

# Innovation slowdown?

## ARE WE OUT OF BIG IDEAS?

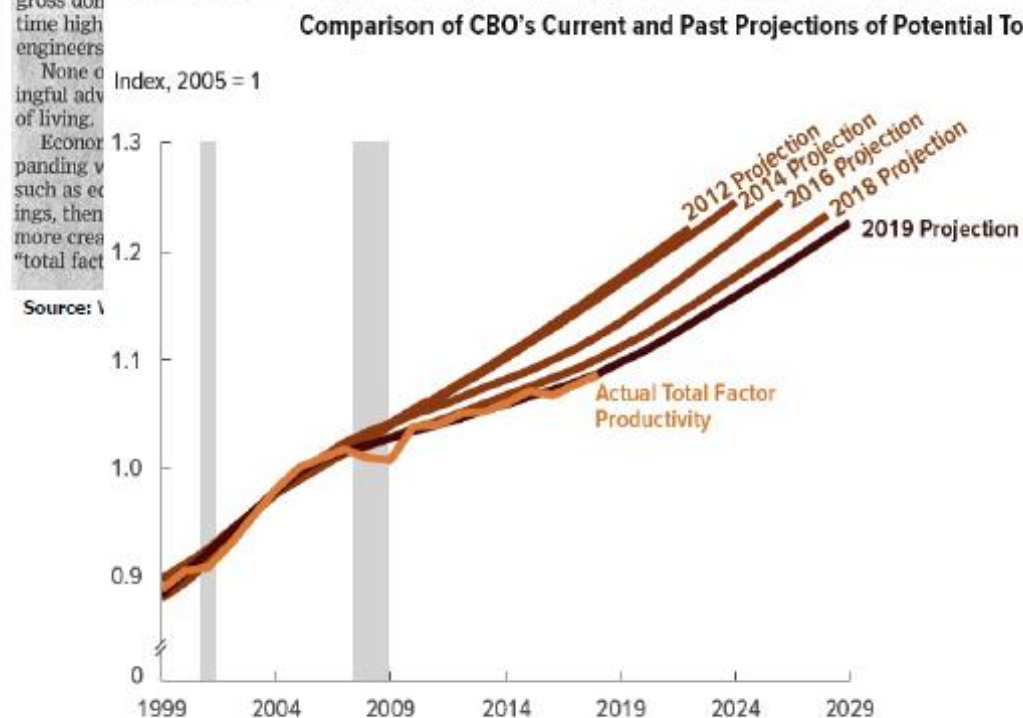
Dwindling gains in science, technology and medicine are a hidden drag on economic growth

By GREG IP

By all appearances, we're in a golden age of innovation. Every month sees new advances in artificial intelligence, gene therapy, robotics and software apps. Research and development as a share of gross domestic product is at a time high. None of the gains of the 19th century. Economies are expanding at a rate such as we have not seen in more than a century.

### THE INNOVATION PARADOX

There is a yawning chasm between what innovation promises for the economy and what it is delivering. A Wall Street Journal series, running in full online, shows that improvements in everyday life have been incremental, not revolutionary. Houses, appliances and cars look much like they did a generation ago. Airplanes fly no faster than in the 1960s. None of the 20 most prescribed drugs in the U.S. came to market in the past decade.



Source: Congressional Budget Office.

## Is US economic growth over? Faltering innovation confronts the six headwinds

Robert J Gordon  
Northwestern University and CEPR

### 1. Introduction

The prospects for future long-run US economic growth were already dismal in 2007 but were little noticed in the continuing euphoria over the invention of the internet and the related developments in information technology and communications (ICT). This Policy Paper pulls back from the past five years of financial crisis to pose a question with implications that will persist for decades even if the current international economic disorder is eventually resolved.

This paper is about US economic growth through 2007 and the future post-2007 path of potential or trend output for the subsequent 20 to 50 years. The analysis abstracts almost entirely from the recovery since 2007. The questions of recovery have been answered and the output and growth path and

growth by all nations as the pace of productivity growth in the US fades out.

The paper makes these basic points:

1. Since Solow's seminal work in the 1950s, economic growth has been regarded as a continuous process that will persist forever. But there was virtually no economic growth before 1750, suggesting that the rapid progress made over the past 250 years could well be a unique episode in human history rather than a guarantee of endless future advance at the same rate.
2. The frontier established by the US for output per capita, and the UK before it, gradually began to grow more rapidly after 1750, reached its fastest growth rate in the middle of the 20th century, and has slowed down since. It is in the process of slowing down further.

3. A useful organising principle to understand the pace of growth since 1750 is the sequence of three Industrial revolutions. The first (IR1) with its main inventions between 1750 and 1830 created steam engines, cotton spinning, and railroads. The second (IR2) was the most important, with its three central inventions of electricity, the internal combustion engine, and running water with indoor plumbing, in the relatively short interval of 1870 to 1900. Both the first two revolutions required about 100 years for their full effects to percolate through the economy. During the two decades 1950-70, the benefits of the IR2 were still transforming the economy, including air conditioning, home appliances, and the interstate highway system. After 1970, productivity growth slowed markedly, most plausibly because the main ideas of IR2 had by and large been implemented by then.

and other Policy Insights, visit [www.cepr.org](http://www.cepr.org)

Because slow growth in actual total factor productivity (TFP) has persisted for an increasingly lengthy period, CBO has lowered its projected rates of potential TFP growth.

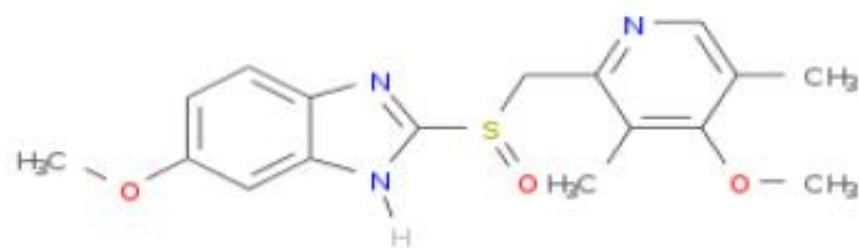
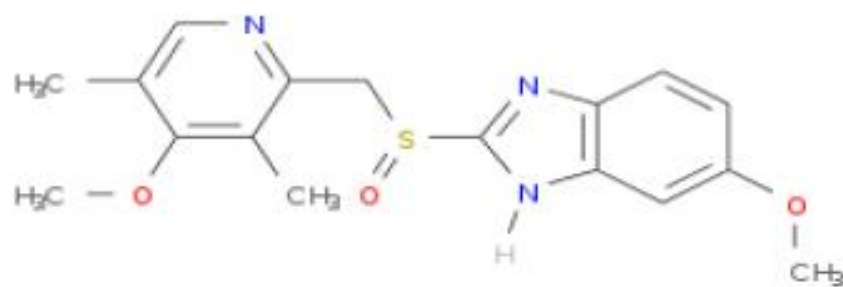
# Quality and quantity of innovation?

An innovation is valuable if

- It is novel (i.e., it does not copy an existing idea)
- It is useful (i.e., others use it or build on it)

We have a mechanism for tracking innovations: **patents**

Sadly, many patents are neither novel nor useful.



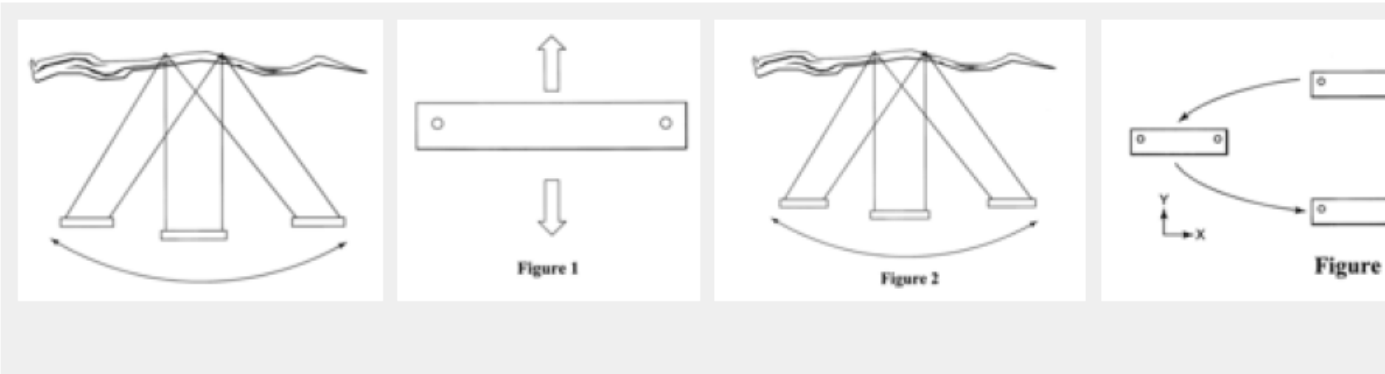
“A new medicine that isn’t any better for ordinary heartburn than the one it will succeed” (WSJ, 2002)

# Method of swinging on a swing

## Abstract

A method of swing on a swing is disclosed, in which a user positioned on a standard swing suspended by two chains from a substantially horizontal tree branch induces side to side motion by pulling alternately on one chain and then the other.

## Images (4)



## Classifications

[A63G9/00](#) Swings

US6368227B1

US Grant



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**Inventor:** [Steven Olson](#)

**Original Assignee:** [Steven Olson](#)

**Priority date :** [2000-11-17](#)

**Family:** [US \(1\)](#)

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2000-11-17	US09715198	Expired - Fee Related
2002-04-09	US6368227B1	Grant

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Cited By (11)

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Publication number	Priority date	Publication date	Assignee	Title
<a href="#">US6932710B1</a>	2004-09-15	2005-08-23	William T. Hartin	Board swing
<a href="#">US20060036552A1</a> *	2003-01-31	2006-02-16	Microsoft Corporation	Secure machine counting
<a href="#">US20060293926A1</a> *	2003-02-18	2006-12-28	Khury Costandy K	Method and apparatus for reserve measurement
<a href="#">US20070232449A1</a> *	2004-11-26	2007-10-04	Nordisk Terapi As	Training apparatus
<a href="#">US20080293545A1</a> *	2004-11-26	2008-11-27	Redcord As	Training Apparatus
<a href="#">USRE41363E1</a> *	1995-11-21	2010-06-01	Samsung Electronics Co., Ltd.	Thin film transistor substrate
<a href="#">US20110003669A1</a> *	2004-11-26	2011-01-06	Redcord	Training apparatus
<a href="#">US20110239315A1</a> *	2009-01-12	2011-09-29	Ulla Bonas	Modular dna-binding domains and methods of use
<a href="#">US8420782B2</a>	2009-01-12	2013-04-16	Ulla Bonas	Modular DNA-binding domains and methods of use
<a href="#">US8586526B2</a>	2010-05-17	2013-11-19	Sangamo Biosciences, Inc.	DNA-binding proteins and uses thereof
<a href="#">US8697853B2</a>	2009-12-10	2014-04-15	Regents Of The University Of Minnesota	TAL effector-mediated DNA modification
Family To Family Citations				

\* Cited by examiner, † Cited by third party, ‡ Family to family citation

# Automated patent quality measurement

Need to 'read' 9MM USPTO patent since 1836 to see how each is

- Novel: distinct from previous patents
- Impactful: related to subsequent patents

Automate this:

- Featurize patent text to capture info that was key *when it appeared*
- Train ML to infer past and future patents from these features

Low past similarity implies novelty, good future predictors have impact.

# Automated patent quality measurement

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Document featurization: words  $w$  in patent  $d$  at time  $t$  are given value

$$TFBIDF_{wd} = \frac{\text{count}_{wd}}{\sum_{w'} \text{count}_{w'd}} \times \log \frac{D_t}{1 + D_{tw}}$$

where  $D_{tw}$  is the # patents by  $t$  containing  $w$  and  $D_t = \sum_w D_{tw}$

# Automated patent quality measurement

Need to 'read' 9MM USPTO patent since 1836 to see how each is

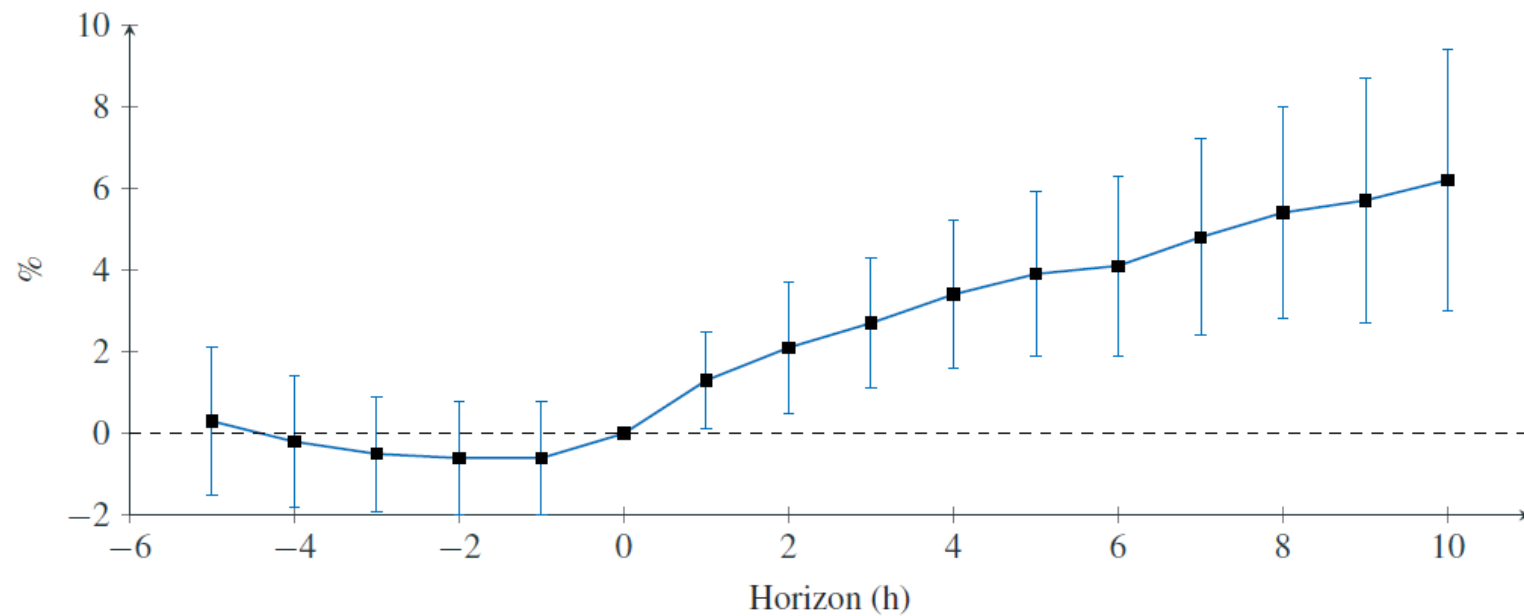
- Novel: distinct from previous patents
- Impactful: related to subsequent patents

Connecting to past and future:

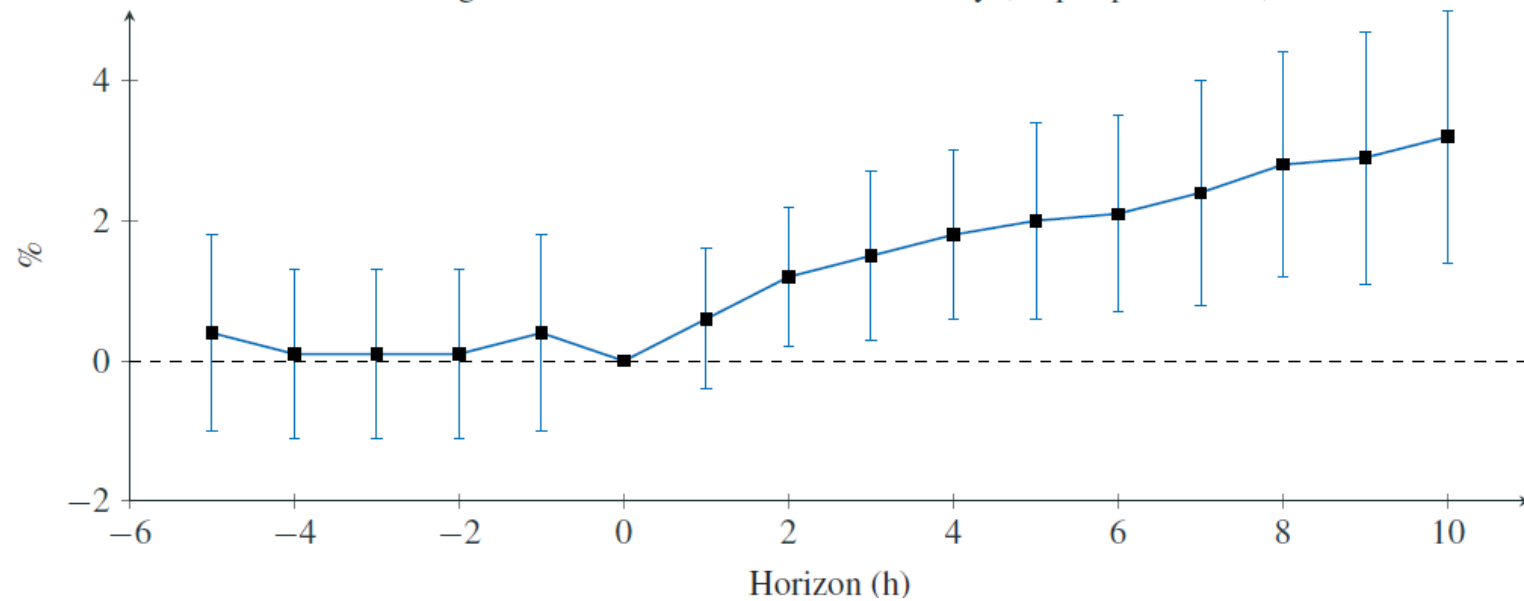
- Calculate cosine similarity on TFBIDF vectors,  $\rho_{dk}$  for patents  $d, k$
- Sum similarities for each patent with future ( $f_d$ ) and past patents ( $b_d$ )
- Define *quality* as ratio of future over past similarity  $q_d = \log \frac{f_d}{b_d}$



A. Breakthrough Innovations and Firm Profits



B. Breakthrough Innovations and Labor Productivity (output-per-worker)



# An index of innovation

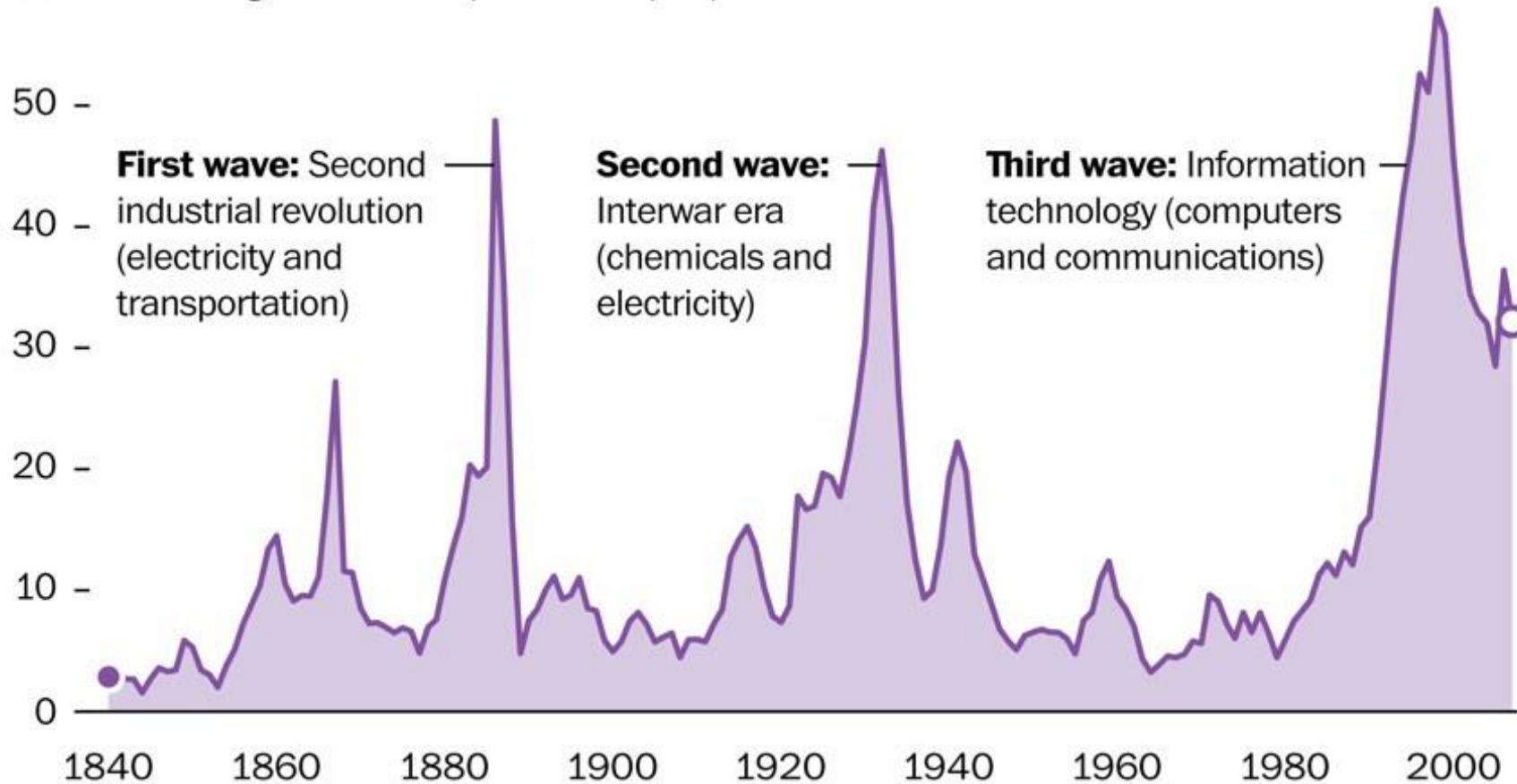
Decompose quality for patent  $d$  from year  $t$  as  $q_d = \alpha_t + \beta_d$   
(control for the temporal changes in language usage)

Count the number of patents for year  $t$  with  $\beta_d$  in the 95<sup>th</sup> percentile  
(dampen estimation noise)

# When the most influential U.S. inventions were patented

Annual count of breakthrough patents, adjusted for population

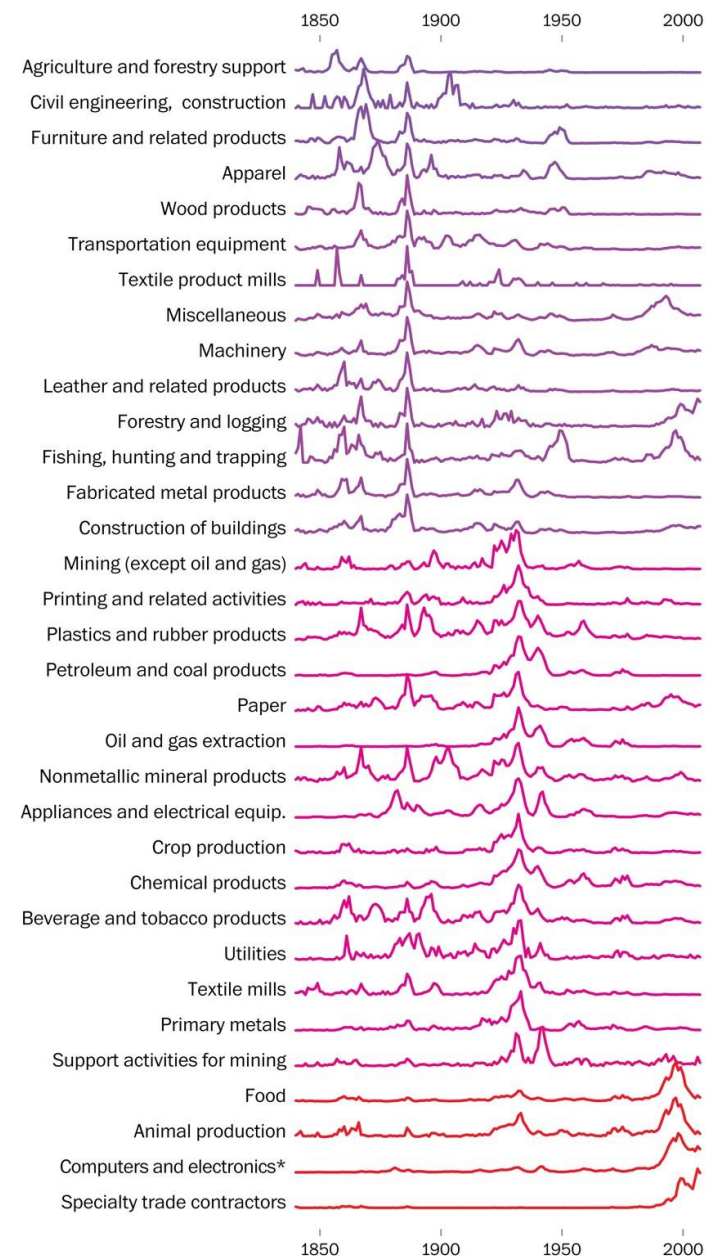
60 breakthrough inventions per million people



Source: Analysis of U.S. Patent Office data by Bryan Kelly, Dimitris Papanikolaou, Amit Seru, Matt Taddy  
THE WASHINGTON POST

## When each industry's top innovations were patented

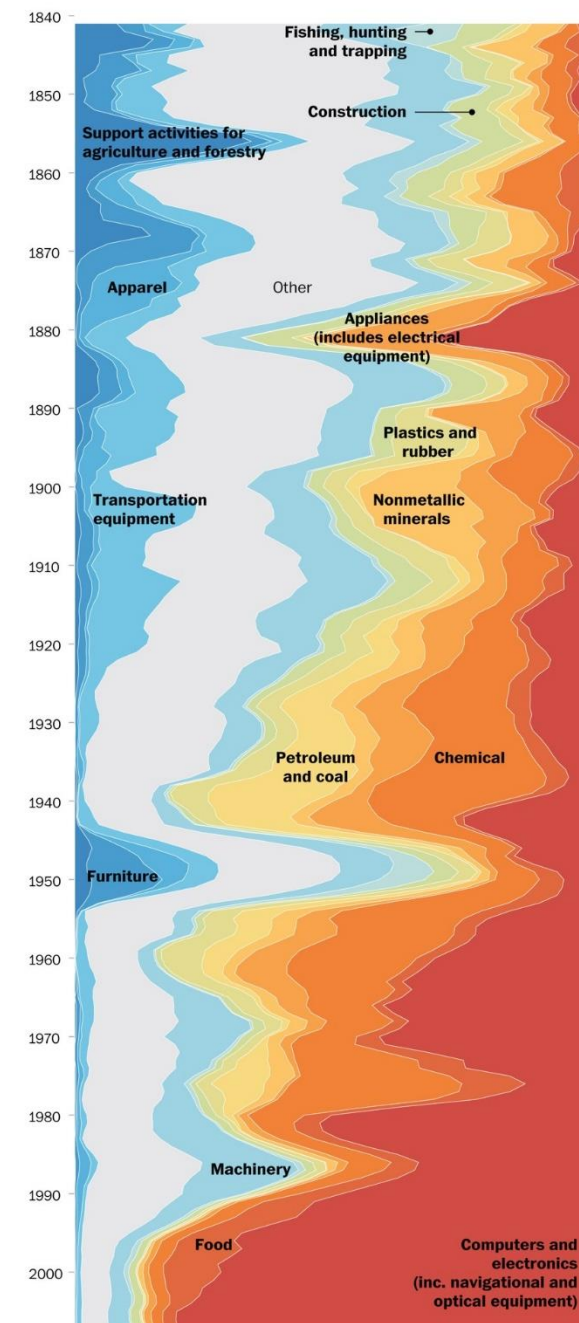
Indexed relative to each industry's individual peak



\* Includes navigational and optical equipment

Source: Analysis of U.S. Patent Office data by Bryan Kelly, Dimitris Papanikolaou, Amit Seru, Matt Taddy  
THE WASHINGTON POST

## Distribution of influential U.S. inventions by industry



Source: Analysis of U.S. Patent Office data by Bryan Kelly, Dimitris Papanikolaou, Amit Seru, Matt Taddy  
THE WASHINGTON POST

# What is AI?

Domain Structure + Data Generation + General Purpose ML

Econ/Biz Framework  
Hands off the Wheel  
Causal Inference

Reinforcement Learning  
Sensor/Camera networks  
Simulation/GANs



Auto ML, Sagemaker,  
Inferentia, DNNS, GPUs,  
Comp Vision, NLU, NLG

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

# Hybrid Reward Architecture



Level: 201

-	30425 × 10 =	304250
■	801 × 50 =	40050
	17 × 200 =	3400
	6 × 400 =	2400
	3 × 800 =	2400
	1 × 1600 =	1600
	42 × 100 =	4200
	40 × 200 =	8000
	33 × 500 =	16500
	43 × 700 =	30100
	48 × 1000 =	48000
	47 × 2000 =	94000
	89 × 5000 =	445000

999900







# Example: short-term price elasticity for Beer

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

Problem: both prices and sales respond to underlying demand

Solution: write down a model for sales of beer  $b$  at transaction  $t$

$$y_{tb} = \gamma_{tb} p_{tb} + f(\mathbf{w}_{tb}) + \varepsilon_{tb},$$

$$p_{tb} = h(\mathbf{w}_{tb}) + v_{tb}$$

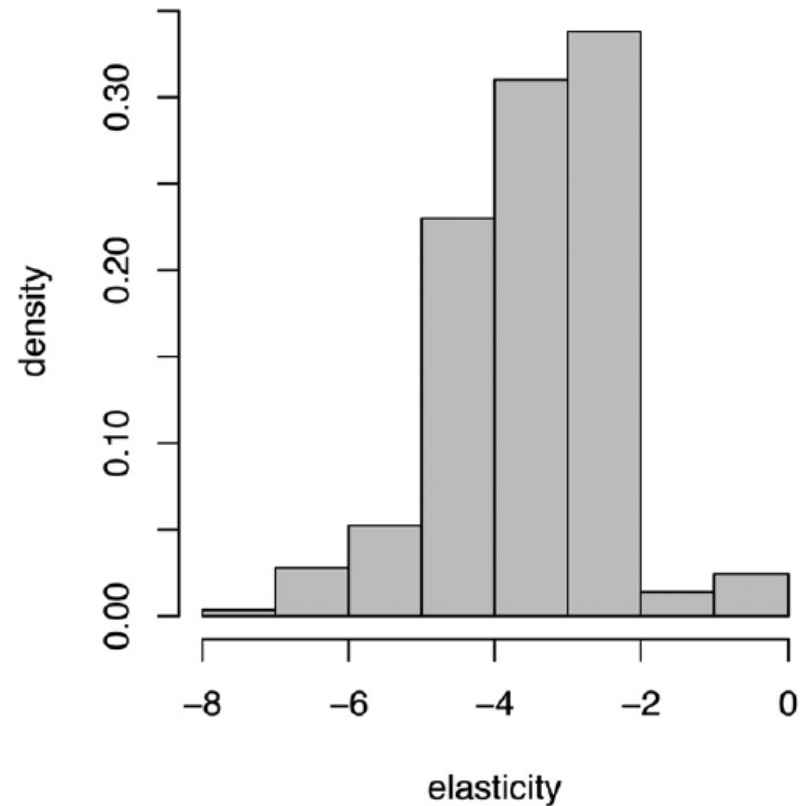
Predict sales ( $\hat{y}_{tb}$ ) and prices ( $\hat{p}_{tb}$ ) using demand variables ( $\mathbf{w}_{tb}$ ), then regress residuals on residuals:

$$y_{tb} - \hat{y}_{tb} \sim p_{tb} - \hat{p}_{tb}$$

This regression relationship is the causal effect of price on sales.



# Orthogonal ML for Beer



**FIGURE 6.3:** Beer-specific elasticities obtained by lasso regression on the orthogonal ML residuals.

The text encodes a natural hierarchy

Many beers are *IPA* or *Cider*

But individual brands also load

Most Price Sensitive

```
> names(sort(e1)[1:5])  
[1] "GUINNESS 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
```

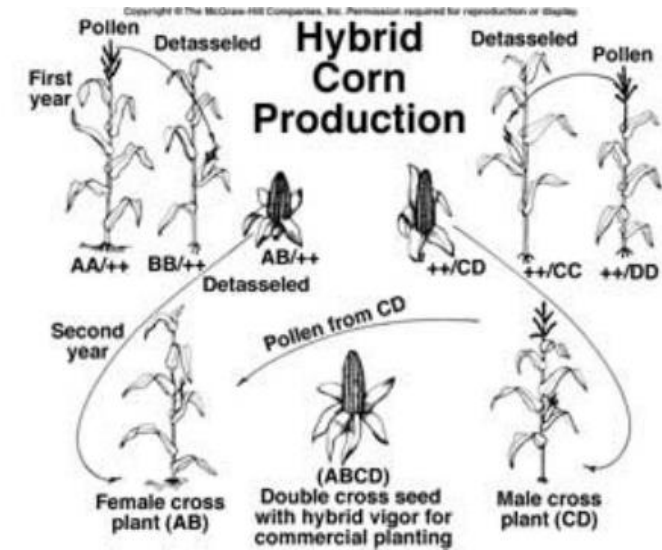
Least Price Sensitive

```
> names(sort(-e1)[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
```

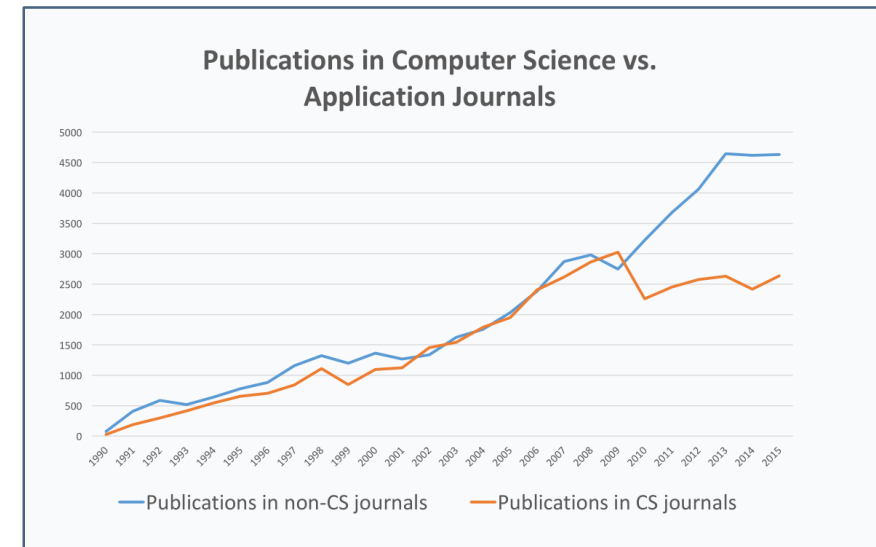
# The Economics of AI

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

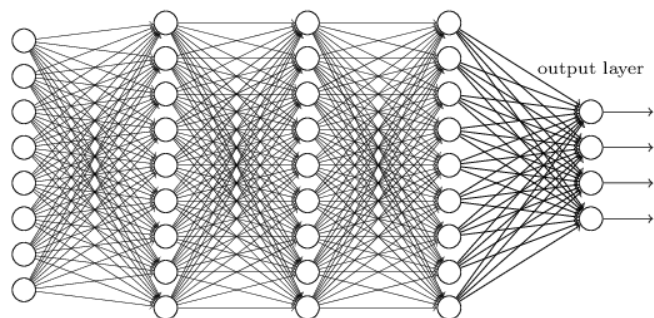


**AI research in computer science journals vs. other application sectors.**



Graph from Cockburn/Henderson/Stern

# DEEP NEURAL NETWORKS

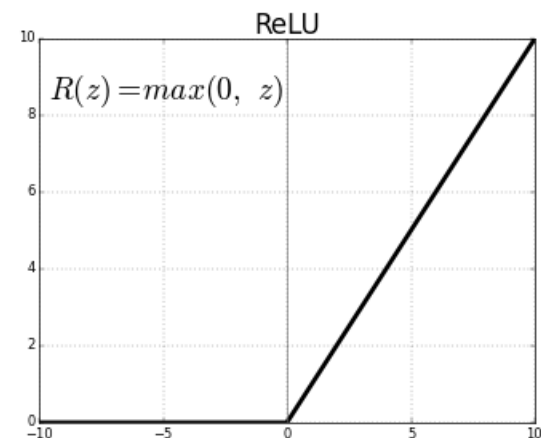
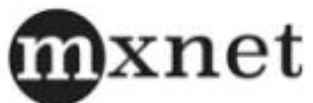


Train faster, generalize better:  
Stability of stochastic gradient descent

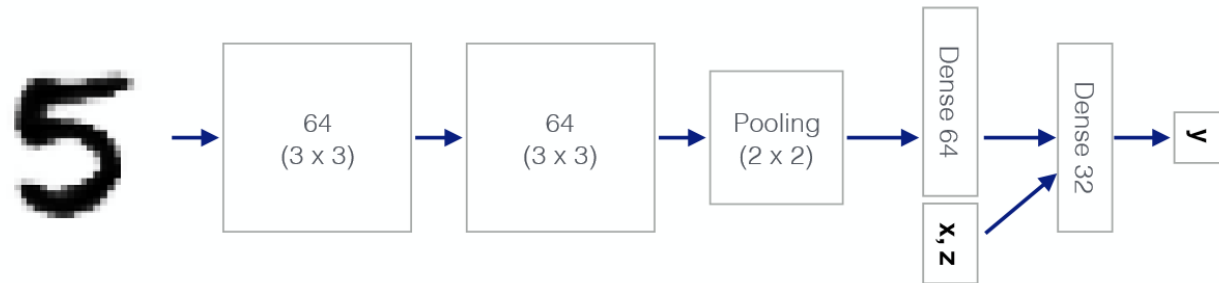
## Adaptive Subgradient Methods for Online Learning and Stochastic Optimization\*

Dropout: A Simple Way to Prevent Neural Networks from  
Overfitting

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

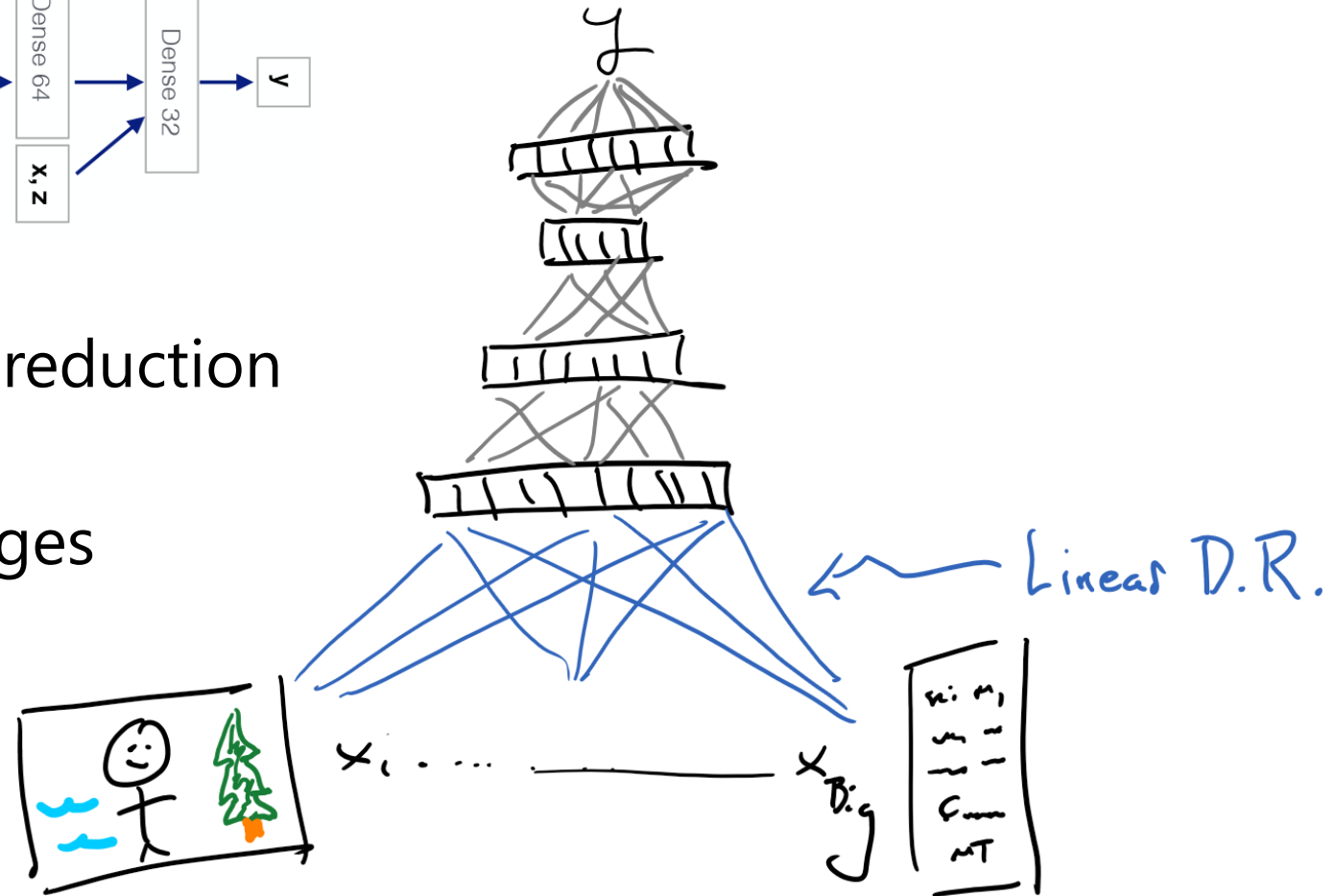


# Deep nets are **not** nonparametric sieves



The 1<sup>st</sup> layer is a big dimension reduction

- word embedding for text
- matrix convolution for images



The learning machine

# Amazon's empire rests on its low-key approach to AI

*Unflashy but high-powered machine learning powers everything from its fulfilment centres to the cloud*



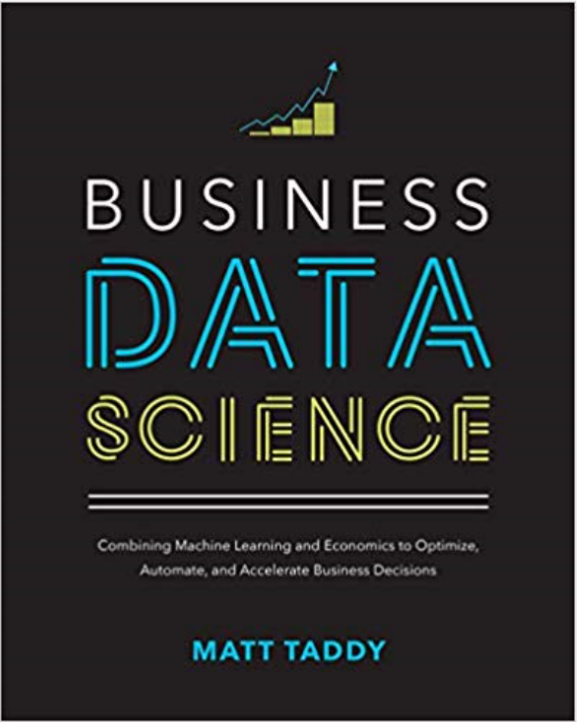
Getty Images

- Key business reviews ask: *How are you using ML?*
- Science and Business break big questions into ML tasks
- Need to answer “Why?”
- AI impacting physical world – boxes, robots, humans!
- Improving ML: Sagemaker, Auto ML, Inferential, CV ...




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