Microsoft

Economic AI

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What do economists do?

320 THE AMERICAN ECONOMIC REVIEW JUNE 1980

TABLE 2—TOTAL EXPENDITURE AND OWN-PRICE ELASTICITES

	Levels Model			First-Differences Model		
	Unconstrained		Homogeneous	Unconstrained		Homogene
	e_i	e_{ii}	e_i	e_i	e_{ii}	e_i
Food	0.21	0.07	0.04	0.04	0.22	0.17
Clothing	2.00	−0.92	1.51	2.83	−0.94	2.92
Housing	0.30	−0.31	0.79	0.04	−0.31	−0.02
Fuel	1.67	−0.28	1.37	1.00	0.00	0.8
Drink and Tobacco	1.22	−0.60	1.22	1.37	−0.67	1.1
Transport and Communication	1.23	−1.21	1.73	1.14	−1.23	
Other goods	1.21	−0.72	1.15	2.03	−0.52	
Other services	1.40	−0.93	1.28	1.03	−0.78	

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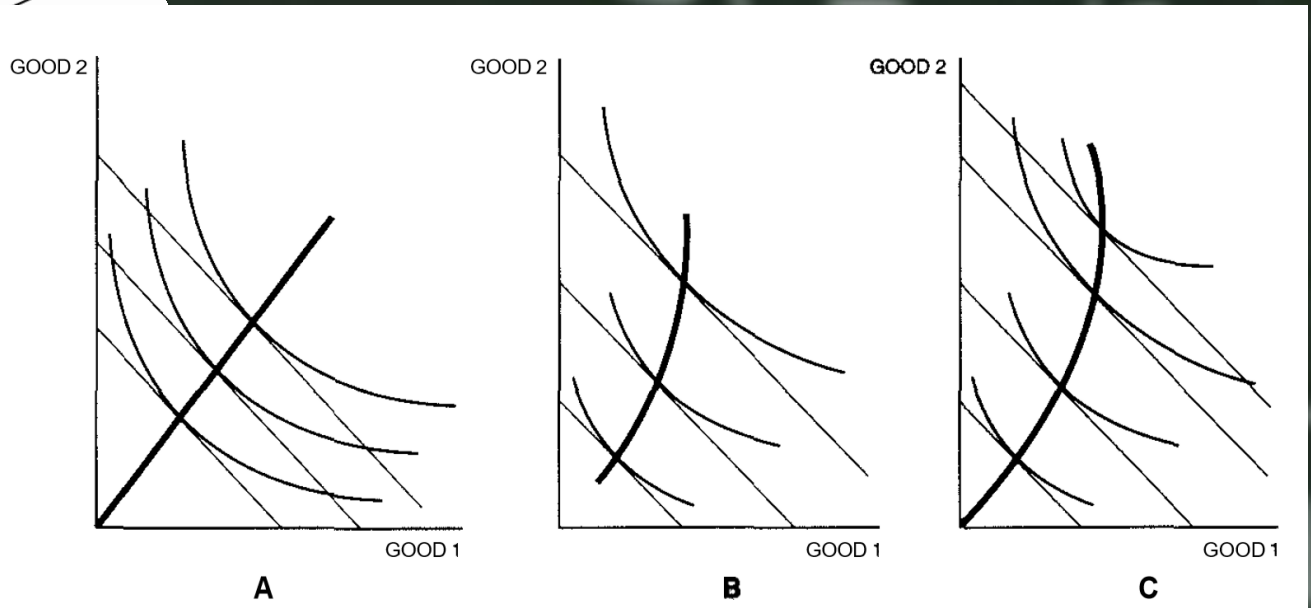
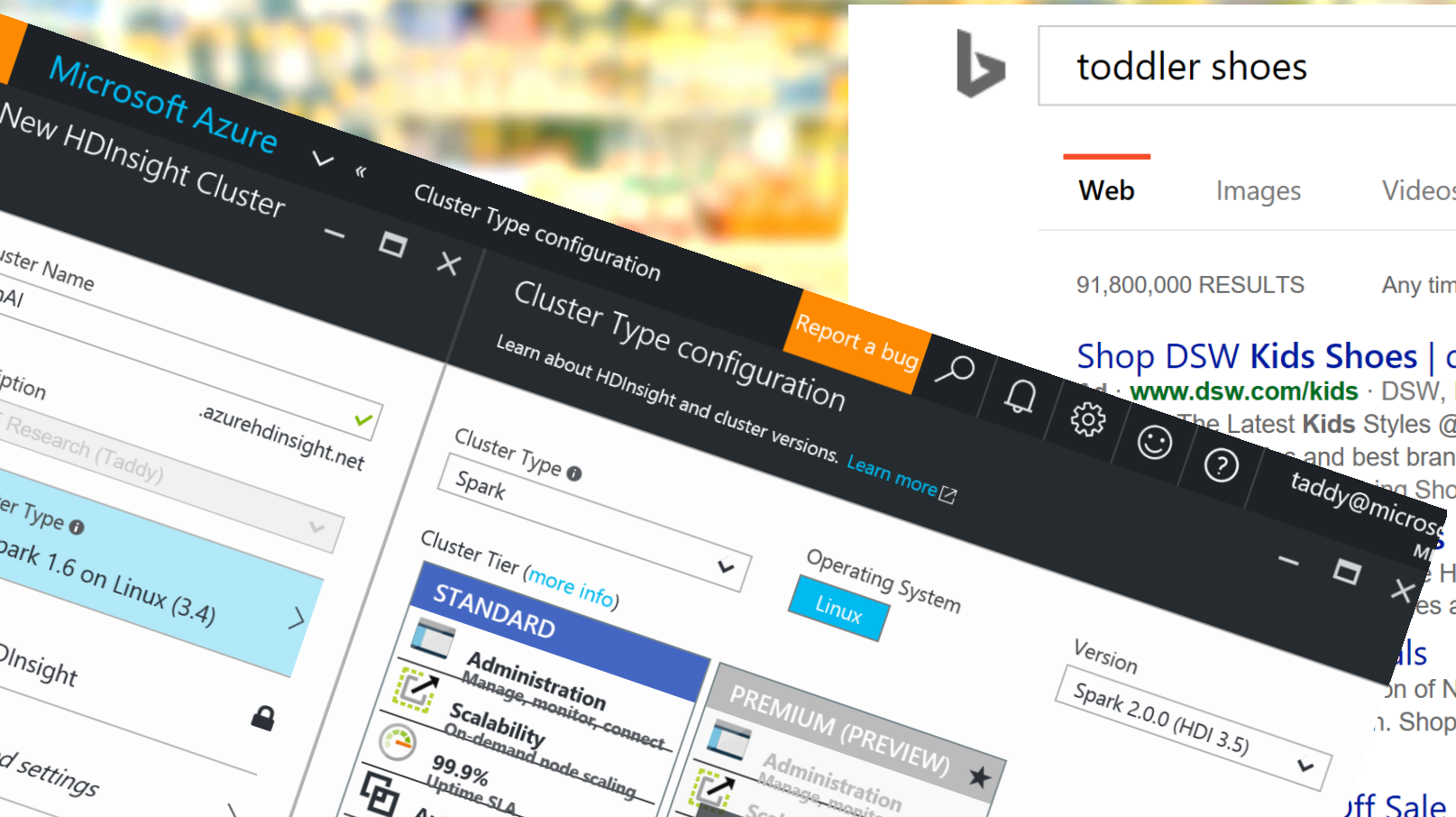
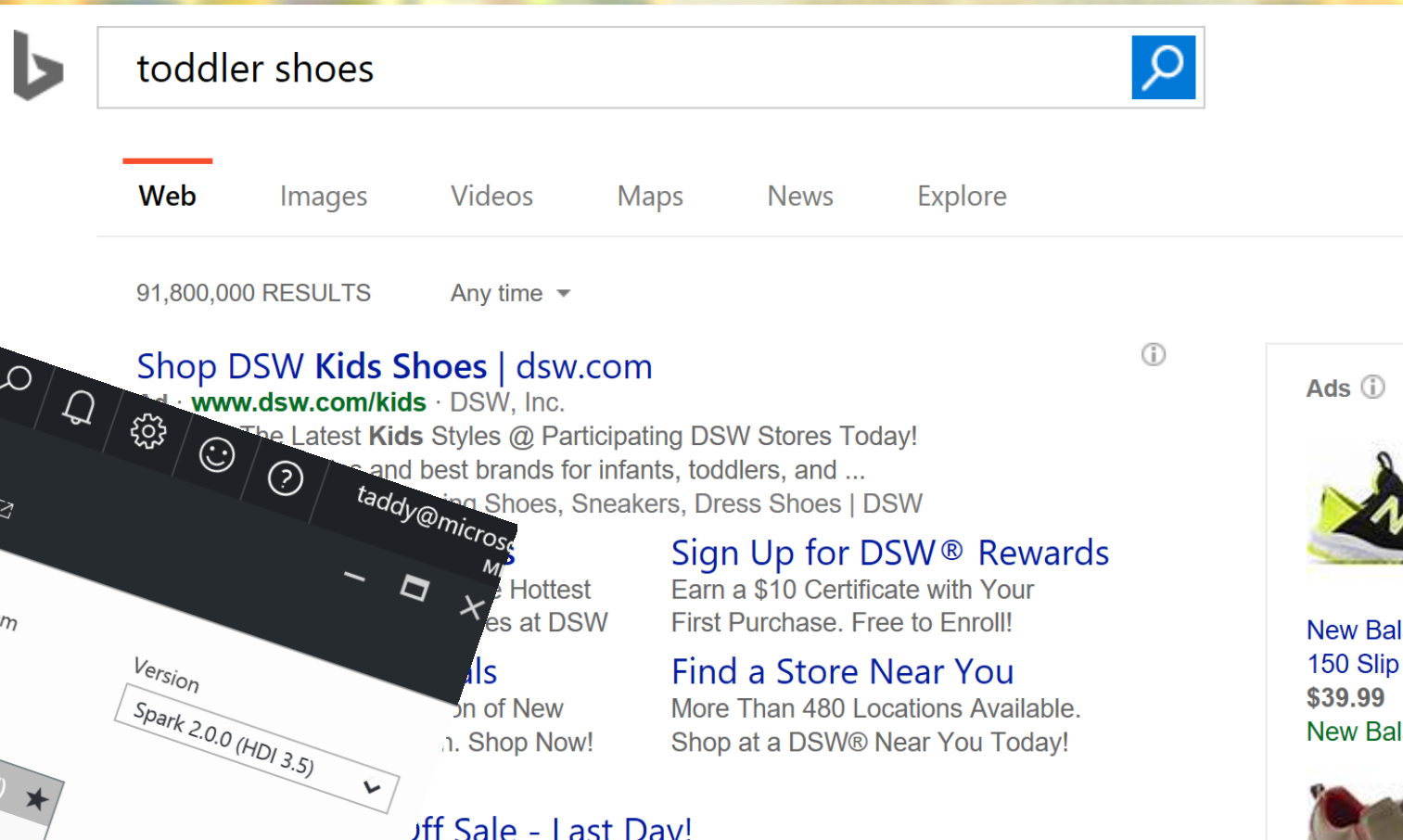


Income expansion paths. Panel **A** depicts unit elastic demands, in panel B good 2 is a luxury good, and in panel C, good 1 is an inferior good.

What do they need to do today?





Economic AI breaks complex business questions into a structure of ML tasks

We need to scale-up causal inference

Causality links actions to their consequences

Good decisions are a direct result of causal understanding (or luck!)

Pricing: Ex. How much will sales rise *if I lower prices?*

Education: Ex. How does learning change if I *reduce class size*?

Marketing: Ex. What is the *causal ROI* from this ad campaign?

This type of reasoning is absent in most AI systems

Without experiments (AB tests)
causal inference is notoriously difficult

Traditional methods don't scale

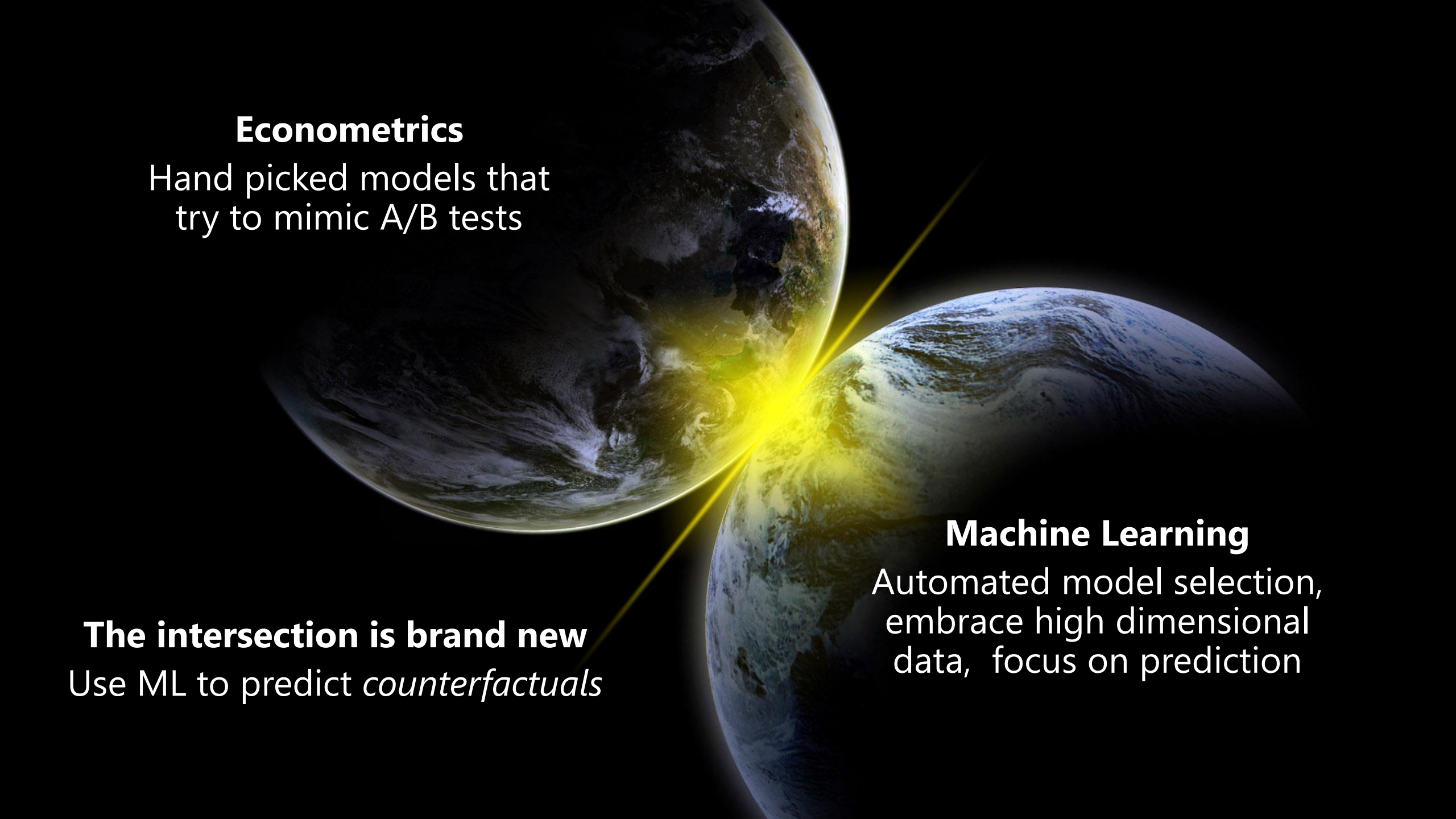
Economists and statisticians look for and analyze natural experiments

Example

- Question: What is the impact of going to charter school on college success?
- Confound: students who seek charter schools are different *to begin with*
- Experiment: compare similar students who live close to catchment boundary

Limitations

- Hugely labor intensive
- Econometric methods limit what data you can work with
- Too cute: these natural experiments are often special scenarios


Econometrics
Hand picked models that try to mimic A/B tests
Machine Learning
Automated model selection, embrace high dimensional data, focus on prediction
The intersection is brand new
Use ML to predict *counterfactuals*

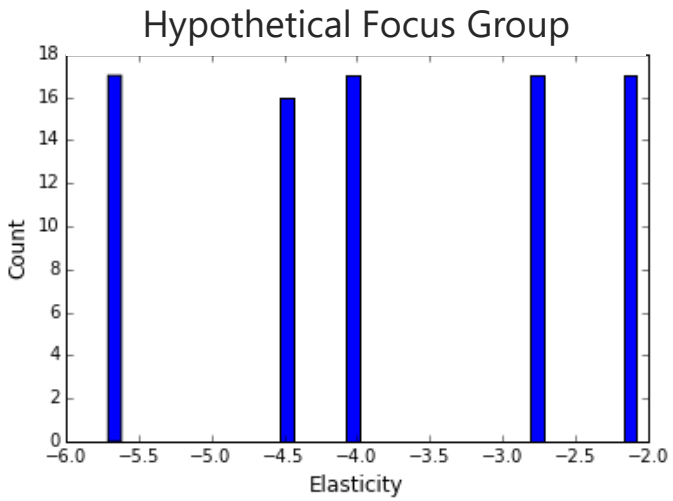
Application: measuring price sensitivity

If I **drop** price 1%, by what % will quantity sold **increase**?
Ex. -3 → drop price 1%, quantity sold goes up 3%

Problem: both prices and sales respond to underlying demand
Need the causal effect of price on sales, not their co-movement

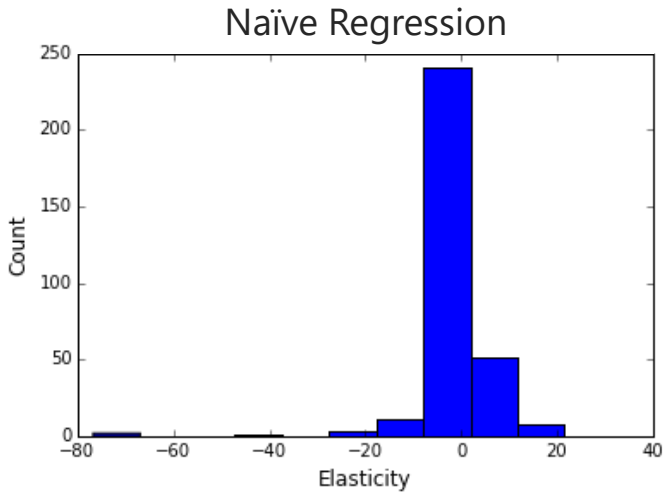
Buying Beer

Typical status quo

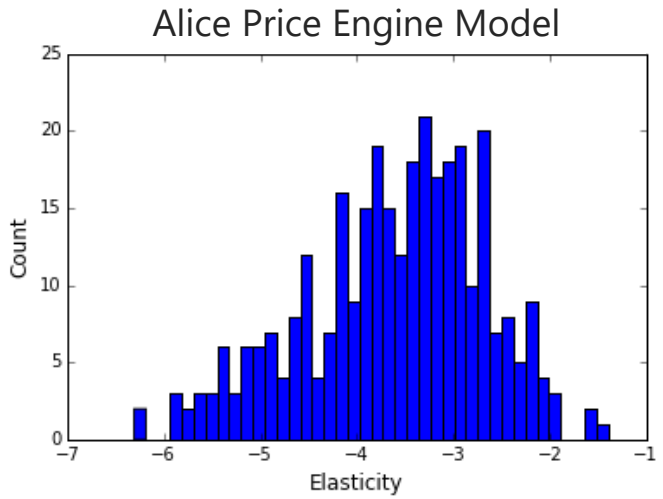


Model is too simple, unreliable

Old school econometrics

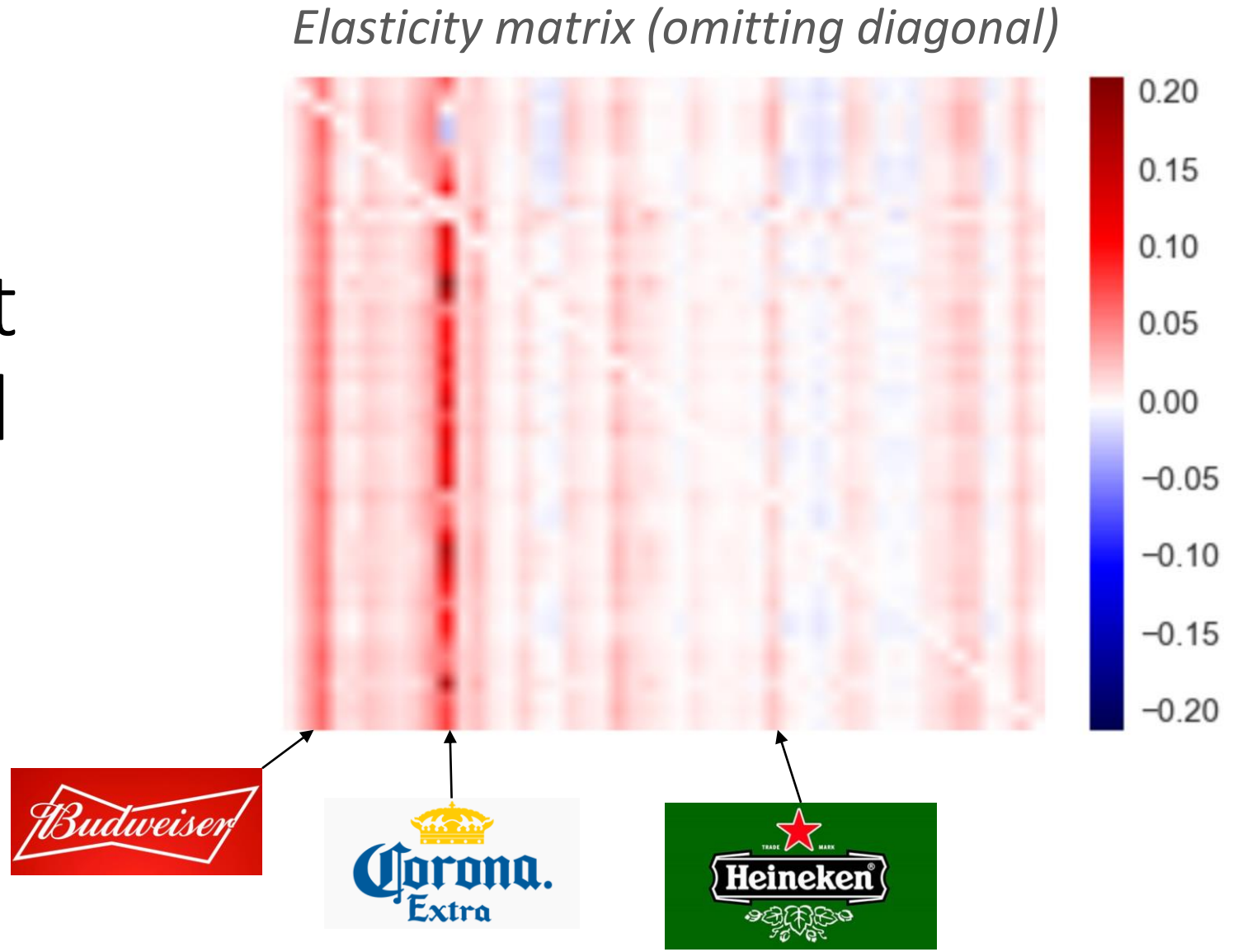


Model can't handle complexity



Selects right level of complexity
Encourages active experimentation

Beer Store cross-product compensated elasticities



How do we do this? How is it automatic?

If we have all of the price setter's information about demand

(product characteristics, demographics, holidays, competitors)

then causal inference breaks into two ML tasks:

1. Predict prices from the demand variables: $\boldsymbol{p} \sim \boldsymbol{x}$
2. Predict sales from the demand variables: $\boldsymbol{y} \sim \boldsymbol{x}$

The effect of residuals from 1 on those from 2 is causal:

$$\left(\boldsymbol{y} - \widehat{\boldsymbol{y}}(\boldsymbol{x})\right) \sim \left(\boldsymbol{p} - \widehat{\boldsymbol{p}}(\boldsymbol{x})\right)$$

`double ML' by Chernozhukov et al.

But what if you don't have all demand variables? Use upstream randomization

Endogenous Errors

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

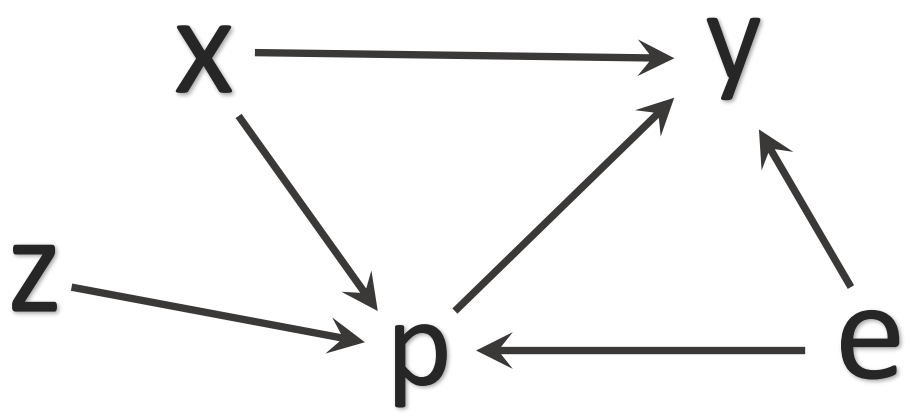
If you estimate this using naïve ML, you'll get

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

This works for prediction. It doesn't work for counterfactual inference:

*What happens if I change **p** independent of **e** ?*

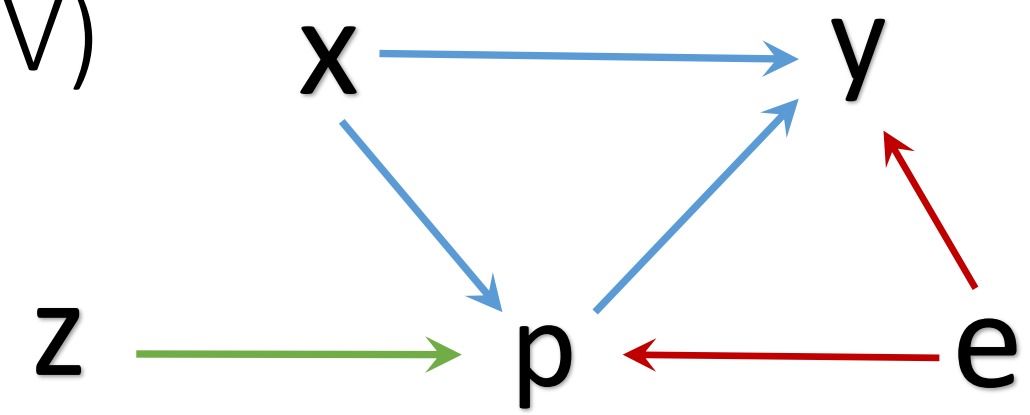
Instrumental Variables (IV)



In IV we have a special $z \perp e$ that influences policy p but not response y.

- Supplier costs that move price independent of demand (e.g., fish, oil)
- Any source of treatment randomization (intent to treat, AB tests, lottery)

Instrumental Variables (IV)



The *exclusion structure* implies

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

You can observe and estimate $\widehat{\mathbb{E}}[y|x,z]$ 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 $\hat{\tau}$.

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

Or nonparametric sieves where $g(p, x_i) \approx \sum_k \gamma_k \varphi_k(p, x_i)$ and

$$\mathbb{E}_F[\varphi_k(p, x_i)] \approx \sum_j \alpha_{kj} \beta_j(x_i, z_i)$$ (Newey+Powell)

or

$$\mathbb{E}_F[\, y_i - \sum_k \gamma_k \varphi_k(p, x_i)\,] \approx \sum_j \alpha_j \beta_j(x_i, z_i)$$ (BCK, Chen+Pouzo)

Also Darolles et al (2011) and Hall+Horowitz (2005) for kernel methods.

But this requires careful crafting and will not scale with $\dim(x)$

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

Instead, we propose to target the integral loss function directly

For discrete (or discretized) treatment

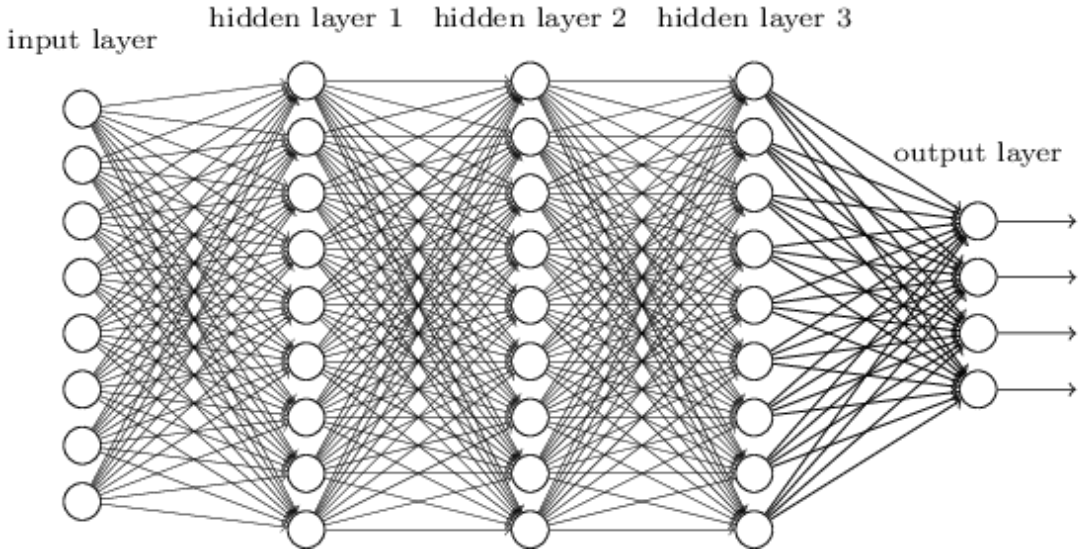
- Fit distributions $\hat{\mathrm{F}}(p|x_i, z_i)$ with probability masses $\hat{f}(p_b|x_i, z_i)$
- Train $\hat{g}$ to minimize $\left[\mathrm{y_i} - \sum_b g(\hat{p}_b, x_i) \hat{f}(p_b|x_i, z_i) \right]^2$

And you've turned IV into two *generic* machine learning tasks

Deep Neural Networks

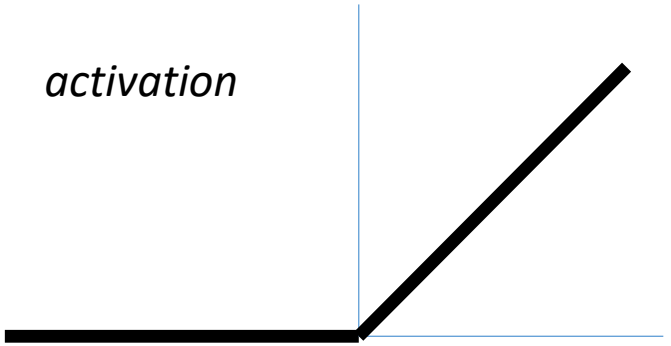
Massive number of parameters, mapping output of each layer to each node activation in the next

$$\boldsymbol{z}_i^L \rightarrow h_k\left(\left\langle W_k^{L+1}, \boldsymbol{z}_i^L \right\rangle\right)$$



Regularize

- deviance penalties $\lambda \|W\|$
- dropout training (zeros in grad)



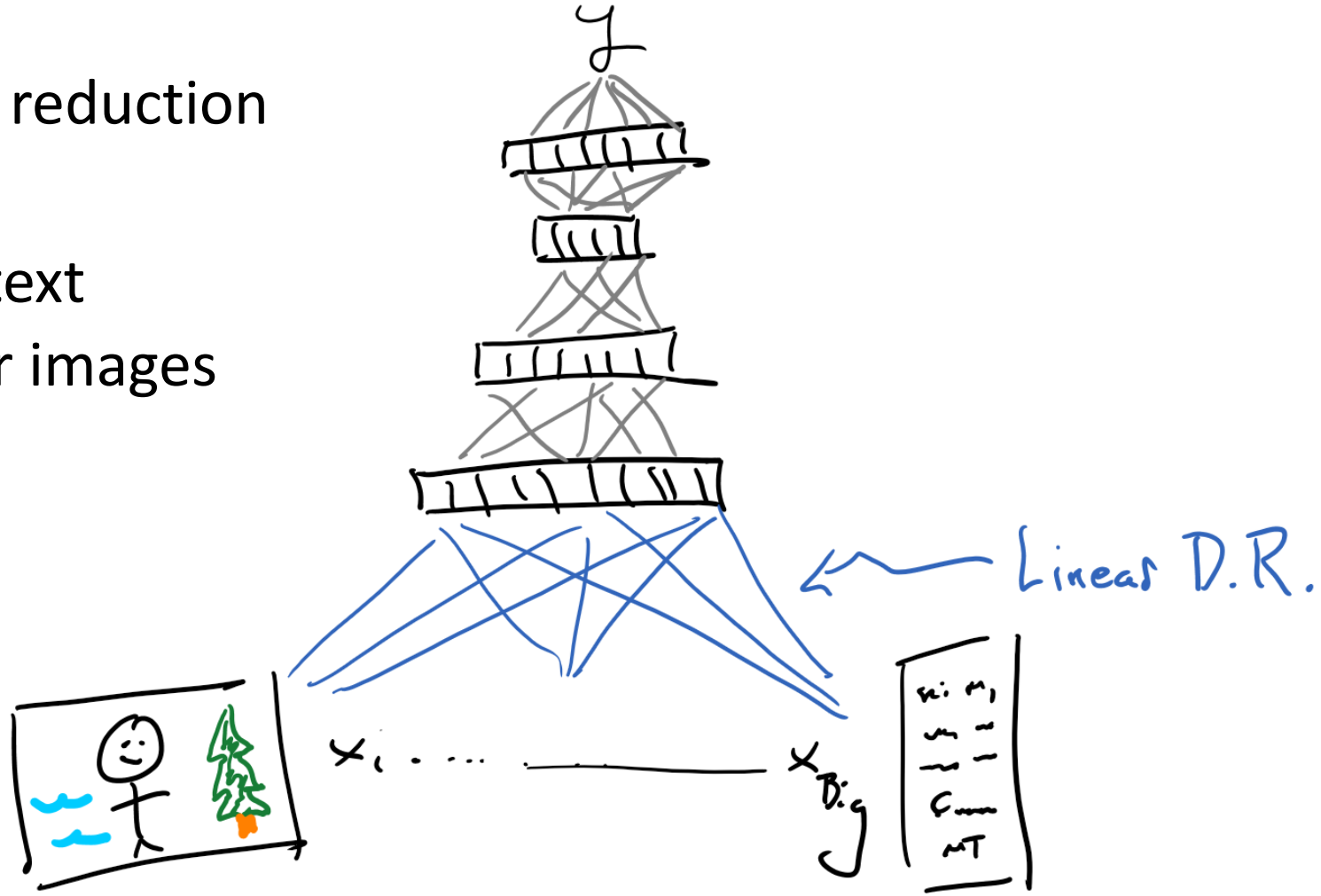
Deep nets are not really sieves

1st layer is a big dimension reduction

e.g.,

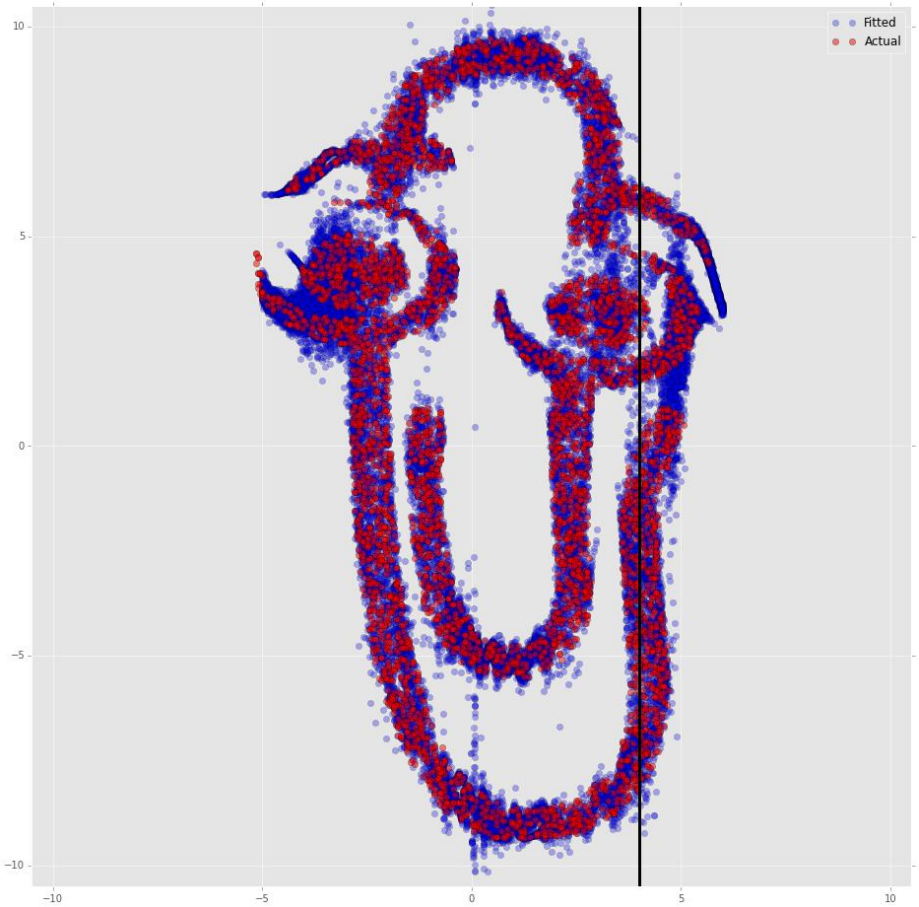
- word embedding for text
- matrix convolution for images

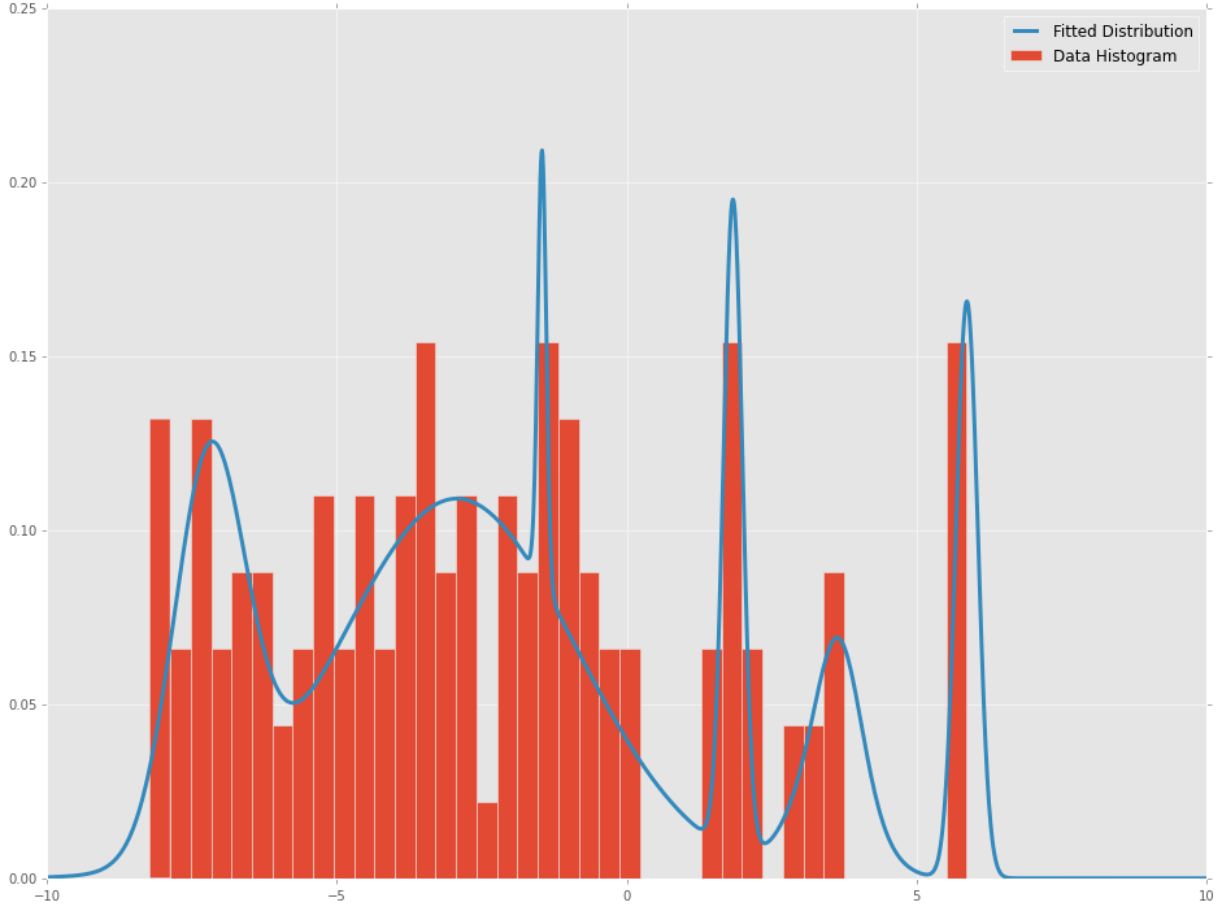
We need to study these…



e.g., first-stage learning for $\mathrm{F}(p|x_i, z_i)$

Bishop 96: Final layer of network parametrizes a mixture of Gaussians





Stage 2: Integral Loss

The second stage involves an integral loss function

If p is not discrete or can take many values, not easy!

Brute force just samples from $\hat{\mathrm{F}}(p|x_i, z_i)$ and you take gradients on

$$\frac{1}{N}\sum_i \left(y_i - \frac{1}{B}\sum_b g(p_b, x_i; \theta)\right)^2, \quad p_b \sim \hat{\mathrm{F}}(p|x_i, z_i)$$

This is what economists usually do, but this is super inefficient

Stochastic Gradient Descent

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

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

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

SGD for integral loss functions

Our one-observation stochastic gradient is

$$\nabla L(d_i, \theta) = -2\left(y_i - \int g_\theta(p, x_i) d\hat{F}(p|x_i, z_i)\right) \int g_\theta{}'(p, x_i) d\hat{F}(p|x_i, z_i)$$

Do SGD by pairing each observation with *two independent* treatment draws

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

So long as the draws are independent, $\mathbb{E}\nabla \hat{L}(d_i, \theta) = \mathbb{E}\nabla L(d_i, \theta) = L(\boldsymbol{D}, \theta)$

Validation and model tuning

We can do OOS *causal validation*

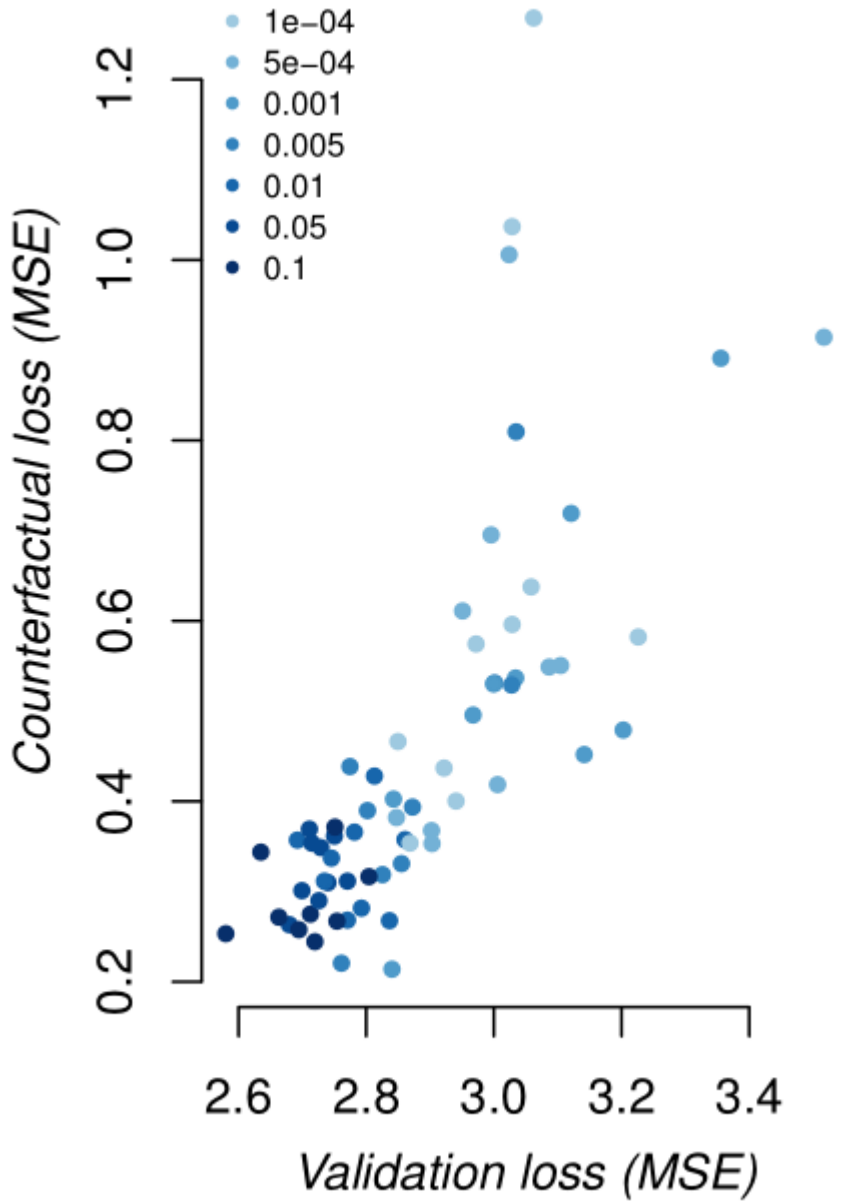
Leave-out deviance on first stage

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

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).

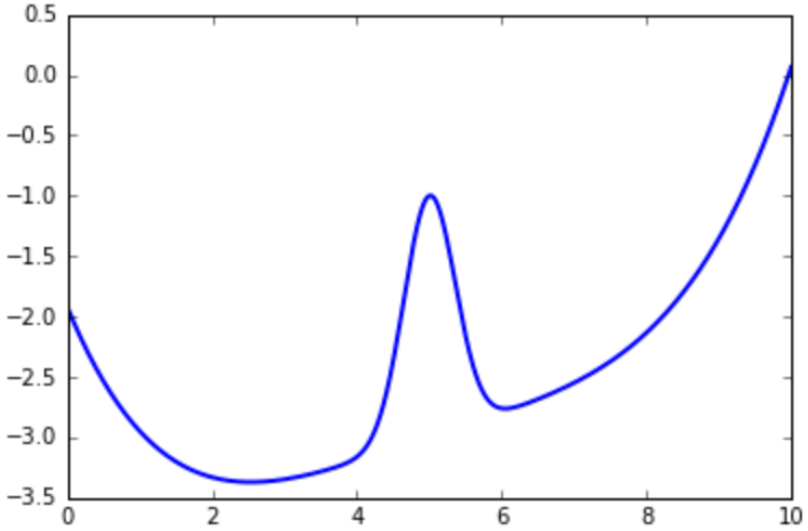


heterogeneous price effects

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

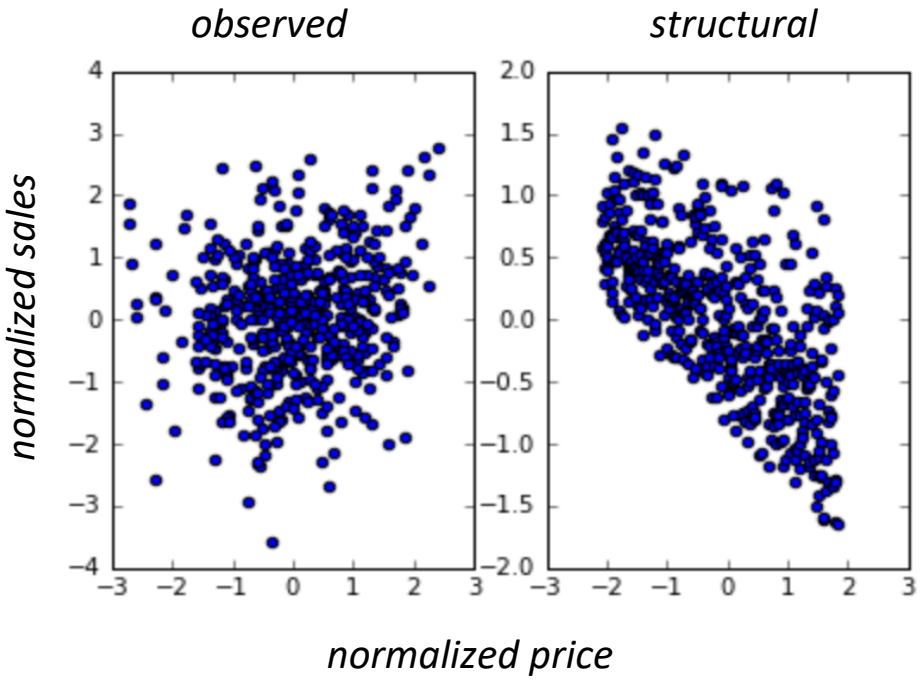
$$p = 25 + (z+3)\psi_t + v$$

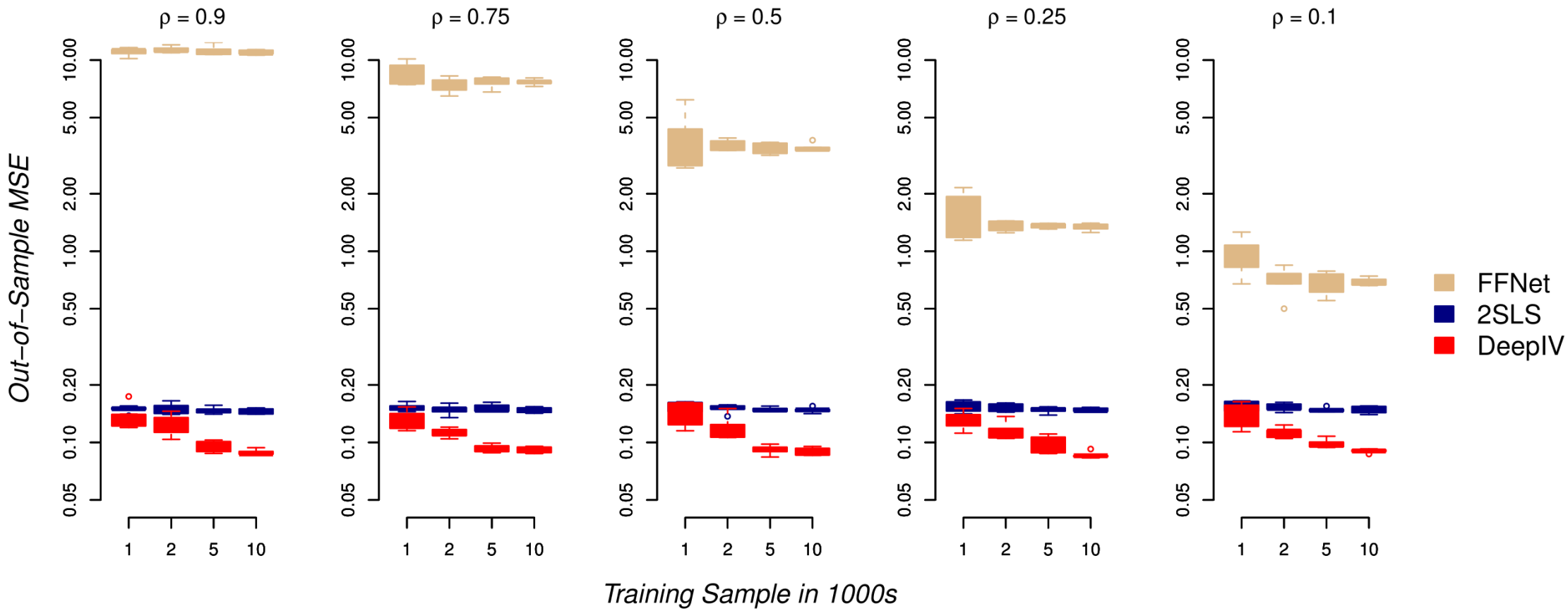
$$z,\ v \sim \mathrm{N}(0,1) \ \text{ and } \ e \sim \mathrm{N}(\rho v, 1-\rho^2),$$



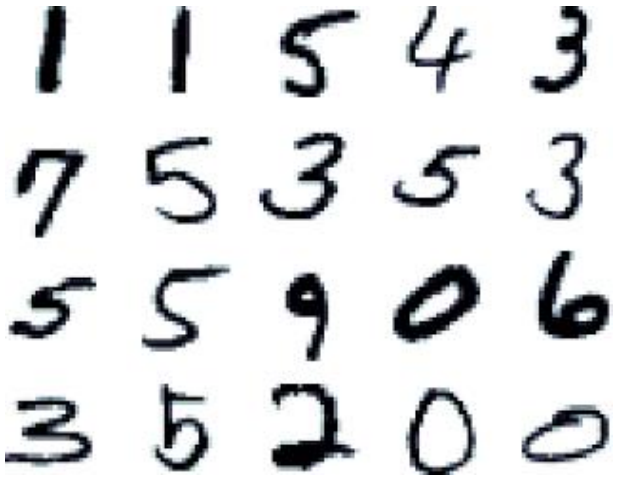
‘time’ dependent prices, sensitivity, utility

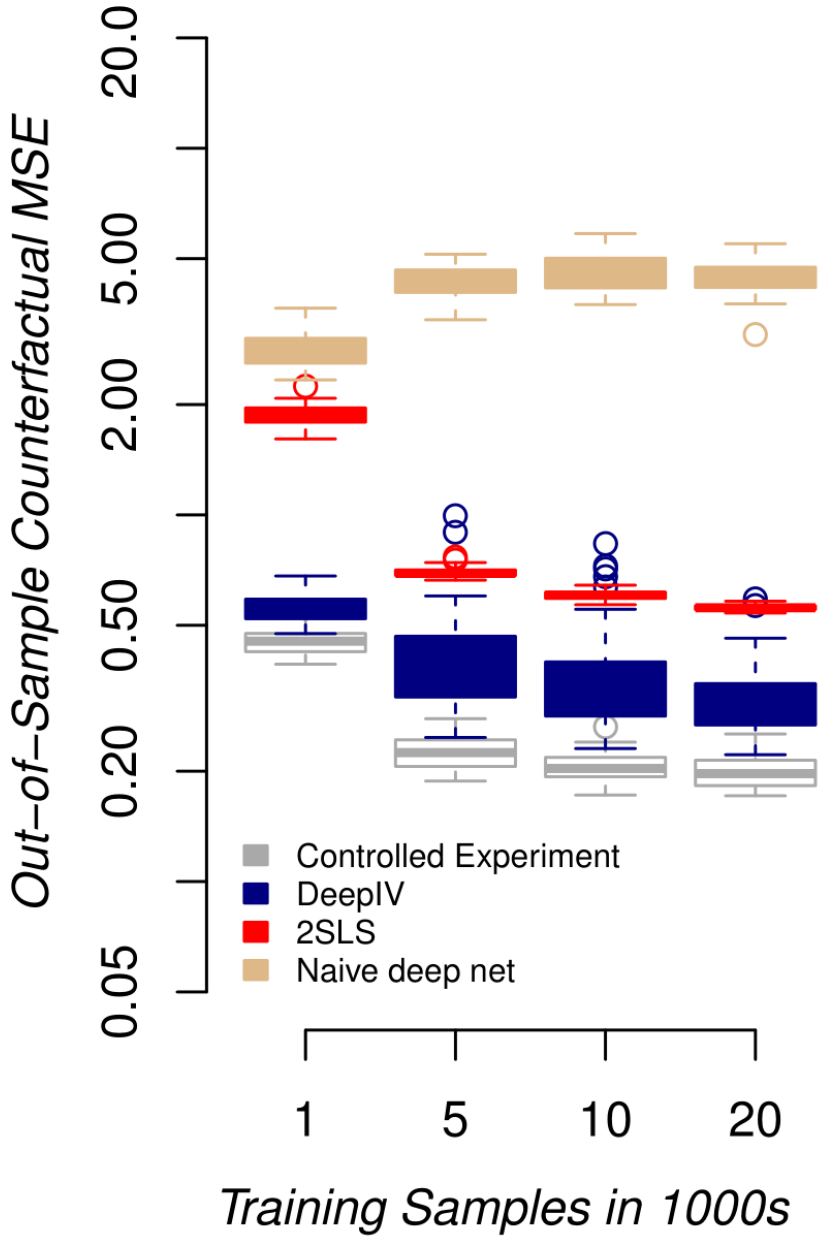
Customer ‘type’ 1-7 impacts demand




ρ = 0.9
ρ = 0.75
ρ = 0.5
ρ = 0.25
ρ = 0.1
Out−of−Sample MSE
0.05
0.10
0.20
0.50
1.00
2.00
5.00
10.00
1
2
5
10
Training Sample in 1000s
FFNet
2SLS
DeepIV

Make it harder…





Inference? Good question

Frequentist inference

Data split! Get top node values and averages on left-out data:

$$\eta_{ik} = \eta_k(x_i, p_i) \quad \text{and} \quad \bar{\eta}_{ik} = \mathbb{E}_{\hat{F}(p|x_i,z_i)}\eta_k(x_i, p)$$

Stack as instruments $\bar{\mathrm{H}} = [\bar{\eta}_1 \cdots \bar{\eta}_L]'$ and treatments $\mathrm{H} = [\eta_1 \cdots \eta_L]'$

Post-net 2SLS coefficients are $\hat{\beta} = (\bar{H}'H)^{-1}\bar{H}'y$ with variance V_β and

$$\mathrm{var}[\hat{g}(x, p)] = \boldsymbol{\eta}'(x, p)\, V_\beta\, \boldsymbol{\eta}(x, p)$$

Bayesian inference

Variational Bayes: fit q to minimize $\mathbb{E}_{\mathrm{q}}[\log q(W) - \log p(W|D]$

Diversion… in training we use dropout:

At each SGD update, calculate gradients against $W^l = \Xi^l \Omega^l$ at layer l where

$$\Xi^l = \mathrm{diag}\big(\, \xi_{l1} \;\; \ldots \xi_{lK_l}\big), \qquad \xi_{kj} \sim \mathrm{Bern}(c)$$

i.e., dropout randomly drops *rows* of each layer's weight matrix

Dropout is Variational Bayes!

VB minimizes $KL(q) \propto \mathbb{E}_{\mathrm{q}}[\log q(W) - \log p(\boldsymbol{D}|W) \ - \log p(W) \ ]$

If $q(W) = \prod_l \prod_k (c\mathbb{1}_{\left[W_k^l = \Omega_k^l\right]} + (1-c)\,\mathbb{1}_{\left[W_k^l = 0\right]})$ and $w \sim \mathrm{N}(0, \lambda^{-1})$,

$$KL(q) \propto \mathbb{E}_q L(\boldsymbol{D}|W) + c\lambda|W|_2 + \mathrm{K}\,[c\log c + (1-c)\log(1-c)]$$

(see also Gal and Ghahramani)

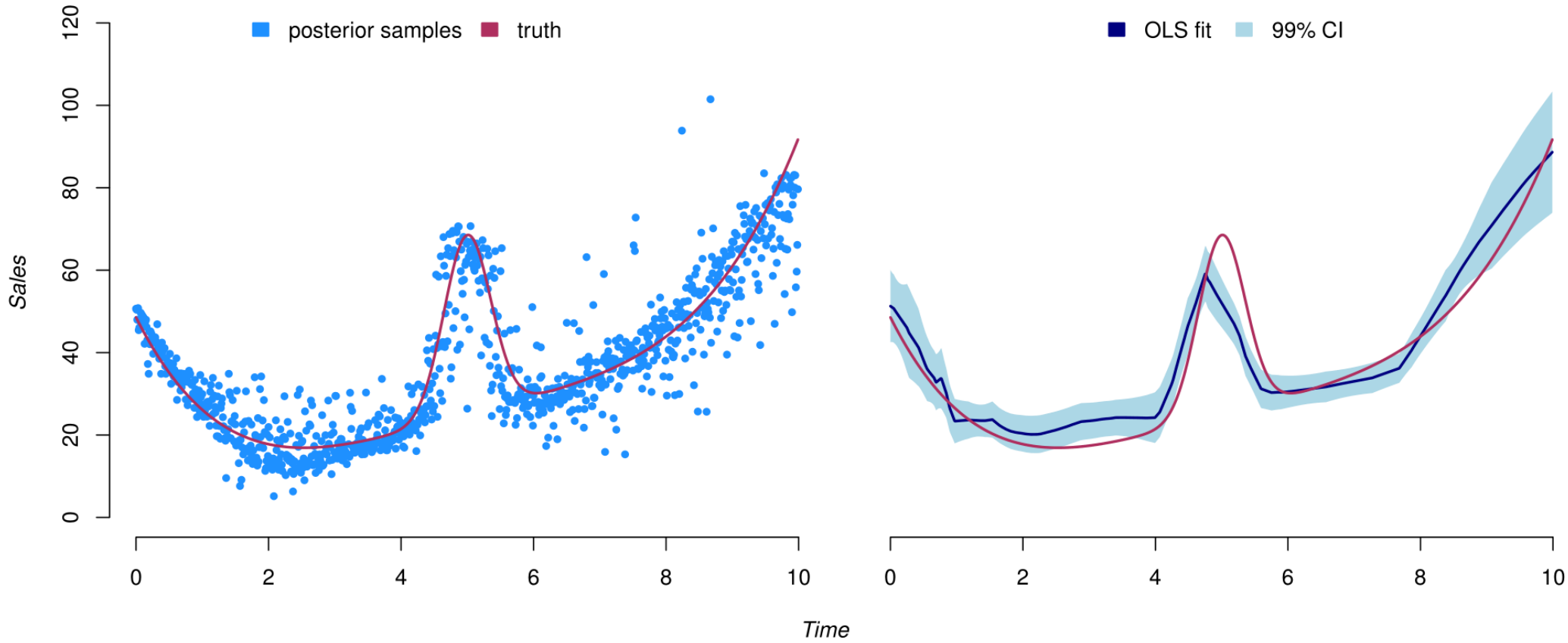
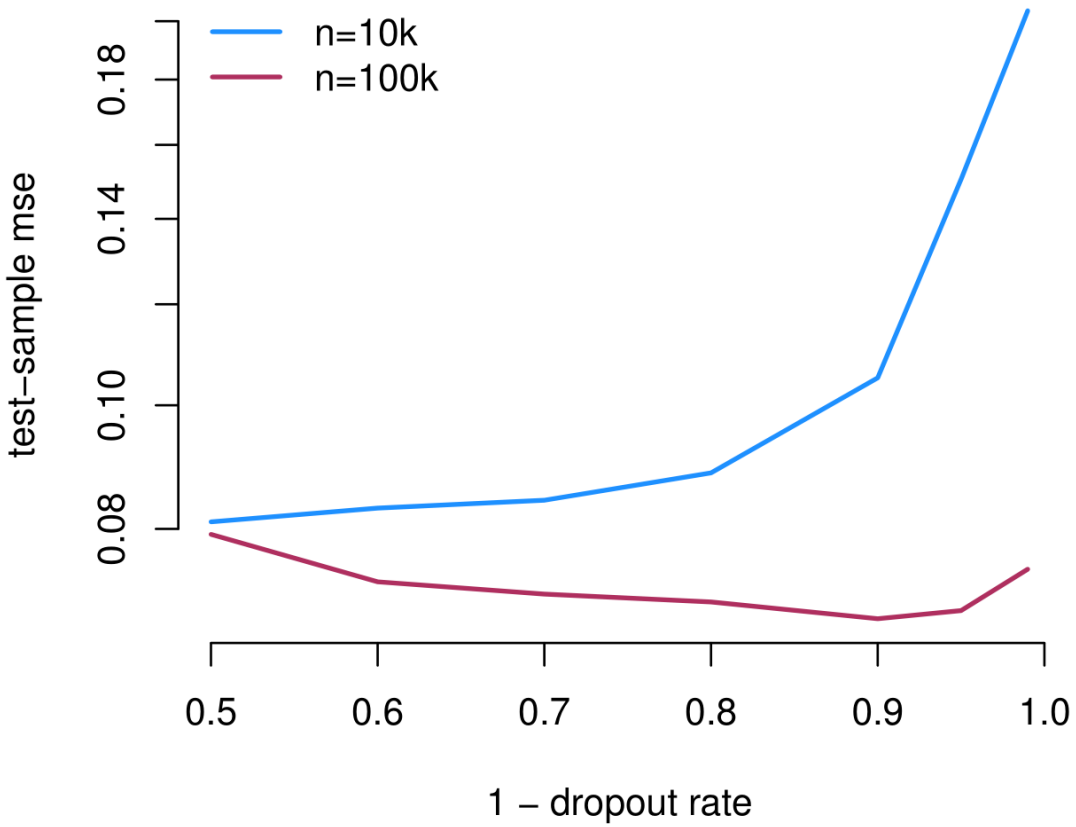
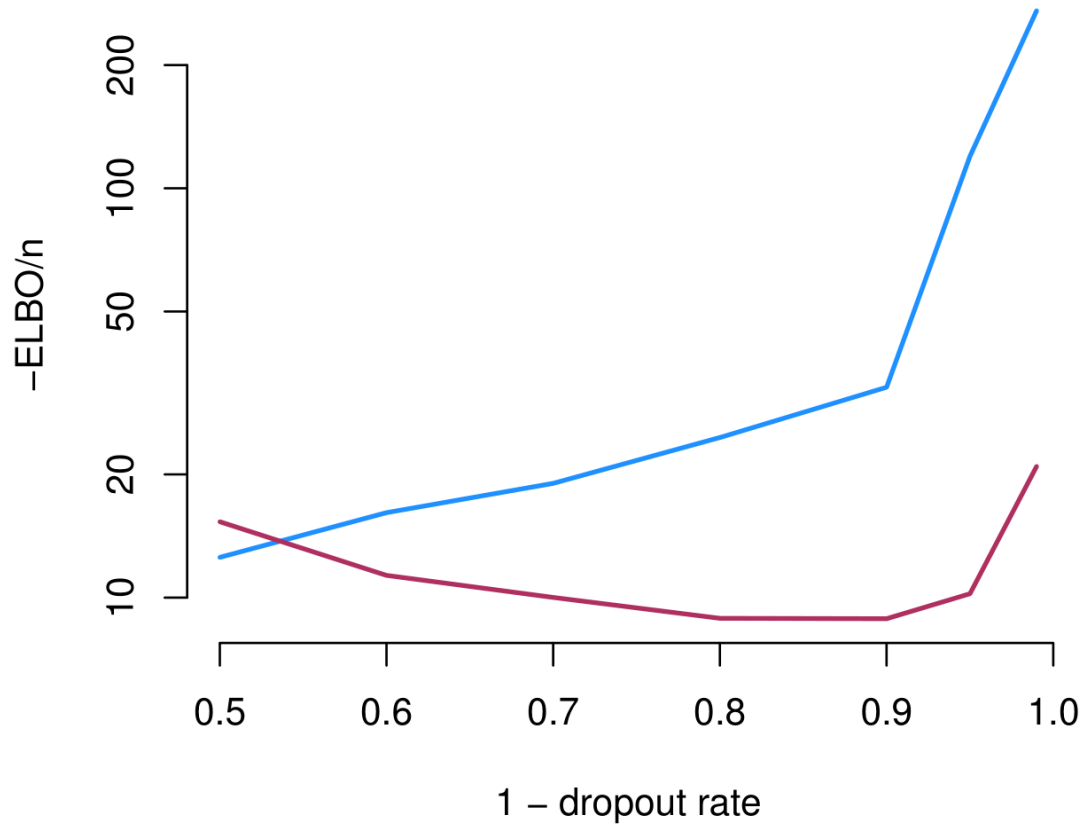


Figure 3: Bayesian (left) and Frequentist (right) inference for a central slice of the counterfactual function, taken at the average price and in our 4^{th} customer category. Since the price effect for a given customer at a specific time is constant in (27), the curves here are a rescaling of the customer *price sensitivity* function.

Tuning the dropout rate is like treating it as a variational parameter





Ads Application

Taken from Goldman and Rao (2014)

We have 74 mil click-rates over 4 hour increments for 10k search terms

Treatment: ad position 1-3

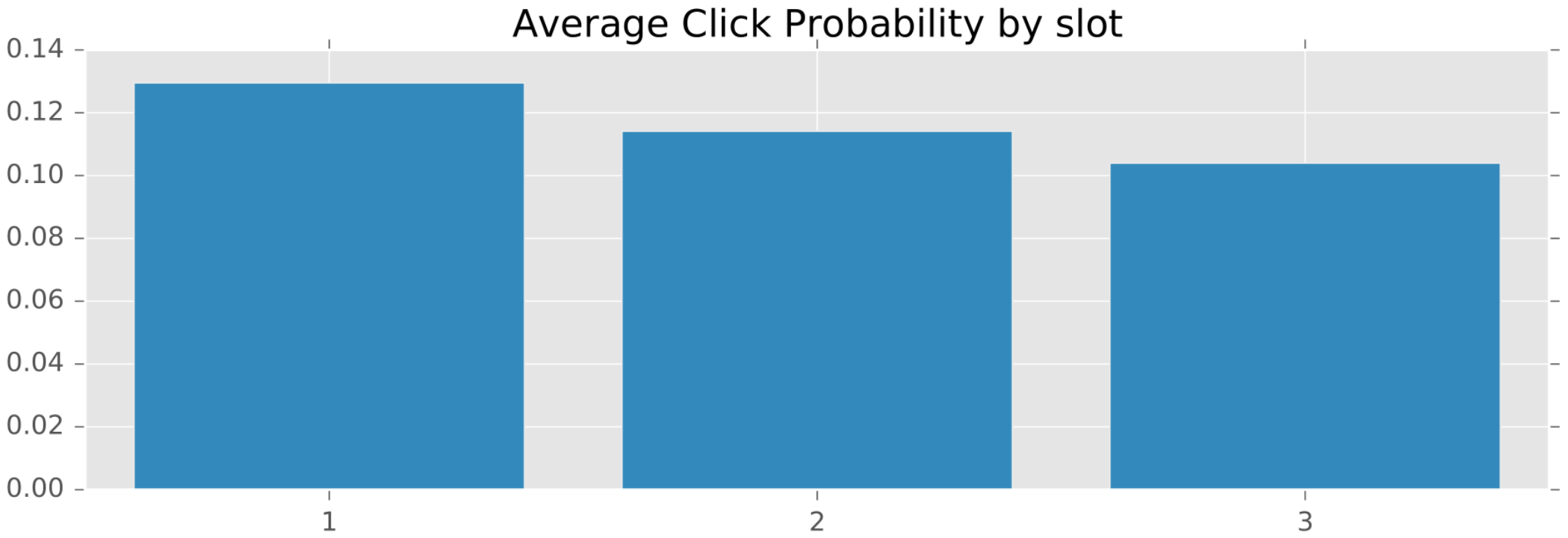
Instrument: background AB testing (bench of ~ 100 tests)

Covariates: advertiser id and ad properties, search text, time period

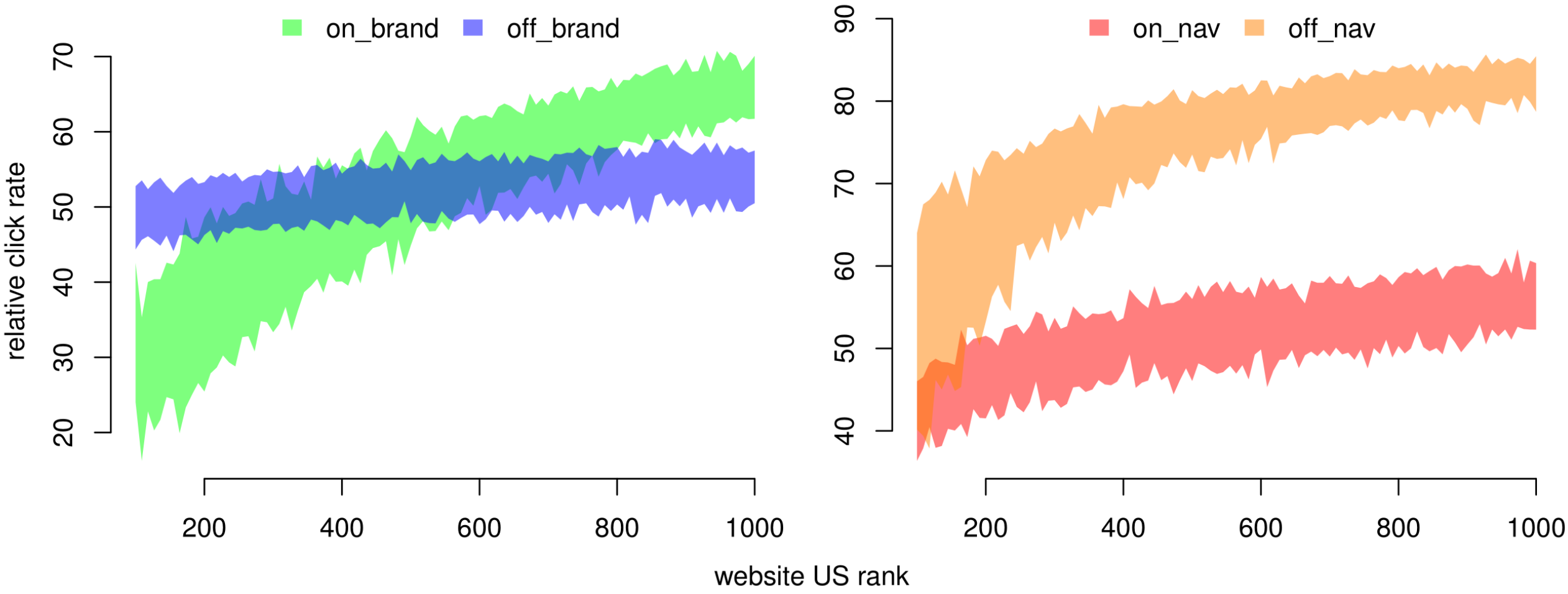
Ads in slot 1 are inherently different (better?) than those in slot 2

We need causal inference for the effect of position on clicks

Average Treatment Effects



These compare to observed click probabilities of 0.33, 0.1, and 0.05.



Heterogeneity across advertiser and search

How do we do this?

The ML behind ad click-probability is regularly AB tested

This gives upstream randomization – many natural experiments

We can then break causal inference into

1. Model ad position changes with huge number of AB tests
2. Model how ad click rates change with the same tests

And again: you can combine 1+2 to get causal position effects

Alice

Established: December 5, 2016

Automated Learning and Intelligence for Causation and Economics

We use economic theory to build systems of tasks that can be addressed with deep nets and other state-of-the-art ML.

This is the construction of systems for *Economic* AI