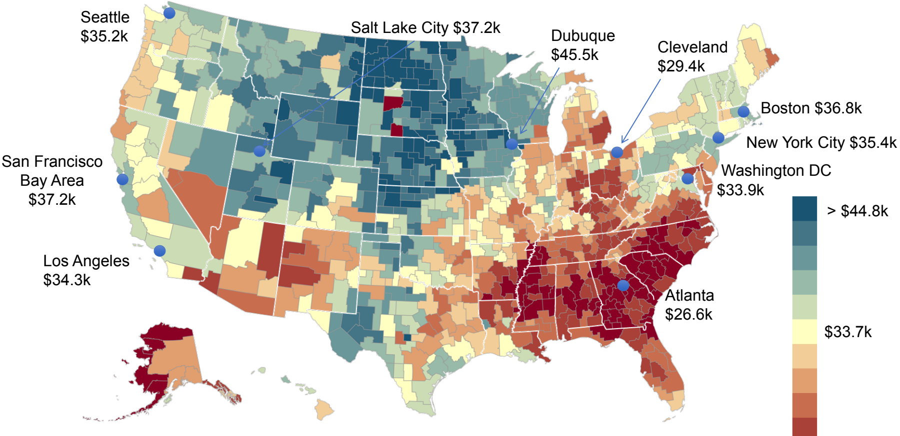
But another Harvard economist has a different idea of how to introduce students to economics.

Raj Chetty, a prominent faculty member whom Harvard recently poached back from Stanford, this spring unveiled **"Economics 1152: Using Big Data to Solve Economic and Social Problems."** Taught with the help of lecturer Greg Bruich, the class garnered 375 students, including 363 undergrads, in its first term. That's still behind the 461 in Ec 10 — but not by much.

Figure: Raj Chetty

The Geography of Upward Mobility in the United States

Average Household Income for Children with Parents Earning $27,000 (25th percentile)

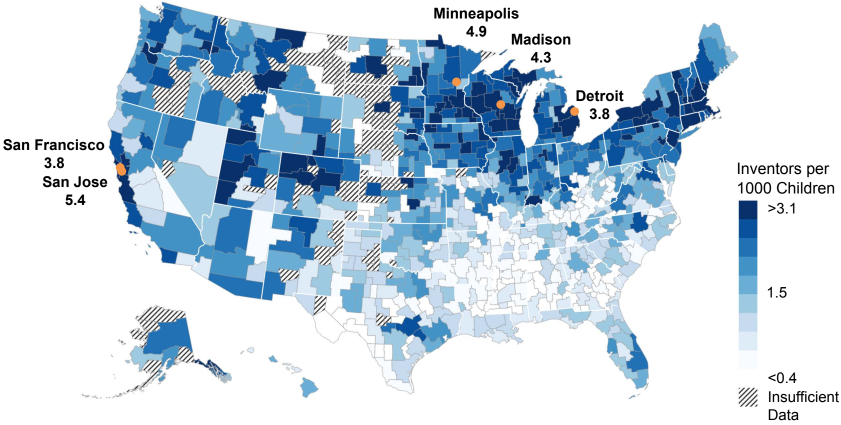


Note: Blue = More Upward Mobility, Red = Less Upward Mobility
Source: The Opportunity Atlas. Chetty, Friedman, Hendren, Jones, Porter 2018

https://opportunityinsights.org/wp-content/uploads/2019/05/Lecture-1-intro-and-mobility.pdf
https://www.opportunityatlas.org/

The Origins of Inventors in America

Patent Rates by Childhood Commuting Zone



https://opportunityinsights.org/wp-content/uploads/2019/05/Lecture-5-innovation.pdf

Big Data and Machine Learning: New Way to Study Economics?

REVIEW

Economics in the age of big data

Liran Einav[1,2,*], **Jonathan Levin**[1,2]

+ See all authors and affiliations

Science 07 Nov 2014:
Vol. 346, Issue 6210, 1243089
DOI: 10.1126/science.1243089

Article | Figures & Data | Info & Metrics | eLetters | PDF

Structured Abstract

Background

Economic science has evolved over several decades toward greater emphasis on empirical work. The data revolution of the past decade is likely to have a further and profound effect on economic research. Increasingly, economists make use of newly available large-scale administrative data or private sector data that often are obtained through collaborations with private firms, giving rise to new opportunities and challenges.

Figure: *Science* Review on the Economics in the Age of Big Data

Big Data and Machine Learning: New Way to Study Economics?

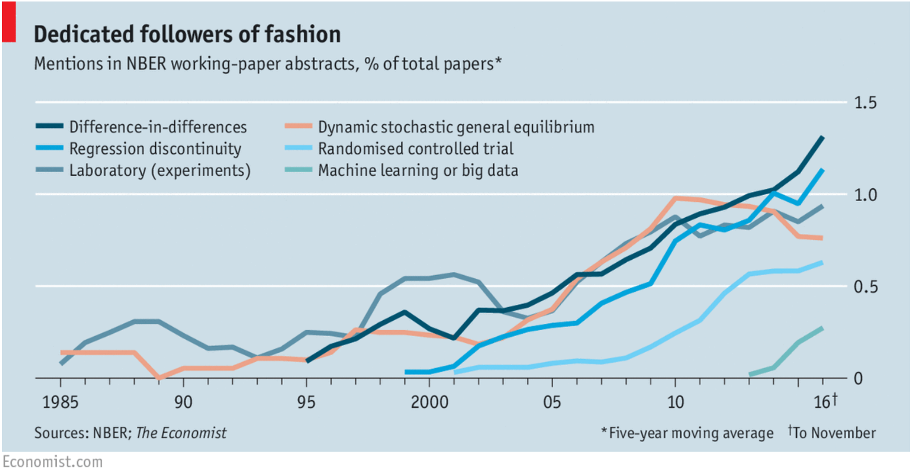


Figure: Upward Trend is persistent after 2016

Big Data and ML in Prominent Conferences for Macro

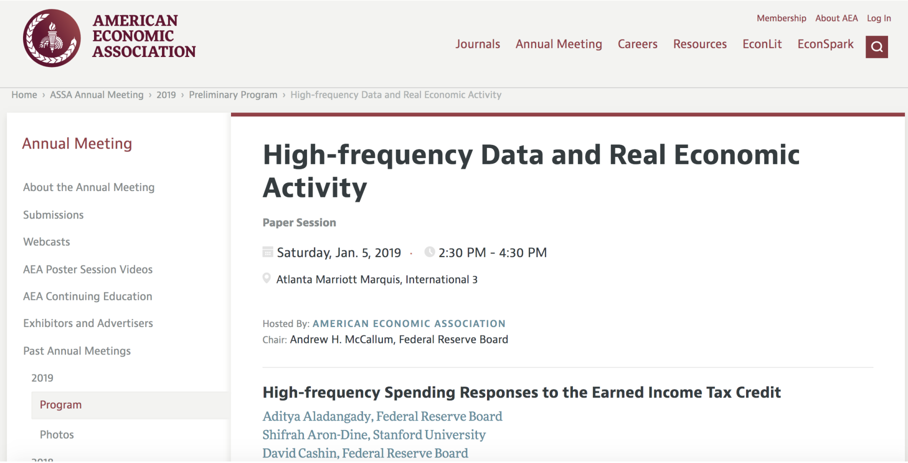


Figure: One Session in AEA 2019 Annual Conference

Big Data and ML in Prominent Conferences for Macro

Figure: One Session in AEA 2019 Annual Conference

Big Data and ML in Prominent Conferences for Macro

SI 2019 Micro Data and Macro Models

Erik Hurst, Greg Kaplan, and Giovanni L. Violante, Organizers
July 15-18, 2019
Longfellow Room
Royal Sonesta Hotel
40 Edwin H. Land Blvd.
Cambridge, MA

Conference Code of Conduct
Summer Institute 2019 master schedule

Monday, July 15

8:30 am	Coffee & Pastries
9:00 am	Rohan Kekre, University of Chicago Moritz Lenel, Princeton University *Redistribution, Risk Premia, and the Macroeconomy*
9:45 am	Laura Liu, Indiana University Mikkel Plagborg-Møller, Princeton University *Full-Information Estimation of Heterogeneous Agent Models Using Macro and Micro Data*
10:30 am	Break
10:45 am	Sushant Acharya, Federal Reserve Bank of New York Edouard Challe, Ecole Polytechnique Keshav Dogra, Federal Reserve Bank of New York *Optimal Monetary Policy in HANK Economies*

http://papers.nber.org/sched/SI19EFMM

Big Data and ML in Prominent Conferences for Macro

CRIW Conference: Big Data for 21st Century Economic Statistics

Katharine G. Abraham, Ron S. Jarmin, Brian Moyer, and Matthew D. Shapiro, Organizers

March 15-16, 2019

Supported by the Alfred P. Sloan Foundation

Hyatt Regency Bethesda
Cabinet/Judiciary Room
One Bethesda Metro Center
Bethesda, MD

Conference Code of Conduct

Friday, March 15

8:30 am	Continental Breakfast
	Session 1, Chair: Katharine Abraham, University of Maryland and NBER
9:00 am	Welcome from Conference Organizers and Opening Remarks from James Poterba, Massachusetts Institute of Technology and NBER
9:10 am	Gabriel Ehrlich, University of Michigan John C. Haltiwanger, University of Maryland and NBER Ron S. Jarmin, Bureau of the Census David Johnson, University of Michigan Matthew D. Shapiro, University of Michigan and NBER *Re-Engineering Key National Economic Indicators*

https://conference.nber.org/conferences/2019/CRIWs19/summary.html

Book on “Big Data for 21st Century Economic Statistics”

Table of Contents

https://www.nber.org/books/abra-7

7. Improving the Accuracy of Economic Measurement with Multiple Data Sources: The Case of Payroll Employment Data: Tomaz Cajner, Leland D. Crane, Ryan A. Decker, Adrian Hamins-Puertolas, Christopher Kurz (bibliographic info) (download)

8. Automating Response Evaluation for Franchising Questions on the 2017 Economic Census: Andrew L. Baer, J. Bradford Jensen, Shawn D. Klimek, Lisa Singh, Joseph Staudt, Yifang Wei (bibliographic info) (download) (Working Paper version)

9. Valuing Housing Services in the Era of Big Data: A User Cost Approach Leveraging Zillow Microdata: Marina Gindelsky, Jeremy Moulton, Scott A. Wentland (bibliographic info) (download)

10. Quantifying Productivity Growth in Health Care Using Insurance Claims and Administrative Data: John A. Romley, Abe Dunn, Dana Goldman, Neeraj Sood (bibliographic info) (download)

11. Nowcasting the Local Economy: Using Yelp Data to Measure Economic Activity: Edward L. Glaeser, Hyunjin Kim, Michael Luca (bibliographic info) (download) (Working Paper version)

12. Transforming Naturally Occurring Text Data into Economic Statistics: The Case of Online Job Vacancy Postings: Arthur Turrell, Bradley J. Speigner, Jyldyz Djumalieva, David Copple, James Thurgood (bibliographic info) (download) (Working Paper version)

13. Using Public Data to Generate Industrial Classification Codes: John Cuffe, Sudip Bhattacharjee, Ugochukwu Edudo, Justin Smith, Nevada Basdeo (bibliographic info)

14. Measuring Export Price Movements with Administrative Trade Data: Don A. Fast, Susan E. Fleck (bibliographic info) (download)

15. Big Data in the U.S. Consumer Price Index: Experiences and Plans: Crystal G. Konny, Brendan K. Williams, David M. Friedman (bibliographic info) (download) version of June 27, 2019

16. Estimating the Benefits of New Products: Some Approximations: W. Erwin Diewert, Robert C. Feenstra (bibliographic info) (download) version of April 24, 2019

17. Securing Commercial Data for Economic Statistics: Katharine G. Abraham, Margaret Levenstein, Matthew D. Shapiro (bibliographic info)

Big Data and ML for Policy Makers

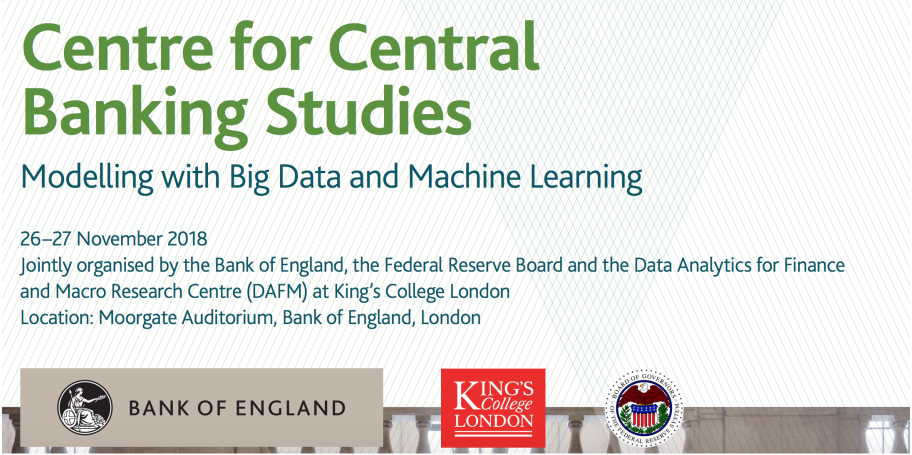


Figure: Conference Organized by Bank of England and US Federal Reserve Board

https://www.bankofengland.co.uk/events/2018/november/modelling-with-big-data-and-machine-learning

Big Data and ML for Policy Makers

Cabinet Office

HM Treasury

Independent report

Press notice: 'Take economic statistics back to the future,' says Charlie Bean

Updated 11 March 2016

UK economic statistics need to be transformed in order to fully capture all the activity in the economy according to a new report published by Professor Sir Charlie Bean today (Friday 11 March 2016).

Charlie Bean, a former deputy governor of the Bank of England, set out his findings in his final report into UK economic statistics which was launched at Europe's largest data observatory, the Data Science Institute at Imperial College London.

https://www.gov.uk/government/publications/independent-review-of-uk-economic-statistics-final-report

ONS Big Data Team

Data Science for Official Statistics

- UK
- Our ONS Page
- Email
- GitHub

Published work

A list of all the Big Data Teams published work. Code repository links where available via Recently added publications are marked with a ⭐

Please contact us at ons.big.data.project@ons.gov.uk if you would like more information about any of the work we have done or are doing!

Methodology working papers

- ⭐ **Špakulová I., Gask K., Hopper, N.A. and James, M.** (2019) Using data science for the address matching service
- ⭐ **Šakulová I., Dove I., Bates, A. and Turner, A.** (2019) Synthetic data pilot

https://onsbigdata.github.io/publications

Big Data and ML in the Industry

J.P.Morgan

May 2017

Big Data and AI Strategies

Machine Learning and Alternative Data Approach to Investing

Google the title to get a copy by yourself.

Table of Contents of Data Providers

In this section we provide a comprehensive list of alternative data and technology providers. In order to navigate this handbook, we provide a table of contents below.

Big Data and ML in Practice

Big Data and ML in Practice

	数据来源	数据类别	条数	字段数量	起始日期
☐	原始爬虫数据	工程建设	9591	14	0001-01-01 00:00:00
☐	原始爬虫数据	政府采购	5876	14	2018-07-30 00:00:00
☐	原始爬虫数据	产权交易	5297	14	2017-10-19 00:00:00
☐	原始爬虫数据	大众点评	81856	17	2019-01-16 14:42:32
☐	原始爬虫数据	前程无忧招聘	9414481	15	2018-12-08 21:34:54
☐	原始爬虫数据	链家新房	677	18	2018-11-20 18:06:08
☐	原始爬虫数据	链家二手房	261980	25	2018-11-27 19:45:45
☐	原始爬虫数据	智联招聘	2302919	15	2018-12-08 16:59:45
☐	互联网数据	百度新闻	571375	6	2018-11-26 03:51:47
☐	互联网数据	佰腾专利	150482	15	2018-11-26 03:56:37
☐	互联网数据	工程建设	9591	11	2018-11-25 04:06:41
☐	互联网数据	大众点评	81856	16	2018-11-25 04:04:48

How Much Does Big Data and ML Really Help in Macroeconomics?

How Much Does Big Data and ML Really Help in Macroeconomics?

Talk is Cheap, Show Me the Results.

Introduction to Some Empirical Work

Combining Satellite Imagery and Machine Learning to Predict Poverty (2016, Science)

- Background: Nightlight display little variation at lower expenditure levels.
- Research Question: Estimate expenditure and asset wealth with satellite imagery.
- Main Data: survey and satellite data from five African countries.
- Model: Transfer Learning from ImageNet to Daytime Satellite images + ridge regression for prediction.
- Results: explain up to 75% of the variation in local-level economic outcomes.

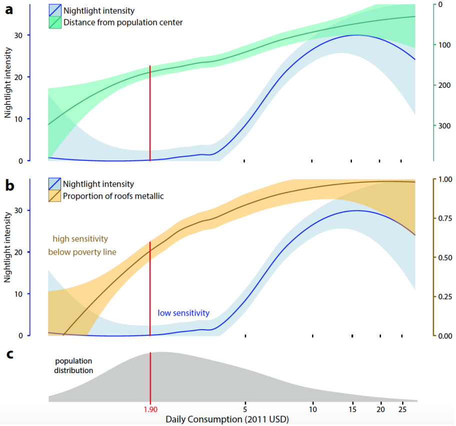


Figure: Consumption vs. Nightlight Intensity and Other Features

Combining Satellite Imagery and Machine Learning to Predict Poverty (2016, Science)

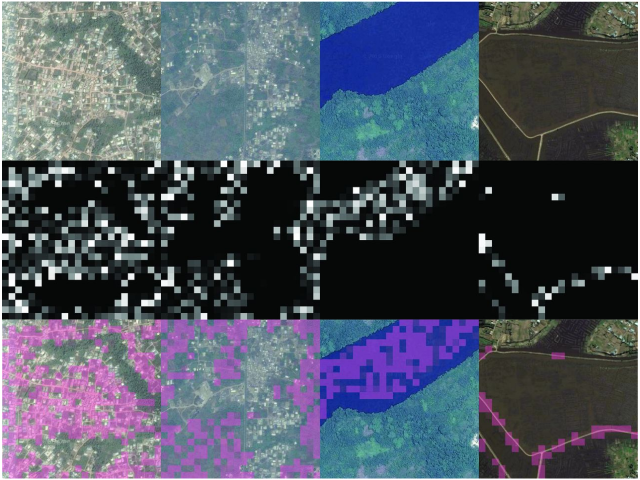


Figure: Feature Extraction from Daytime Satellite Images with Transfer Learning

Combining Satellite Imagery and Machine Learning to Predict Poverty (2016, Science)

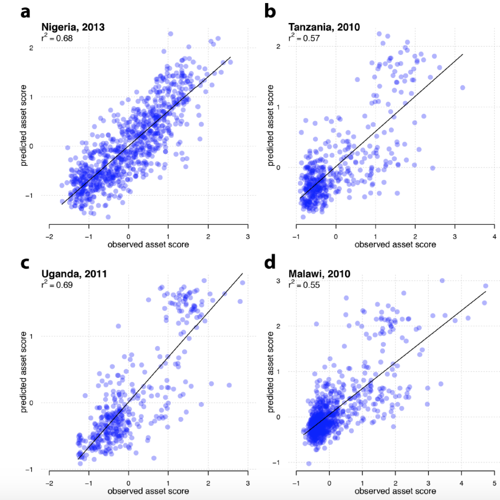


Figure: Cluster-level Asset: TL Based Prediction vs. Survey Measure

Predicting Poverty and Wealth from Mobile Phone Metadata (2015, Science)

- Research Question: Use individual's mobile phone use history to infer his/her socioeconomic status, and reconstruct the distribution and aggregates of wealth of an entire nation.
- Main Data:

Table 1. Summary statistics for primary data sets. Phone survey data were collected by the authors in Kigali, in collaboration with the Kigali Institute of Science and Technology. Call detail records were collected by the primary mobile phone operator in Rwanda at the time of the phone survey. Demographic and Health Survey (DHS) data were collected by the Rwandan National Institute of Statistics. N/A, not applicable.

Summary statistic	Phone survey	Call detail records	DHS (2007)	DHS (2010)
Number of unique individuals	856	1.5 million	7377	12,792
Data collection period	July 2009	May 2008–May 2009	Dec. 2007–Apr. 2008	Sept. 2010–Mar. 2011
Number of questions in survey	75	N/A	1615	3396
Primary geographic units	30 districts	30 districts	30 districts	30 districts
Secondary geographic units	300 cell towers	300 cell towers	247 clusters	492 clusters

- Model: (1) combinatorial method for feature engineering; (2) elastic net for prediction; (3) aggregate.
- Results: see next two pages.

Predicting Poverty and Wealth from Mobile Phone Metadata (2015, Science)

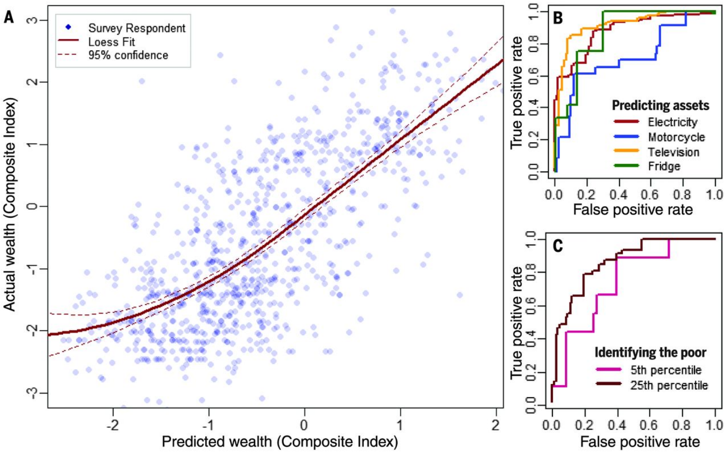


Figure: Predicting survey responses with phone data at individual level

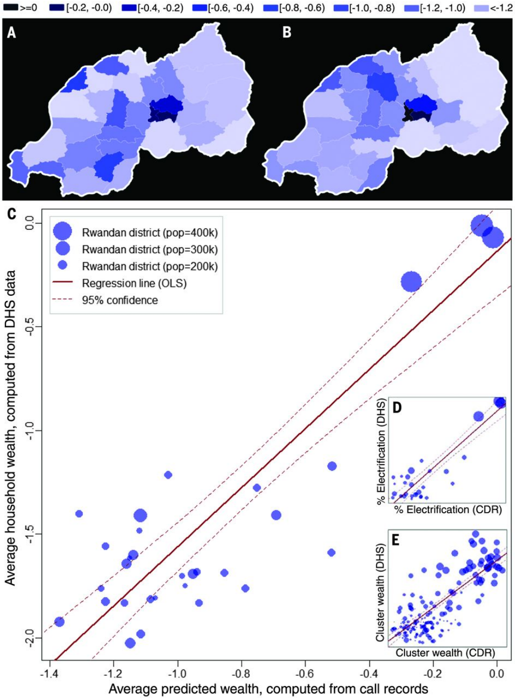


Figure: Comparison of wealth predictions to government survey data at district level

Estimating Unemployment Rate with Administrative Data (E, Huang, Yang, Yang, Zheng, et al., 2019)

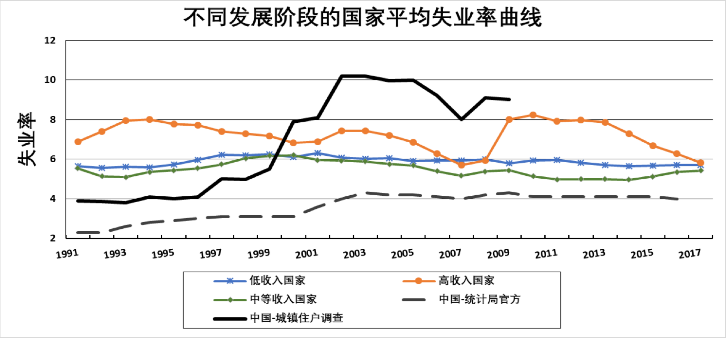


Figure: Replication from Feng et al. (2017)

- Background: China's unemployment data are very uninformative.
- Research Question: Predict individual employment status with administrative data and aggregate up.
- Main Data: administrative data from a city with 4M population.

Estimating Unemployment Rate with Administrative Data

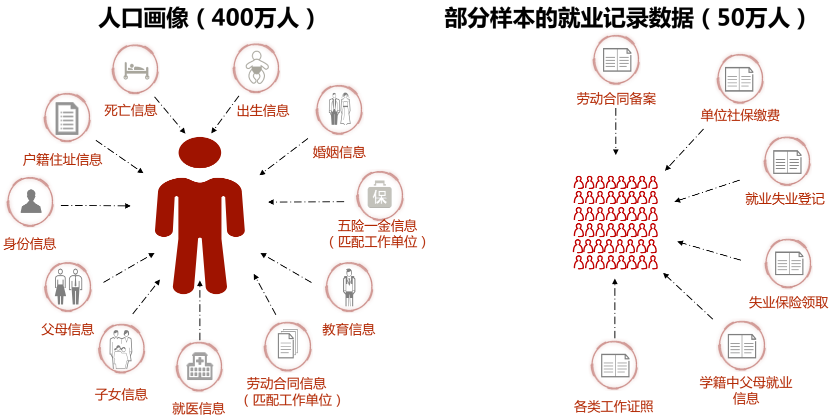


Figure: Left: Construction of Input Variables; Right: Construction of Output Labels. (Source: Beijing Institute of Big Data Research)

Estimating Unemployment Rate with Administrative Data

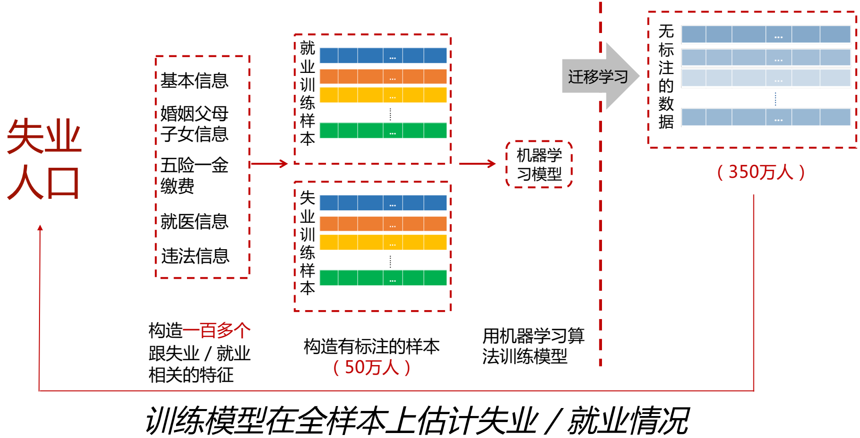


Figure: Model Illustration (Source: Beijing Institute of Big Data Research)

Estimating Unemployment Rate with Administrative Data

1010110
1001001
1101010
模型集成结果

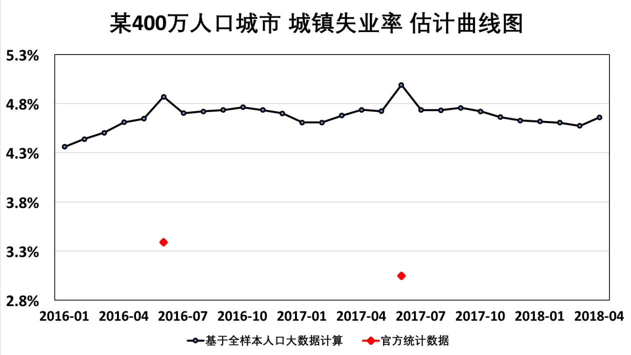
交叉验证结果	预测为失业	预测为就业
真实失业样本	24624 ☺	24 ☹
真实就业样本	1164 ☹	409925 ☺

交叉验证准确率：99.72%，失业标签召回率：99.90%

BIBDR
北京大数据研究院

Figure: Model Results (Source: Beijing Institute of Big Data Research)

Estimating Unemployment Rate with Administrative Data



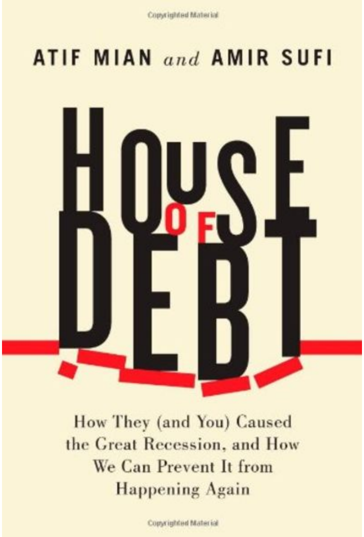
主要发现

- 估计出的失业率曲线有明显周期性特征，数值水平处于合理区间
- 2017年7月的失业高峰与当地经验高度一致

Figure: Model Results (Source: Beijing Institute of Big Data Research)

Mian and Sufi Narrative on the Great Recession

- 2002 to 2006: Housing boom $\rightarrow$ house prices $\uparrow \rightarrow$ sub-prime mortgage supply $\uparrow$ & households leverage $\uparrow$.
- 2007 to 2009: Housing bust $\rightarrow$ house prices $\downarrow \rightarrow$ household wealth $\downarrow$.
- In areas with highest leverage and largest $\downarrow$ in house prices $\rightarrow$ consumption $\downarrow$ most.
- Due to real frictions, house prices $\downarrow \rightarrow$ housing net worth $\downarrow \rightarrow$ employment in non-tradable industries $\downarrow$.



Mian and Sufi Narrative on the Great Recession

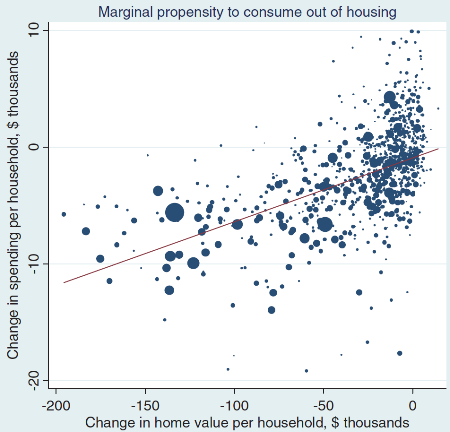


Figure: Change in Home Value vs. Consumption

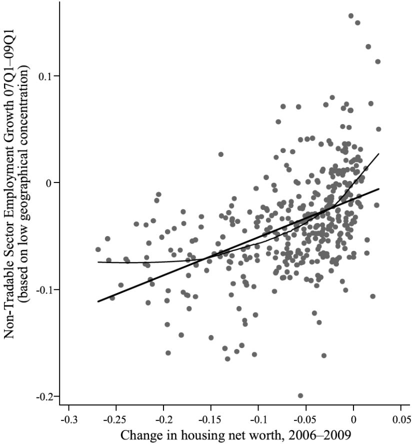


Figure: Change in Home Value vs. Non-tradable sector Employment

Most of the Mian-Sufi narratives are based on empirical work with small regional (eg ZIP code) level data.

Using High-Frequency Detailed Transaction Data to Study Consumption

Baker, S.R., 2018. Debt and the response to household income shocks: Validation and application of linked financial account data. *Journal of Political Economy*, 126(4), pp.1504-1557.

- Research Question: How consumption elasticity vary among households? Through what channels?
- Main Data: A large online personal finance website with 4 million users' (1) Transaction data: time-stamped spending and income records with detailed information (source, category, instrument, etc.) (2) Balance sheet data: daily updated in investment, equity, retirement, real estate, and loan accounts. (3) Demographic data.
- Model: IV regression.
- Results: (1) Elasticity of consumption is significantly higher in households with more debt and fewer assets. (2) Debt is not significant after controlling credit and liquidity constraints.

Using High-Frequency Detailed Transaction Data to Study Consumption

IMPACT OF DEBT AND CREDIT ON ΔLOG(SPENDING) FOLLOWING INCOME SHOCKS

	SAMPLE: ALL (IV)					
	(1)	(2)	(3)	(4)	(5)	(6)
ΔLog(Income)	.321***	.343***	.346***	.329***	.334***	.324***
	(.032)	(.026)	(.023)	(.022)	(.021)	(.023)
ΔLog(Income)×[Debt/(Debt+Assets)]	.087***	.073***	.052***	.031**	.024*	.016
	(.026)	(.024)	(.016)	(.015)	(.014)	(.016)
ΔLog(Income)×(Credit Score)		−.037***	−.030**	−.026**	−.019*	−.026**
		(.014)	(.011)	(.012)	(.011)	(.012)
ΔLog(Income)×(Unused Credit)			−.062***	−.059***	−.051***	−.043***
			(.012)	(.011)	(.012)	(.011)
ΔLog(Income)×(Liquid Assets)				−.073***	−.071***	−.068***
				(.015)	(.016)	(.019)
ΔLog(Income)×(Credit Limit Decline)					.063*	.069*
					(.034)	(.036)
ΔLog(Income)×(Marginal Interest Rate)						.094**
						(.046)
Observations	3,014,721	3,014,721	3,014,721	3,014,721	3,014,721	3,014,721

Macroeconomic Nowcasting and Forecasting with Big Data

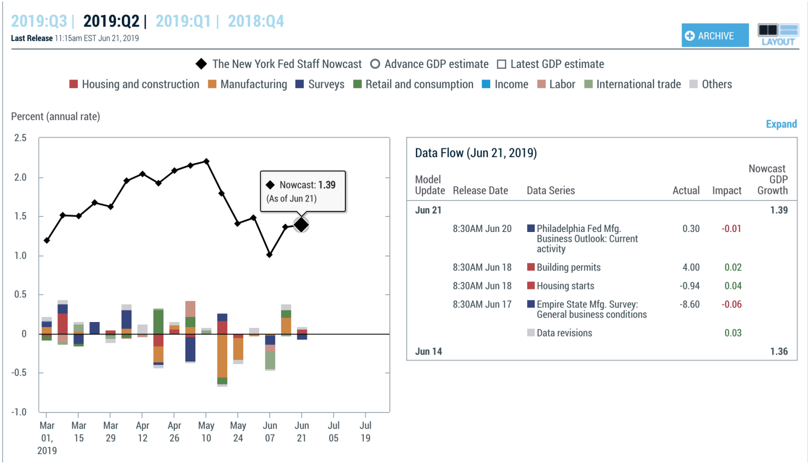


Figure: Nowcasting GDP growth with a wide range of macroeconomic data.

https://www.newyorkfed.org/research/policy/nowcast

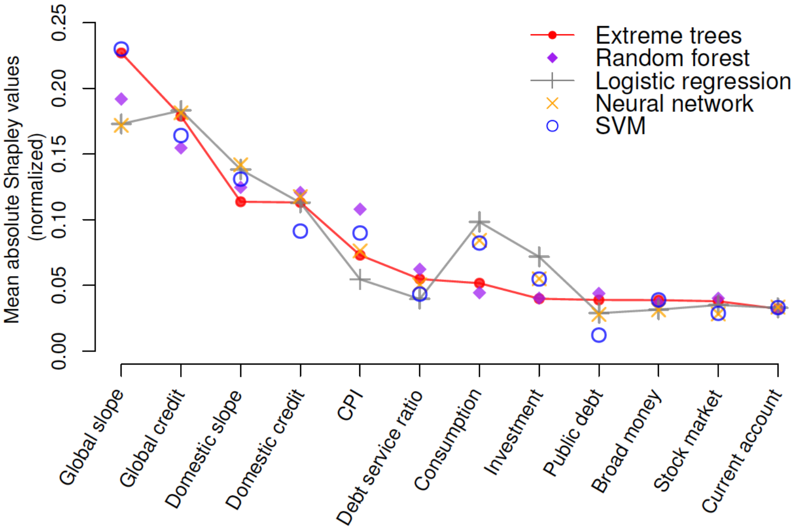
Bok, B., D. Caratelli, D. Giannone, A. Sbordone, and A. Tambalotti. 2017. Macroeconomic Nowcasting and Forecasting with Big Data. Federal Reserve Bank of New York *Staff Reports*, no. 830, November.

Predicting Financial Crisis with Machine Learning

Bluwstein et al. (2019): by Economists at the Bank of England.

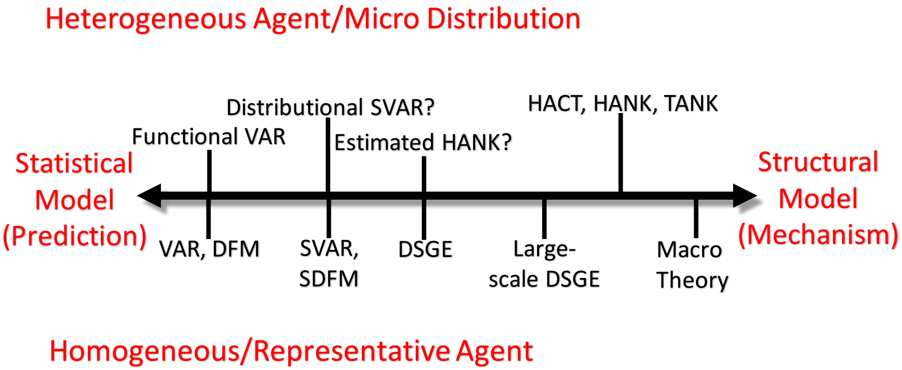
- Research Question: Build early warning models for financial crises using ML techniques and identify the key drivers of financial crises.
- Main Data: macroeconomic and financial time series data set for 17 countries between 1870-2016 (Jordà-Schularick-Taylor Macrohistory Database).
- Model: (1) ML models for prediction; (2) Shapley value framework for key driver detection.
- Results: (1) ML models outperform linear or logistic regressions; (2) The most important predictors are the slope of the yield curve and credit growth, and the importance order is persistent in different models.

Variable Importance for Crisis Prediction in Different ML Models

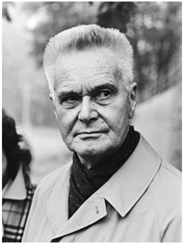
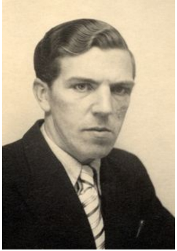
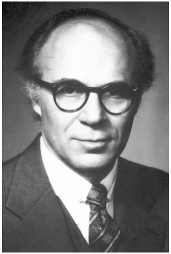
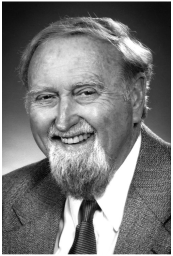
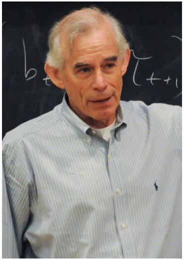


Introduction to Some Methodological Work

The Spectrum of Macro Methodology



Statistical Approach of Macroeconomics

- Pioneered by Nobel laureates Jan Tinbergen (1939), Trygve Haavelmo (1943), Lawrence Klein et al. (1965, 1969), Clive Granger (1969), Christopher Sims (1972, 1980).
- Vector Autoregressive (VAR) Model: $Y_t = \sum_{i=1}^{p} A_i Y_{t-i} + \epsilon_t$. Natural extension to machine learning models for time series.
- Structural VAR:

$$B_0 Y_t = \sum_{i=1}^{p} B_i Y_{t-i} + \eta_t$$

so that different dimensions of η_t are independent.

Dynamic Factor Model (DFM): Major Big Data Tool for Macroeconomists

- DFM with $N \times 1$ observable X_t to $p \times 1$ factor F_t ($N \gg p$):

$$X_t = C + \Lambda F_t + e_t, e_t \overset{iid}{\sim} \mathcal{N}(0, R)$$
$$F_t = \Phi(L) F_{t-1} + u_t, u_t \overset{iid}{\sim} \mathcal{N}(0, Q)$$

- Particularly useful when input data X_t is high dimensional. Can handle mixed frequency input.
- Low dimensional factors F_t can be used for measurement, nowcasting, forecasting, etc.
- Special case of state space models, or hidden Markov models, which is closely connected to ML models like RNN and LSTM.

Structural Approach of Macroeconomics

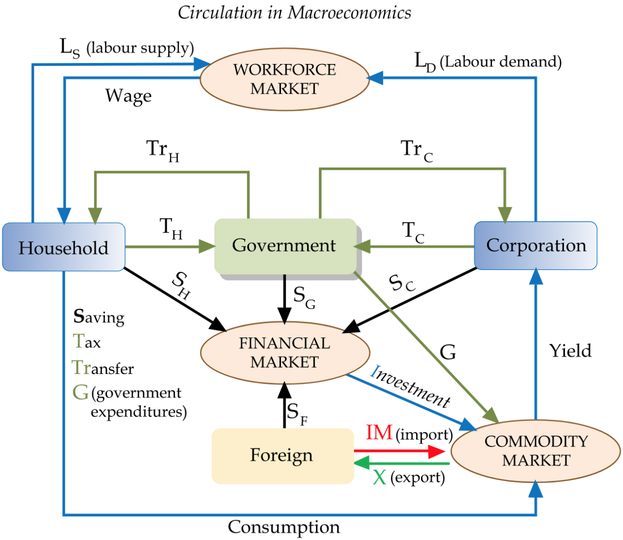


Figure: Illustration of Structural Models. (source: Wikipedia)

Krusell and Smith (1998)

- Uninsurable idiosyncratic income risk $\rightarrow$ heterogeneous agents.
- Distribution of agents' wealth Γ_t come into the state space $\rightarrow$ computationally hard.

$$v\left(k_t, \varepsilon_t; \Gamma_t, z_t\right) = \max_{c_t, k_{t+1} \geq 0} u\left(c_t\right) + \beta E_t\left[v\left(k_{t+1}, \varepsilon_{t+1}; \Gamma_{t+1}, z_{t+1}\right)\right]$$

s.t.

$$c_t + k_{t+1} = r\left(K_t, L_t, z_t\right) k_t + w\left(K_t, L_t, z_t\right) \bar{e} \varepsilon_t + (1-\delta) k_t$$

$$\Gamma_{t+1} = H\left(\Gamma_t, z_t, z_{t+1}\right)$$

- Krusell-Smith method: "approximate aggregation". Capture the whole distribution with limited moments $\Gamma_t \approx \{m_1, m_2, ..., m_M\}_t$.
- Conclusion: heterogeneity does not matter, and the first moment accounts for most variation.

HANK: Heterogeneous Agent New Keynesian Model

Monetary policy according to HANK

G Kaplan, B Moll, GL Violante - American Economic Review, 2018 - aeaweb.org

We revisit the transmission mechanism from monetary policy to household consumption in a Heterogeneous Agent New Keynesian (HANK) model. The model yields empirically realistic distributions of wealth and marginal propensities to consume because of two features …

- One of the most popular methodological advances in macro recently.
- Building blocks of HANK:
  1. Uninsurable idiosyncratic income risk (HA).
  2. Nominal price rigidities (NK).
  3. Assets with different degrees of liquidity (HtM).
  4. Continuous time approach (HACT).
- Contribution: New framework for quantitative analysis of the transmission mechanism of monetary policy that matches data much better.

HACT: The Hero behind HANK

Yves Achdou, Jiequn Han, Jean-Michel Lasry, Pierre-Louis Lions and Benjamin Moll. Income and Wealth Distribution in Macroeconomics: A Continuous-Time Approach. revise & resubmit, *Review of Economic Studies*.

- Formulate heterogeneous agent models as coupled PDEs - mean field games (MFG).
- Efficient computational algorithms are available.
- New theoretical results.

HACT: PDE Formulation

- Hamilton-Jacobi-Bellman equation:

$$\rho v_i(a,t) = \max_c u(c) + \partial_a v_i(a,t)\left[z_i + r(t)a - c\right] \\ +\lambda_i\left[v_j(a,t) - v_i(a,t)\right] + \partial_t v_i(a,t)$$

  with terminal condition $v_i(a,T) = v_{i,\infty}(a)$.
- Kolmogorov Forward equation:

$$\partial_t g_i(a,t) = -\partial_a\left[s_i(a,t)g_i(a,t)\right] - \lambda_i g_i(a,t) + \lambda_j g_j(a,t)$$

  for $i = 1,2$ and $j \neq i$ with initial condition $g_i(a,0) = g_{i,0}(a)$.
- State constraint boundary condition:

$$u'\left(z_i + r(t)\underline{a}\right) \geq \partial_a v_i(\underline{a},t), \quad i = 1,2.$$

Deep Learning: Possible Tool to Solve HA Models

DL to solve stochastic dynamic programming:

- Han, Jiequn and E, Weinan, 2016. Deep learning approximation for stochastic control problems. *NIPS Workshop*.

DL to solve high-dimensional PDEs:

- Han, Jiequn, Jentzen, A. and E, Weinan, 2018. Solving high-dimensional partial differential equations using deep learning. *Proceedings of the National Academy of Sciences*, 115(34), pp.8505-8510.

DL to solve the Krusell-Smith problem:

- Fernández-Villaverde, J., Hurtado, S. and Nuno, G., 2019. Financial Frictions and the Wealth Distribution.

DL to solve continous time DSGE models:

- Duarte, V., 2018. Machine Learning for Continuous-Time Finance. revise & resubmit, *Review of Financial Studies*.

Deep Learning for Stochastic Control

- Look for a feedback control: $a_t = a_t(s_t)$ to

$$\min_{\{a_t\}_{t=0}^{T-1}} \mathbb{E}\Big\{ \sum_{t=0}^{T-1} c_t(s_t, a_t(s_t)) + c_T(s_T) \mid s_0 \Big\}$$

- Traditional methods in operation research: discretize state and/or control into finite spaces + approximate dynamic programming.
- Neural network approximation:

$$a_t(s_t) \approx a_t(s_t|\theta_t),$$

Solve directly the approximate optimization problem

$$\min_{\{\theta_t\}_{t=0}^{T-1}} \mathbb{E}\Big\{ \sum_{t=0}^{T-1} c_t(s_t, a_t(s_t|\theta_t)) + c_T(s_T) \Big\},$$

rather than dynamic programming principle.

Deep Learning for Stochastic Control

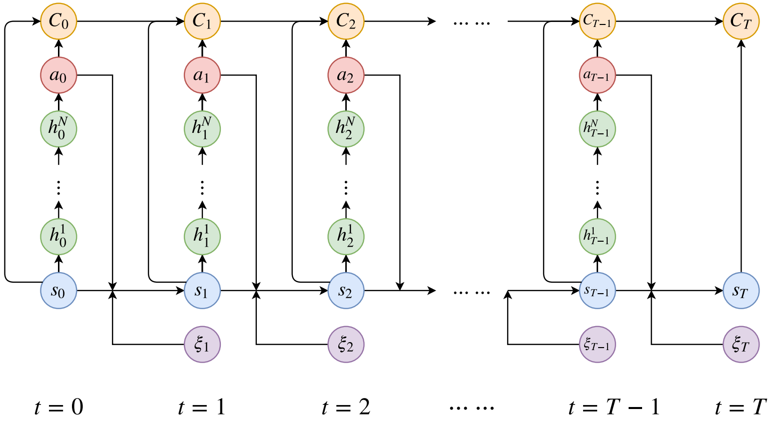


Figure: Network architecture for solving stochastic control in discrete time (Han and E, 2016). The whole network has $(N+1)T$ layers in total that involve free parameters to be optimized simultaneously. Each column (except ξ_t) corresponds to a sub-network at t.

Deep Learning for Semilinear Parabolic PDEs

Consider a general semilinear parabolic PDE in $[0, T] \times \mathbb{R}^d$:

$$\frac{\partial u}{\partial t}(t,x) + \frac{1}{2}\left(\sigma\sigma^{\mathsf{T}}(t,x)(\mathrm{Hess}_x u)(t,x)\right) + \nabla u(t,x)\cdot\mu(t,x) \\ + f\left(t,x,u(t,x),\sigma^{\mathsf{T}}(t,x)\nabla u(t,x)\right) = 0.$$

The terminal condition $u(T,x) = g(x)$ is given. Under suitable regularities, given a stochastic process satisfying

$$X_t = \xi + \int_0^t \mu(s,X_s)\,ds + \int_0^t \sigma(s,X_s)\,dW_s,$$

the solution of PDE satisfies the following SDE

$$\begin{aligned} &u(t,X_t) - u(0,X_0) \\ = &-\int_0^t f\left(s,X_s,u(s,X_s),\sigma^{\mathsf{T}}(s,X_s)\,\nabla u(s,X_s)\right) ds \\ &+\int_0^t [\nabla u(s,X_s)]^{\mathsf{T}}\,\sigma(s,X_s)\,dW_s. \end{aligned}$$

Deep Learning for Semilinear Parabolic PDEs

Time Discretization:

$$X_{t_{n+1}} - X_{t_n} \approx \mu(t_n, X_{t_n})\,\Delta t_n + \sigma(t_n, X_{t_n})\,\Delta W_n,$$

$$\begin{aligned} & u(t_{n+1}, X_{t_{n+1}}) - u(t_n, X_{t_n}) \\ \approx & - f\big(t_n, X_{t_n}, u(t_n, X_{t_n}), \sigma^{\mathsf{T}}(t_n, X_{t_n})\,\nabla u(t_n, X_{t_n})\big)\,\Delta t_n \\ & + [\nabla u(t_n, X_{t_n})]^{\mathsf{T}}\,\sigma(t_n, X_{t_n})\,\Delta W_n, \end{aligned}$$

Key step: approximate the function $x \mapsto \sigma^{\mathsf{T}}(t, x)\,\nabla u(t, x)$ at each discretized time step $t = t_n$ by a feedforward neural network

$$\begin{aligned} \sigma^{\mathsf{T}}(t_n, X_{t_n})\,\nabla u(t_n, X_{t_n}) &= (\sigma^{\mathsf{T}}\nabla u)(t_n, X_{t_n}) \\ &\approx (\sigma^{\mathsf{T}}\nabla u)(t_n, X_{t_n}|\theta_n), \end{aligned}$$

where θ_n denotes neural network parameters.

Deep Learning for Parabolic PDEs: Similar Structure

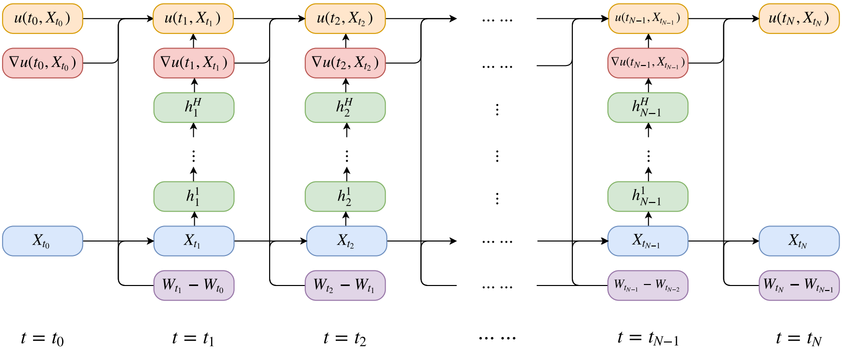


Figure: Network architecture for solving parabolic PDEs (Han, Jentzen and E, 2016). Each column corresponds to a subnetwork at time $t = t_n$. The whole network has $(H+1)(N-1)$ layers in total that involve free parameters to be optimized simultaneously.

Summary: What can Big Data and ML Bring to Macro?

Summary: What can Big Data and ML Bring to Macro?

- New Data Sources:
  1. More important role for micro big data in macro research, especially granular level administrative data and proprietary data on households, firms, small areas, etc..
  2. Alternative data as proxies, instruments or data input.
  3. Use ML to generate new data (eg. textual data, image data).
- New Modeling Tools:
  1. Tools to handle big data. New tools for both microeconometrics and macroeconometrics.
  2. Tools to handle micro-founded high dimensional models.
- New Knowledge System:
  1. New indicator system.
  2. New knowledge of macro.

Organization of the Course

Administrative Information

- Quite intense course: we meet (at least) three times every week.
- A course with lots of new stuff - we also learn by teaching.
- Lectures: T, Th 9:00 - 12:00.
- In-class presentations: F 10:00 - 12:00 from the second week.
- Grading: 50% class participation and presentation. 50% final project.
- Auditing students are welcome, but should also participate in the in-class presentation.
- All the feedbacks are welcome!

Organization of Lectures

- Overview
  1. Introduction
  2. Basics of Machine Learning for Macroeconomics
- Statistical Model in Macroeconomics and Machine Learning
  1. Vector Autoregressive Model and Structural VAR
  2. State Space Model, Filtering Problem and EM Algorithm
  3. Recurrent Neural Network and LSTM Network
  4. State Space Model with Non-standard Data
- Structural Model in Macroeconomics and Machine Learning
  1. Representative Agent Model and DSGE
  2. Heterogeneous Agent Model: Krusell-Smith and Variants
  3. Heterogeneous Agent Model in Continuous Time: HACT and HANK
  4. Solving High-dimensional Stochastic Control and PDEs using Deep Neural Networks
  5. Solving Structural Model using Deep Neural Networks

In-Class Presentation

- 8 potential topics are posted on the syllabus.
- Almost all the papers listed use big data to address important macroeconomic questions, published or to be published in decent journals.
- Each group pick up one core paper to present, and are encouraged to talk about other relevant papers under that topic.
- Each group send me the group member names and at least top 3 choices of papers by 6 pm this Thursday.
- Each group present for 30 minutes (including Q&A).
- Presenters should meet the instructor at least 3 days in advance (on or before Tuesday) to talk about the key points of the paper.
- Requirements: clear presentation on the paper's motivation, research question, institutional background, data, empirical specification, empirical findings, model setup, model results, implications, conclusion, with your own critical discussion.

Final Project

- Two options for the final project: a detailed 5-page proposal with preliminary results on a relevant original research; or a replication of one of the method papers covered in the class.
- Potential projects for original research would be discussed by the instructors in class.
- Students should meet the instructor to talk about the choice of the final project before the third week of class (July 14).

Course Sign-up

Any Questions?