Asian Bureau of Finance and Economic Research
10TH Annual Conference: Corporate Finance (May 22-25, 2023)

Learning Production Process Heterogeneity Across Industries:

Implications of Deep Learning for Corporate M&A Decisions

Jongsub Lee
Seoul National University

Hayong Yun
Michigan State University

Recent Advances in Intelligent Algorithms

- AlphaGo

TECH

AlphaGo Software Storms Back to Beat Human in Final Game

South Korean Go champion Lee Se-dol grabbed a victory from the a
intelligence in fourth game, but couldn't repeat the feat

Science & technology | Artificial intelligence

The latest AI can work things out without being taught

Learning to play Go is only the start

- Deepfake & Generative AI

The Economist explains

What is a deepfake?

Computers can generate convincing representations of events that never happened

FORBES > INNOVATION > AI

AI Gets Creative Thanks To GANs Innovations

- *Transfer Learning*

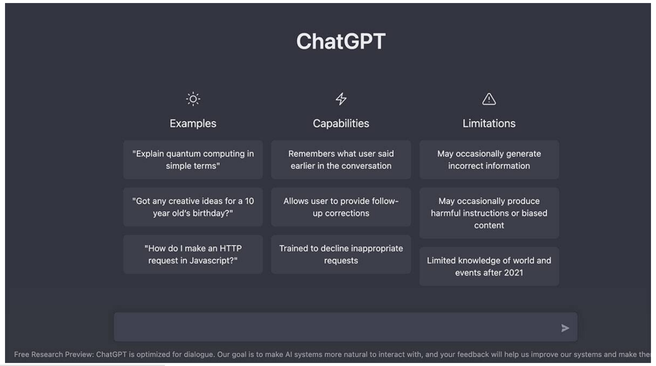
FORBES > INNOVATION

The Promise Of Transfer Learning For Crowd Analytics

FORBES > INNOVATION

Machines Are Learning From Each Other, But It's A Good Thing

- ChatGPT



Business | Intelligence services

Investors are going nuts for ChatGPT-ish artificial intelligence

Even Elon Musk wants his own AI chatbot

Culture | Johnson

ChatGPT is a marvel of multilingualism

It may make things up, but it does so fluently in more than 50 languages

FORBES > INNOVATION > AI

GPT-4 Heralds An Enormous Productivity Boost, And A Wrenching Transformation Of Work

Concerns…

The limits and challenges of deep learning - TechTalks

HDSR

Search Dashboard Login or Sign

The limits and challenges of deep learning

Issu ·· **Published on** Nov 22, 2019 **DOI** 10.1162/99608f92.5a8a3a3d SHOW DETAILS

Why Are We Using Black Box Models in AI When We Don't Need To? A Lesson From an Explainable AI

DOW

COI

WORLDLINE

Ever heard of the AI black box problem?

E

Menu

VentureBeat

Why machine learning struggles with causality

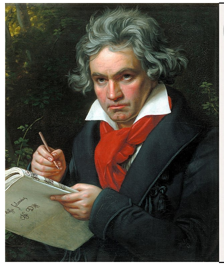
Science & technology | Generative AI

How generative models could go wrong

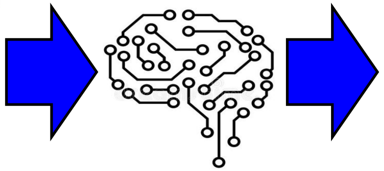
A big problem is that they are black boxes

Despite these concerns, can we make use of recent advances in intelligent algorithms in economics & finance studies?

Analogy: When are blackbox predictors useful?





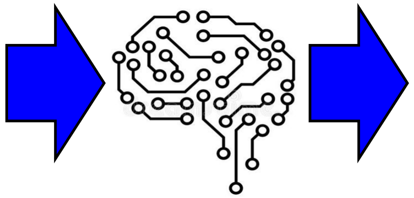



INNOVATION

How Artificial Intelligence Completed Beethoven's Unfinished Tenth Symphony

https://youtu.be/RESb0QVkLcM

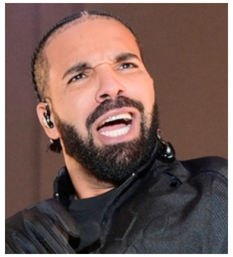


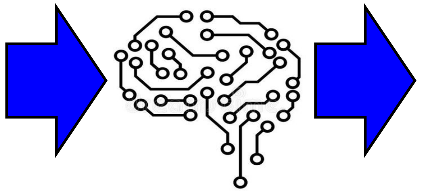

YouTube

Three AI Mozart Pieces -- composed using MuseNet artificial intelligence by OpenAI

https://youtu.be/bRroa-Xip7o







VARIETY AI-Generated Fake 'Drake'/'Weeknd' Collaboration, 'Heart on My Sleeve,' Delights Fans and Sets Off Industry Alarm Bells

Visualizing music similarity: clustering and mapping 500 classical music composers

Research Article
Music Similarity Detection Guided by Deep Learning Model

Research Article
A Music Genre Classification Method Based on Deep Learning

Quantifying a complex process, even with a blackbox, can be useful – measure similarity

Today’s Main Idea: Quantifying Complex I/O Mapping Using A Blackbox

Quantify production process/organization, and measure distances (compare functions).

Retail Firm

Manufacturing Firm

What if a manufacturing firm acquires a retail firm?

Using deterioration of prediction performance as a distance of industry’s production function

Other Application: Generative AI-based Counterfactuals

Wealth

A 32-Year-Old Nears Billionaire Status by Using AI to Broker Japan Mergers

Shunsaku Sagami has built an M&A firm that uses a proprietary database and AI to broker deals for companies whose founders are about to retire.

By Yoojung Lee, Min Jeong Lee and Yasutaka Tamura
May 15, 2023 at 4:00 PM EDT

Shunsaku Sagami saw firsthand the growing succession problem among entrepreneurs in Japan, which is grappling with the world's oldest population.

The 32-year-old's solution: using a proprietary database and artificial intelligence to broker deals for small- and medium-sized companies – largely those founded by clients now on the brink of retirement.

Most Read

Markets
Stock Market Keeps Rallying, Defying Doom Scenarios

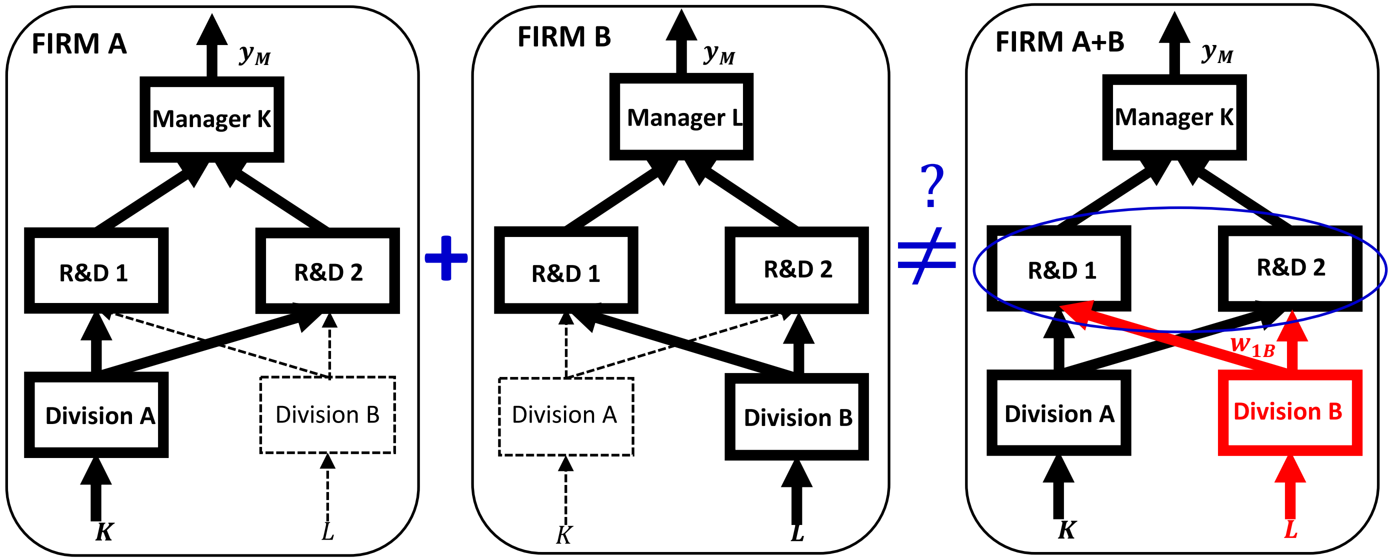
Markets
Hedge Funds' Ultra-Bearish Oil Bets Signal US Recession Angst

Pursuits
Disney Closes Florida Star Wars Hotel, Scraps Plan to Move 2,000 Employees

Business
Morgan Stanley CEO Gorman to Step Down Within 12 Months

Markets
BlackRock's Wei Li Says the 'Goldilocks' Era is Over for Markets

Why Quantify Production Process/Organization?



1. *More load per division*
2. *Accommodation necessary*

BARRON'S

COMPANIES FEATURE

Synergy Is a Myth: Cost-Cutting Breaks Mergers and Acquisitions

Bristol-Myers Squibb (ticker: BMY) claims it can achieve $2.5 billion in cost savings by 2022 from its takeover of biotech firm Celgene (CELG), for which it is paying a whopping $90 billion, including debt. Those equate to around a sixth of the combined operating expenses of the two companies.

The consultancy examined 1,000 of the largest deals among public companies struck during the past 10 years globally and found that the synergy estimates in deals have increased to a new high every year since 2013. In 2017, the synergies announced publicly by acquirers reached 2.1% of combined sales almost twice 2011's level of 1.1%.

Bosses like to boast about synergies because, in theory, they should boost earnings or cash flows of the combined companies by making a target worth more to the acquirer than it is worth on a stand-alone basis. But those who are too optimistic in their ability to cut costs run the risk of accounting write-offs if the economic outlook deteriorates or the merged company fails to deliver on its revenue and cost projections.

According to financial consultancy Duff & Phelps, goodwill impairments increased by 23% to $35.1 billion in 2017 from the previous year, even though the number of impairments remained roughly stable. That suggests some bidders overstated the expected gains from their acquisitions.

Synergy estimates of cost cutting mergers (layoff of duplicate departments) frequently grossly overstated!

Why Half of All M&A Deals Fail, and What You Can Do About It

Forbes Leadership Forum Contributor
News, Commentary, and Advice About Leadership

Most research indicates that M&A activity has an overall success rate of about 50%—basically a coin toss. Chief executives of mid-market companies (generally

Why is M&A success such a crap shoot? The sad fact is that most deals look great on paper, but few organizations pay proper attention to the integration process—

The Three Reasons Why Tech M&A Deals Fail To Deliver Value

Chris Barbin Forbes Councils
Forbes Technology Council CommunityVoice

The failure rate for mergers and acquisitions is a depressing figure, hovering somewhere between 70-90% depending on which study you use. Yet the ones that

Avoid A Culture Clash

Bringing two companies together is not unlike a marriage. Sometimes opposites

Integration teams can play a pivotal role in the first months or year of an acquisition. They make it clear what needs to get done, who's in charge and can

MERGERS & ACQUISITIONS

The Big Idea: The New M&A Playbook

by Clayton M. Christensen, Richard Alton, Curtis Rising, and Andrew Waldeck

Avoiding Integration Mistakes

Your approach to integration should be determined almost entirely by the type of acquisition you've made. If you buy another company for the purpose of improving your current business model's

Risks for Synergies

Synergies are not effective immediately after the merger takes place. Typically, these synergies are realized two or three years after the transaction. This period is known as the "phase in" period, where operational efficiencies, cost savings, and incremental new revenues are slowly absorbed into the newly merged firm.

Integration is pivotal for synergy!

Related Literature

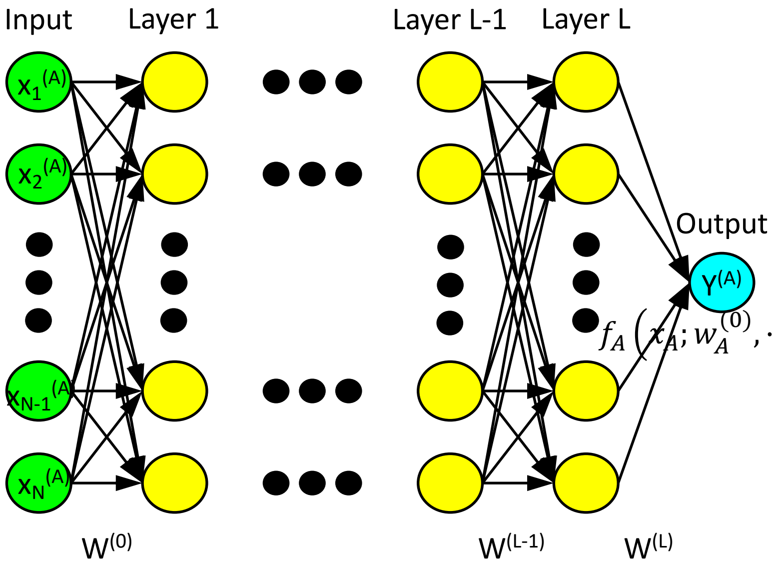
- **Merger theory and cross-industry merger dynamics**
  - Jovanovic and Rousseau, 2001, 2002; Rhodes-Kropf and Robinson, 2008.
  - Harford, 2005; Hoberg and Phillips, 2010, 2016; Hoberg, Phillips, and Prabhala, 2014; Ahern, 2012; Ahern and Harford, 2014.
  - We offer a dynamic view of how firm boundary is reconfigured and influences corporate value and operating performance.
  - We also supplement the important product-based industry classifications pioneered by Hoberg, Phillips, and Prabhala (2014) by providing a novel approach to quantify production process (comparing functions; focus on inner workings of firms) (dis)similarity between a pair of industries under the conventional industry classifications (e.g., SIC, FF).

- **Firm boundary and organizational capital**
  - Grossman & Hart, 1986; Hart, 1988; Hart & Moor, 1990; Bolton & Dewatripont, 1994; Hart & Holmstrom, 2010; Baker, Gibbons & Murphy, 2002
  - Sah and Stiglitz, 1986; Dessein, 2002; Dessein and Santos, 2006
  - We relate organizational capital as latent factors of the underlying decision-making process of a firm in making corporate M&A decisions.

- **Merger synergy and post-merger integration efficiency**
  - Devos, Kadapakkam, and Krishnamurthy, 2008; Hoberg and Phillips, 2010; Deng, Kang, and Low, 2013
  - We examine dynamic integration process and its performance implications.

Industry Distance

Step 1. Train Network for Acquiror Industry (A)



$f_A\left(x_A; w_A^{(0)}, \cdots, w_A^{(L)}\right) = \hat{y}_A$

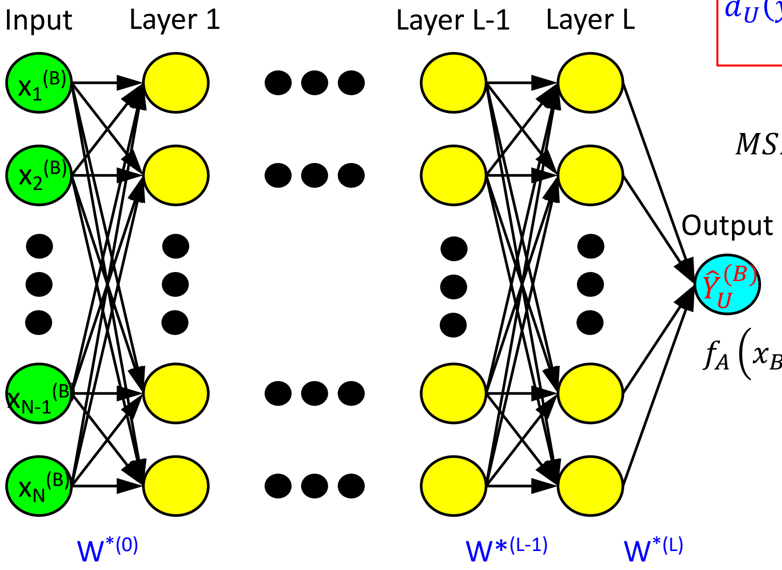
- In: log(A), CPX/A, STD/A, LTD/A, EMP/A, PPE/A, ADV/A, RD/A
- Out: log(Q)

Step 2. Test Network for Target Industry (B)

[Measure 1] Unadjusted Distance

$$d_U(y_A, y_B) = \frac{MSE\left(\hat{y}_{U,B}, y_B; w_A^{(0)}, \cdots, w_A^{(L)}\right)}{MSE\left(\hat{y}_B, y_B; w_B^{(0)}, \cdots, w_B^{(L)}\right)}$$

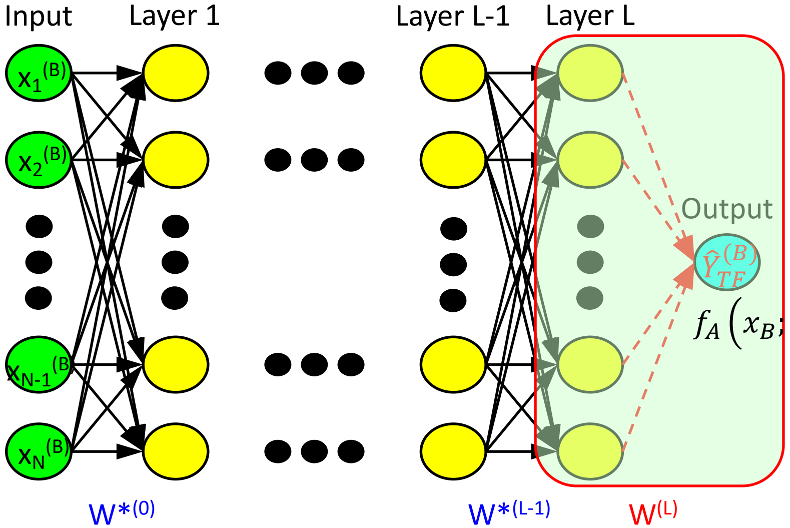
$$MSE\left(x_B; w_A^{(0)}, \cdots, w_A^{(L)}\right) = \sqrt{\frac{1}{N}\sum_{j=1}^{N}\left(y_{B,j} - \hat{y}_{U,B,j}\right)^2}$$



$f_A\left(x_B; w_A^{(0)}, \cdots, w_A^{(L)}\right) = \hat{y}_{U,B}$

[Measure 2] Transfer Learning-Based Distance

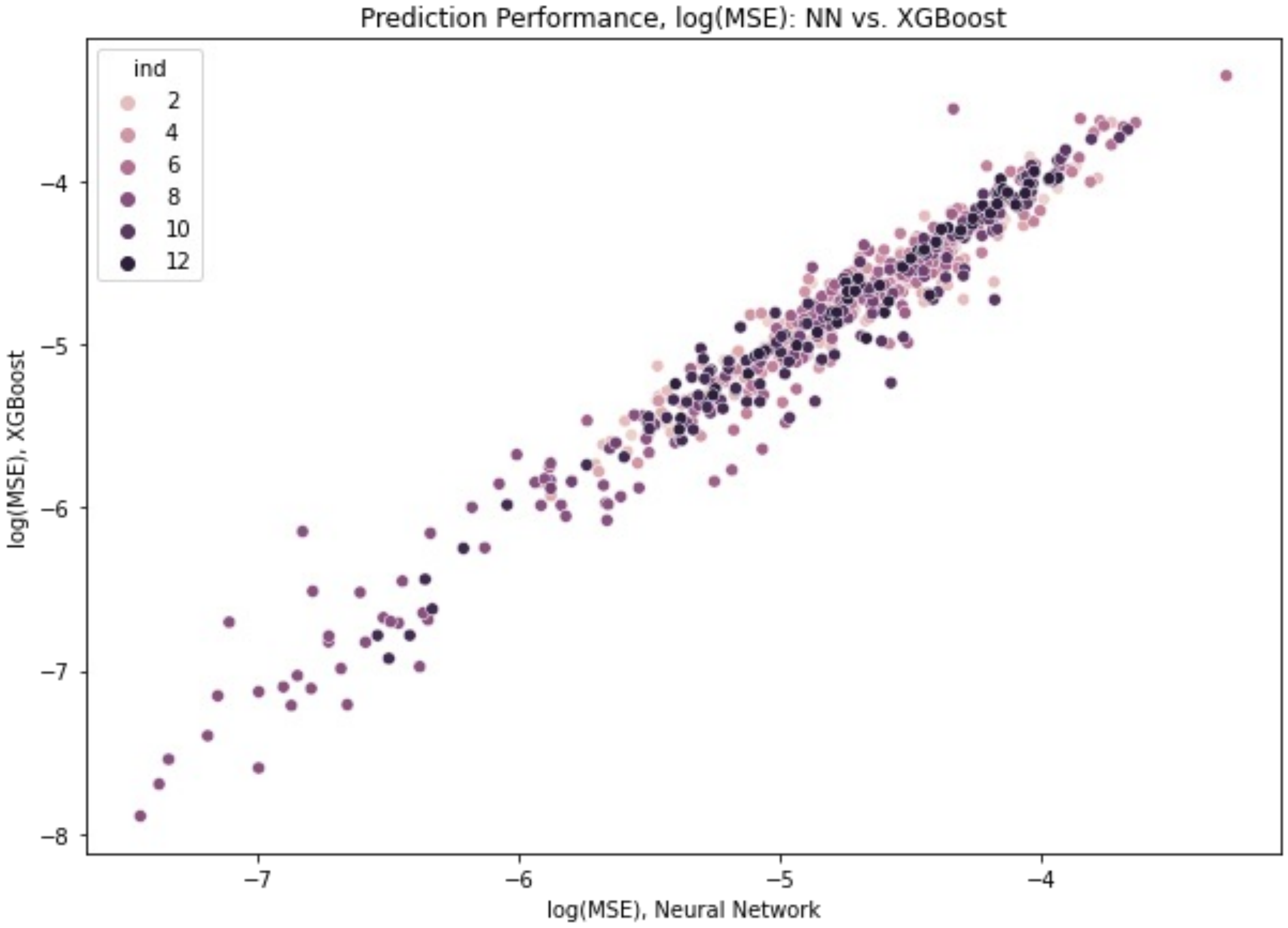
$$d_{TF}(y_A, y_B) = \frac{MSE\left(\hat{y}_{TF,B}, y_B; w_A^{(0)}, \cdots, w_A^{(L-1)}, w_B^{(L)}\right)}{MSE\left(\hat{y}_B, y_B; w_B^{(0)}, \cdots, w_B^{(L)}\right)}$$



$f_A\left(x_B; w_A^{(0)}, \cdots, w_B^{(L)}\right) = \hat{y}_{TF,B}$

Example

Fitting Production Function, log(MSE): Neural Network vs. XGBoost (Figure 1)



For each FF12 industry in each year (1970-2021), we train by NN or XGBoost (10-fold cross validation) and report MSE or log(MSE) by each method.

Table 1. Summary Statistics

Panel A. Industry Pair-Year Data (1990-2021)						
Variables	N	Mean	Std. Dev.	p5	Median	p95
Unadjsuted Distance	4608	1.320	0.278	1.000	1.266	1.785
TF Distance	4608	1.285	0.214	1.074	1.219	1.715
log(Unadjusted Distance)	4608	0.261	0.173	0.000	0.236	0.580
log(TF Distance)	4608	0.239	0.149	0.071	0.198	0.540
Number of M&A Deals	4608	65	208	0	9	295
log(Number of M&A Deals)	4608	2.433	1.731	0.000	2.303	5.690

- Input layer: the logarithm of total assets, capital expenditures divided by assets, short-term debt divided by assets, long-term debt divided by assets, employees divided by assets, tangible assets divided by assets, advertisement expense divided by assets, and R&D expense divided by assets.
- Output layer: the logarithm of Tobin's Q and utilizes a linear activation function.
- All variables are deviation from industry average in each year.
- Each industry distance measures are average of ten estimates.
- e.g., Telcm-BusEq=0.101, Telcm-Money=0.218

	TNIC3 Score	log(Unadjusted Distance)	log(TF Distance)
log(Unadjusted Distance)	-0.1046*		
log(TF Distance)	-0.0744*	0.5370*	
log(XGB Distance)	-0.2094*	0.6275*	0.2355*

* denote significance at the 1% level.

Table 2. M&A Activities (Year-By-Year: 1990 - 2021)

Year	Log(Unadjusted Distance)		log(TF Distance)		Year	Log(Unadjusted Distance)		log(TF Distance)	
	Estimate	t-stat	Estimate	t-stat		Estimate	t-stat	Estimate	t-stat
	(I)	(II)	(III)	(IV)		(I)	(II)	(III)	(IV)
1990	-4.819***	[-6.82]	-3.844***	[-5.07]	2006	-3.545***	[-3.71]	-4.015***	[-4.21]
1991	-3.007***	[-4.59]	-4.264***	[-4.57]	2007	-3.374***	[-3.86]	-4.235***	[-4.10]
1992	-2.917***	[-3.80]	-4.531***	[-4.63]	2008	-2.278***	[-4.50]	-2.172***	[-3.73]
1993	-2.258***	[-2.99]	-6.706***	[-6.27]	2009	-4.346***	[-5.05]	-3.722***	[-4.72]
1994	-2.595***	[-3.16]	-6.334***	[-5.66]	2010	-3.577***	[-4.11]	-3.741***	[-4.41]
1995	-1.438**	[-2.14]	-5.948***	[-4.99]	2011	-3.957***	[-5.32]	-2.990***	[-4.26]
1996	-4.134***	[-4.73]	-6.277***	[-6.07]	2012	-3.770***	[-4.41]	-3.693***	[-4.34]
1997	-4.864***	[-5.00]	-7.631***	[-5.23]	2013	-2.402***	[-3.28]	-5.264***	[-5.91]
1998	-5.420***	[-5.99]	-7.839***	[-6.53]	2014	-2.937***	[-3.81]	-4.018***	[-4.95]
1999	-2.195***	[-3.26]	-7.360***	[-6.62]	2015	-1.862**	[-2.27]	-3.244***	[-3.37]
2000	-5.134***	[-5.53]	-5.492***	[-5.01]	2016	-2.716***	[-3.51]	-2.722***	[-3.79]
2001	-2.930***	[-5.08]	-4.064***	[-5.50]	2017	-0.984	[-1.02]	-3.095***	[-2.84]
2002	-7.227***	[-7.37]	-4.425***	[-4.70]	2018	-2.709***	[-2.76]	-4.032***	[-4.02]
2003	-5.641***	[-5.40]	-3.879***	[-3.44]	2019	-1.848**	[-2.27]	-4.189***	[-4.54]
2004	-5.051***	[-5.27]	-4.682***	[-4.75]	2020	-1.513*	[-1.91]	-3.537***	[-4.02]
2005	-3.378***	[-3.20]	-4.535***	[-4.09]	2021	-1.122	[-1.24]	-5.251***	[-4.53]

***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Number of M&A Deals (FF12 Pair-Level; Table 3, Table 6, Table 5)

Dependent Variable	log(Number of M&A Deals)				
	Table 3 (V)	Table 3 (VI)	Table 6 (III)	Table 5 (III)	Table 5 (VI)
TNIC3 Score				8.596**	10.910***
				[2.67]	[2.97]
log(Unadjusted Distance)	-4.620***		-4.519***	-4.564***	
	[-18.97]		[-18.01]	[-17.09]	
log(TF Distance)		-4.132***	-0.571		-4.019***
		[-17.35]	[-1.20]		[-16.15]
log(Unadjusted Distance)			-4.140**		
x log(TF Distance) Residual			[-2.10]		
Intercept	3.279***	3.120***	3.260***	3.027***	2.789***
	[47.00]	[42.27]	[43.60]	[21.73]	[19.13]
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Observations	4,608	4,608	4,608	4,300	4,300
R-squared	0.511	0.444	0.533	0.521	0.454

Sample Period: 1990-2021 (Tables 3,6), 1990-2019 (Table 5).
Standard errors are clustered at the year level.
***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Likelihood of Deal Completion (Table 4, Deal-Level)

Dependent Variable	Indicator for Deal Completion							
	All Deals				Public Acquiror		Acquiror & Target Public	
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
log(Unadjusted Distance)	-0.401***		-0.322***		-0.316**		-0.563	
	[-4.34]		[-3.45]		[-2.02]		[-1.40]	
log(TF Distance)		-0.438***		-0.433***		-0.460**		-1.013**
		[-3.38]		[-3.75]		[-2.30]		[-2.15]
Model	Probit	Probit	Probit	Probit	Probit	Probit	Probit	Probit
Public Acquiror					Yes	Yes	Yes	Yes
Public Target							Yes	Yes
Year FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	No	No	Yes	Yes	Yes	Yes
Pseudo R2	0.046	0.045	0.060	0.060	0.081	0.080	0.157	0.157
Observations	35,613	35,613	35,613	35,613	12,365	12,365	3,304	3,304

Other Controls: Diversify, Hostile, High Tech, Tender Offer, Stock Deal, Relative Deal Size (Columns I,II,III,IV); Plus Acquiror Firm Size, Tobin's Q Book Leverage, Cash Flow-To-Asset (Columns V, VI); Plus Target Firm Size, Tobin's Q Book Leverage, Cash Flow-To-Asset (Columns VII, VIII).

Standard errors are clustered at the year level. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively

Announcement Effects (Table 9) & Ex-Post Survival (Table 10)

Dependent Variable	Anouncement Effect CAR(t-1 to t+1)		Anouncement Effect CAR(t-1 to t+1)		Survival Analysis Survival Indicator (t+2)	
	Table 9 (III)	Table 9 (IV)	Table 9 (V)	Table 9 (VI)	Table 10 (III)	Table 10 (IV)
log(Unadjusted Distance)	-0.184**		-0.055**		-0.556***	
	[-2.55]		[-2.09]		[-4.32]	
log(TF Distance)		-0.359***		-0.044*		-0.622***
		[-3.08]		[-1.83]		[-2.75]
Model	Linear	Linear	Probit	Probit	Probit	Probit
Acquiror-Target Weighting	Equal	Equal	Value	Value		
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,003	1,003	1,003	1,003	14,666	14,666
(Pseudo) R-squared	0.196	0.199	0.141	0.138	0.034	0.033

Other Controls: Merger Completed, Diversify, Hostile, High Tech, Tender Offer, Stock Deal, Relative Deal Size; Acquiror Firm Size, Tobin's Q Book Leverage, Cash Flow-To-Asset; Target Firm Size, Tobin's Q Book Leverage, Cash Flow-To-Asset.

Standard errors are clustered at the year level. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively

Robustness

- Alternative specifications: ROA-Based Distances (Table 7, Table 8)
- Alternative fitting model: XGBoost (Table 11, Table 12, Table 13)
- Exclude Self-Industry Pairs (Table 12)

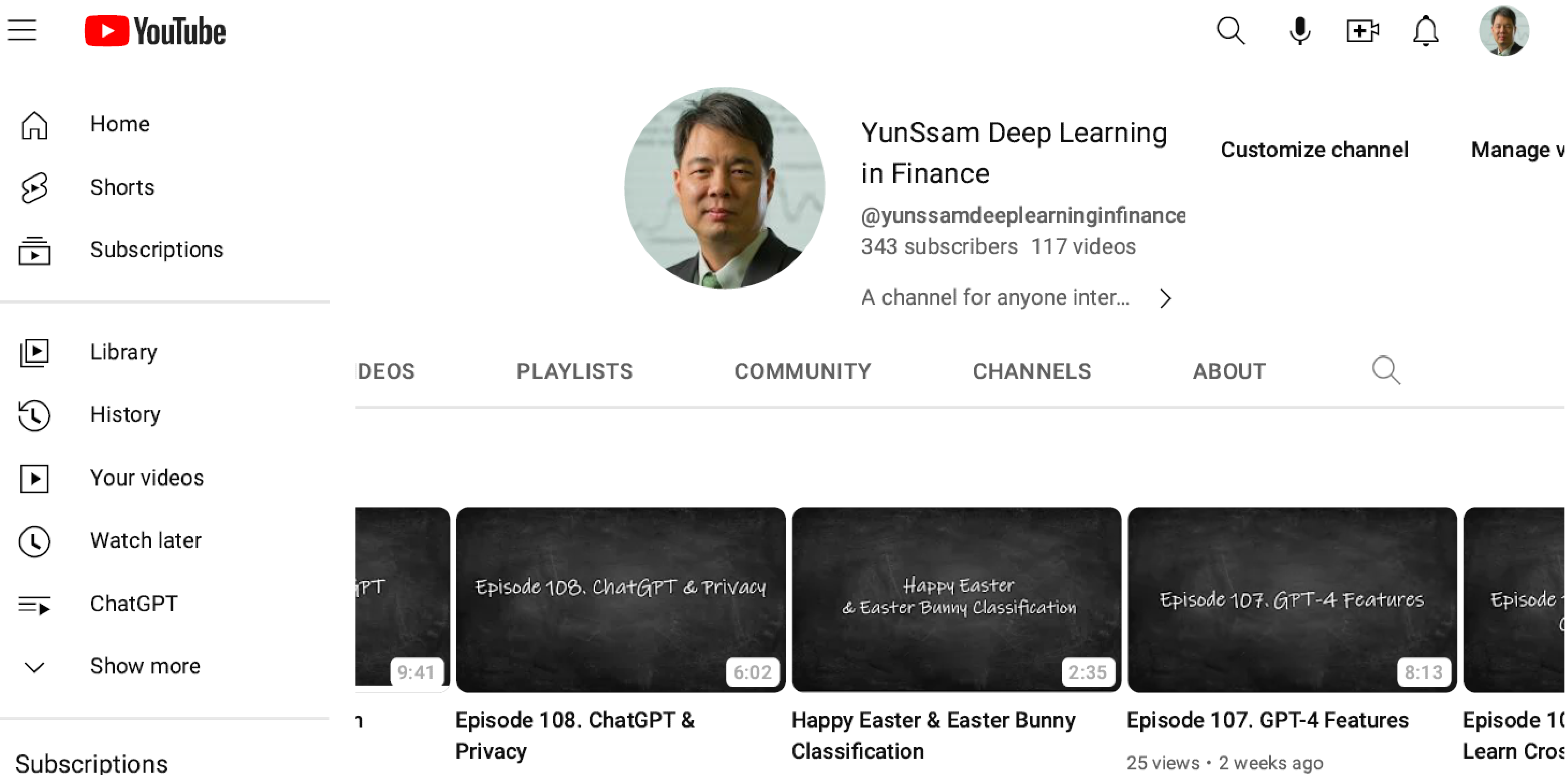
Conclusions

- New measure of industry distance by incorporating recent AI-based algorithms in econometrics
  - Our measure captures the differences in the underlying production processes across industries
  - Using both canonical and transfer-learning-based deep learning techniques, our measure helps compare the layer-level differences between two industries' production decision-making processes.
  - This novel approach is both economically and computationally meaningful.

- We show that the cost of integration of merged organizations is important in explaining likelihood of mergers and the post-merger survival of the new organization.
  - Our economically motivated industry distances tend to better capture the economic outcomes of cross-industry M&A activities.

- Future Applications: task similarity (labor skills), bundling products, legal environment

Additional Slides


YouTube
Home
Shorts
Subscriptions
Library
History
Your videos
Watch later
ChatGPT
Show more
Subscriptions
YunSsam Deep Learning in Finance
@yunssamdeeplearninginfinance
343 subscribers 117 videos
A channel for anyone inter...
Customize channel
Manage v
IDEOS
PLAYLISTS
COMMUNITY
CHANNELS
ABOUT
9:41
Episode 108. ChatGPT & Privacy
6:02
Happy Easter & Easter Bunny Classification
2:35
Episode 107. GPT-4 Features
8:13
Episode 108. ChatGPT & Privacy
Happy Easter & Easter Bunny Classification
Episode 107. GPT-4 Features
25 views • 2 weeks ago
Episode 1(
Learn Cros

Transfer Learning

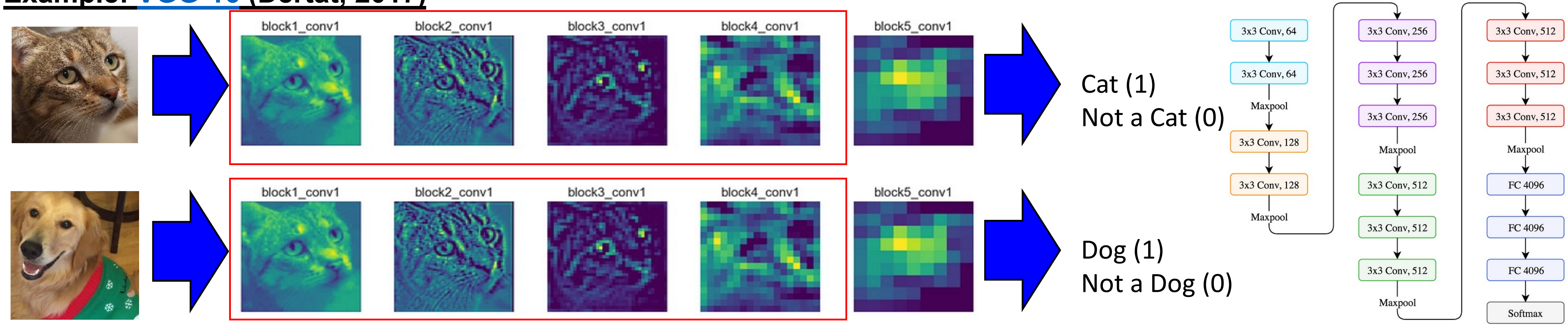
Definition

Transfer learning and domain adaptation refer to the situation where what has been learned in one setting … is exploited to improve generalization in another setting (Ian Goodfellow, Yoshua Bengio, Aaron Courville, 2016, *Deep Learning*, Page 526). i.e., Transfer learning is the improvement of learning in a new task through the transfer of knowledge from a related task that has already been learned (e.g., save training time).

How does it work?

First train a base network on a base dataset and task, and then we repurpose the learned features, or transfer them, to a second target network to be trained on a target dataset and task.

Example: VGG-16 (Dertat, 2017)



Jacot et.al (2018) on Neural Tangent Kernel; Roberts and Yaida (2022).

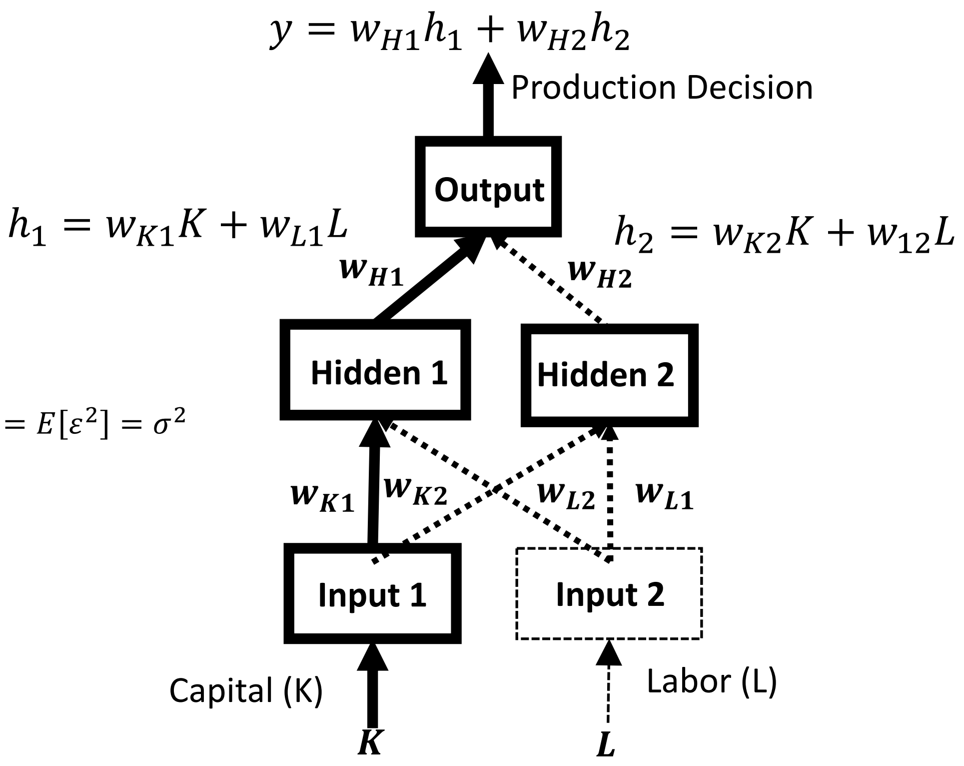
Applications

LLMs like Google's word2vec, BERT, OpenAI's GPTs.

Back

Simple Example: Unadjusted vs. TF Distance

(Two-Factor Linear Output Production)



e.g., Production Function for Baseline

$w_1^* = \{w_{K1}, w_{K2}, w_{L1}, w_{L2}, w_{H1}, w_{H2}\} = \{1,0,0,0,1,0\}$

$$MSE_U = E\left[\int_0^1\int_0^1 \left(y(K,L;w_1^*) - y_1(K,L)\right)^2 dK\,dL\right] = E\left[\int_0^1\int_0^1 \left(K-(K+\varepsilon)\right)^2 dK\,dL\right] = E\left[\int_0^1\int_0^1 \varepsilon^2 dK\,dL\right] = E[\varepsilon^2] = \sigma^2$$

$$MSE_{NTF,12} = E\left[\int_0^1\int_0^1 (4K^2 - 4K\varepsilon + \varepsilon^2)dK\,dL\right] = E\left[\frac{4}{3} - 2\varepsilon + \varepsilon^2\right] = \frac{4}{3} + \sigma^2.$$

$$MSE_{NTF,13} = E\left[\int_0^1\int_0^1 \left(K-(L+\varepsilon)\right)^2 dK\,dL\right] = E\left[\int_0^1 \left(\frac{4}{3} + L^2 + \varepsilon^2 - L + \varepsilon - 2L\varepsilon\right) dL\right] = \frac{13}{6} + \sigma^2$$

Industry	Production Function	MSE Unadjusted	MSE Transfer Learning
1. Baseline	$y_1(K,L) = K + \varepsilon$	σ^2	σ^2
2. Same Factor	$y_2(K,L) = -K + \varepsilon$	$\frac{4}{3} + \sigma^2$	σ^2
3. Different Factor	$y_3(K,L) = L + \varepsilon$	$\frac{13}{6} + \sigma^2$	$\frac{4}{3} + \sigma^2$

Back

Table 3. M&A Activities (Industry Pair-Year Panel: 1990-2021)

Dependent Variable	log(Number of M&A Deals)					
	(I)	(II)	(III)	(IV)	(V)	(VI)
log(Unadjusted Distance)	-2.962***		-3.000***		-4.620***	
	[-13.85]		[-13.76]		[-18.97]	
log(TF Distance)		-4.137***		-4.157***		-4.132***
		[-15.83]		[-16.38]		[-17.35]
Intercept	3.206***	3.420***	3.216***	3.425***	3.279***	3.120***
	[54.76]	[51.70]	[56.48]	[56.55]	[47.00]	[42.27]
Year FE	No	No	Yes	Yes	Yes	Yes
Industry FE	No	No	No	No	Yes	Yes
Observations	4,608	4,608	4,608	4,608	4,608	4,608
R-squared	0.087	0.126	0.097	0.132	0.511	0.444

Back

Table 5. Hoberg-Phillips TNIC3 Score (1990-2019)

Panel A. Correlations

	TNIC3 Score	log(Unadjusted Distance)
log(Unadjusted Distance)	-0.1046*	
log(TF Distance)	-0.0744*	0.5370*

Panel C. Panel Regression For log(NumDeal)

Dependent Variable	log(Number of M&A Deals)					
	(I)	(II)	(III)	(IV)	(V)	(VI)
TNIC3 Score	12.132***	12.467**	8.596**	12.547***	12.811***	10.910***
	[2.81]	[2.73]	[2.67]	[2.89]	[2.80]	[2.97]
log(Unadjusted Distance)	-2.938***	-2.963***	-4.564***			
	[-13.79]	[-13.79]	[-17.09]			
log(TF Distance)				-4.000***	-3.997***	-4.019***
				[-14.37]	[-14.87]	[-16.15]
Intercept	2.835***	2.831***	3.027***	3.008***	2.999***	2.789***
	[18.09]	[17.20]	[21.73]	[18.84]	[18.01]	[19.13]
Year FE	No	Yes	Yes	No	Yes	Yes
Industry FE	No	No	Yes	No	No	Yes
Observations	4,300	4,300	4,300	4,300	4,300	4,300
R-squared	0.117	0.128	0.521	0.150	0.156	0.454

Back

Table 6. M&A Activities (Industry Pair-Year Panel: 1990-2021): Interaction Between Distance Measures

Dependent Variable	log(Number of M&A Deals)		
	(I)	(II)	(III)
log(Unadjusted Distance)	-2.832***	-2.872***	-4.519***
	[-14.11]	[-14.07]	[-18.01]
log(TF Distance) Residual	0.365	0.312	-0.571
	[0.65]	[0.57]	[-1.20]
log(Unadjusted Distance)	-7.097***	-6.929***	-4.140**
x log(TF Distance) Residual	[-3.03]	[-3.00]	[-2.10]
Intercept	3.172***	3.183***	3.260***
	[53.79]	[59.73]	[43.60]
Year FE	No	Yes	Yes
Industry FE	No	No	Yes
Observations	4,608	4,608	4,608
R-squared	0.118	0.126	0.533

Back

Table 7. An Alternative Specification for Industry Distance: M&A Activities (Industry Pair-Year Panel: 1990-2021)

Panel A. FF12 Industry Pair-Year Panel

Dependent Variable	log(Number of M&A Deals)					
	(I)	(II)	(III)	(IV)	(V)	(VI)
ROA-Based log(Unadjusted Distance)	-1.860***		-1.927***		-2.618***	
	[-17.84]		[-18.84]		[-20.95]	
ROA-Based log(TF Distance)		-2.894***		-3.036***		-2.992***
		[-8.42]		[-8.92]		[-9.70]
Intercept	3.161***	3.221***	3.187***	3.260***	2.996***	2.942***
	[60.82]	[36.48]	[79.56]	[35.17]	[42.56]	[30.03]
Year FE	No	No	Yes	Yes	Yes	Yes
Industry FE	No	No	No	No	Yes	Yes
Observations	4,608	4,608	4,608	4,608	4,608	4,608
R-squared	0.097	0.091	0.109	0.102	0.487	0.414

Back

Panel B. SDC Platinum M&A Data (Dependent Variable: Deal Completed Indicator)

Dependent Variable	Indicator for Deal Completion							
	All Deals				Public Acquiror		quiror & Target Pul	
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
ROA-Based log(Unadjusted Distance)	-0.257***		-0.219***		-0.268**		-0.306	
	[-4.35]		[-3.32]		[-2.48]		[-1.39]	
ROA-Based log(TF-Distance)		-0.323***		-0.278***		-0.297		-0.918***
		[-4.23]		[-3.57]		[-1.52]		[-2.79]
Model	Probit	Probit	Probit	Probit	Probit	Probit	Probit	Probit
Public Acquiror					Yes	Yes	Yes	Yes
Public Target							Yes	Yes
Year FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	No	No	Yes	Yes	Yes	Yes
Observations	35,615	35,615	35,615	35,615	12,378	12,378	3,318	3,318

Back

Table 8. An Alternative Specification for Industry Distance: Hoberg-Phillips TNIC3 Score (1990-2019)

Panel A. Correlations

	TNIC3 Score	ROA-Based log(Unadjusted Distance)
ROA-Based log(Unadjusted Distance)	-0.0717*	
ROA-Based log(TF Distance)	-0.0489*	0.5902*

Panel C. log(NumDeal) Regression

Dependent Variable	log(Number of M&A Deals)					
	(I)	(II)	(III)	(IV)	(V)	(VI)
TNIC3 Score	12.868***	13.104***	9.203***	13.502***	13.733***	11.929***
	[3.02]	[2.92]	[2.94]	[2.93]	[2.85]	[3.02]
ROA-Based log(Unadjusted Distance)	-1.829***	-1.894***	-2.588***			
	[-18.73]	[-19.92]	[-20.30]			
ROA-Based log(TF Distance)				-2.758***	-2.882***	-2.867***
				[-7.81]	[-8.22]	[-8.96]
Intercept	2.762***	2.780***	2.735***	2.777***	2.804***	2.579***
	[19.42]	[19.10]	[20.57]	[16.87]	[15.82]	[16.00]
Year FE						
Industry FE						
Observations	4,300	4,300	4,300	4,300	4,300	4,300
R-squared	0.124	0.137	0.495	0.115	0.127	0.423

Back

Table 9. M&A Announcement Effect (SDC Platinum Deal Level: 1990-2021)

Dependent Variable	CAR(t-1 to t)		CAR(t-1 to t+1)		CAR(t-1 to t+1)	
	(I)	(II)	(III)	(IV)	(V)	(VI)
log(Unadjusted Distance)	-0.155**		-0.184**		-0.055**	
	[-2.34]		[-2.55]		[-2.09]	
log(TF Distance)		-0.142		-0.359***		-0.044*
		[-1.57]		[-3.08]		[-1.83]
Acquiror-Target Weighting	Equal	Equal	Equal	Equal	Value	Value
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,235	1,235	1,003	1,003	1,003	1,003
R-squared	0.126	0.124	0.196	0.199	0.141	0.138

Back

Table 10. Post-Merger Real Effects (SDC Platinum Deal Level: 1990-2021): Post-Merger Acquiror Survival

Sample	All Deals				Deals with Public Acquirors				:als with Public Acquirors-Public Tar;			
Forecast Horizon	t+1	t+1	t+2	t+2	t+1	t+1	t+2	t+2	t+1	t+1	t+2	t+2
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)	(X)	(XI)	(XII)
log(Unadjusted Distance)	-0.646***		-0.556***		-0.410*		-0.394***		0.633		-0.059	
	[-3.34]		[-4.32]		[-1.92]		[-2.66]		[1.35]		[-0.17]	
log(TF Distance)		-0.709***		-0.622***		-0.673**		-0.624**		0.242		-0.258
		[-2.85]		[-2.75]		[-2.35]		[-2.47]		[0.34]		[-0.47]
Model	Probit	Probit	Probit	Probit	Probit	Probit	Probit	Probit	Probit	Probit	Probit	Probit
Public Acquiror	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Public Target	No	No	No	No	No	No	No	No	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R2	0.037	0.036	0.034	0.033	0.063	0.064	0.058	0.058	0.137	0.136	0.113	0.113
Observations	14,939	14,939	14,666	14,666	11,493	11,493	11,266	11,266	2,935	2,935	3,130	3,130

Back

Table 11. Alternative Specification (XGBoost)

Year	Log(Unadjusted Distance)		log(TF Distance)		log(XGB Distance)	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
	(I)	(II)	(III)	(IV)	(V)	(VI)
1990	-4.819***	[-6.82]	-3.844***	[-5.07]	-2.939***	[-9.03]
1991	-3.007***	[-4.59]	-4.264***	[-4.57]	-2.739***	[-8.81]
1992	-2.917***	[-3.80]	-4.531***	[-4.63]	-3.033***	[-9.33]
1993	-2.258***	[-2.99]	-6.706***	[-6.27]	-2.703***	[-7.72]
1994	-2.595***	[-3.16]	-6.334***	[-5.66]	-3.015***	[-8.03]
1995	-1.438**	[-2.14]	-5.948***	[-4.99]	-3.092***	[-8.05]
1996	-4.134***	[-4.73]	-6.277***	[-6.07]	-3.282***	[-8.47]
1997	-4.864***	[-5.00]	-7.631***	[-5.23]	-3.363***	[-8.23]
1998	-5.420***	[-5.99]	-7.839***	[-6.53]	-3.124***	[-8.71]
1999	-2.195***	[-3.26]	-7.360***	[-6.62]	-2.552***	[-6.75]
2000	-5.134***	[-5.53]	-5.492***	[-5.01]	-2.785***	[-7.39]
2001	-2.930***	[-5.08]	-4.064***	[-5.50]	-2.676***	[-7.83]
2002	-7.227***	[-7.37]	-4.425***	[-4.70]	-2.821***	[-7.06]
2003	-5.641***	[-5.40]	-3.879***	[-3.44]	-3.229***	[-8.50]
2004	-5.051***	[-5.27]	-4.682***	[-4.75]	-3.097***	[-7.84]
2005	-3.378***	[-3.20]	-4.535***	[-4.09]	-3.031***	[-8.07]

Year	Log(Unadjusted Distance)		log(TF Distance)		log(XGB Distance)	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
	(I)	(II)	(III)	(IV)	(V)	(VI)
2006	-3.545***	[-3.71]	-4.015***	[-4.21]	-2.526***	[-6.46]
2007	-3.374***	[-3.86]	-4.235***	[-4.10]	-2.676***	[-6.20]
2008	-2.278***	[-4.50]	-2.172***	[-3.73]	-3.198***	[-8.32]
2009	-4.346***	[-5.05]	-3.722***	[-4.72]	-2.065***	[-5.32]
2010	-3.577***	[-4.11]	-3.741***	[-4.41]	-1.872***	[-5.03]
2011	-3.957***	[-5.32]	-2.990***	[-4.26]	-2.375***	[-6.89]
2012	-3.770***	[-4.41]	-3.693***	[-4.34]	-2.738***	[-7.90]
2013	-2.402***	[-3.28]	-5.264***	[-5.91]	-2.627***	[-7.35]
2014	-2.937***	[-3.81]	-4.018***	[-4.95]	-2.470***	[-6.97]
2015	-1.862**	[-2.27]	-3.244***	[-3.37]	-2.642***	[-7.02]
2016	-2.716***	[-3.51]	-2.722***	[-3.79]	-2.870***	[-7.72]
2017	-0.984	[-1.02]	-3.095***	[-2.84]	-1.989***	[-5.85]
2018	-2.709***	[-2.76]	-4.032***	[-4.02]	-2.054***	[-5.25]
2019	-1.848**	[-2.27]	-4.189***	[-4.54]	-2.185***	[-6.00]
2020	-1.513*	[-1.91]	-3.537***	[-4.02]	-2.548***	[-6.15]
2021	-1.122	[-1.24]	-5.251***	[-4.53]	-2.405***	[-6.09]

Back

Table 12. Alternative Specification (XGBoost) & Robustness (FF12 Pair level)

Dependent Variable	log(Number of M&A Deals)					
Sample	Full Sample			Exclude Self FF12 Pair		
	(VII)	(VIII)	(IX)	(VII)	(VIII)	(IX)
log(Unadjusted Distance)	-4.620***			-2.306***		
	[-18.97]			[-14.68]		
log(TF Distance)		-4.132***			-3.635***	
		[-17.35]			[-17.56]	
log(XGB Distance)			-2.951***			-1.512***
			[-51.54]			[-12.63]
Intercept	3.279***	3.120***	2.442***	2.445***	2.707***	2.111***
	[47.00]	[42.27]	[59.83]	[41.44]	[40.91]	[49.72]
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,608	4,608	4,608	4,224	4,224	4,224
R-squared	0.511	0.444	0.628	0.509	0.585	0.483

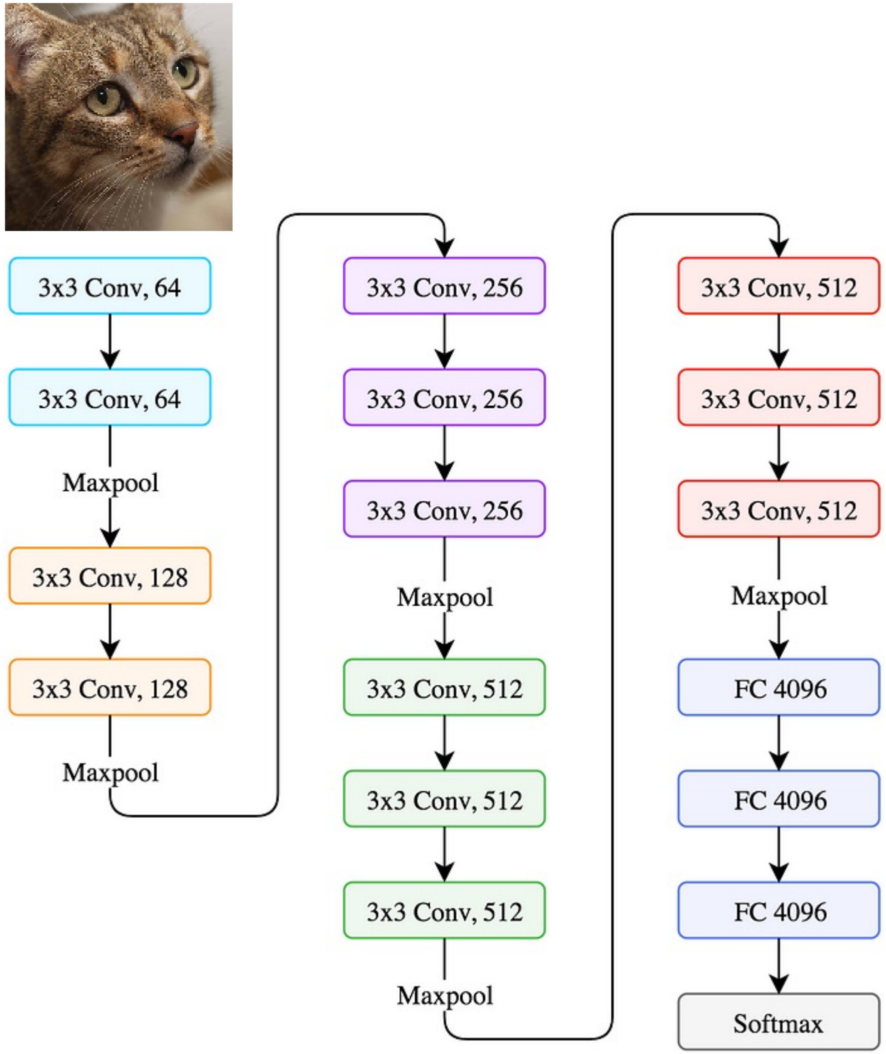
Back

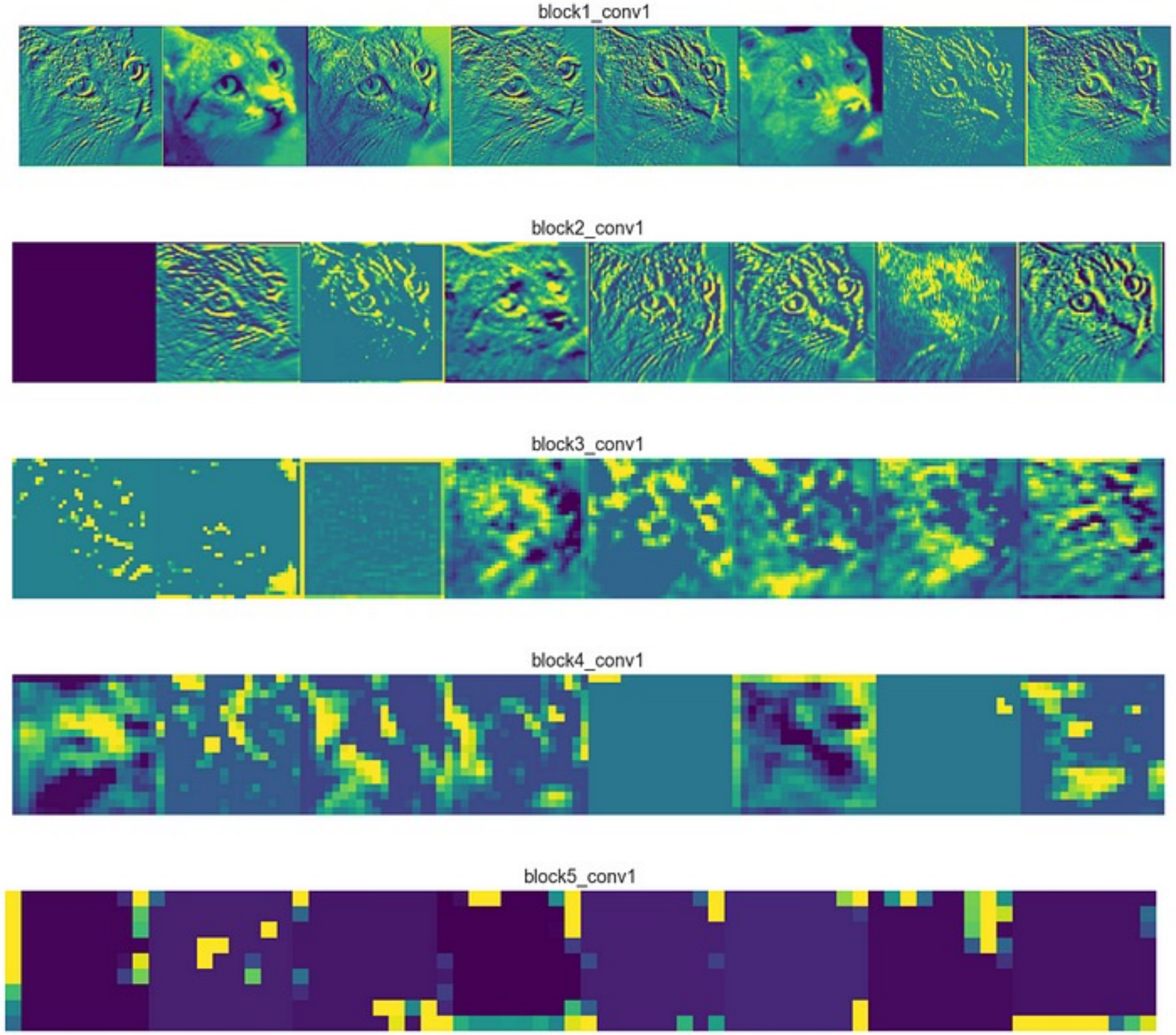
Table 13. Alternative Specification (XGBoost): Announcement Effect & Survival

Dependent Variable	CAR(t-1 to t+1)			CAR(t-1 to t+1)			Survival Indicator (t+2)		
	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)	(IV)	(V)	(VI)
log(Unadjusted Distance)	-0.170**			-0.055**			-0.561***		
	[-2.27]			[-2.05]			[-4.34]		
log(TF Distance)		-0.330***			-0.044*			-0.618***	
		[-2.86]			[-1.82]			[-2.74]	
log(XGB Distance)			-0.047			-0.016			-0.186***
			[-1.69]			[-1.64]			[-3.47]
Intercept	0.243***	0.292***	0.207***	0.073***	0.079***	0.061**	1.326***	1.458***	1.182***
	[3.16]	[3.67]	[2.76]	[2.82]	[2.98]	[2.46]	[13.78]	[14.50]	[11.53]
Model	Linear	Linear	Linear	Linear	Linear	Linear	Probit	Probit	Probit
Acquiror-Target Weighting	Equal	Equal	Equal	Value	Value	Value			
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	999	999	999	999	999	999	14,668	14,668	14,668
R-squared	0.191	0.193	0.190	0.141	0.139	0.141			

Back

VGG16 Image Classification





Arden Dertat, 2017, Applied Deep Learning - Part 4: Convolutional Neural Networks, Medium.com

[Back]

Other Application: Deepfake-based Counterfactuals

Back

Generative-AI, Deepfake, GAN

Music

The New York Times | https://www.nytimes.com/2023/04/19/arts/music/ai-drake-the-weeknd-fake.html

An A.I. Hit of Fake 'Drake' and 'The Weeknd' Rattles the Music World

A track like "Heart on My Sleeve," which went viral before being taken down by streaming services this week, may be a novelty for now. But the legal and creative questions it raises are here to stay.

The New York Times | https://www.nytimes.com/2023/04/25/learning/will-ai-replace-pop-stars.html

STUDENT OPINION

Will A.I. Replace Pop Stars?

An A.I.-generated track with fake Drake and the Weeknd vocals went viral. Would you listen to a song sang by a computer?

Hollywood

How generative AI got cast in its first Hollywood movie

The forthcoming Tom Hanks and Robin Wright on-screen reunion, 'Here,' will feature a starring role for Metaphysic's AI.

Medicine

THE FUTURE OF EVERYTHING

How AI That Powers Chatbots and Search Queries Could Discover New Drugs

Natural language processing algorithms like the ones used in Google searches and OpenAI's ChatGPT promise to slash the time required to bring medications to market

Artificial Intelligence for COVID-19 Drug Discovery and Vaccine Development

The New York Times | https://www.nytimes.com/2023/

A.I. Turns Its Artistry to Creating New Human Proteins

Inspired by digital art generators like DALL-E, biologists are building artificial intelligences that can fight cancer, flu and Covid.

DEFENSE

AI Drug Discovery Systems Might Be Repurposed to Make Chemical Weapons, Researchers Warn

A demonstration with drug design software shows the ease with which toxic molecules can be generated

News & Politics

The Deepfake Dangers Ahead

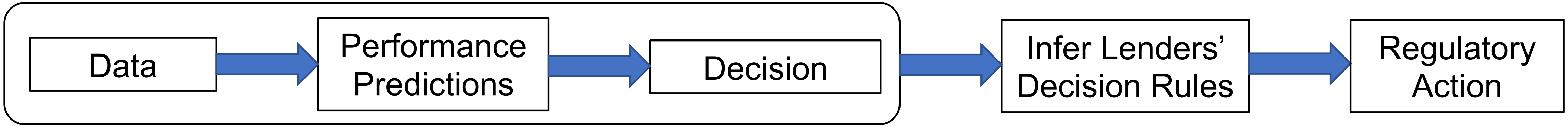
AI-generated disinformation, especially from hostile foreign powers, is a growing threat to democracies based on the free flow of ideas

'Deepfakes' of Celebrities Have Begun Appearing in Ads, With or Without Their Permission

Detecting Discriminatory Lending with Deepfake-Counterfactuals

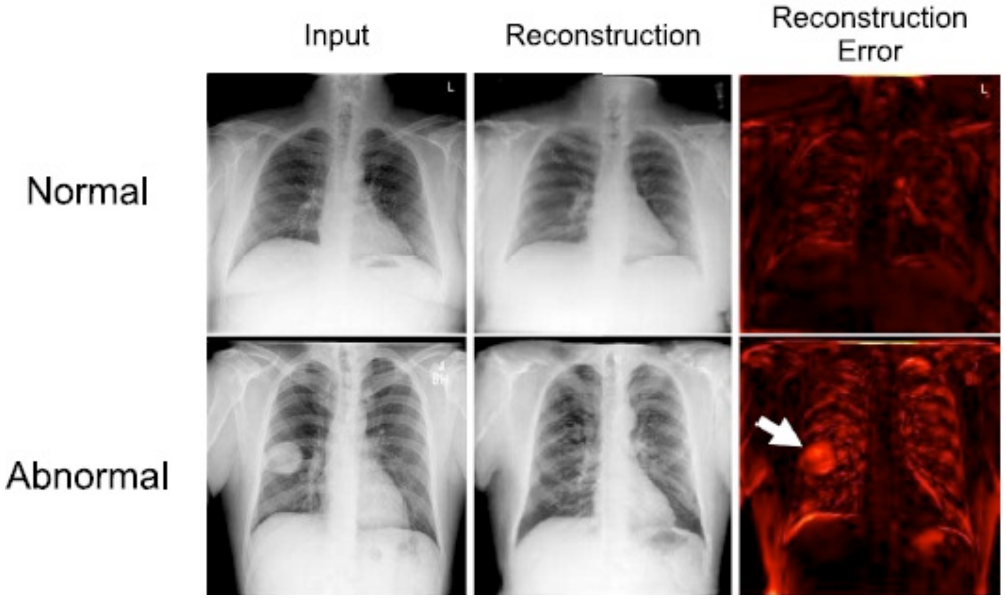
***FinTech**: AI to Screen Borrowers*

***RegTech**: AI to Screen Lenders*

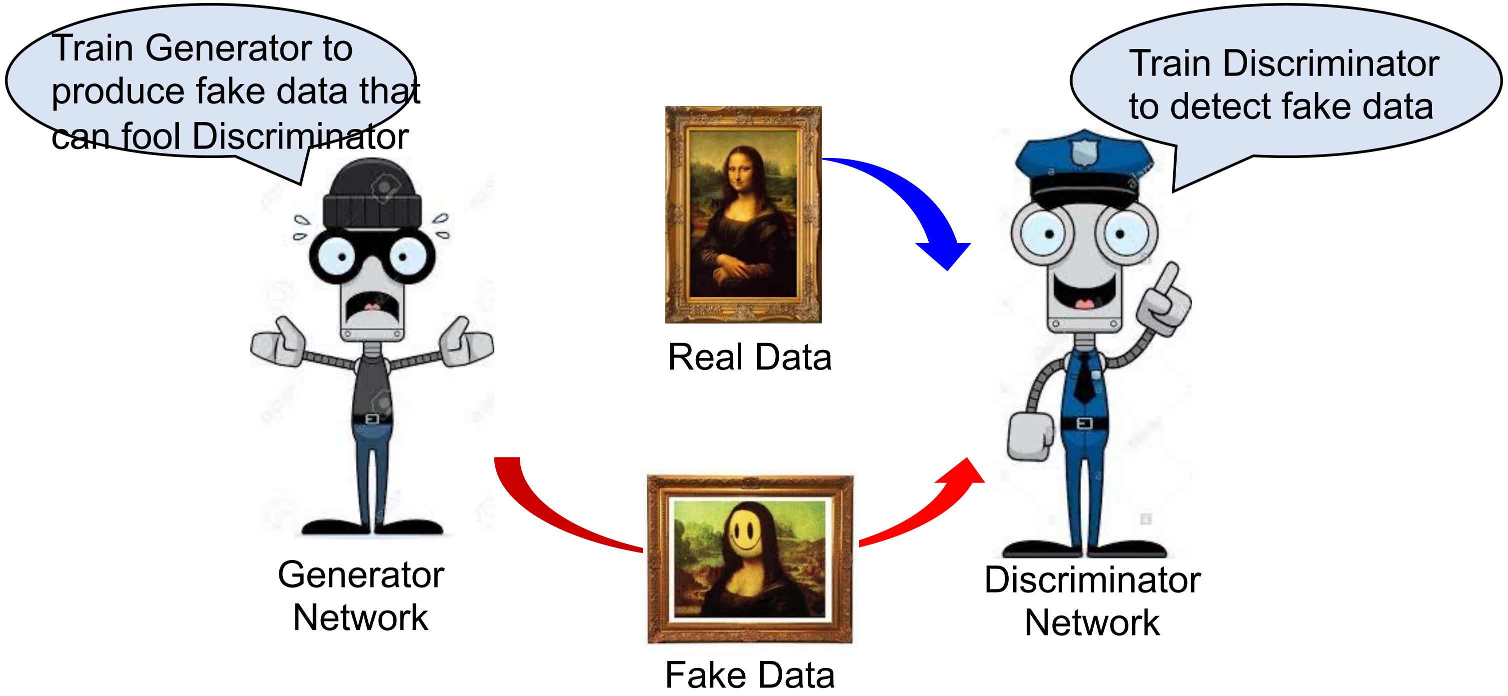


[Component 1] Anomaly Detection

Example from Radiology



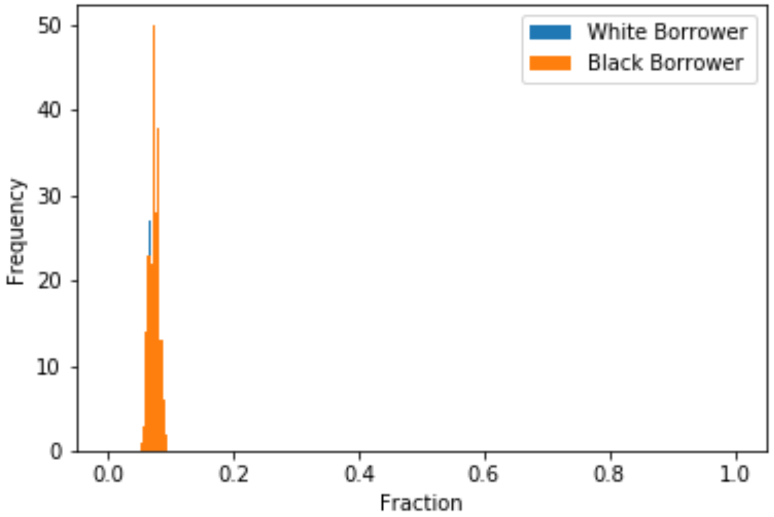
[Component 2] Deepfake Counterfactuals



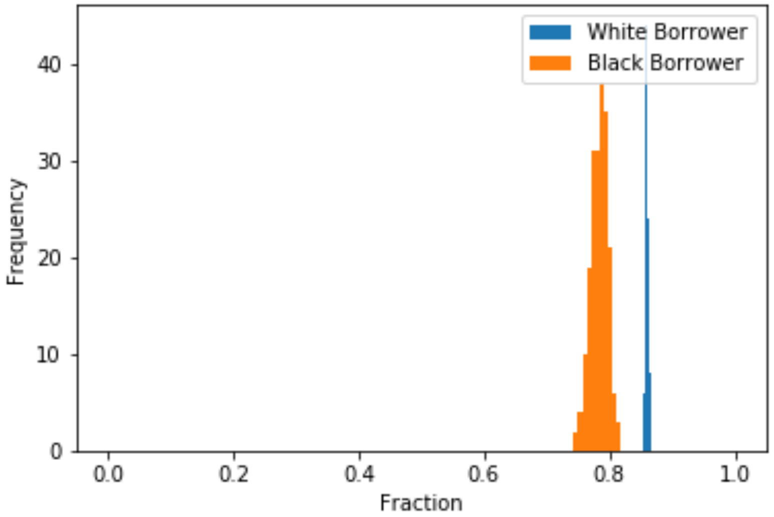
Ref. Nam and Yun (2022)

Back

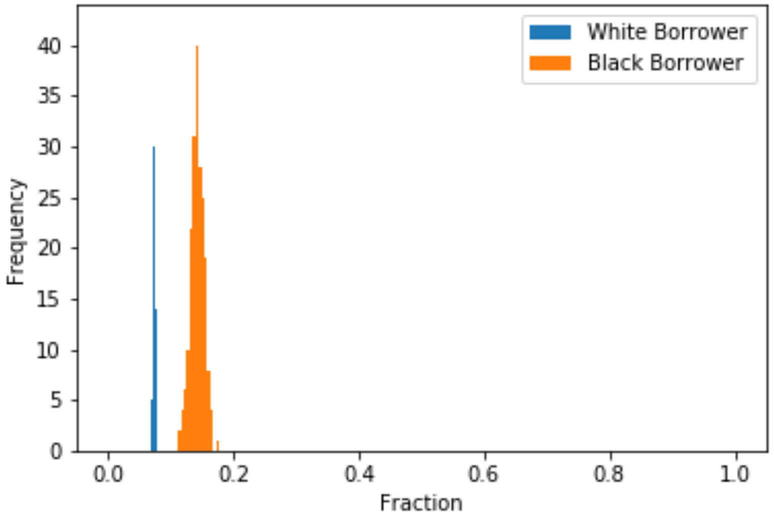
Decomposition of Loan Decisions: ML vs. Human



Favoritism



Model Explained Decisions



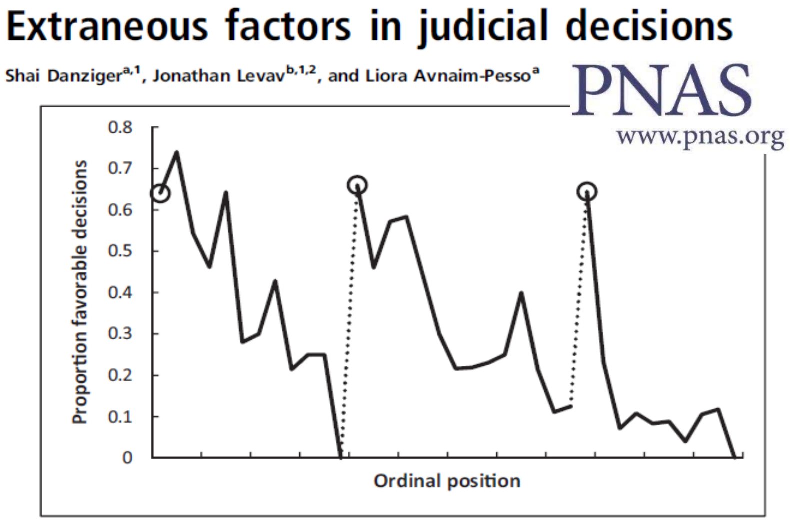
Discrimination

Note: Figures use public data.

Back

- Advantages of Anomaly Detection
  - ➢ Avoid Averaging (e.g., Strategic Discrimination)
  - ➢ Imbalanced Sample
  - ➢ Direction of Discrimination

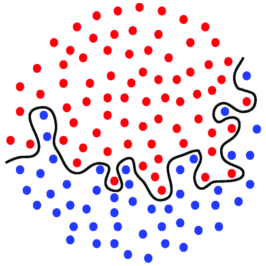
- Advantages of GAN (& Neural Networks)
  - ➢ Generate very realistic synthetic data (GAN)
  - ➢ No a priori parametric assumption on nonlinearity
  - ➢ Scales well for large number of inputs (big data)
  - ➢ Mitigate overfitting (GAN)

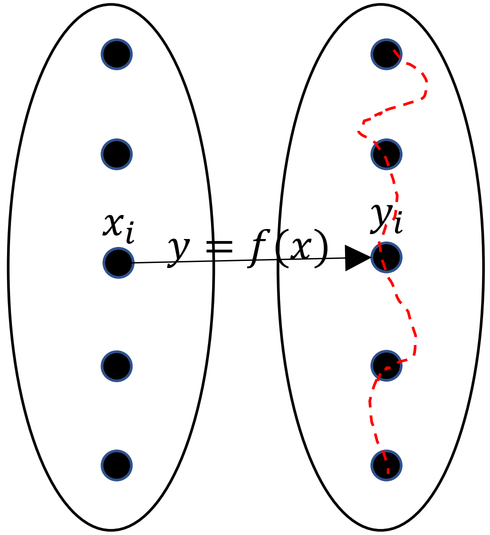


Supervised learning may overfit and incorporate aberrations in learning rules: We test the common caricature of realism that justice is "what the judge ate for breakfast" in sequential parole decisions made by experienced judges.

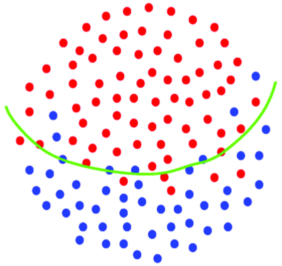
Supervised Learning: $y = f(x)$

Variation comes from realized data points

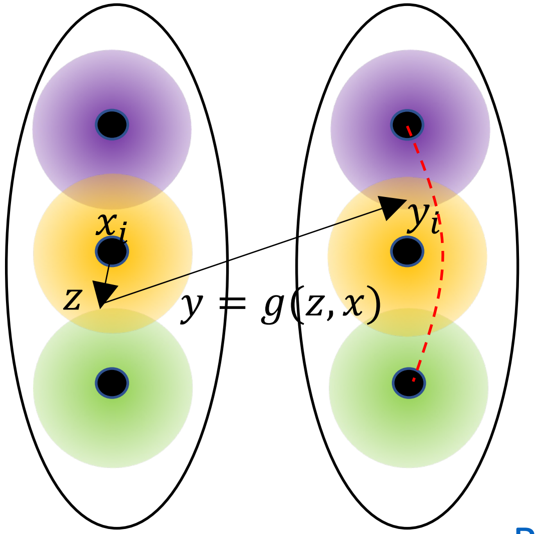




cGAN generator: $y = g(z, x)$



Variation comes from random (latent space) neighborhood of realized data points (***smooth & avoid overfitting***)



Back