Econ.AI | The role for Deep Neural Networks in Economics

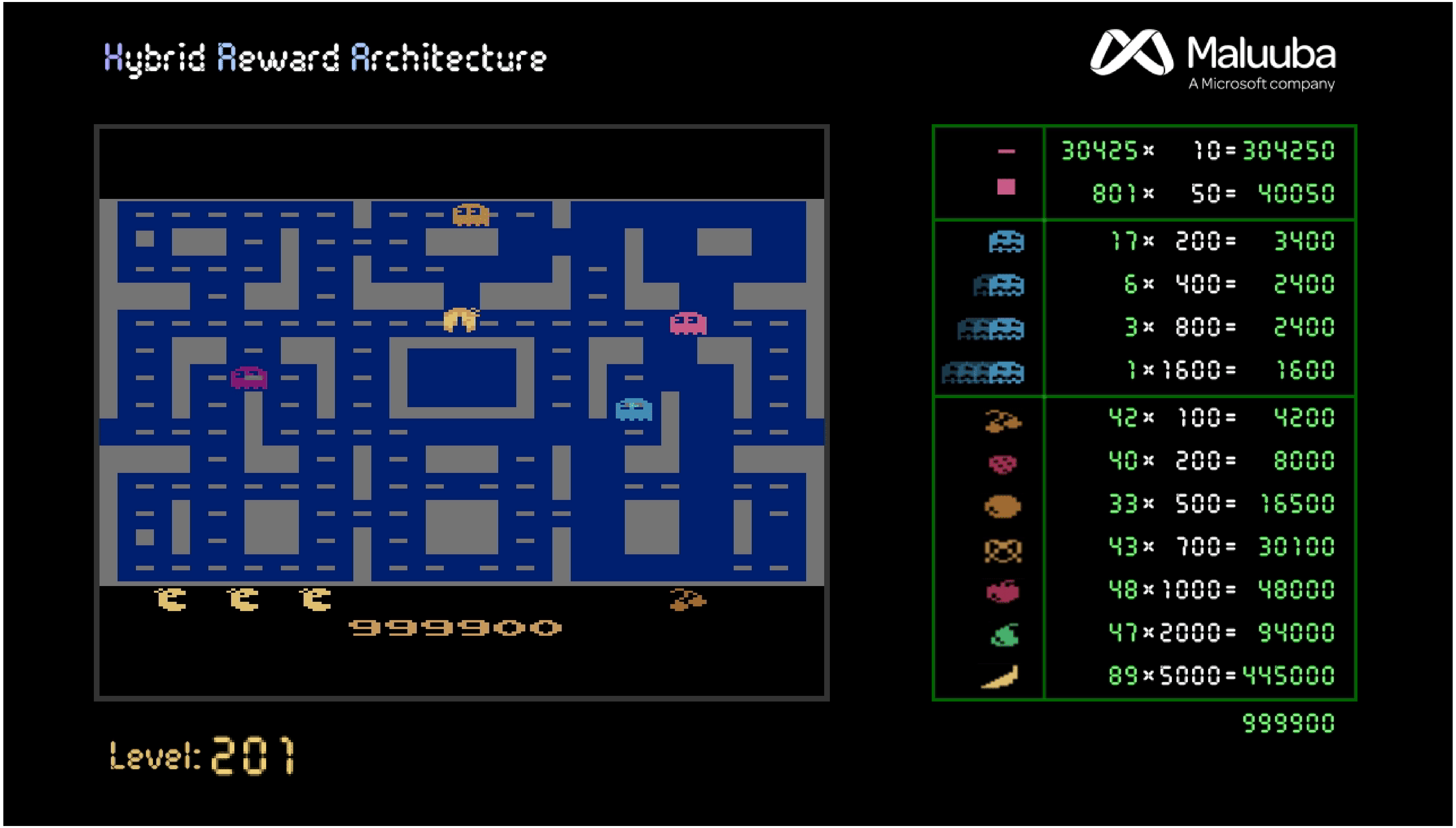
Matt Taddy – UChicago and Microsoft

What is AI?

Domain Structure + Data Generation + General Purpose ML

Domain Structure	Data Generation	General Purpose ML
Econ Theory / Biz Frame	Reinforcement Learning	Deep Neural Nets
Structural Econometrics	Sensor Networks, IOT	SGD + OOS + GPUs
Relaxations and Heuristics	Simulation/GANs	Video/Audio/Text

Self-training structures of ML predictors that automate and accelerate human tasks



https://www.youtube.com/watch?time_continue=13&v=zQyWMHFjewU

Virtual agent (PREVIEW) Start over

Tell me about your problem and I'll help you find the solution you need.

how do I upgrade windows>

Here's what I think you are asking about: *How to install or upgrade to Windows 10.* Is that correct?

Yes

Okay, you're looking for some info on Windows 10. What would you like to do?

Upgrading to Windows 10

How to get Windows 10

1. Windows 10 is available by buying a new device or a full version of the software.
2. The Windows 10 free upgrade through the Get Windows 10 (GWX) app ended on July 29, 2016. Click here to find more information about upgrading to Windows 10

Select an option or enter your response here

THE WALL STREET JOURNAL

TECH

Microsoft Aims to Make Business AI Cheaper, Faster, Simpler

New line of software will take on IBM, others, in growing artificial-intelligence market

By Ted Greenwald

Sept. 25, 2017 9:00 a.m. ET

Microsoft Corp. plans Monday to unveil its first product in a new line of software aimed at taking on International Business Machines Corp. and others in the growing market to apply artificial intelligence to everyday business needs.

The new product, a customer-service virtual assistant, is designed to let people

The Economics *of* AI

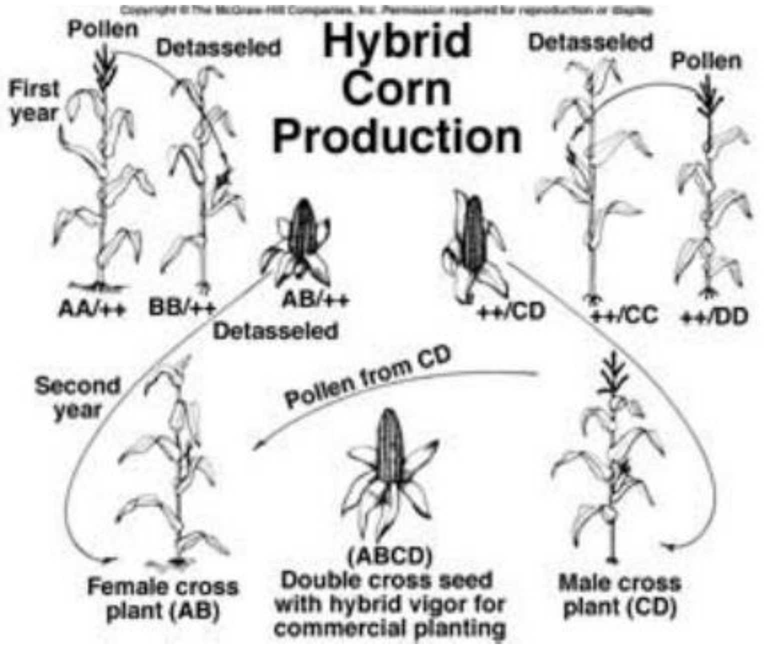
DNNs are GPT and ‘method for invention’

- Broad impact, up and down the value chain
- Gets better, faster, and cheaper in time
- Can suffer from underinvestment
- Productivity gains lag invention

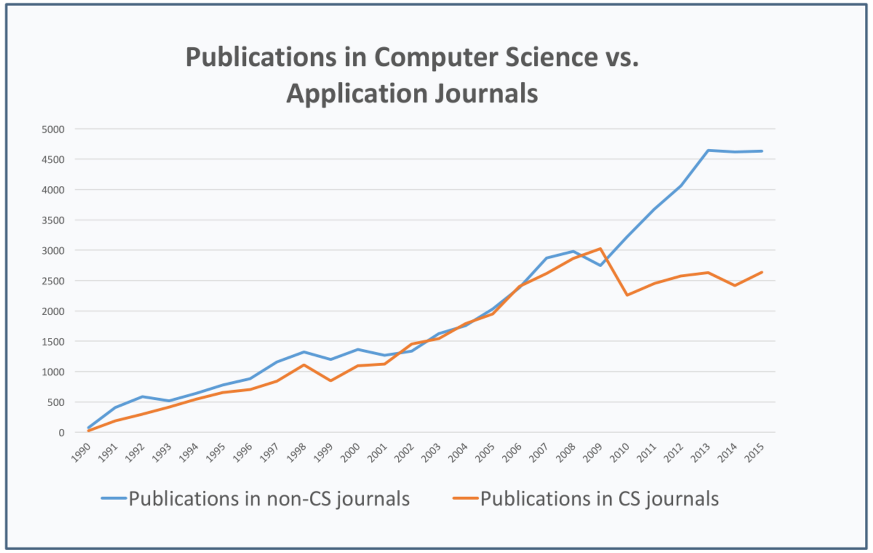
Automation, inequality, skill acquisition

Data ownership, markets, and privacy

High-info contracts and outcome pricing



AI research in computer science journals vs. other application sectors.



Graph from Cockburn/Henderson/Stern

What about the impact of AI on the practice of Econom[etr]ics?

Susan Athey:

Predictions for Economics

- Adoption of off-the-shelf ML methods for their intended tasks (prediction, classification, and clustering, e.g. for textual analysis)
- Extensions and modifications of prediction methods to account for considerations such as fairness, manipulability, and interpretability
- Development of new econometric methods based on machine learning designed to solve traditional social science estimation tasks, e.g. causal inference
- Increased emphasis on model robustness and other supplementary analysis to assess credibility of studies
- Adoption of new methods by empiricists at large scale
- Revival and new lines of research in
- New methods for the design and analysis of large administrative data, including merging these sources
- Increase in interdisciplinary research
- Changes in organization, dissemination, and funding of economic research
- "Economist as engineer" engages with firms, government to design and implement policies in digital environment
- Design and implementation of digital experimentation, both one-time and as an ongoing process, in collaboration with firms and government
- Increased use of data analysis in all levels of economics teaching; increase in interdisciplinary data science programs
- Research on the impact of AI and ML on economy

Alt Text: A close up of a newspaper

Econometrics breaks systemic questions into sets of prediction tasks

- Prediction after controlling for confounders
- Two-stage prediction with IVs
- Heterogeneous treatment effect prediction
- Structural equation systems

Machine Learning can automate and accelerate tasks in applied econometric workflows

Example: short-term price elasticity

If I drop price 1%, by what % will quantity sold increase?

Problem: both prices and sales respond to underlying demand

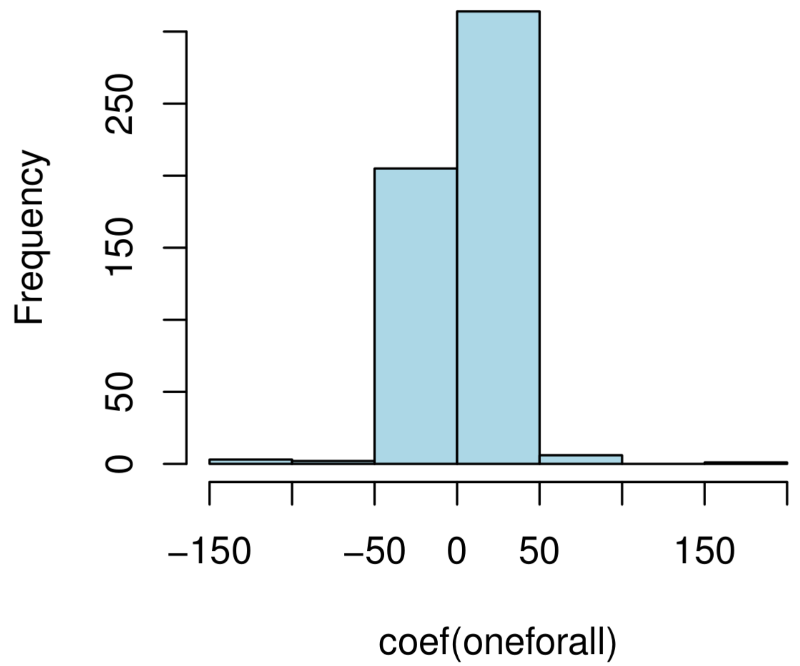
Need a causal effect of price on sales, not their co-movement

Beer Data

A single shared elasticity gives tiny -0.23

Separate elasticity for each: noisy zeros

We need to group the products together using brand, pack, etc.



Beer Elasticity

Say $w_{bk} = 1$ if word k is in description for beer b

@transaction t: $\quad y_{tb} = \gamma_b\, p_{tb} + f_t(\boldsymbol{w}_b) + \varepsilon_{tb},$

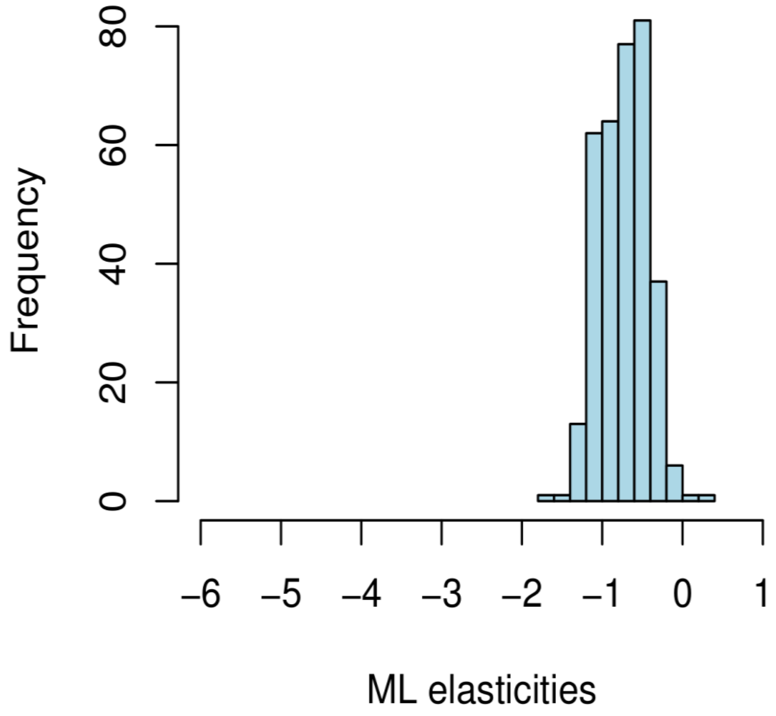
$$\gamma_b = \boldsymbol{w}_b'\boldsymbol{\beta}$$

$$p_{tb} = h_t(\boldsymbol{w}_b) + \nu_{tb}$$

Creates a large number of parameters

Just throw it all in a lasso?

Yields unbelievably small elasticities



The naïve ML conflates two problems:
selecting controls and predicting response after controlling for confounders.

Instead, use Orthogonal ML *(Chernozhukov et al, 2016 and earlier)*

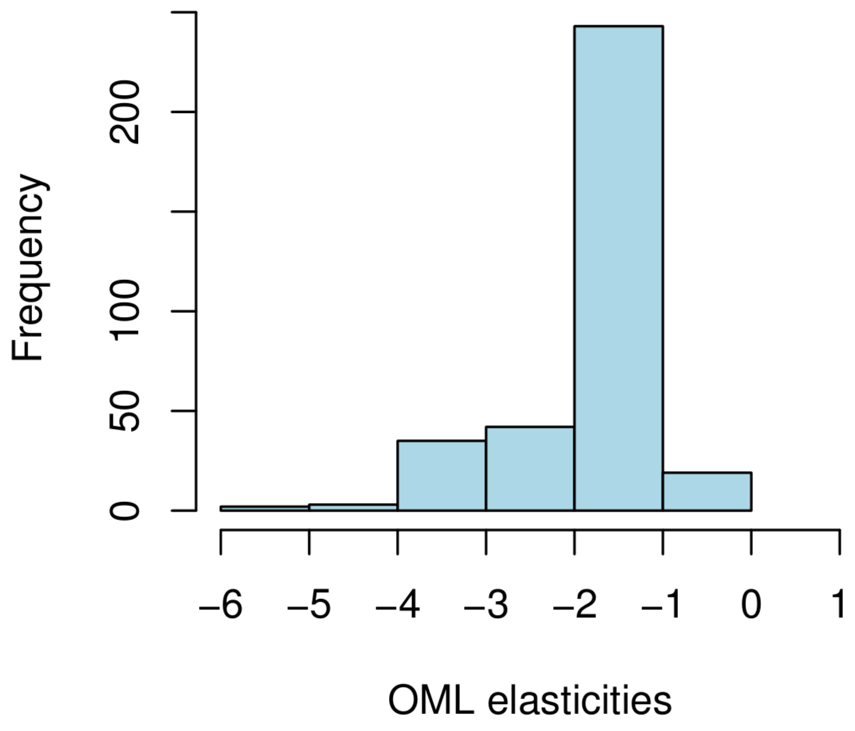
- Estimate nuisance functions $\mathbb{E}[y_{tb}|\boldsymbol{w}_b]$ and $\mathbb{E}[p_{tb}|\boldsymbol{w}_b]$
- Orthogonalize the score against these nuisance functions (data split)
- Then estimation for $\boldsymbol{\gamma}$ is robust to slow-learned nuisances

Estimation breaks into a series of ML tasks:

1. Predict sales from the demand variables: $y_{tb} \approx g(t, \boldsymbol{w}_b)$
2. Predict prices from the demand variables: $p_{tb} \approx h(t, \boldsymbol{w}_b)$
3. Get OOS residuals: $\tilde{\boldsymbol{y}}_t = \boldsymbol{y}_t - \hat{g}_{\bar{t}}(t, \boldsymbol{w}_b)$, $\tilde{\boldsymbol{p}}_t = \boldsymbol{p}_t - \hat{h}_{\bar{t}}(t, \boldsymbol{w}_b)$
4. And fit the final regression: $\mathbb{E}[\tilde{\boldsymbol{y}}_t] = \boldsymbol{\Gamma}\, \tilde{\boldsymbol{p}}_t = \mathrm{diag}(\boldsymbol{\gamma})\, \tilde{\boldsymbol{p}}_t$

Lasso in Step 4 has performance that upper bounds that of naïve lasso

Orthogonal ML for Beer



There's no ground truth,
but these are economically realistic

The text encodes a natural hierarchy

Many beers are `IPA` or `Cider`

But individual brands also load

Most Price Sensitive

```
> names(sort(el)[1:5])
[1] "GUINNESSS DRAUGHT 6PK BTL
[2] "GUINNESS DRAUGHT 4PK CAN
[3] "PYRAMID OUTBURST IMP IPA 6PK
[4] "ELYSIAN IMPORTAL IPA 6PK
[5] "PYRAMID OUTBURST IMP IPA 12PK
```

Least Price Sensitive

```
> names(sort(-el)[1:5])
[1] "2 TOWNS CRISP APPLE CIDER
[2] "2 TOWNS BAD APPLE CIDER
[3] "ATLAS BLKBRY APPLE CIDER
[4] "D'S WICKED BAKED APPLE CIDER
[5] "D'S WICKED GREEN APPLE CIDER
```

with Vira Semenova MIT

Econ + ML

This is what econometricians do: break systems into measurable pieces

Another common example: Instrumental Variables

Endogenous errors:

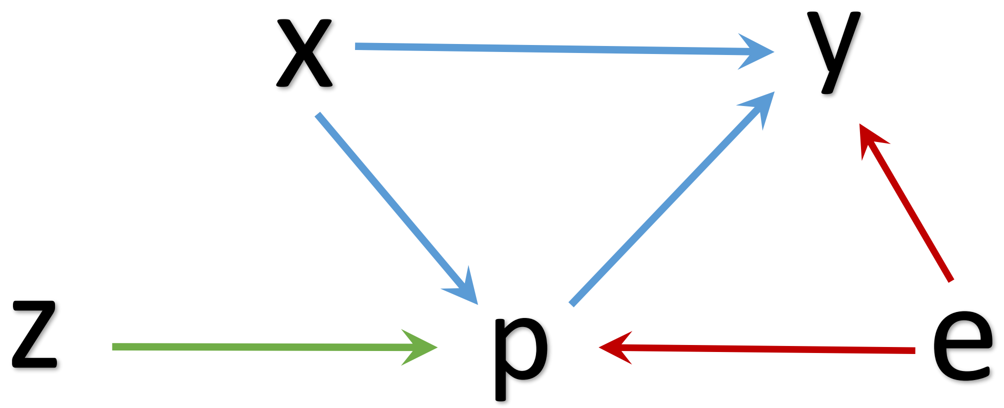
$$y = g(p, \boldsymbol{x}) + e \;\text{ and }\; \mathbb{E}[\,p\,e\,] \neq 0$$

If you estimate this using naïve ML, you'll get

$$E[y|p, \boldsymbol{x}] = \; E_{e|p}[g(p, \boldsymbol{x}) + e] = g(p, \boldsymbol{x}) + E[e|p, \boldsymbol{x}]$$

But, with instruments…

Instrumental Variables



The *exclusion structure* implies

$$\mathbb{E}[y|x,z] = \int g(p,x)dF(p|x,z)$$

You can observe and estimate $\hat{\mathbb{E}}[y|x,z]$ and $\hat{F}(p|x,z)$

$\Rightarrow$ to solve for *structural* $g(p,x)$ we have an inverse problem.

cf Newey+Powell 2003

$$\min_{g \in G} \sum \left(y_i - \int g(p, x_i) dF(p|x_i, z_i) \right)^2$$

2SLS: $p = \beta z + \nu$ and $g(p) = \tau p$ so that $\int g(p) dF(p|z) = \tau \mathbb{E}[p|z]$

So you first regress p on z then regress y on $\hat{p}$ to recover $\hat{\tau}$.

Sieve: $g(p, x_i) \approx \sum_k \gamma_k \varphi_k(p, x_i)$, $\mathbb{E}_F[\varphi_k(p, x_i)] \approx \sum_j \alpha_{kj} \beta_j(x_i, z_i)$

Also Blundell, Chen, Kristensen, , Chen + Pouzo, Darolles et al, Hall+Horowitz

$$\min_{g \in G} \sum \left(y_i - \int g(p, x_i) dF(p|x_i, z_i) \right)^2$$

Deep IV uses DNNs to target the integral loss function directly

- First, fit $\hat{F}$ using a network with multinomial response
- Second (preferably on another sample) fit $\hat{g}$ following

$$\nabla \hat{L}(x_i, y_i, z_i, \theta) = -2(y_i - g_\theta(\dot{p}, x_i))\, g'_\theta(\ddot{p}, x_i), \quad \dot{p}, \ddot{p} \sim \hat{\mathrm{F}}(p|x_i, z_i)$$

Hartford, Lewis, Leyton-Brown, Taddy ICML 2017

Stochastic Gradient Descent

You have loss $L(\boldsymbol{D},\ \theta)$ where $\boldsymbol{D} = [\boldsymbol{d}_1\ \dots \boldsymbol{d}_N]$

In the usual GD, you iteratively descend

$$\theta_t = \theta_{t-1} - \boldsymbol{C}_t \nabla L(\boldsymbol{D}, \theta_{t-1})$$

In SGD, you instead follow *noisy* but *unbiased* sample gradients

$$\theta_t = \theta_{t-1} - \boldsymbol{C}_t \nabla L(\{\boldsymbol{d}_{t_b}\}_{b=1}^{B}, \theta_{t-1})$$

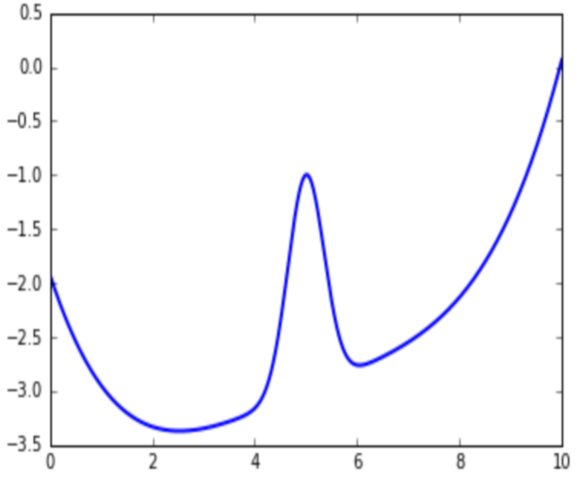
A pricing simulation

$$y = 100 + s\psi_t + (\psi_t - 2)p + e,$$

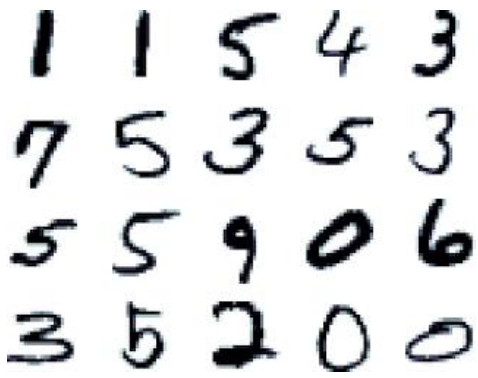
$$p = 25 + (z+3)\psi_t + v$$

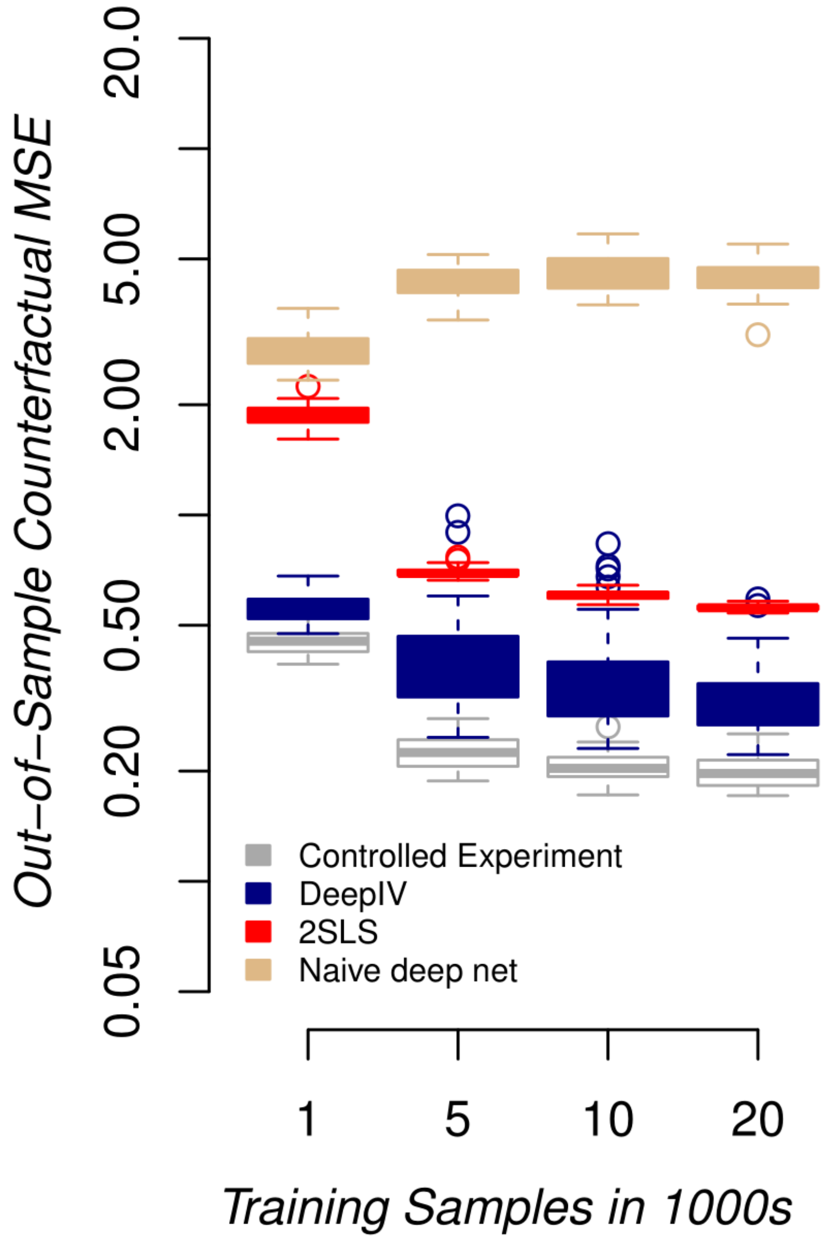
$$z,\ v \sim \mathrm{N}(0,1) \ \text{ and } \ e \sim \mathrm{N}(\rho v, 1-\rho^2),$$

Time-dependent ψ_t



Customer type 's'





Biased?

$\nabla \hat{L}(x_i, y_i, z_i, \theta) = -2(y_i - g_\theta(\dot{p}\,, x_i))\, g'_\theta(\dot{p}\,, x_i)$ is *biased* for our loss but unbiased for an upper bound on that loss (via Jensen's)

It works pretty well on OOS Loss:

Loss Function	# Samples	Mean	Stdev
Upper bound	1	**0.32**	0.085
Unbiased	2	0.48	0.107
Unbiased	4	0.50	0.158
Unbiased	8	0.44	0.100
Unbiased	16	**0.39**	0.098

Validation and model tuning

We can do OOS *causal validation*

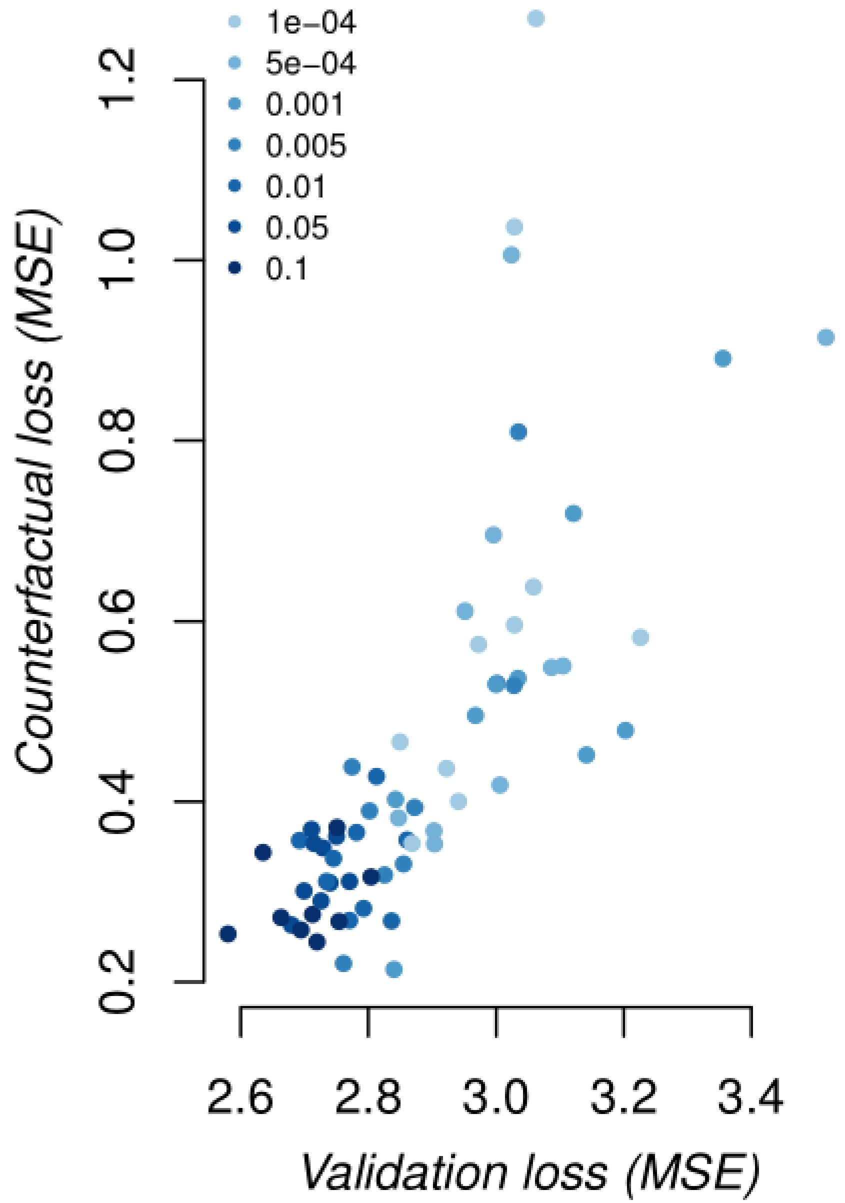
Leave-out deviance on first stage

$$\sum_{i \in LO} -\log \hat{f}(p|x_i, z_i)$$

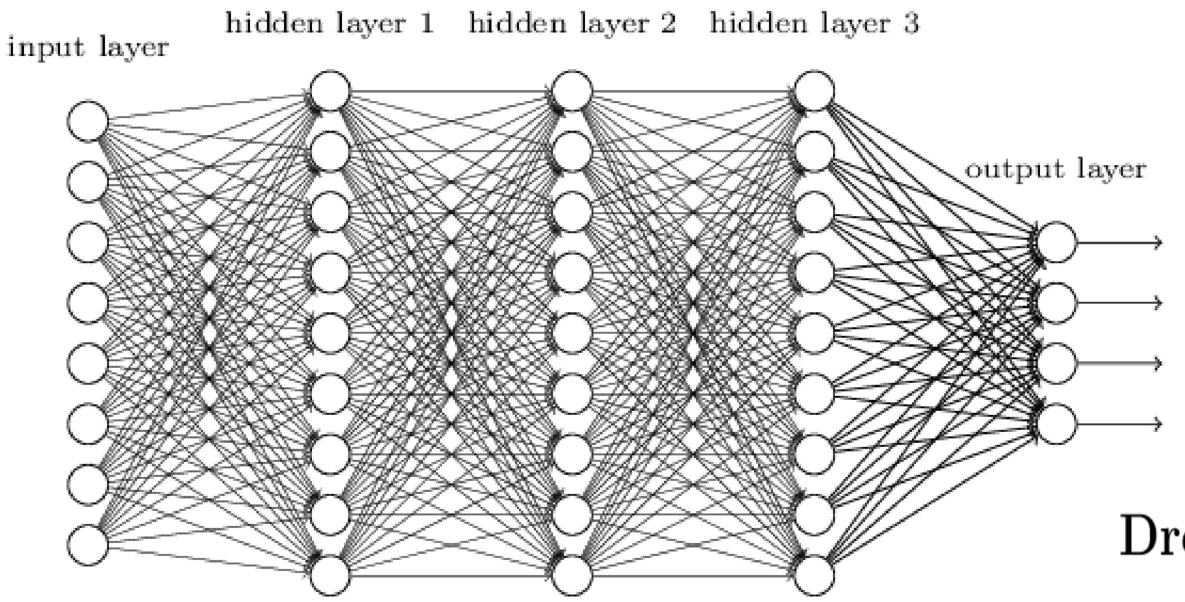
Leave-out loss on second

$$\sum_{i \in LO} \left(y_i - \int g_\theta(p, x_i) d\hat{F}(p|x_i, z_i)\right)^2$$

You want to minimize both of these (in order).



DEEP NEURAL NETWORKS



Train faster, generalize better:
Stability of stochastic gradient descent

Adaptive Subgradient Methods for Online Learning and Stochastic Optimization*

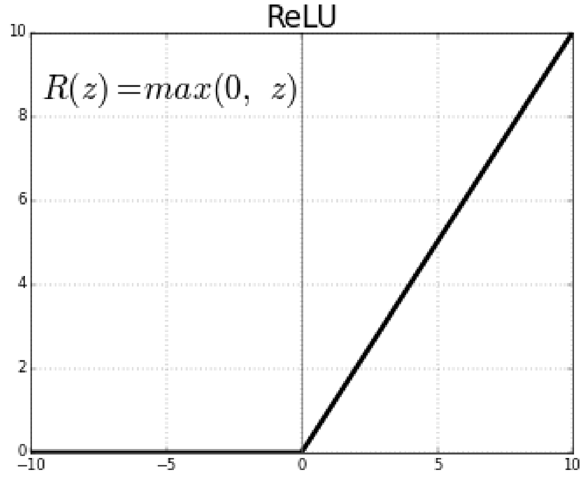
Dropout: A Simple Way to Prevent Neural Networks from Overfitting

The Microsoft Cognitive Toolkit

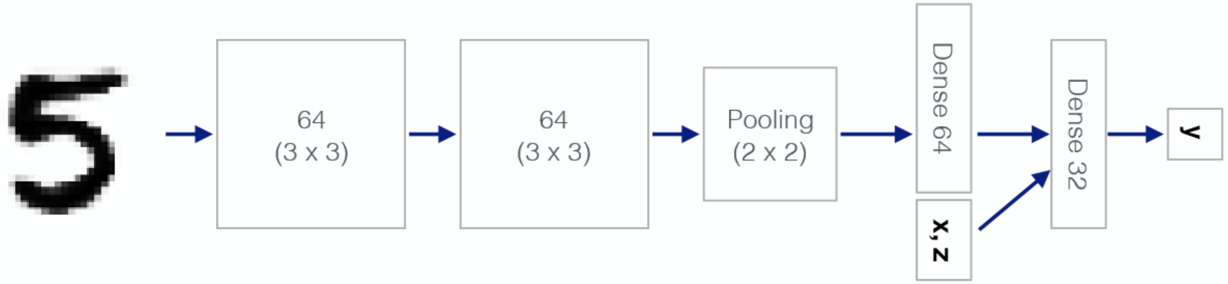
A free, easy-to-use, open-source, commercial-grade toolkit that trains deep learning algorithms to learn like the human brain.

GET STARTED >

$$\mathcal{L} + \beta \underbrace{\frac{1}{2}\|w\|_2^2}$$

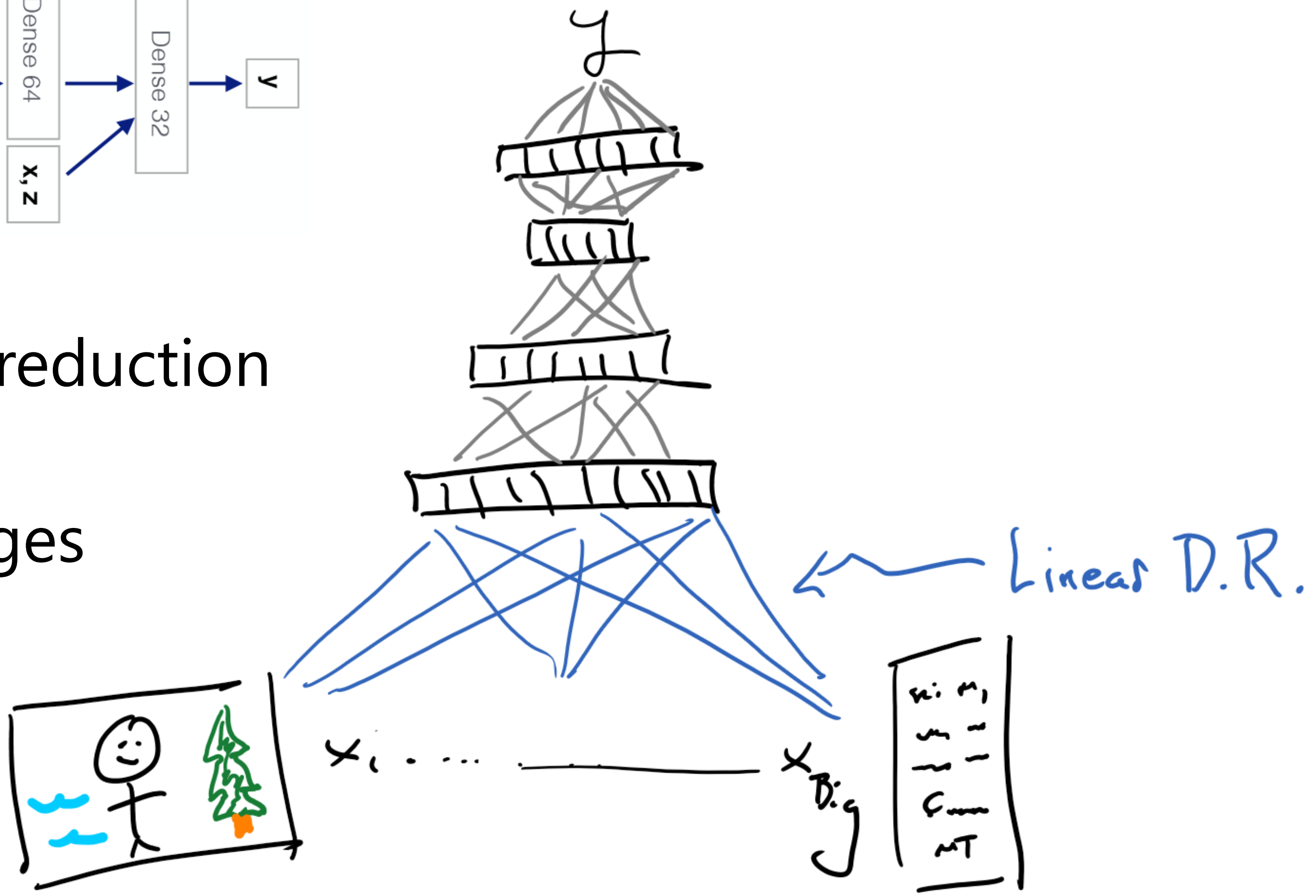


Deep nets are not nonparametric sieves



The 1st layer is a big dimension reduction

- word embedding for text
- matrix convolution for images



Why? Heterogeneity!

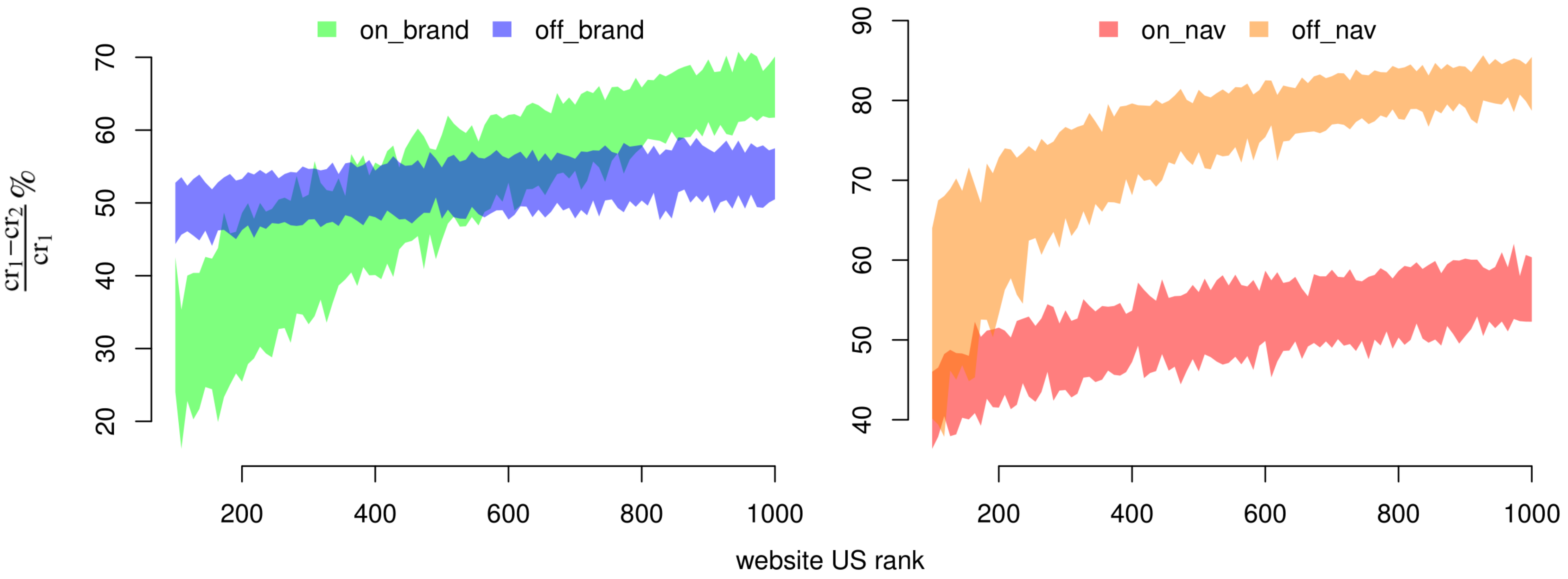
Example: ads application from Goldman and Rao (2014)
74 mil click-rates over 4 hour increments for 10k search terms

Treatment: ad position 1-2
Instrument: background AB testing (bench of ~ 100 tests)
Covariates: advertiser id and ad properties, search text, time period

The reduction in clicks due to a drop in position is search and ad dependent

Example product (click rate response)

- Treatment effect is small for on-navigation queries (`searches' for microsoft.com)
- Effect rises for less popular websites (brands)
- Off brand effect is flat with website popularity

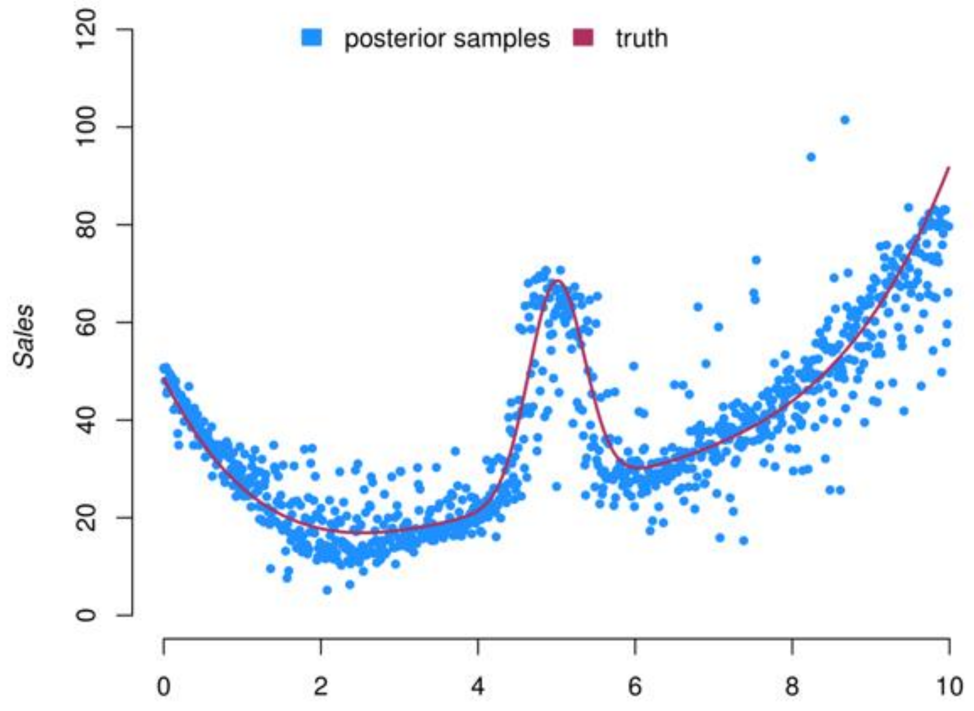


Inference? Good question

Data Splitting

Variational Dropout

Quantile Regression



with Jason Hartford UBC

Data Split

- Fit DNNs that map from inputs to output layer $\psi_k(x), k = 1 \ldots K$
- Use out-of-sample x_i to obtain \`features' $\psi_{ik} = \psi_k(x_i)$
- Possibly do PCA on $\boldsymbol{\psi}_i$ to get a nonsingular design
- Fit OLS $y_i \approx \boldsymbol{\psi}_i'\boldsymbol{\beta}$ to get $\hat{\boldsymbol{\beta}}$ with variance

$$\mathrm{var}(\hat{\boldsymbol{\beta}}) = (\boldsymbol{\Psi}'\boldsymbol{\Psi})^{-1}\boldsymbol{\Psi}'\mathrm{diag}(\boldsymbol{y} - \boldsymbol{\Psi}\hat{\boldsymbol{\beta}})\boldsymbol{\Psi}(\boldsymbol{\Psi}'\boldsymbol{\Psi})^{-1}$$

This can be used to get $\mathrm{var}(\mathbb{E}[y \mid x])$

Variational Bayes and Dropout

- VB fits q to minimize $\mathbb{E}_{\mathrm{q}}[\log q(W) - \log p(\boldsymbol{D}|W) - \log p(W)]$
- We train with dropout SGD:

  At each update of weights ω, use gradients for $w = \xi\omega$, $\xi \sim \mathrm{Bern}(c)$
- This corresponds to VB under

$$q(W) = \prod_{l}\prod_{k} c\mathbb{1}_{[W_k=\Omega_k]} + (1-c)\,\mathbb{1}_{[W_k=0]}$$

This can be used to get $\mathrm{var}(\mathbb{E}[y \mid x])$

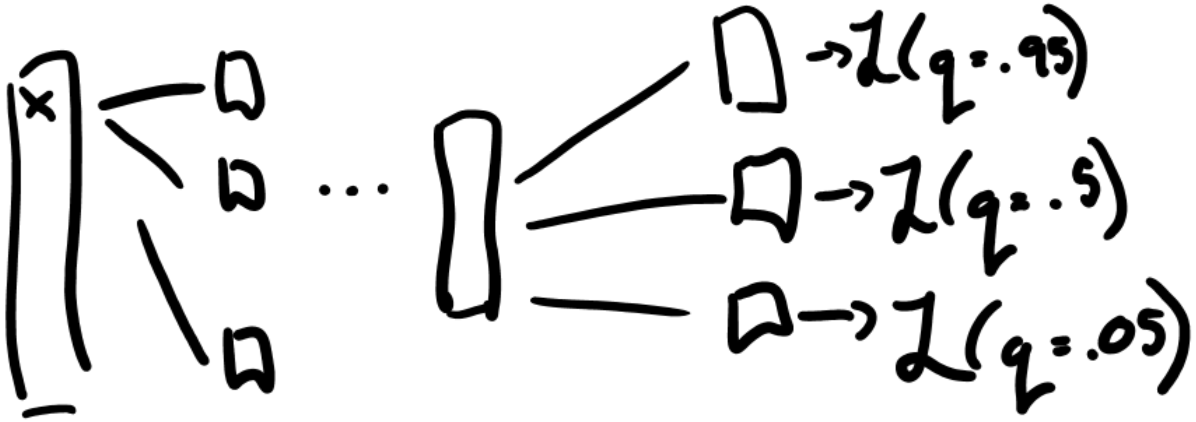
Quantile Regression

Instead of targeting MSE or logit loss, minimize quantile loss

$$L_q = \big(y - \eta_q(x)\big)\left(q \;-\; 1_{y<\eta_q(x)}\right)$$

Where q is your desired probability and $\eta_q(x)$ is the quantile function

Better yet, architect a net to fit multiple quantiles at once...

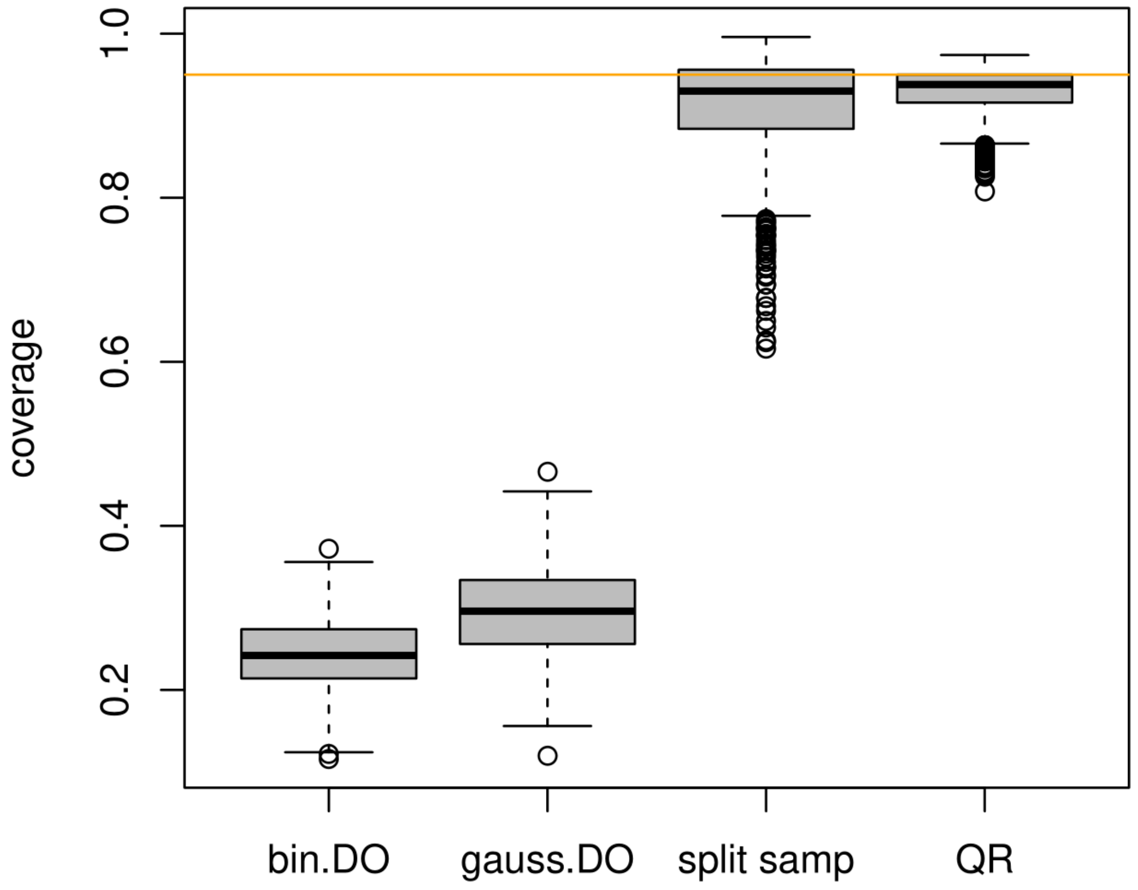


This can be used to get prediction intervals for $y \mid x$

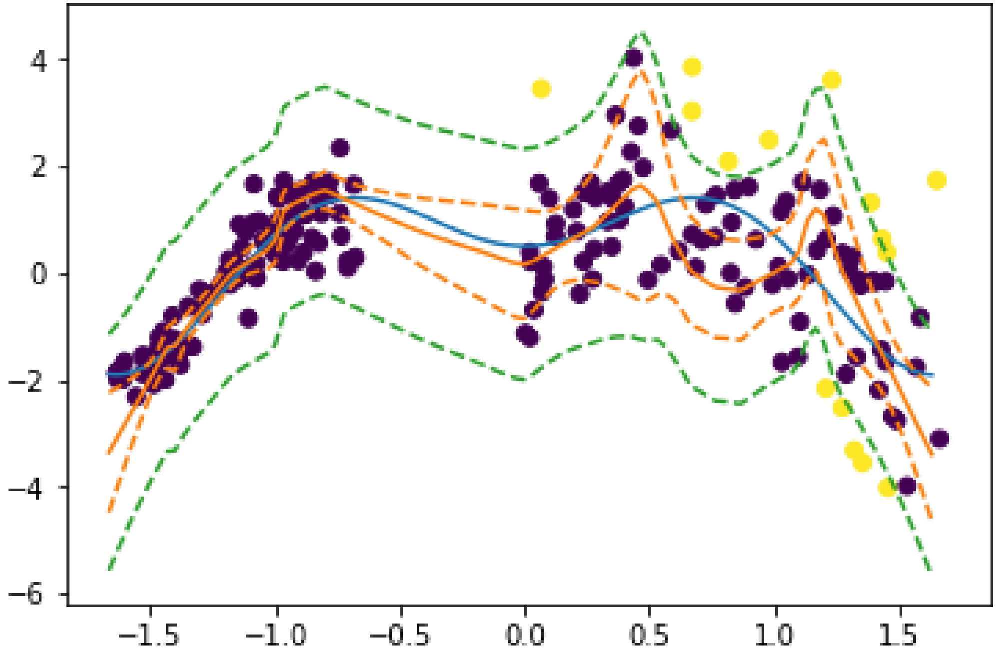
Million Song Dataset

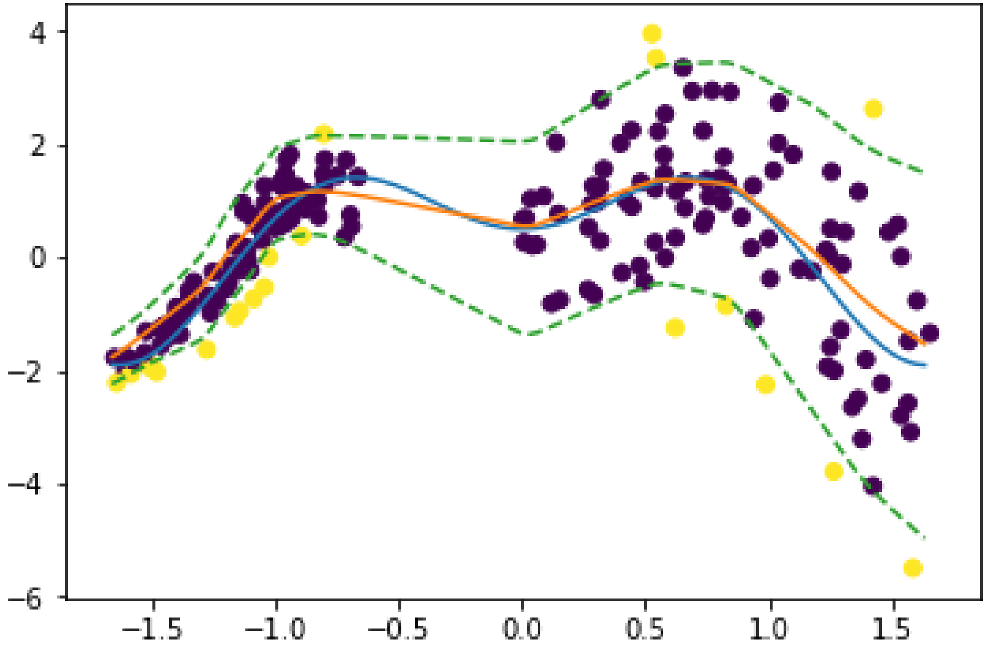
- A dataset of a million songs
- Inputs are timbre features
- Output is the release year
- Test and train are split to have no overlap on artists

PI coverage around random songs



If you want Prediction Intervals, you should use quantile regression





For Confidence Intervals, sample splitting can't be beat

Economic AI

The ML doesn't create new economic insights or replace economists

It automates and accelerates subjective labor-intense measurement

- Instruments are everywhere inside firms
- With reinforcement learning there will be even more
- Reduced forms are low fruit; structural econometrics is next
    - ➢ Need to link long term rewards to short term signals

Business AI

Deep learning revolution: good low-dev-cost off-the-shelf ML

As the tools become plug-n-play, teams get interdisciplinary

The next big gains in AI are coming from domain context

- Use domain structure to break questions into ML problems
- Don't re-learn things you already know with baby AI