Al Masterclass Sergey Karayev ASU GSV 2019

About Me

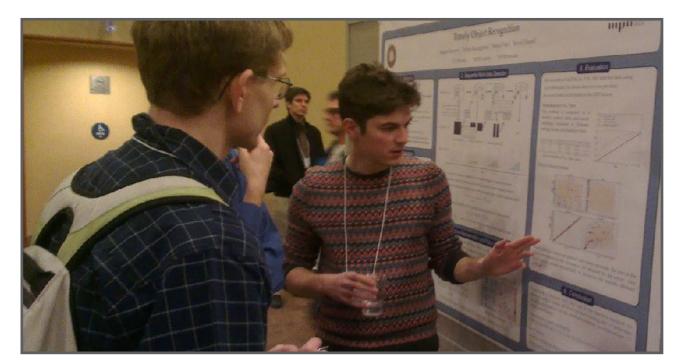
- Head of AI for STEM at **Turnitin** [2018-]
 - 35M students served at 150+ countries. 1B paper submissions.
- Co-founder of **Gradescope** [2014-2018]
 - From TA side project to 80M answers graded by over 10K instructors.
- Co-organizer of Full Stack Deep Learning program
- PhD Computer Science at **UC Berkeley** [2009-2014]
 - Research in computer vision, deep learning

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turnitin







- Reach shared terminology
- Situate ourselves in history and possibility
- Understand AI product development

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My Goals For This Presentation

- Introduction
 - History and terminology
 - What's possible, what's on the horizon, what's unknown
- Developing Al Products
 - Picking the problem
 - Data Flywheel
 - Most Al code is not Al
 - Roles and Hiring
- Example
- Q & A

Outline

Terminology

General idea of "thinking machines"

Making data driven predictions

Machine Learning

Artificial

Intelligence

State-of-the-art method for ML

Deep Learning

Diagram courtesy of Eric Wang

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Applied stats and ML for data analysis and prediction

Data Science

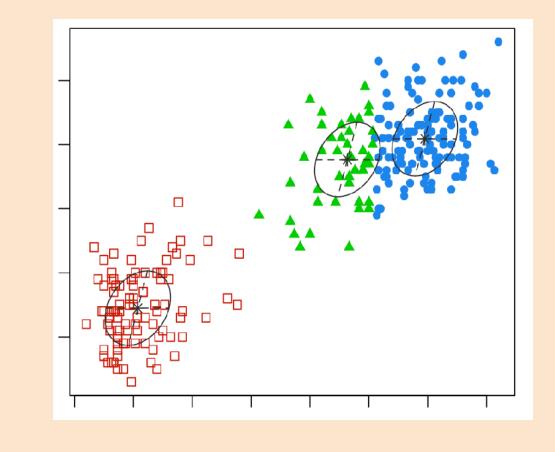


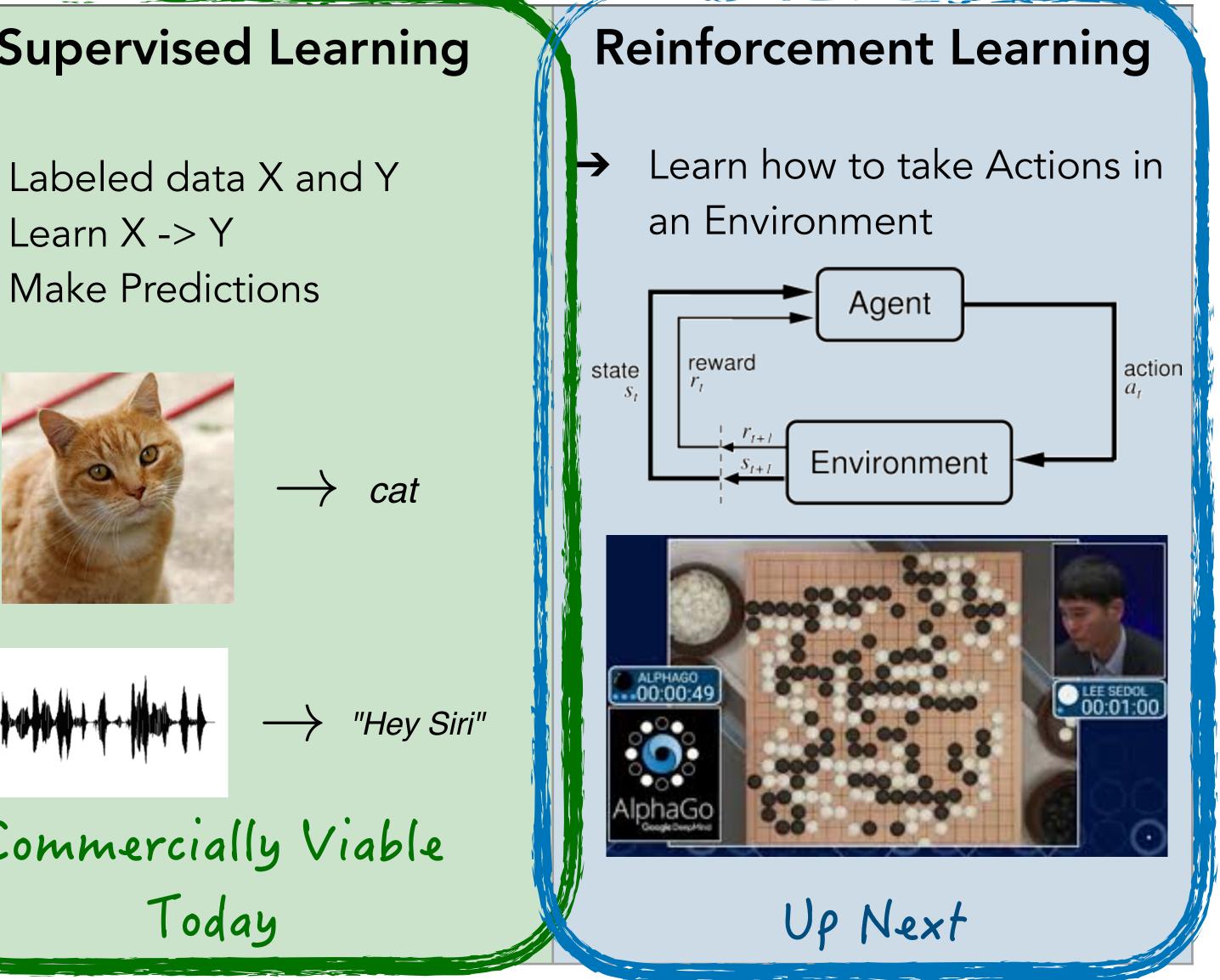
Types of Learning Problems

Unsupervised Learning

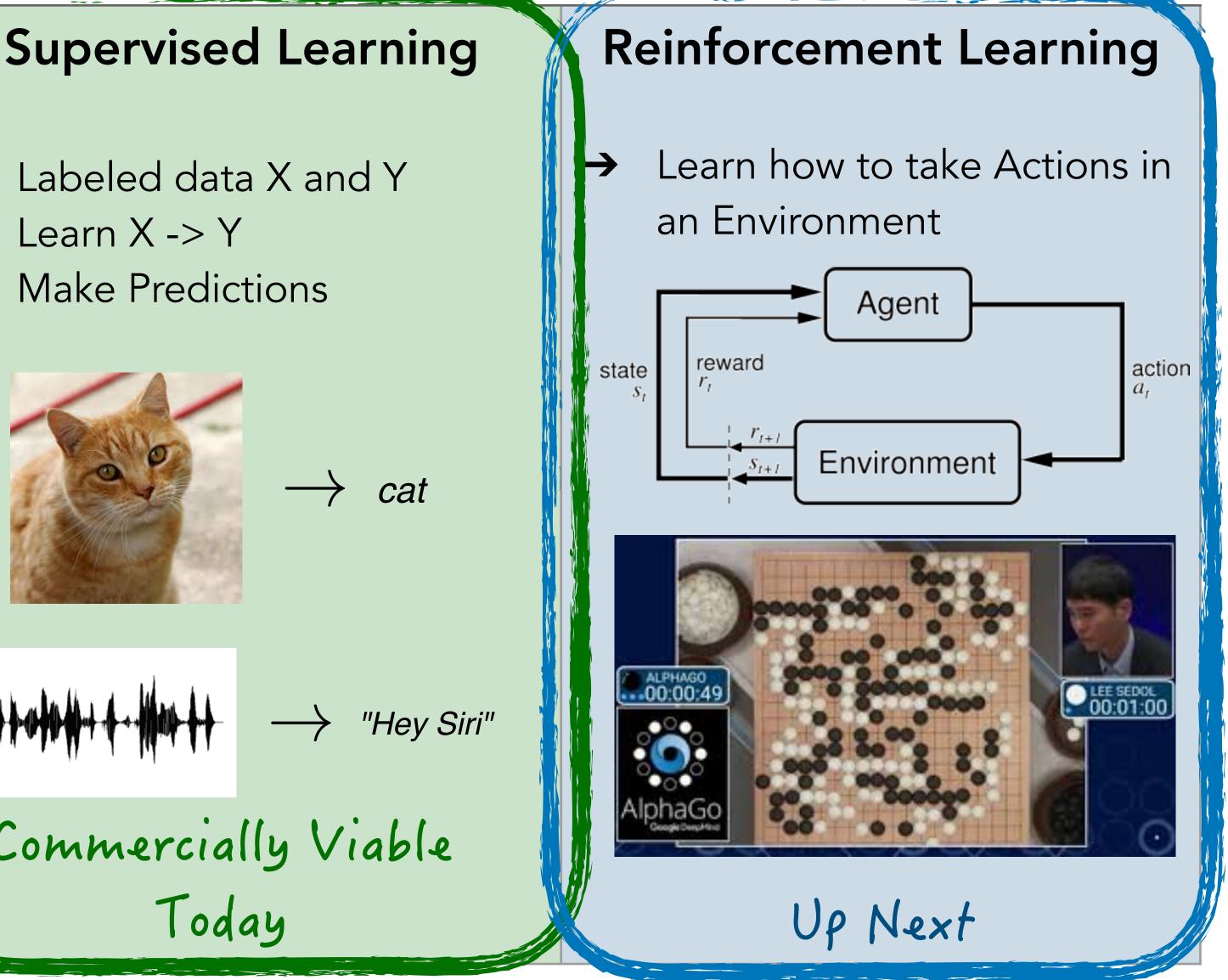
- Unlabeled data X \rightarrow
- Learn X \rightarrow
- Generate fakes, insights \rightarrow

"This product does what it is supposed to. I always keep three of these in my kitchen just in case ever I need a replacement cord."





- \rightarrow



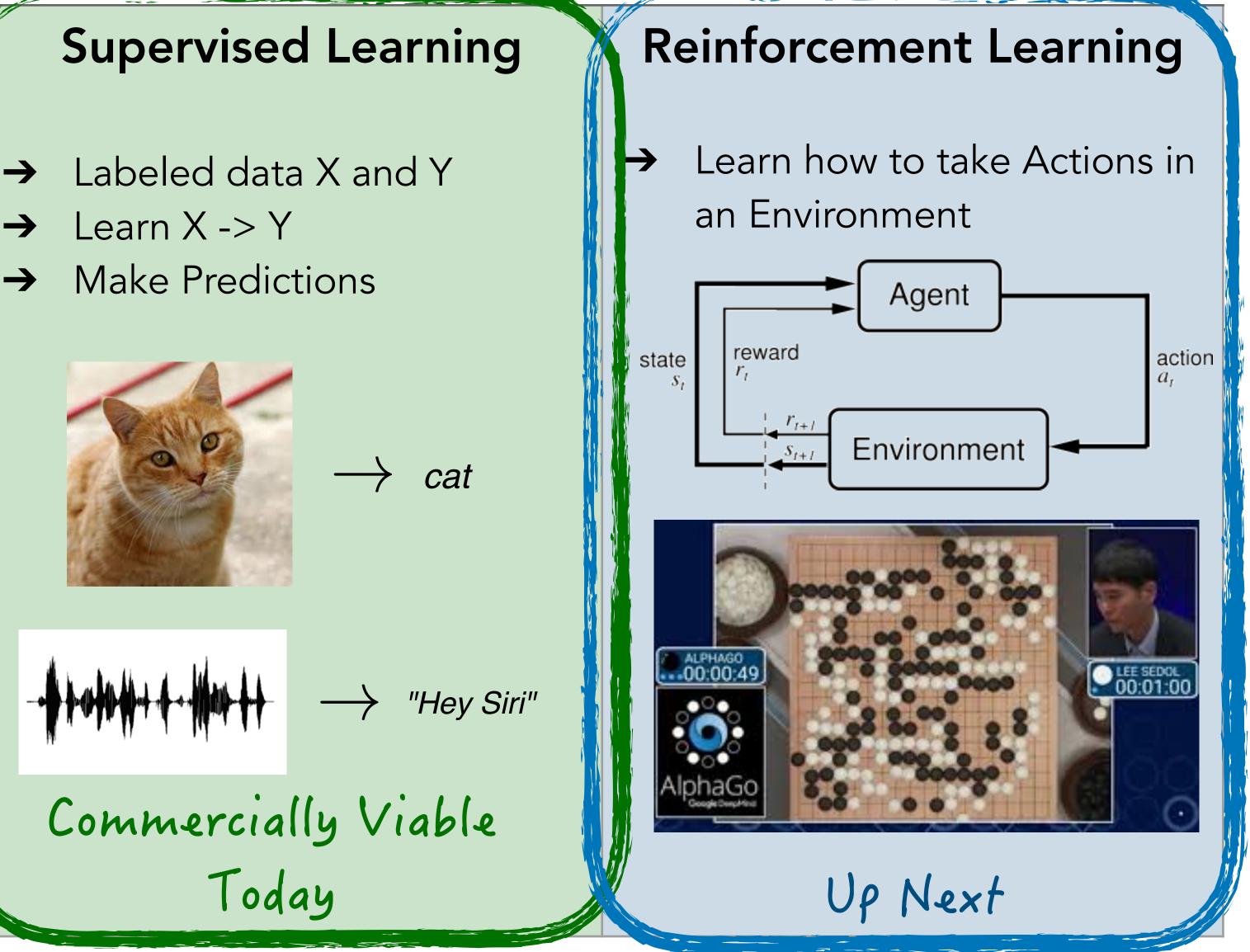
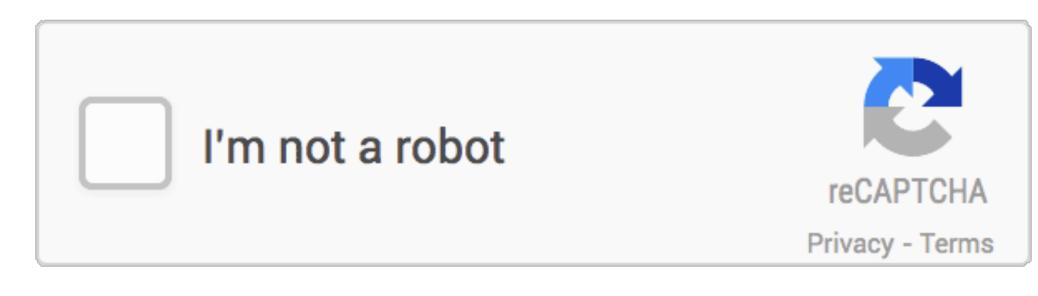


Diagram courtesy of Shayne Miel

- Alan Turing suggests test for determining human-level AI
 - Can the AI convince a human interlocutor that it is another human?

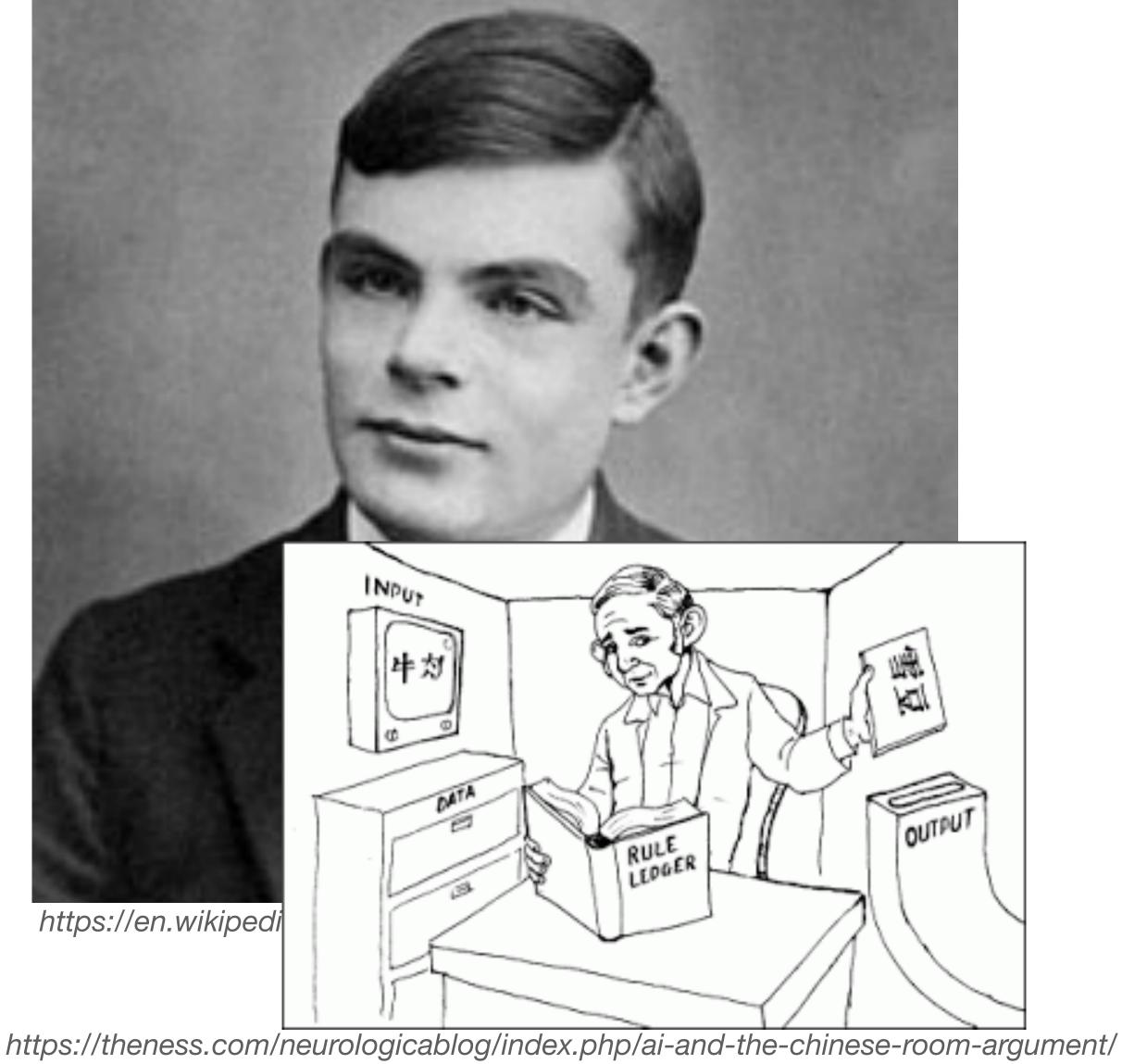
• Today

- Intelligence still defined functionally
- No good argument against possibility of superhuman intelligence



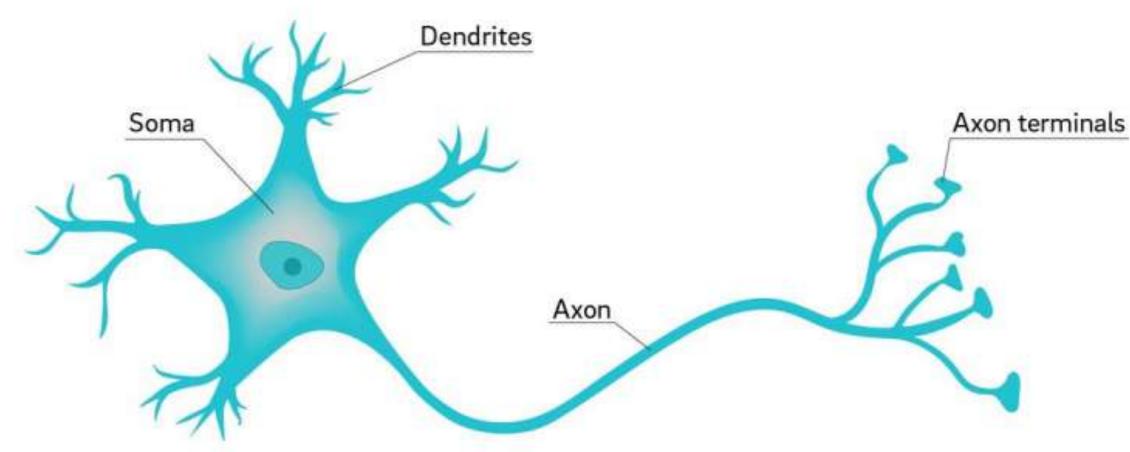
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1950: Turing Test



1957: The Perceptron

- Frank Rosenblatt builds machines inspired by spiking neurons
- Aggregate inputs, take weighted sum, apply non-linearity
- Today:
 - The building block of deep learning
 - Al still informed by neuroscience



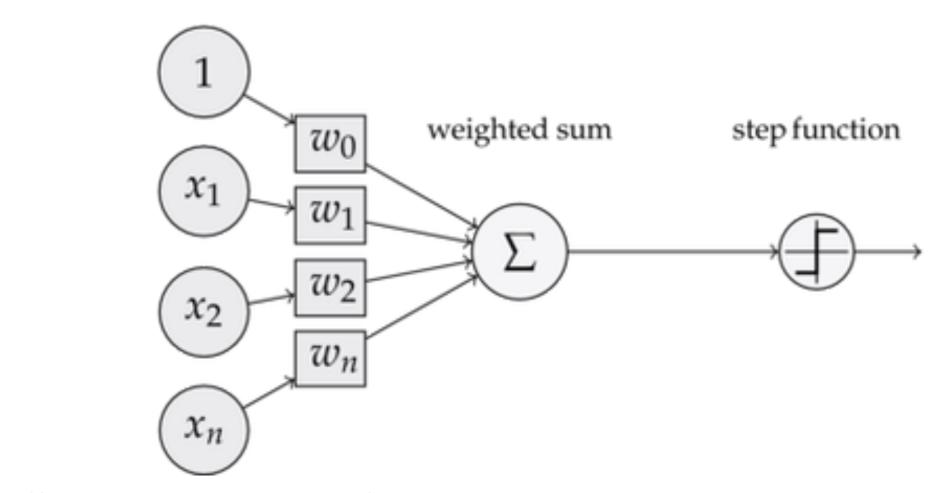
https://medicalxpress.com/news/2018-07-neuron-axons-spindly-theyre-optimizing.html

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https://blogs.umass.edu/comphon/2017/06/15/did-frank-rosenblatt-invent-deep-learning-in-1962/

inputs weights

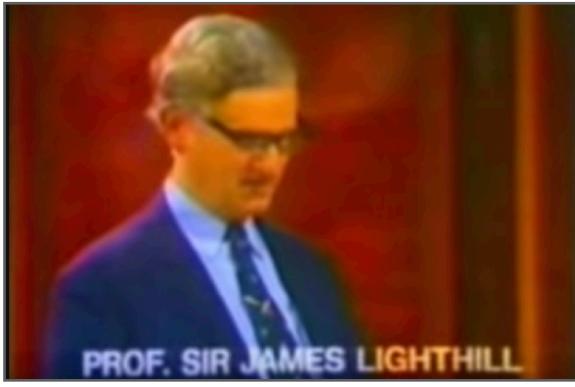


https://www.jessicayung.com/explaining-tensorflow-code-for-a-multilayer-perceptron/



1960s-1970s: first summer and winter

- At first: lots of funding, great expectations
- "In from 3-8 years we will have a machine with the general intelligence of an average human being." - Marvin Minsky (1970)
- 1973: "In no part of the field have the discoveries made so far produced the major impact that was then promised" -Lighthill Report (cut most funding in UK)



https://www.youtube.com/watch?

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https://www.computerhistory.org/internethistory/1960s/

"Our first foray into AI was a program that did a credible job of solving problems in college calculus. Armed with that success, we tackled high school algebra; we found, to our surprise, that it was much harder. An exploration of the child's world of blocks proved insurmountable, except under the most rigidly constrained circumstances.

It finally dawned on us that the overwhelming majority of what we call intelligence is developed by the end of the first year of life."

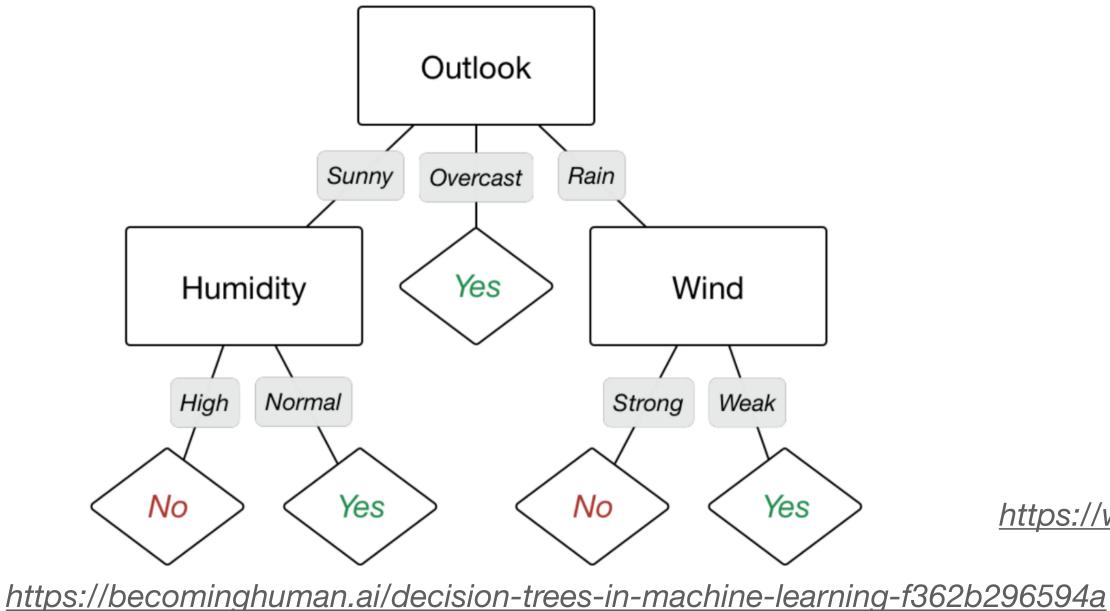
- Marvin Minsky, 1977



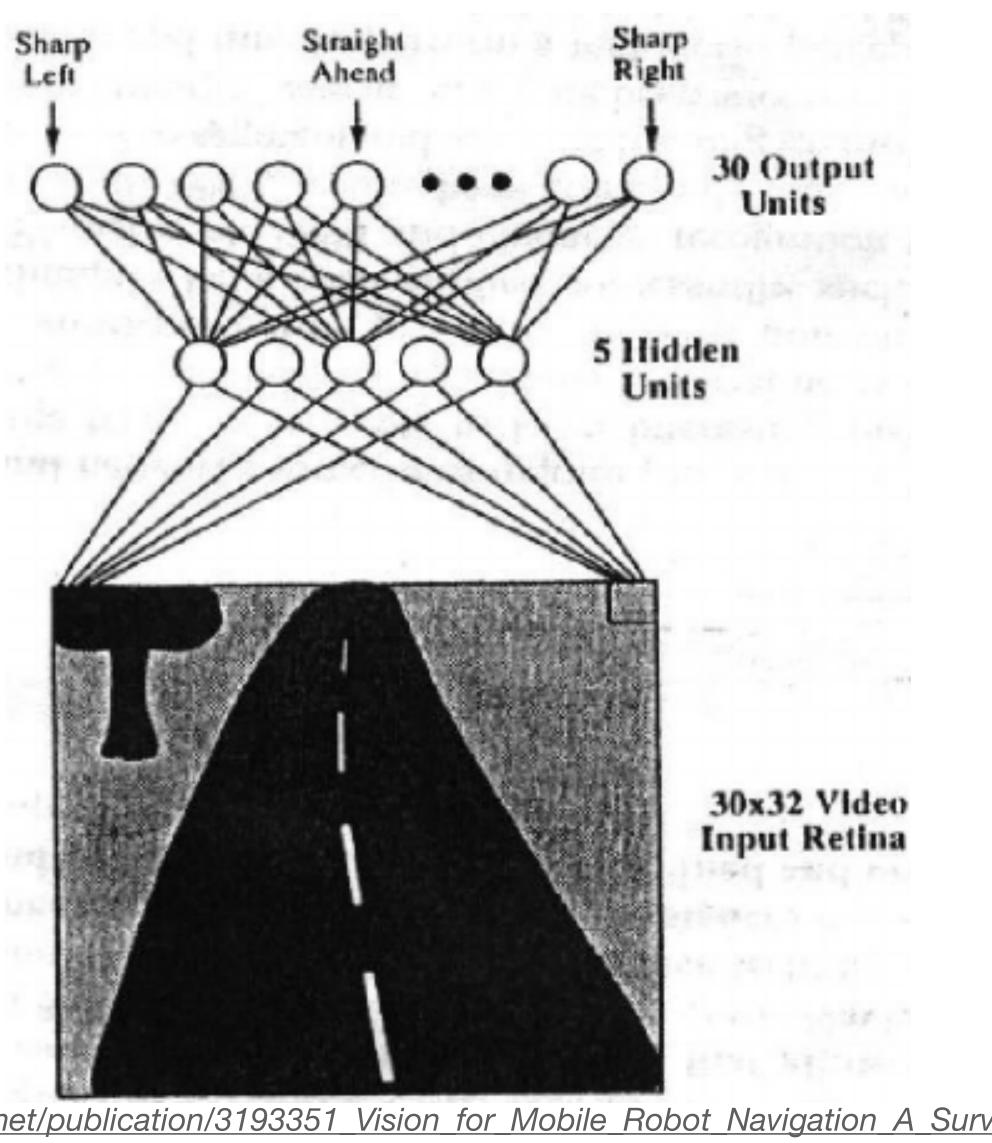
https://unsplash.com/photos/x4jRmkuDImo

1980s and 1990s

- Rise of "expert systems"
- Use of logic languages like PROLOG
- Another rise of neural networks
- Another Al Winter



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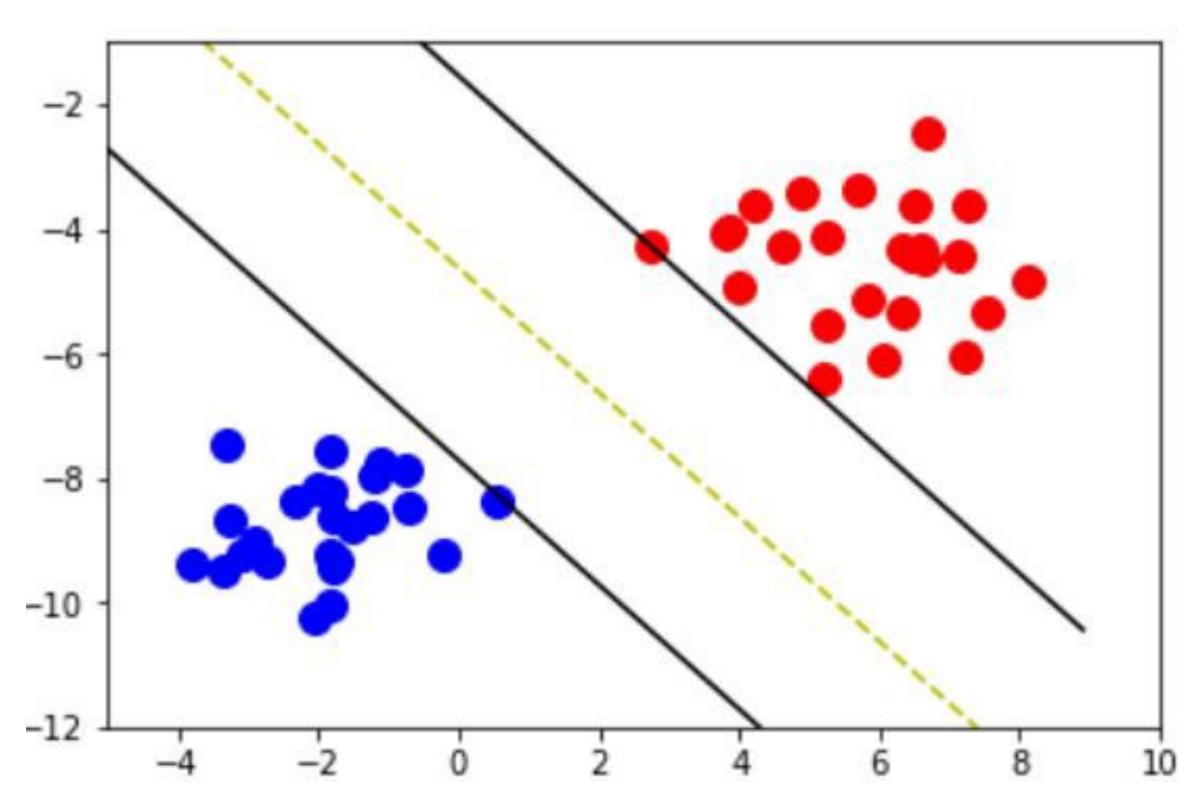


https://www.researchgate.net/publication/3193351 Vision for Mobile Robot Navigation A Surve

2000s: Machine Learning

- Informed by stats, increasingly big data
- Main techniques: SVMs
- Hand-designed data representations
- Today
 - Full understanding that data trumps algorithms

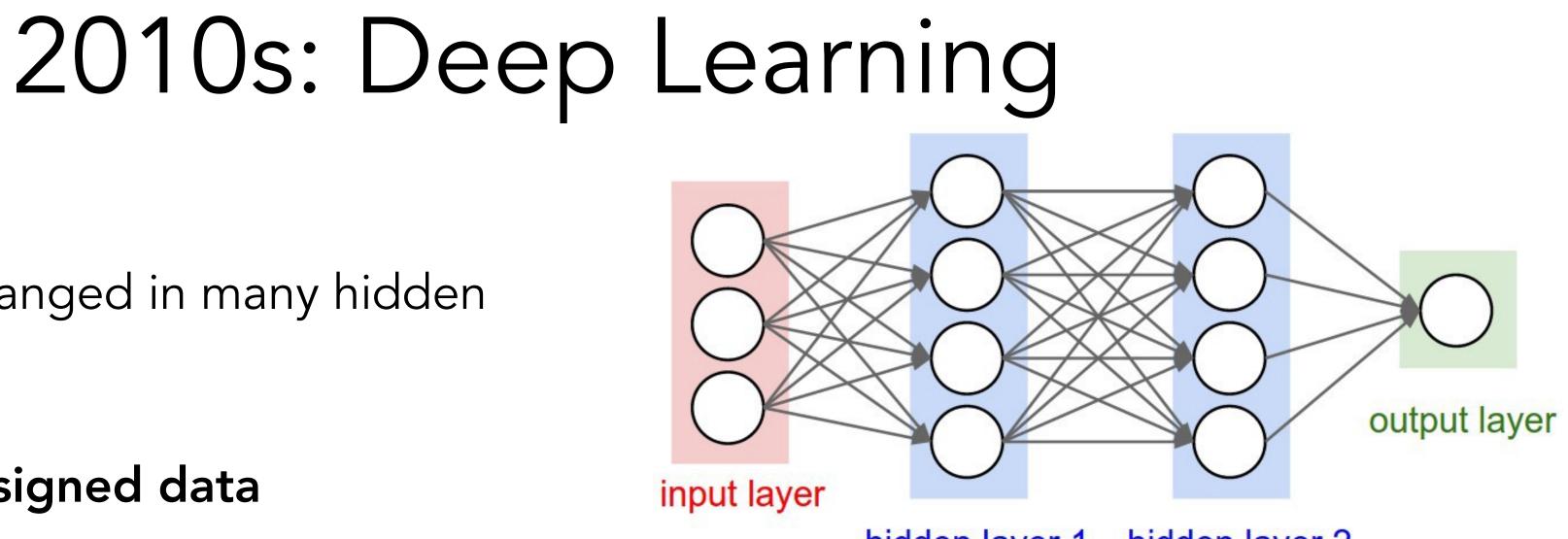




https://medium.com/deep-math-machine-learning-ai/chapter-3-support-vector-machine-with-

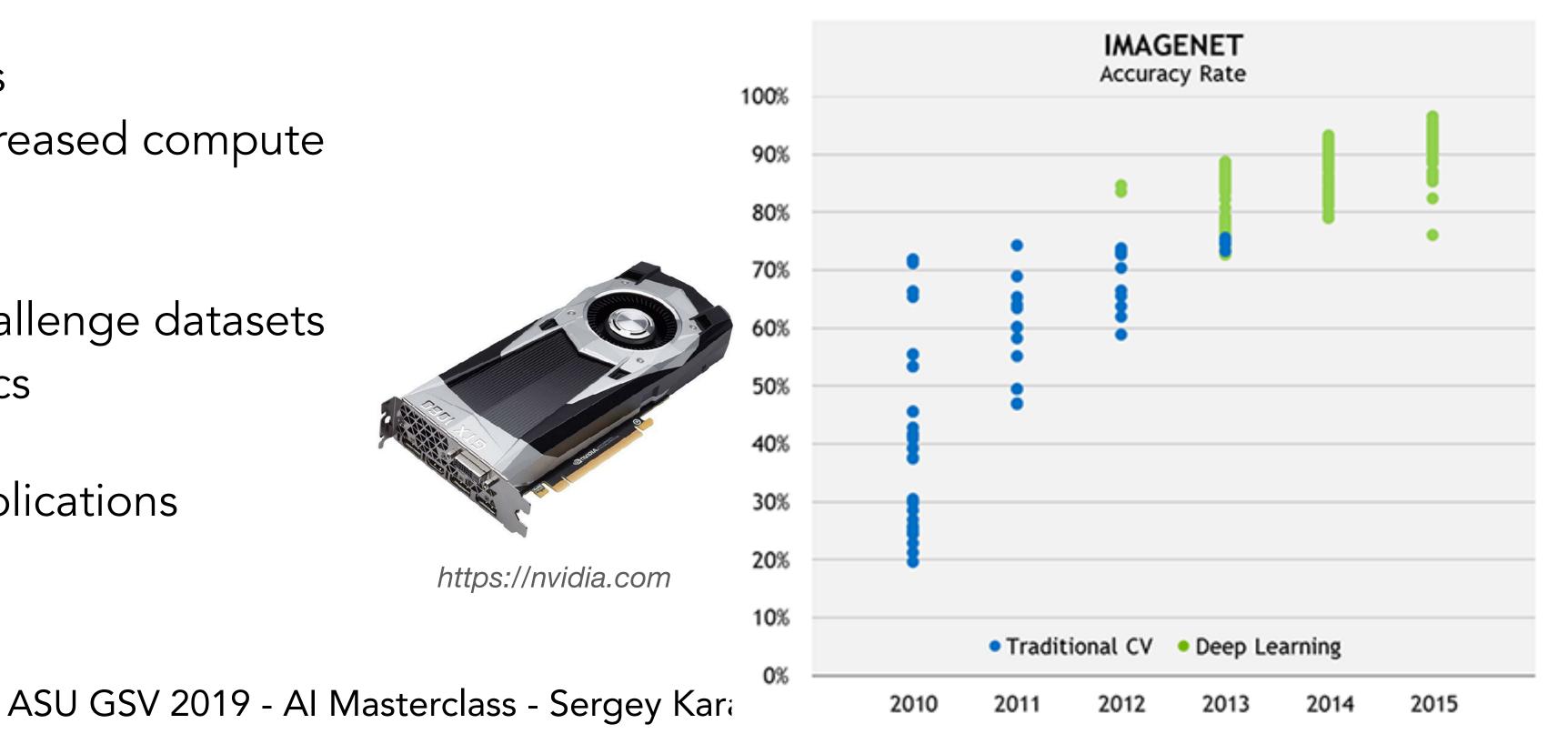


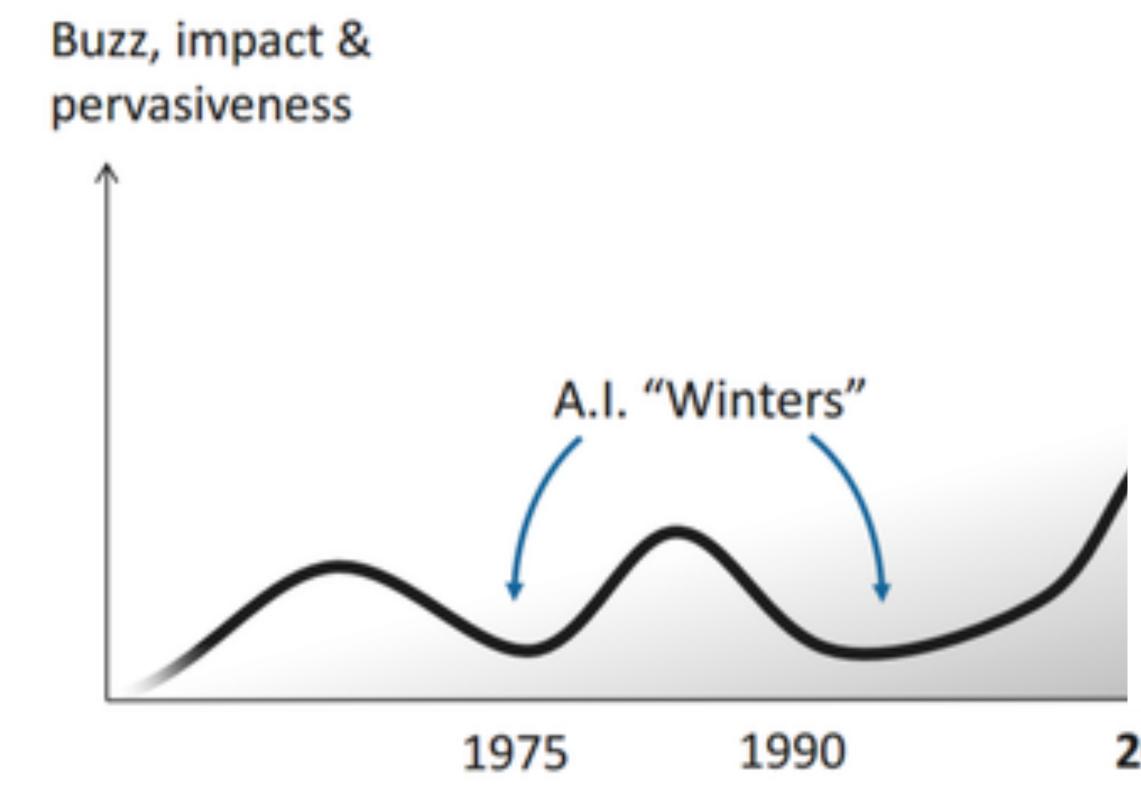
- Many perceptrons arranged in many hidden layers
- Better than hand-designed data representations
- Combination of algorithms (backpropagation) and increased compute power (GPUs)
- Major breakthrough on challenge datasets in vision, language, robotics
- Significant commercial applications



hidden layer 1 hidden layer 2

https://www.digitaltrends.com/cool-tech/what-is-an-artificial-neural-network/





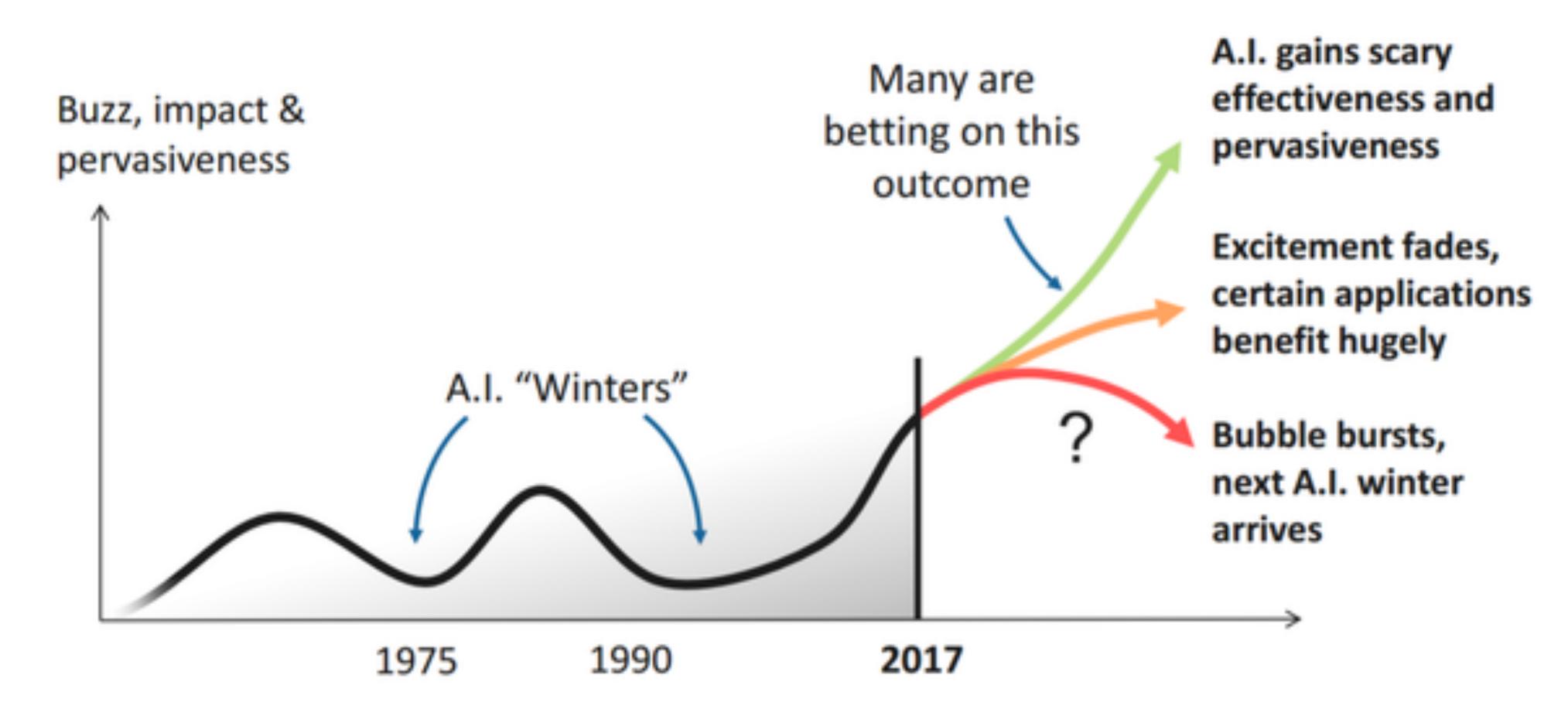
https://www.cambridgewireless.co.uk/media/uploads/resources/AI%20Group/AIMobility-11.05.17-Cambridge_Consultants-Monty_Barlow.pdf

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2020s: ?

2017

2020s: ?



https://www.cambridgewireless.co.uk/media/uploads/resources/AI%20Group/AIMobility-11.05.17-Cambridge_Consultants-Monty_Barlow.pdf

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Al is a Moving Target

Problem	Before computer solution	After computer solution
Advanced mathematical computation	The most difficult task for humans, must be most difficult for machines	Just an algorithm, no intelligence at all!
Chess	A proving ground for human ingenuity and insight	Obviously computers are able to crank through more possible moves!
Speech	Only humans are able to produce and undestand vocal language	Just translating between soundwave and text, no understanding!
Humor	We can't even define what makes something funny, so how will a computer generate it?	?

What was possible yesterday

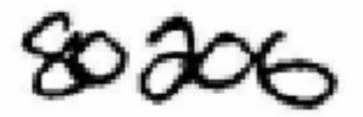
- Recognize handwritten zip codes (1989)
- Self-drive car across the US (1995)
- Beat humans at chess (1997)
- Vacuum the floor (2002)



http://mentalfloss.com/article/503178/brief-history-deep-blue-ibms-chess-computer

https://www.researchgate.net/figure/An-Illustrative-example-for-USPS-Zip-Code-Data-Sample-from-17_fig1_320250462







What's possible today

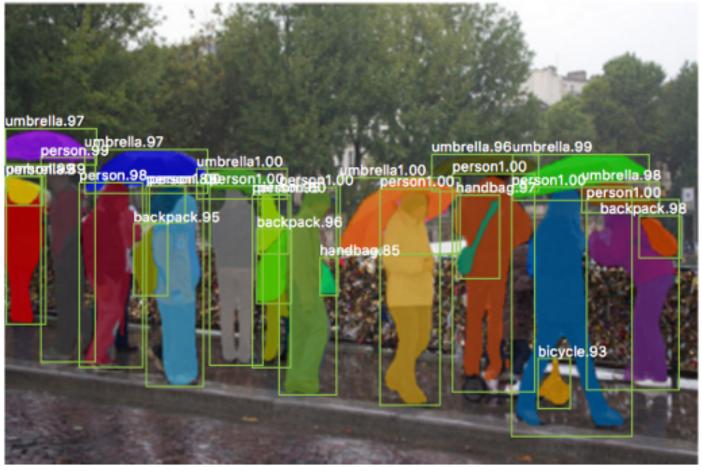
- Car that can self-drive on well-mapped roads in good conditions
- Beat humans at Go
- Recognize general handwriting
- Recognize things and people in photos
- Translate text from one language to another
- Transcribe speech to text and back
- Generate realistic human faces
- Stilted customer support



https://www.wired.com/story/waymo-self-driving-cars-california/



https://thispersondoesnotexist.com/



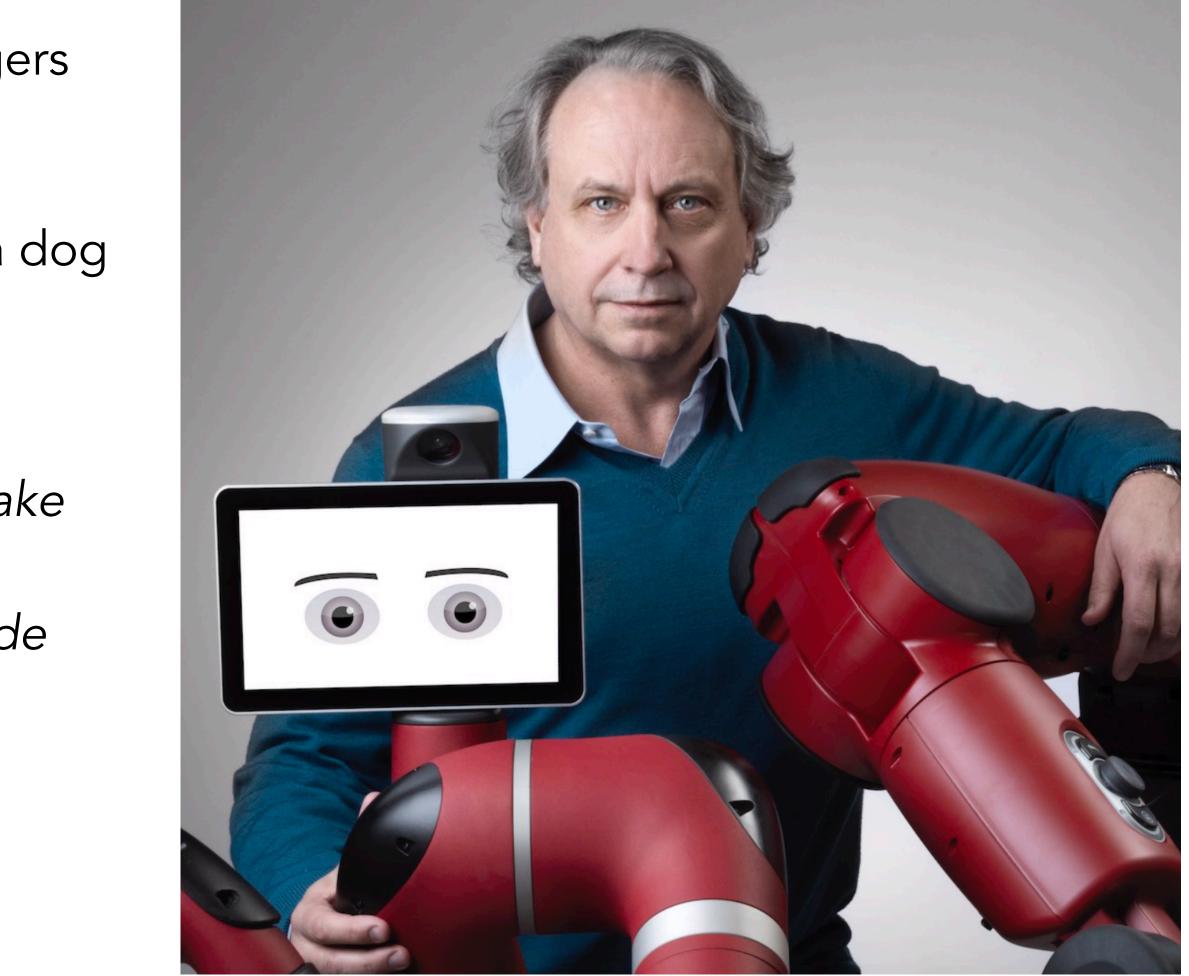
https://arxiv.org/abs/1703.06870

What's likely within 5 years

- Cars that can pick up passengers in restricted environments
- Beat humans at complicated video game
- Generate realistic videos
- Generate realistic news articles
- Generate realistic music
- Customer support good enough to fool humans

What's unknown

- Cars that can self-drive and pick up passengers on all roads at all times
- A robot that is perceived to be as smart as a dog
- An intelligent tutor in all subjects
- "Almost all innovations in Robotics and AI take far, far, longer to get to be really widely deployed than people in the field and outside the field imagine." - Rodney Brooks
- Artificial General Intelligence (AGI) and **Artificial Superhuman Intelligence (ASI)**



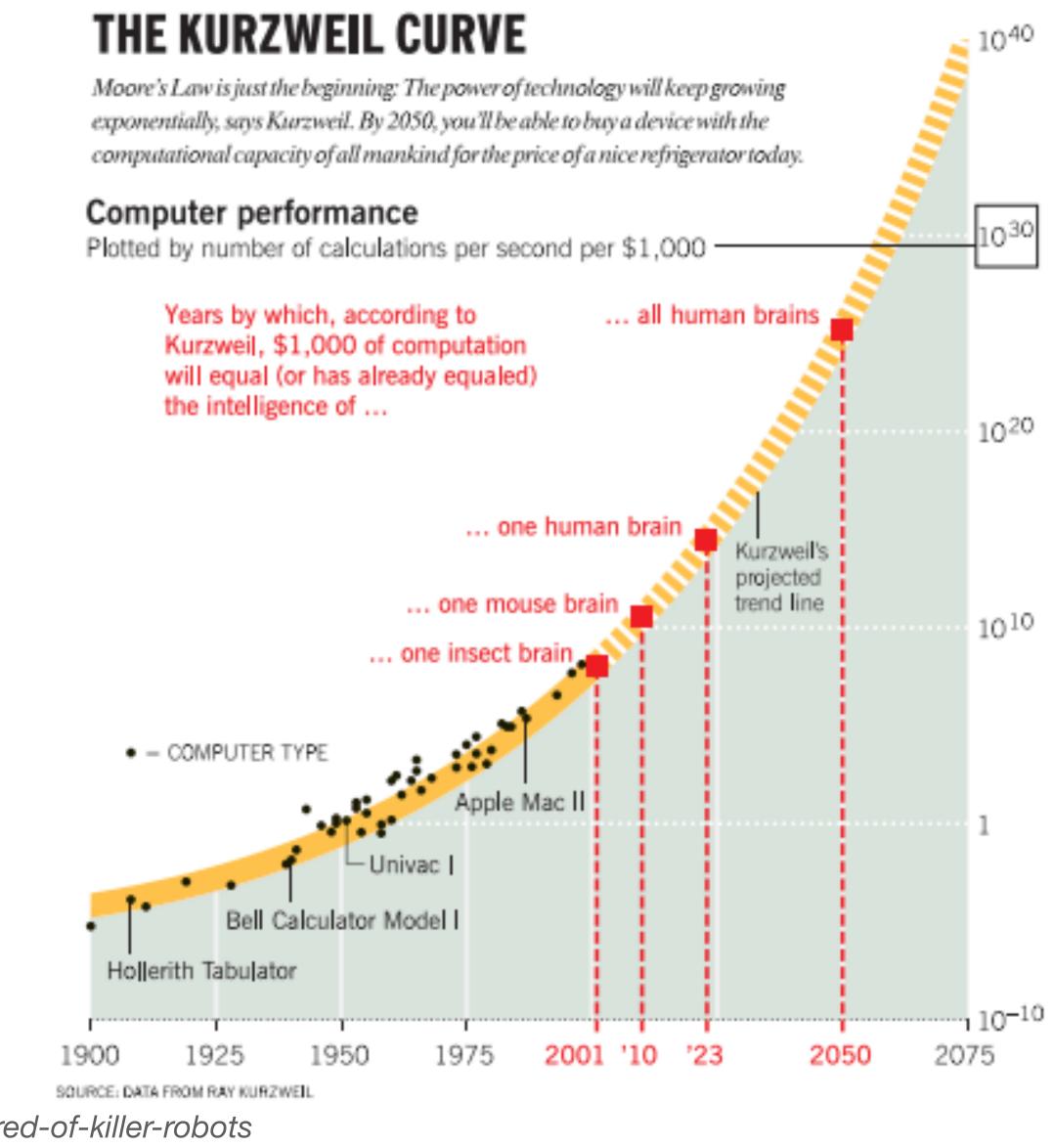
https://rodneybrooks.com/the-seven-deadly-sins-of-predicting-the-future-of-ai/

The Singularity

- Idea that technological progress is exponential, and will enter essentially "vertical" growth
 - Humans -----> AGI -> ASI
- Some notable people are alarmed
- Let's not worry just yet

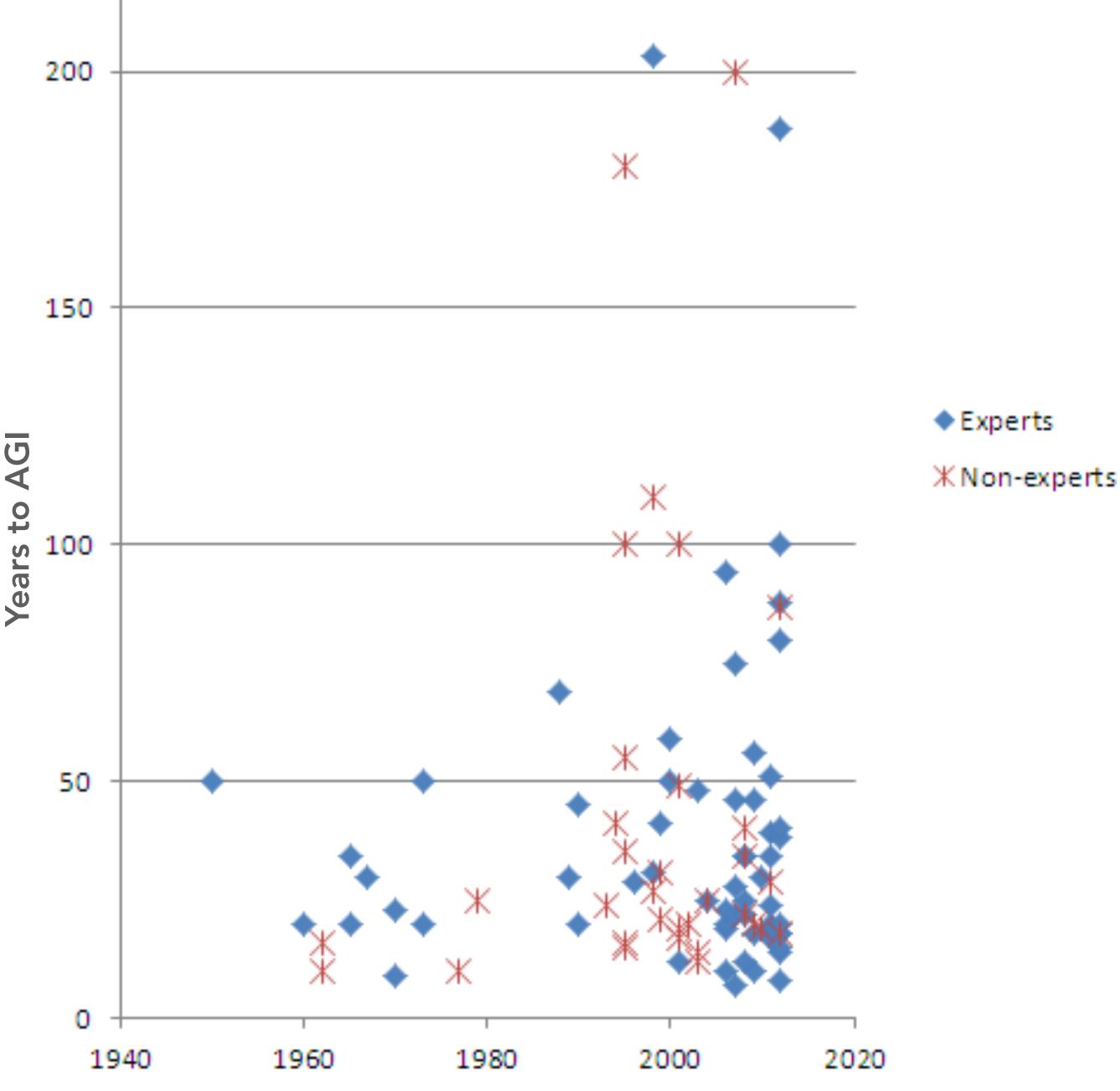


https://www.washingtonpost.com/news/morning-mix/wp/2014/11/18/why-elon-musk-is-scared-of-killer-robots ASU GSV 2019 - Al Masterclass - Sergey Karayev



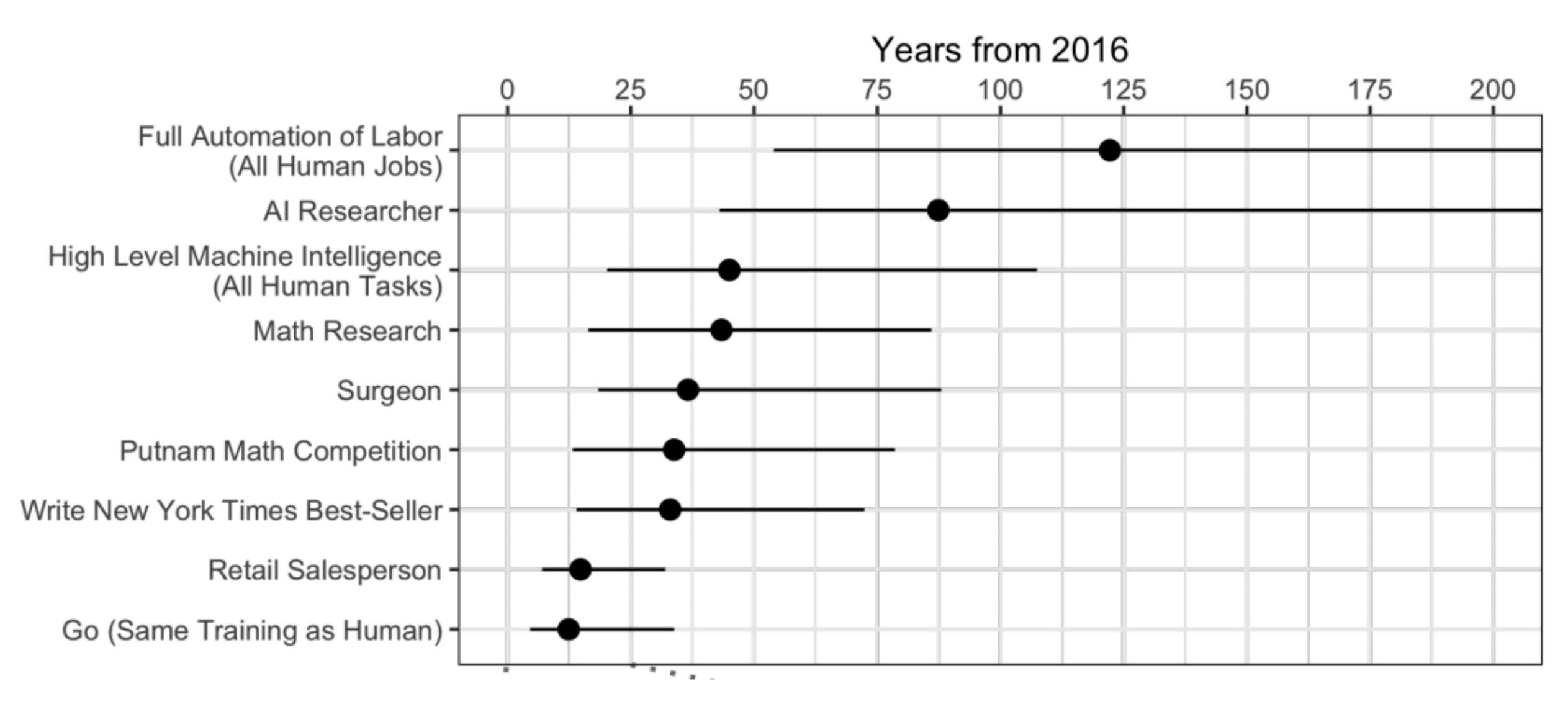
Historical Predictions

People have been predicting that human-level AI is 25 years away for a while.



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Disappearing Lines of Work



When Will AI Exceed Human Performance? Evidence from AI Experts https://arxiv.org/pdf/1705.08807.pdf

Disappearing Lines of Work

• Let's worry right now!	Automati
	Food prep
 Long-term benefit, but short-term 	Construc
	Cleaning
upheaval.	Driving
	Agricultu
• What to do?	Garment
	Personal
	Sales
• 10x more effective education	Customer
	Business
 Stronger support systems 	Informat
ouonger support systems	Science &
	Healthca
 Radical societal re-org? 😳 	Hospitali
A MARCA AND AND AND AND AND AND AND AND AND AN	Upper ma
	Teaching

TRANSHUMANIST COMMUNISM https://www.transhuman-party.org/ transhumanism-and-marxism

Economist.com

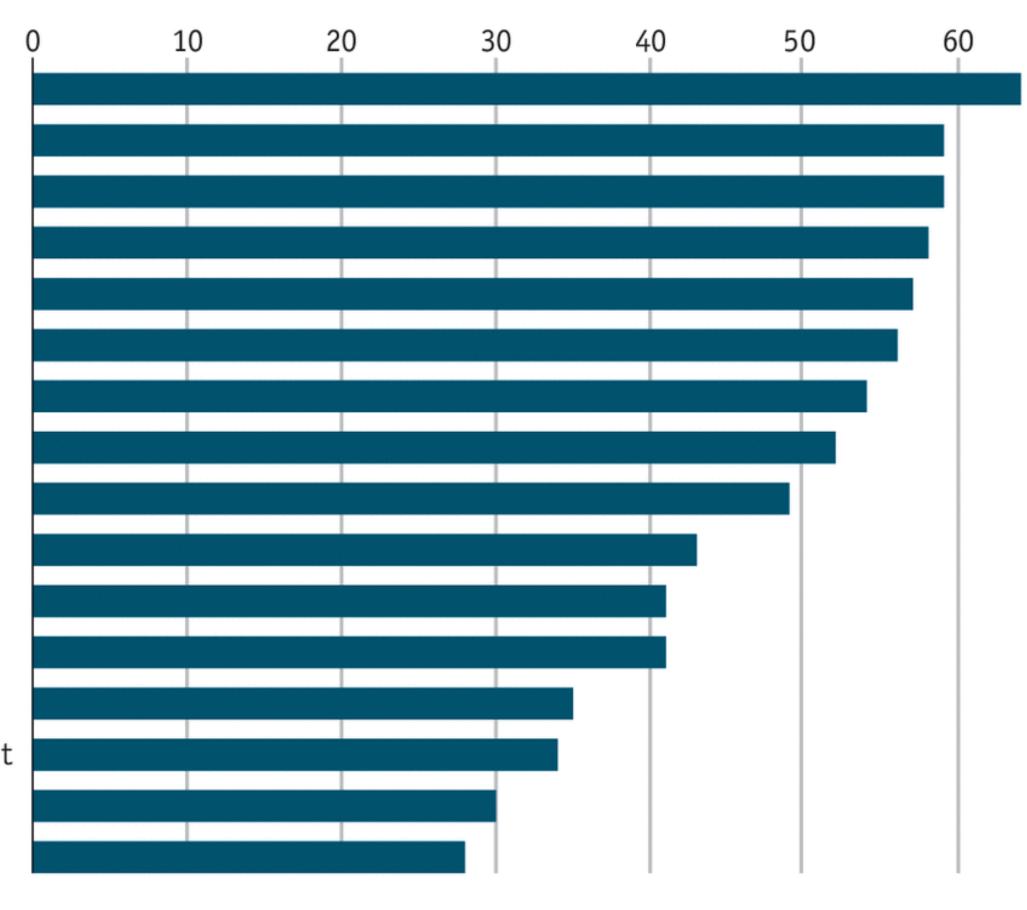
https://www.economist.com/graphic-detail/2018/04/24/a-study-finds-nearly-half-of-jobs-are-vulnerable-to-automation

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tion risk by job type, %

- eparation
- ction

- tural labour
- t manufacturing
- l service
- er service
- s administration
- tion technology
- & engineering
- are
- lity & retail management
- nanagement & politics
- Source: OECD



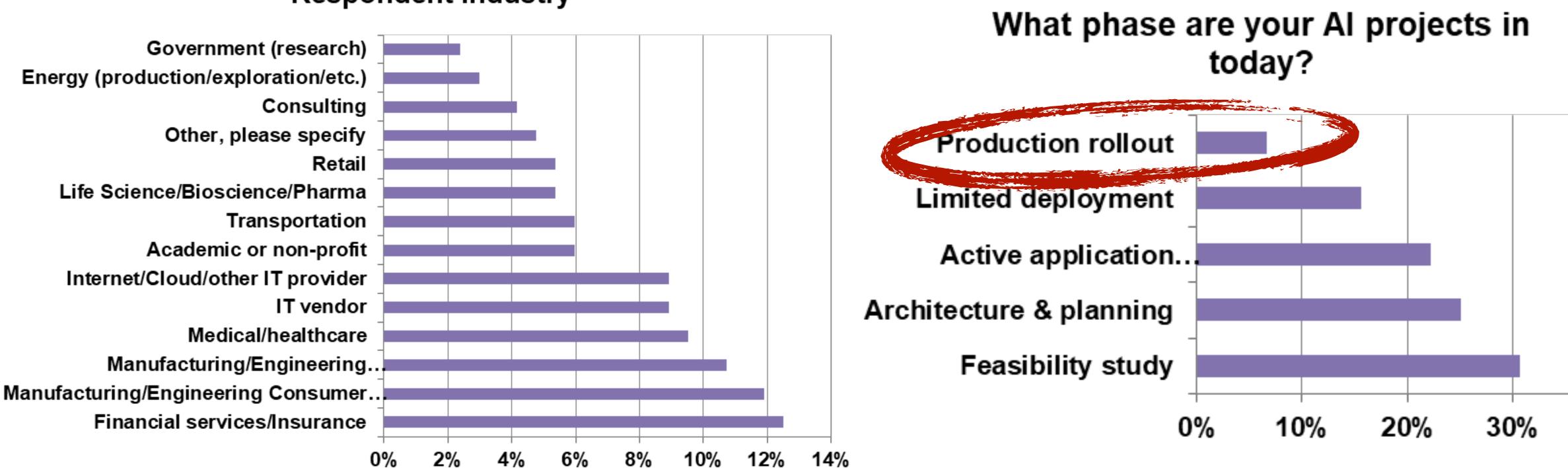


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It's Early Days!

2018 survey of 300+ ML-involved developers



Respondent Industry

https://www.nextplatform.com/2018/04/24/lagging-in-ai-dont-worry-its-still-early/



Evaluating a problem

- 1. Is automated prediction valuable?
- 2. Is the required level of accuracy feasible?
- 3. Will it move the needle for your business?
- 4. Will you be able to build a data moat?

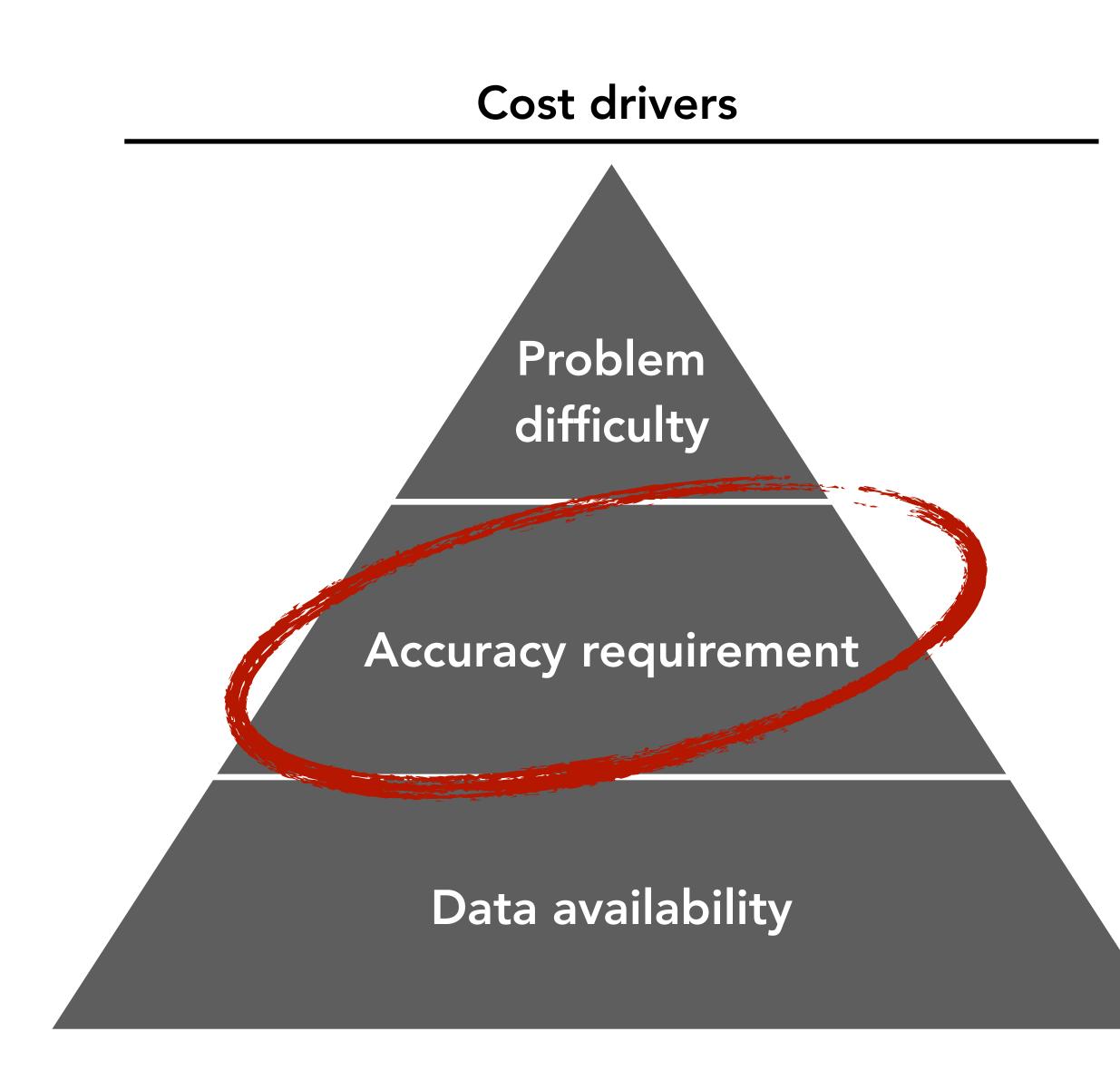


Diagram courtesy of Josh Tobin

- Good published work on similar problems? (newer problems mean more risk & more technical effort)
- How costly are wrong predictions?
- How frequently does the system need to be right to be useful?
- How hard is it to acquire enough data?
- How expensive is data labeling?
- Unique advantage?



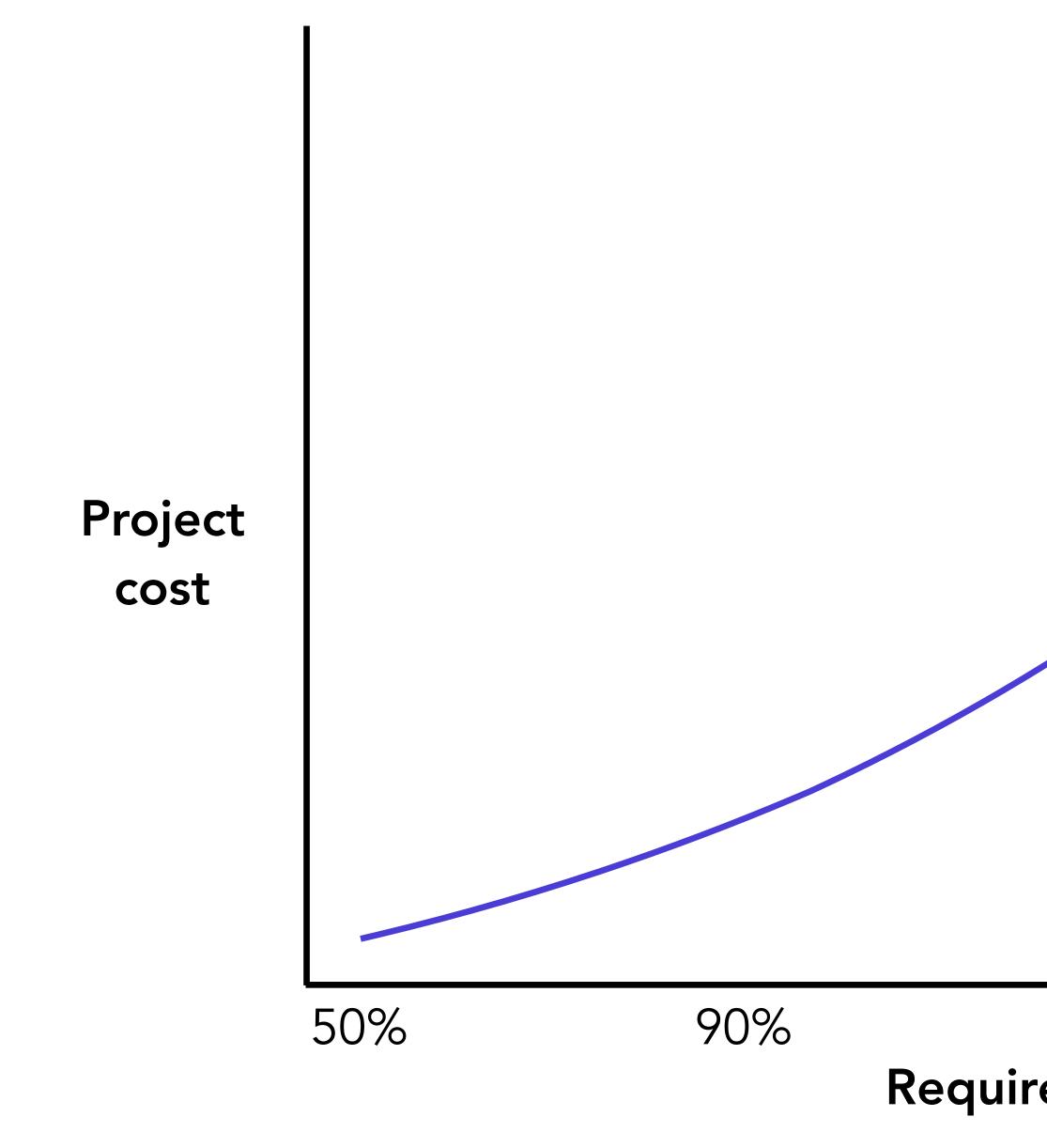


Diagram courtesy of Josh Tobin

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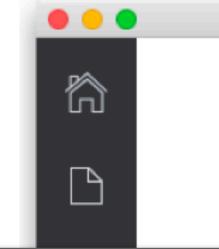
ML project **costs scale super-linearly** with accuracy requirement

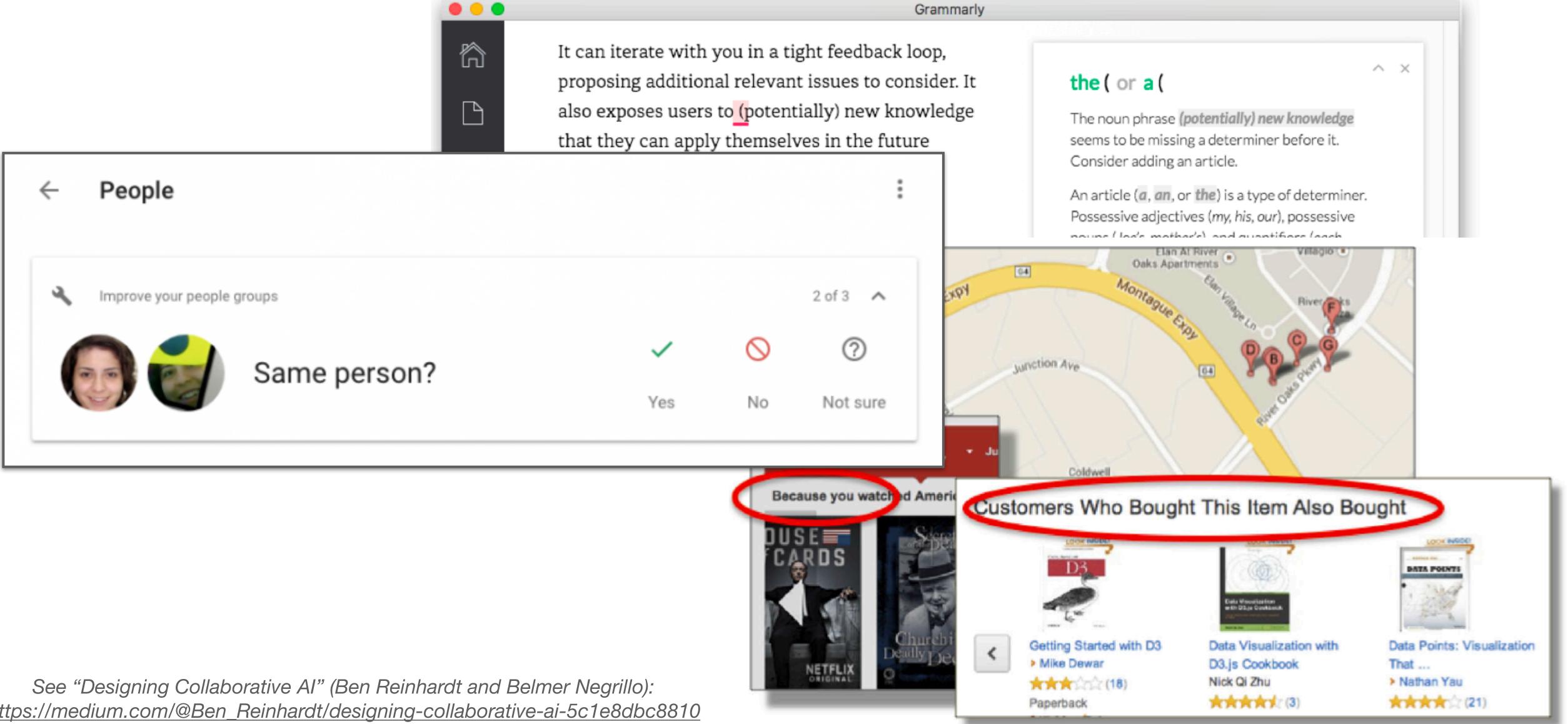
. . .

99% **Required** accuracy

99.9%

Product Design Can Reduce Accuracy Requirements





https://medium.com/@Ben_Reinhardt/designing-collaborative-ai-5c1e8dbc8810



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Defensible Al means

Data is cheap

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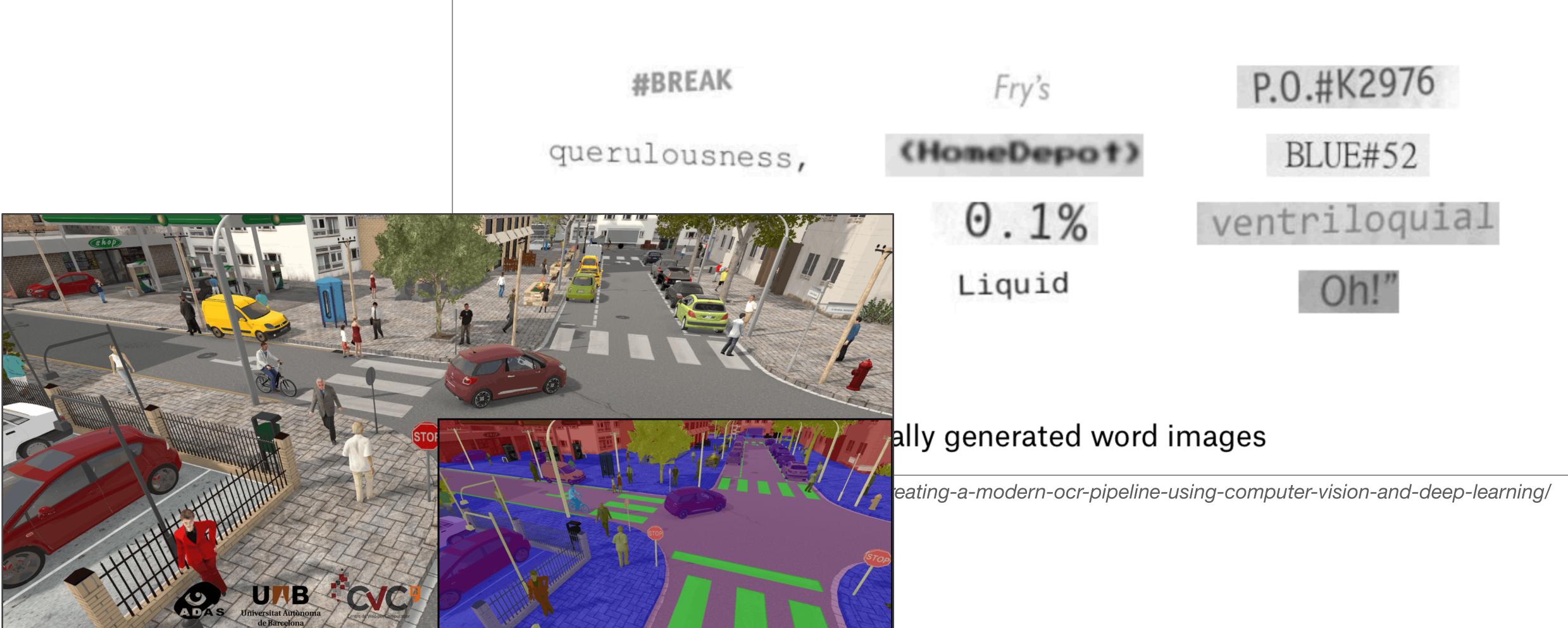
Labels are expensive

Usually: spend time and \$



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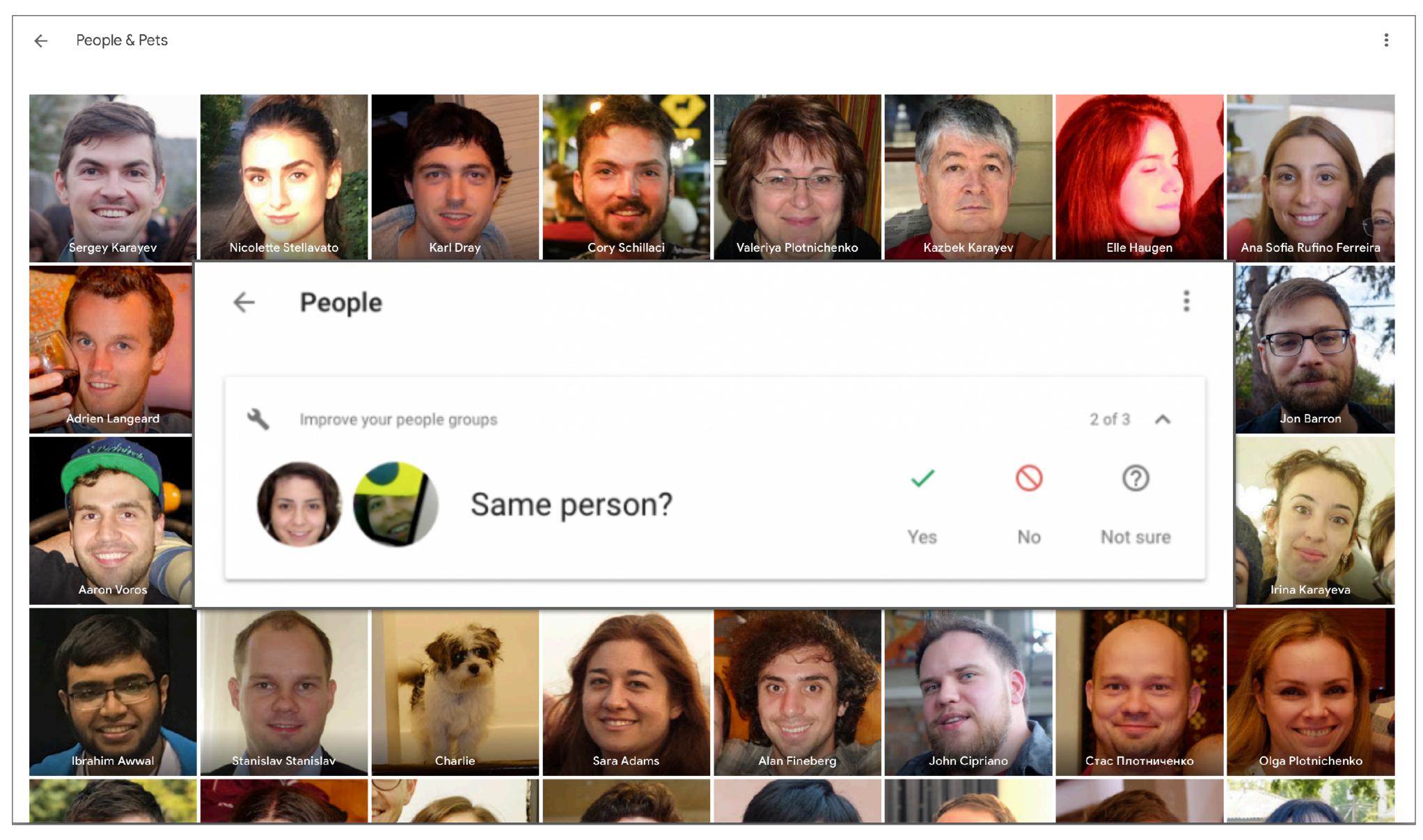
https://cdn-sv1.deepsense.ai/wp-content/uploads/2017/04/sample_image_from_the_training_set.jpg



https://newatlas.com/synthia-dataset-self-driving-cars/43895/

Underrated: Synthetic Data

Ideal: Data Flywheel



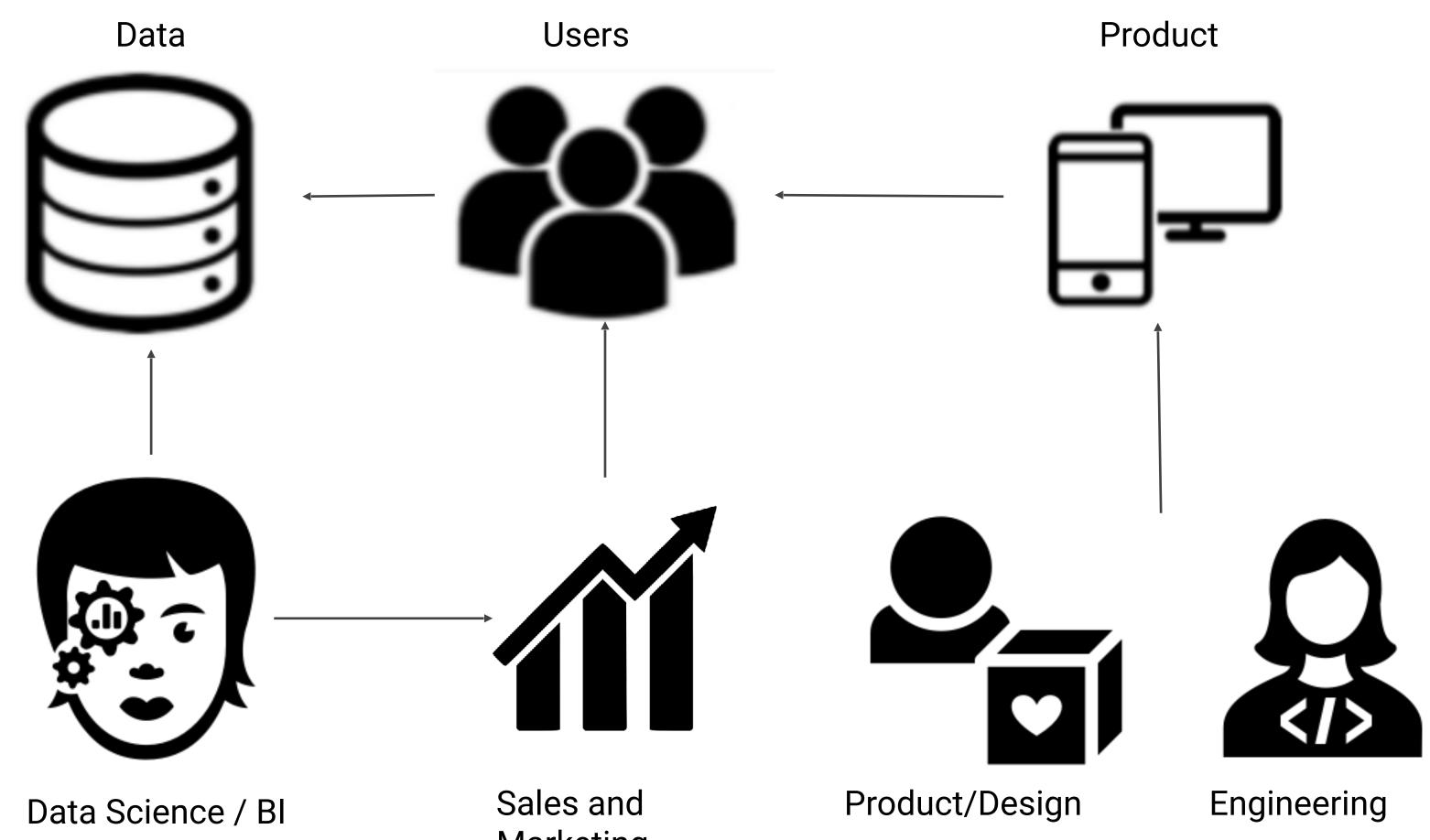
"We believe a new, more powerful, business model has evolved from its software predecessor. These companies structure their business processes to put continuously learning models, built on "closed loop" data, at the center of what they do.

When built right, they create a reinforcing cycle: Their products get better, allowing them to collect more data, which allows them to build better models, making their products better, and onward.

If software ate the world, models will run it."

- Wall Street Journal, Jan. 21, 2019, "Models Will Run the World"

Not Flywheel-Driven



Marketing

Diagram courtesy of Eric Wang

Flywheel-driven



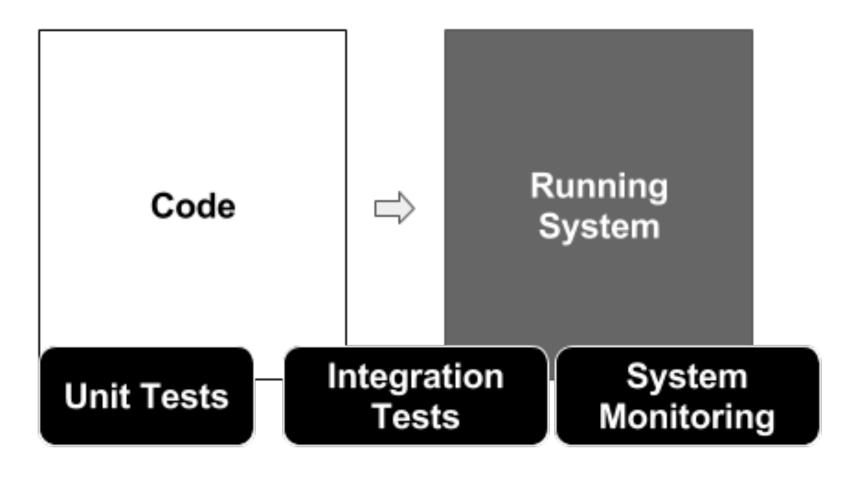
Diagram courtesy of Eric Wang



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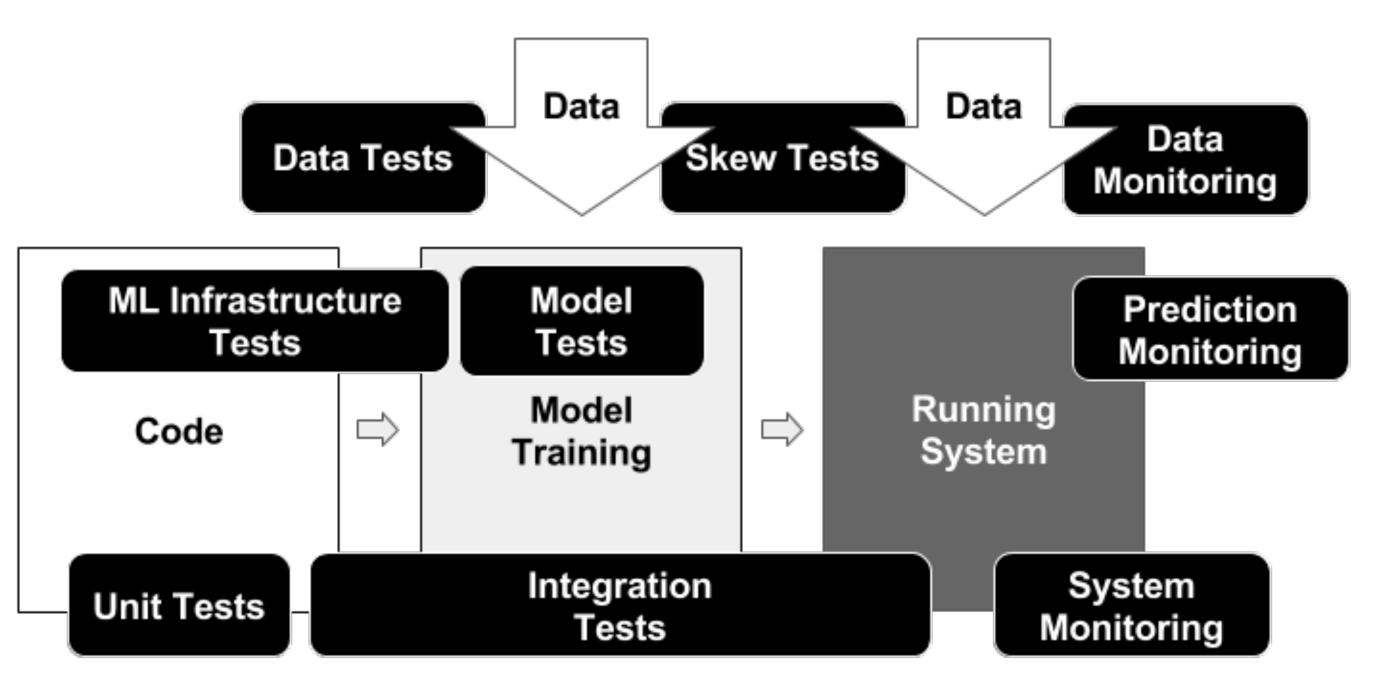
Traditional Software



https://ai.google/research/pubs/pub46555

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Machine Learning Software



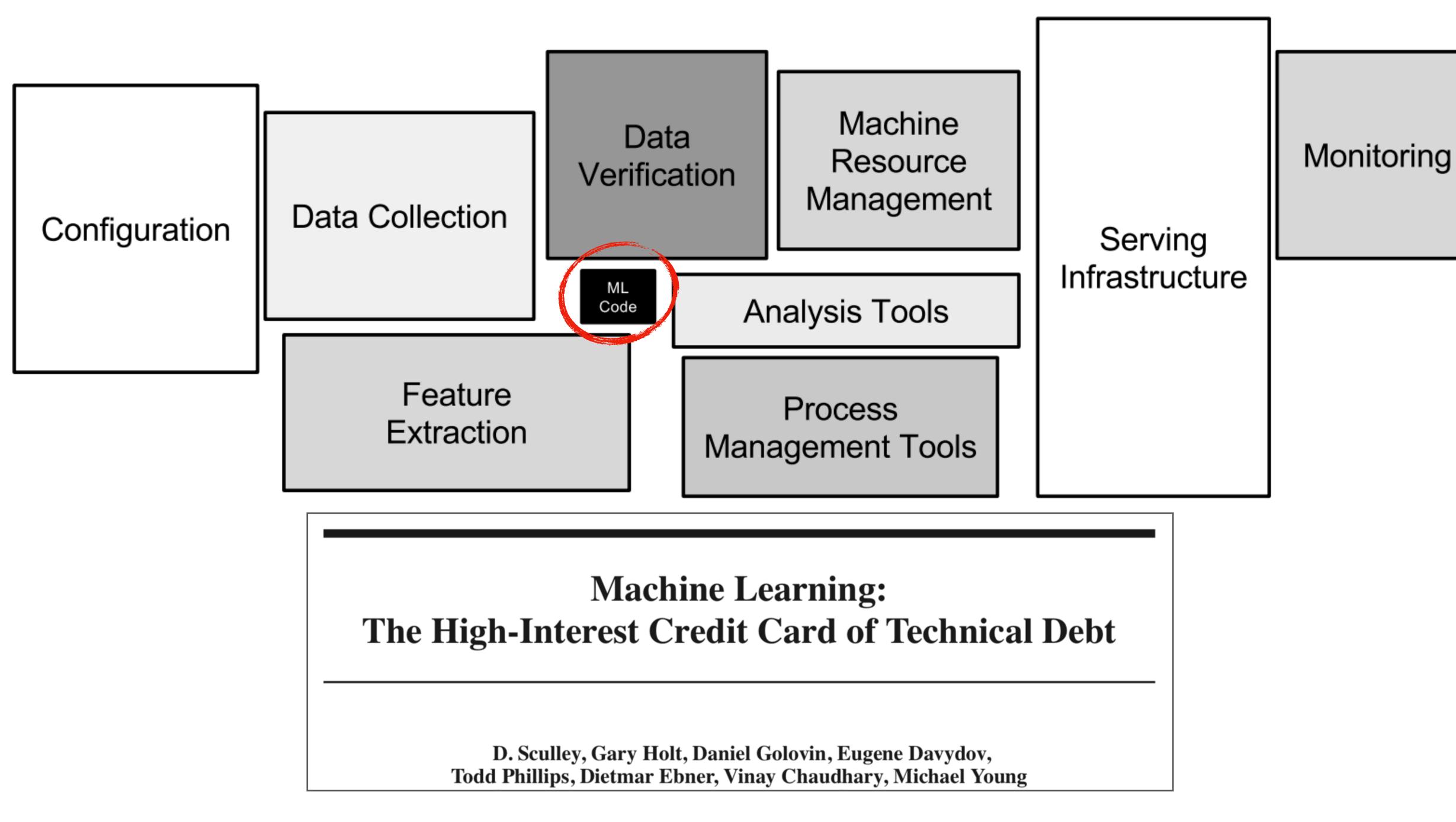
Machine Learning: The High-Interest Credit Card of Technical Debt

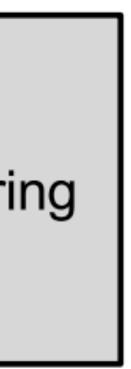
SE4ML: Software Engineering for Machine Learning (NIPS 2014 Workshop)

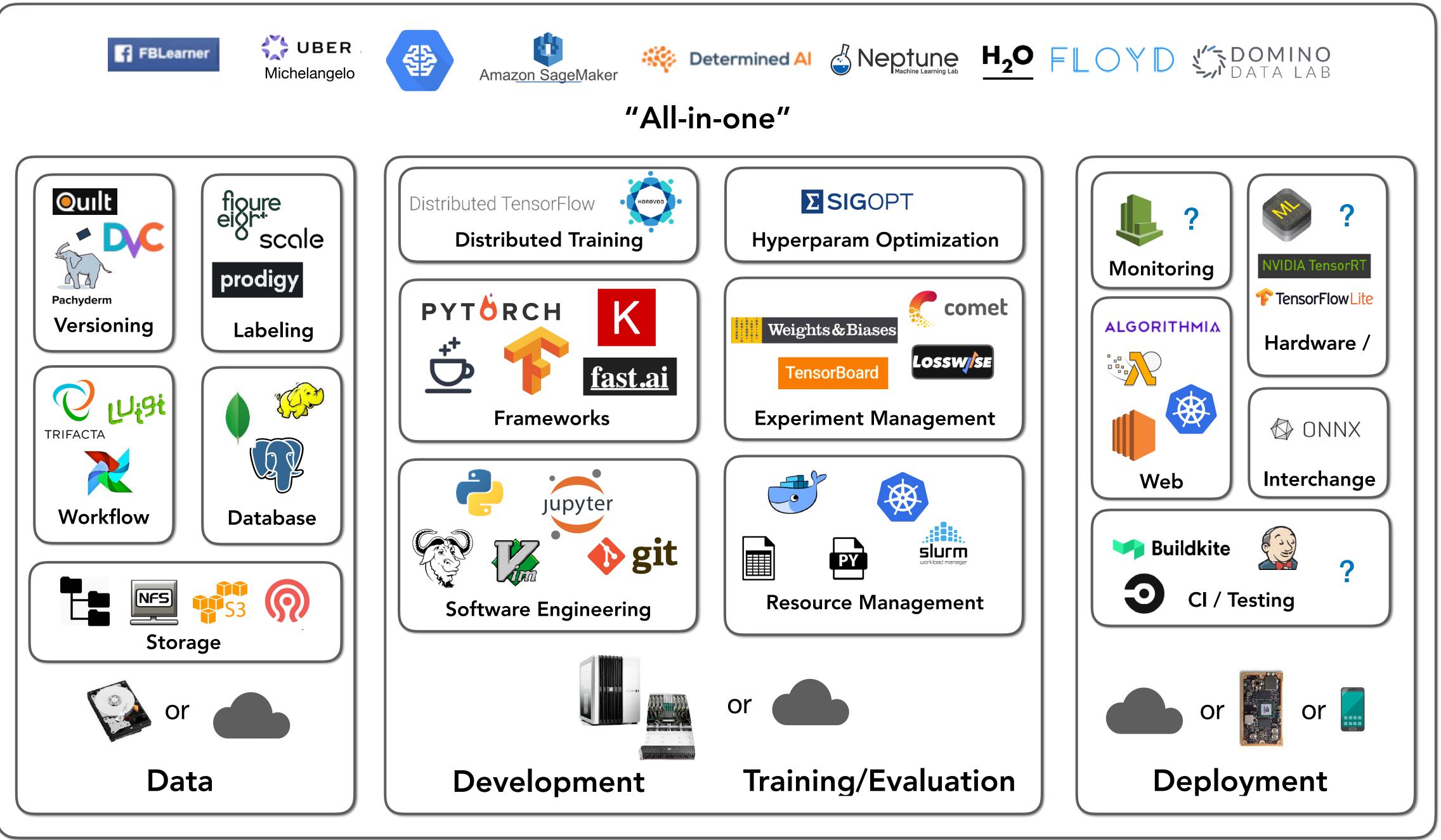
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D. Sculley, Gary Holt, Daniel Golovin, Eugene Davydov, Todd Phillips, Dietmar Ebner, Vinay Chaudhary, Michael Young {dsculley,gholt,dgg,edavydov}@google.com {toddphillips,ebner,vchaudhary,mwyoung}@google.com Google, Inc







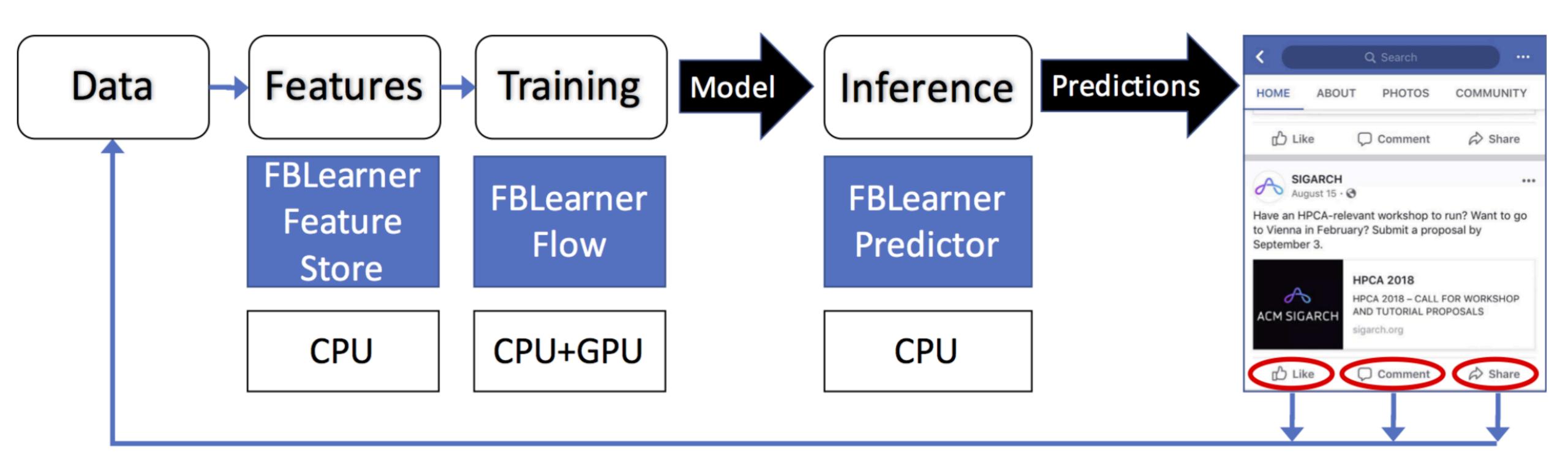




Al Development Workflow

POSTED ON MAY 9, 2016 TO AI RESEARCH, APPLIED MACHINE LEARNING, CORE DATA

Introducing FBLearner Flow: Facebook's AI backbone



FBLearner Workflow Library Models/Features - Help -

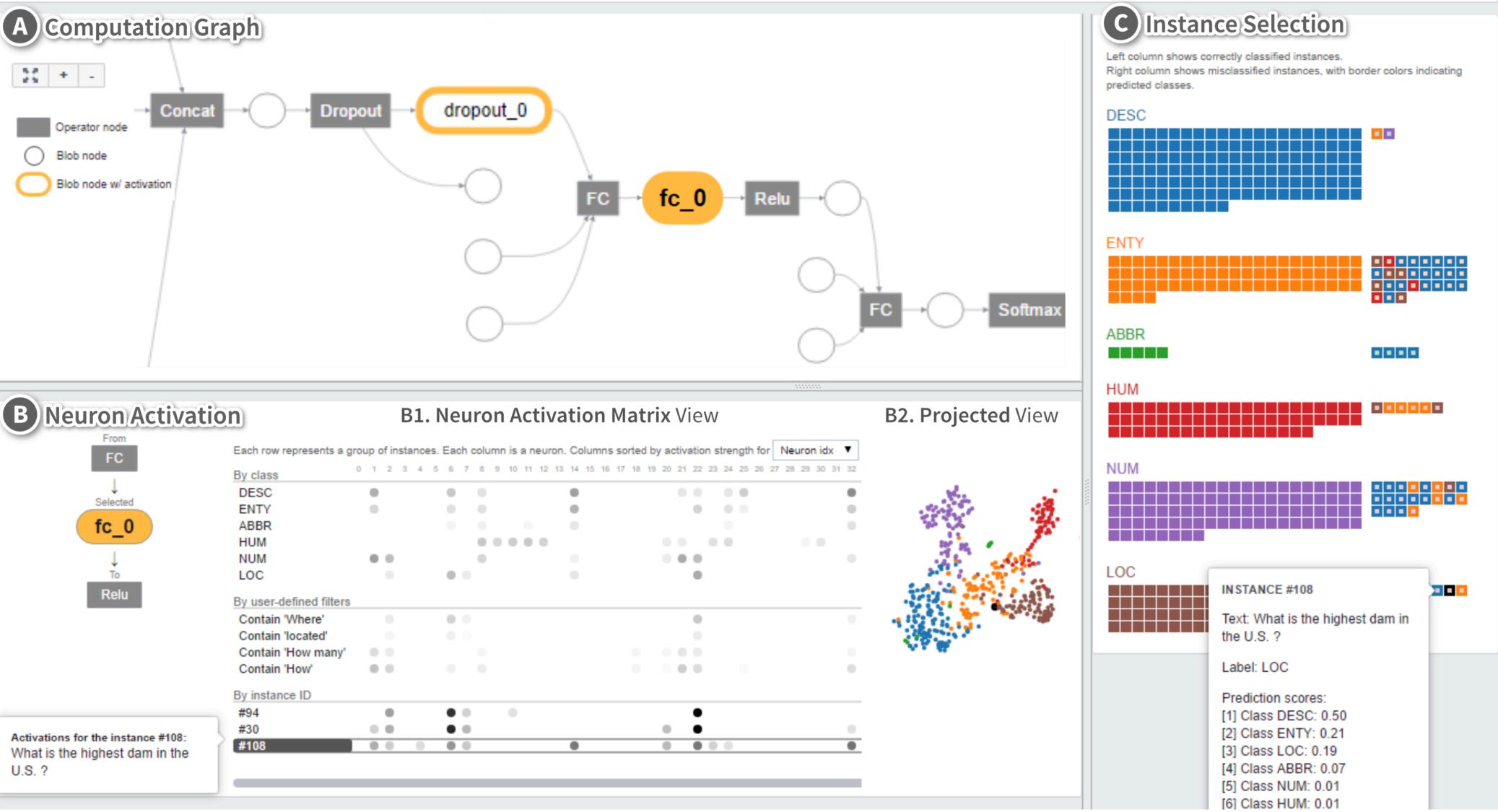
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	10	Owner	Workflow	Name	Progress	Start Time 💌	Tags	LogLoss	AUC
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000	1047295	Mahaveer Jain	Gradient Boosted Decision Tree Training	Learning Rate: 0.1	C.	9/9, 9:19pm	9.8	0.00122	0.95871
000	1047294	Mahaveer Jain	Gradient Boosted Decision Tree Training	Learning Rate: 0.2	C	9/9, 9:19pm		0.00109	0.95796
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020	1047291	Mahaveer Jain	Gradient Boosted Decision Tree Training	Learning Rate: 0.45		9/9, 9:19pm	+	0.00110	0.95293
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020	950428	Li Zhang	Parameter Sweep Example	43)		8/21, 2:40pm	-	((*))	
000	900673	Jiawei Chen	Parameter Sweep Example			8/8, 9:11pm	1		1
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000	832027	Giri Rajaram	Parameter Sweep Example			7/24, 12:34pm	+		1

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FBLearner Workflow Library Projects Tools - Help -

ActiVis: Visualization of Deep Neural Networks #15782570



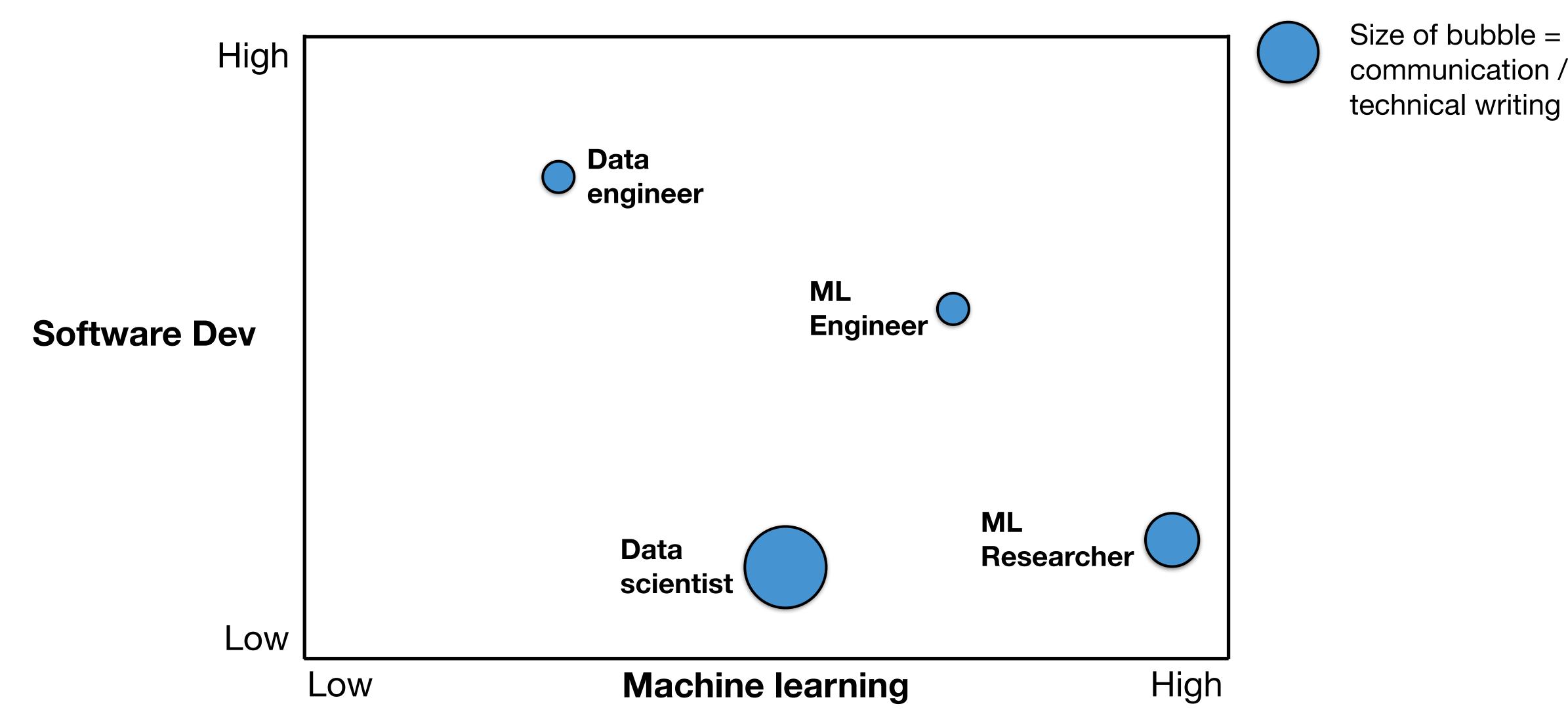
FC	Each row represents a gr	oup of instances	s. Each column is	a neuron. Columns	s sorted by activat
	By class	0 1 2 3 4 9	5 6 7 8 9 10	11 12 13 14 15 16	17 18 19 20 21 3
Ļ	DESC	•			
Selected	ENTY				(
fc_0	ABBR				
	HUM				
Ļ	NUM				
То	LOC				(
Relu	By user-defined filters				
	Contain 'Where'				
	Contain 'located'				
	Contain 'How many'				
	Contain 'How'				
	By instance ID				
	#94	•			
A	#30		• •		
Activations for the instance #108: What is the bighest dam in the	#108		• •	•	
What is the highest dam in the U.S. ?					

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Breakdown of roles

Role	Job Function	Work product
Data engineer	Build data pipelines, aggregation, storage	Data systems
ML Engineer	Train & deploy production-grade prediction models	Overall prediction system
ML Researcher	Develop research-grade prediction models	New models
Data Scientist	Bad orgs: all of the above Good orgs: answer business questions with data	Reports





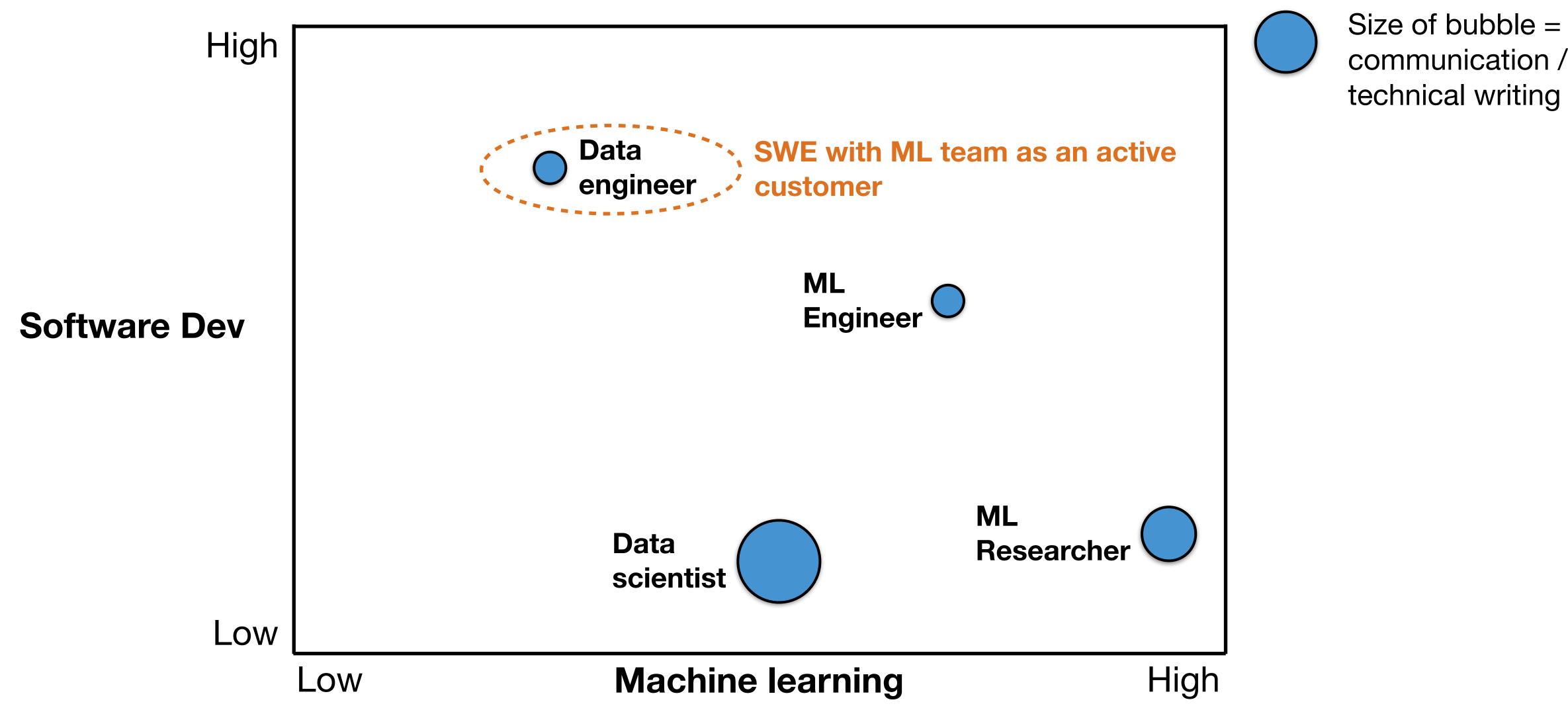
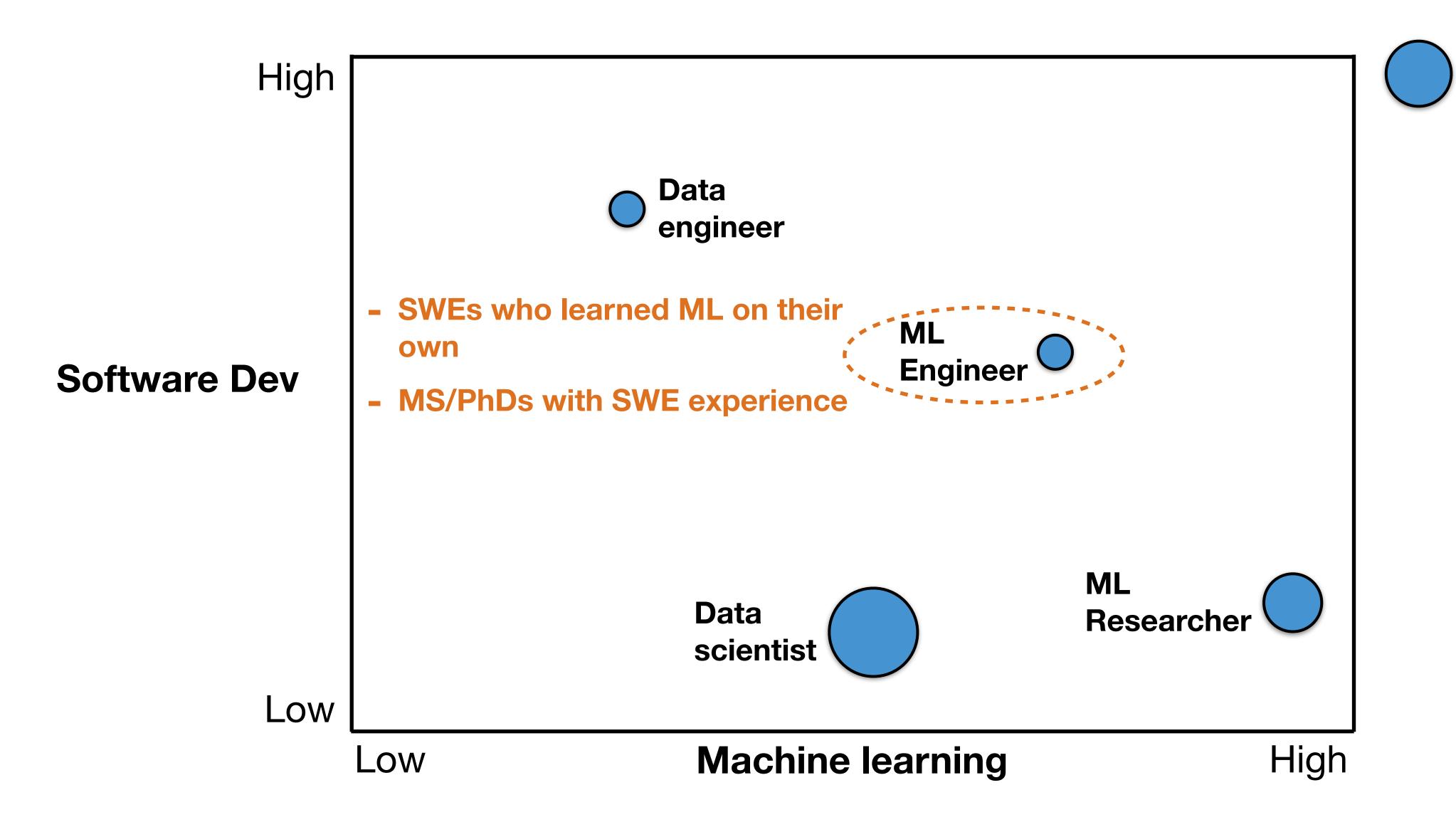


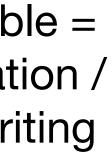
Diagram courtesy of Josh Tobin

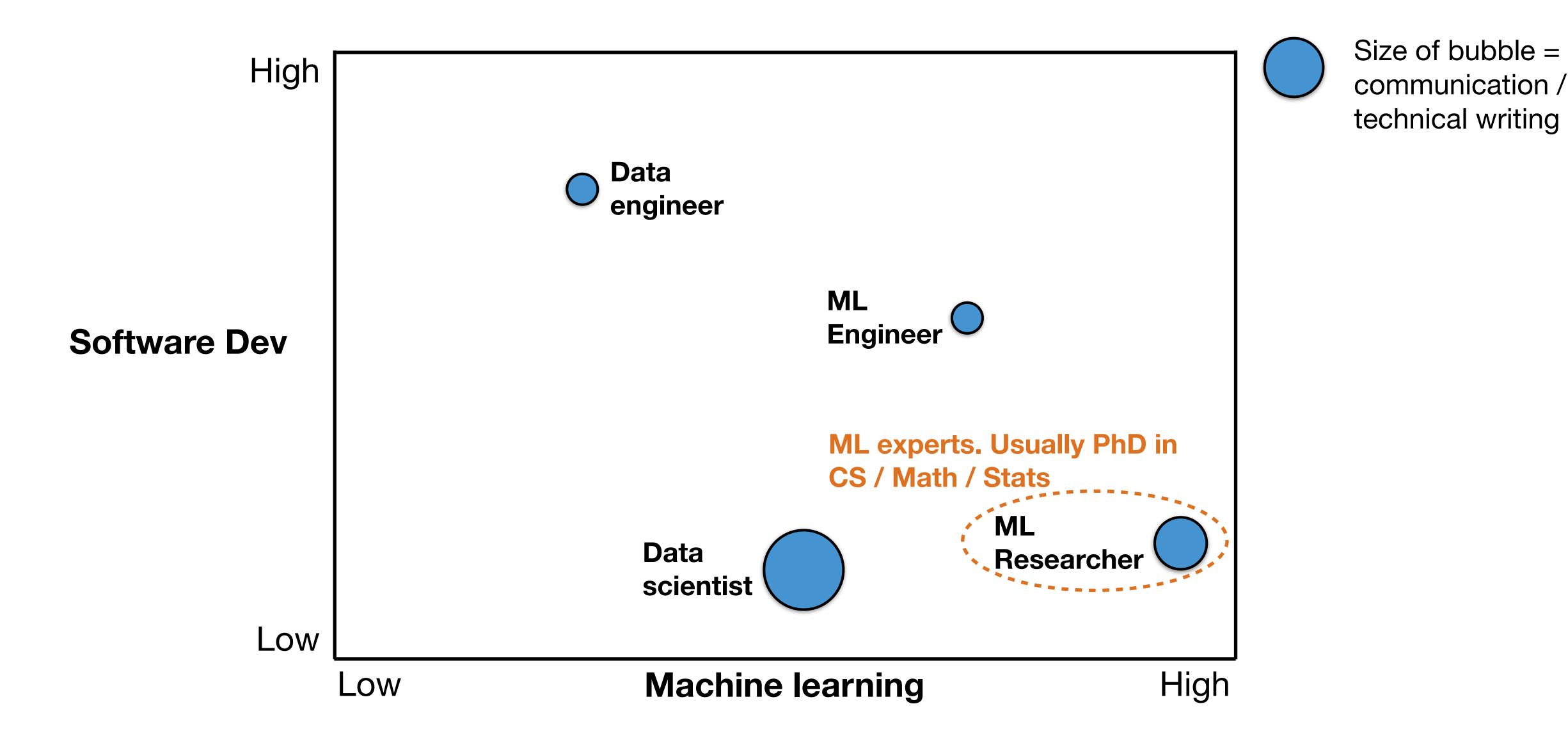


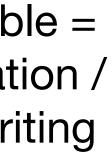


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Size of bubble = communication / technical writing







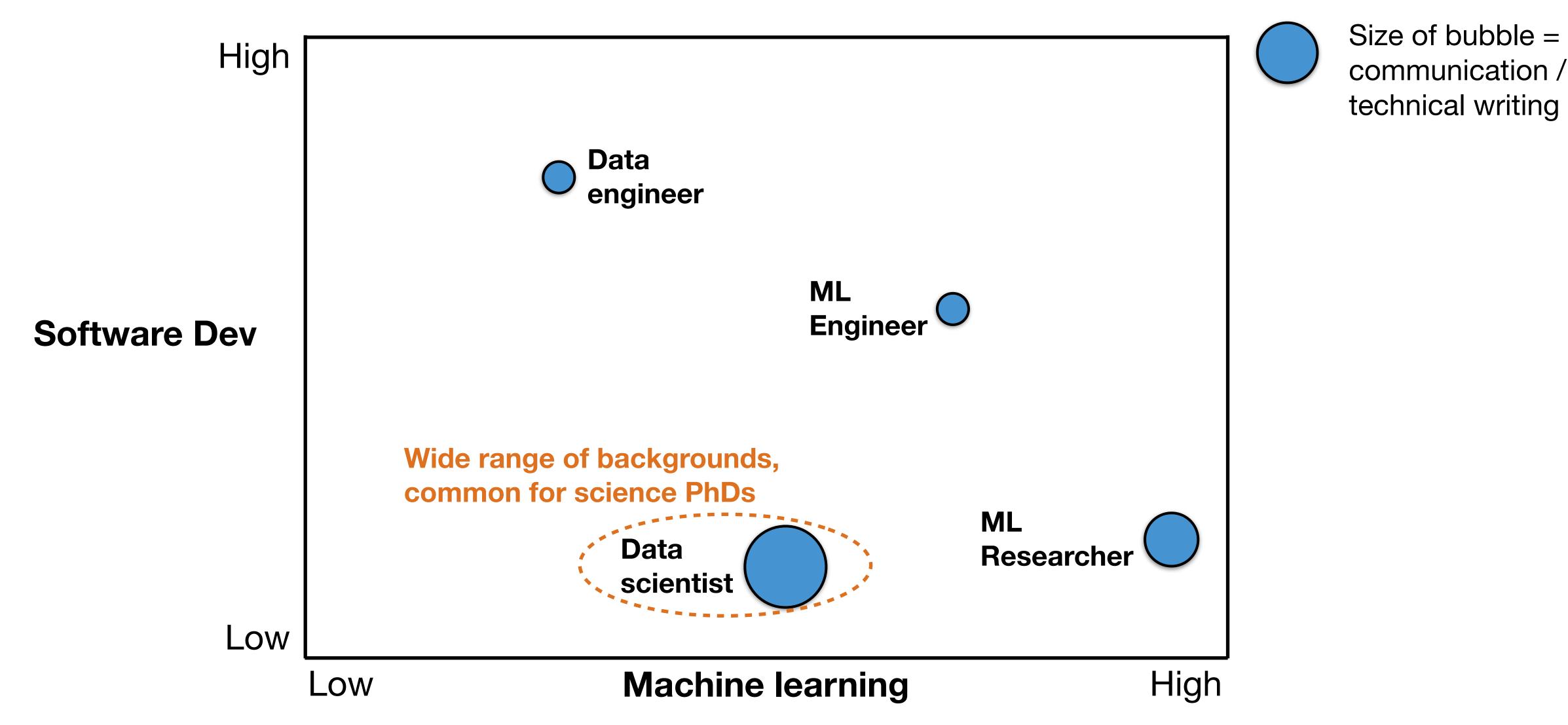


Diagram courtesy of Josh Tobin



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Role	
Data engineer	Peop
ML Engineer	SWEs that
ML Researcher	
Data Scientist	Non-C



Where to hire

ple with "Big Data" experience, ops-focused SWEs

at took ML courses, MS/PhDs interested in software dev

Hardest one. Huge talent gap!

CS PhD with a data science project they can show.

- Introduction
 - History and terminology
 - What's possible, what's on the horizon, what's unknown
- Developing Al Products
 - Picking the problem
 - Data Flywheel
 - Most Al code is not Al
 - Roles and Hiring
- Example
- Q & A

Outline