

The World
of Artificial
Intelligence



Conversation around AI has increased materially in past 5 years



“AI is the ‘runtime’ that is going to shape all what we do”



“AI can make humans more productive than ever imagined”

amazon



“We are now solving problems with machine learning that were in the realm of science fiction for the last several decades”

Comments on AI/ML by Indian Companies

“Multiple Machine Learning based credit models developed, 2000 attributes considered, upto 40%+ lift on GINI over generic bureau models”



“AI Doctor Assistant”



“AI based pre-claim assessment”



“AI led demand and commodity forecasting; ML powered intelligent planning for distributors”



Hindustan Unilever Limited

What is AI/ML?

AI vs. ML

Artificial Intelligence:

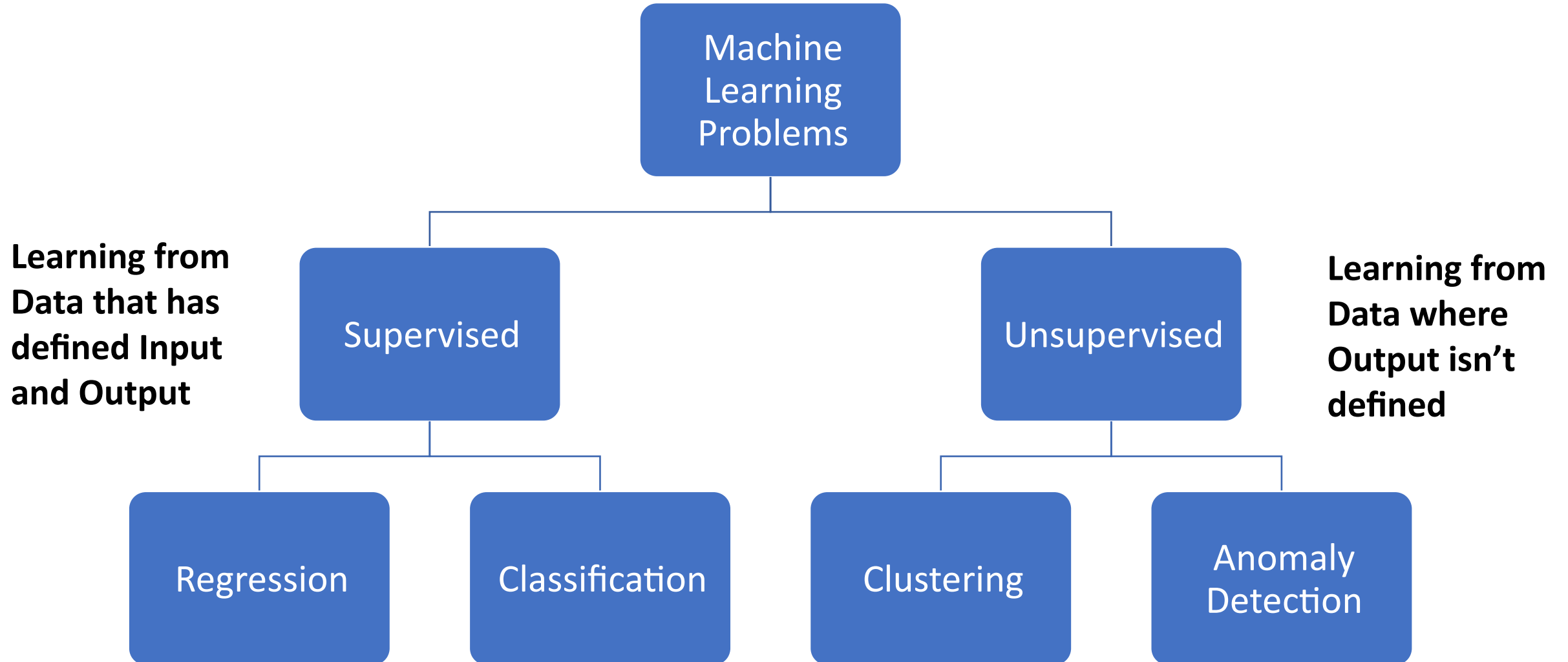
Machines with Intelligence (ability to make decisions/predictions)

**Expert Systems:
Rules based systems**

**Machine Learning:
Learning from data without
explicit programming**

**Deep Learning:
Neural network based
Machine learning, works best
with more data**

Types of Machine Learning Problems

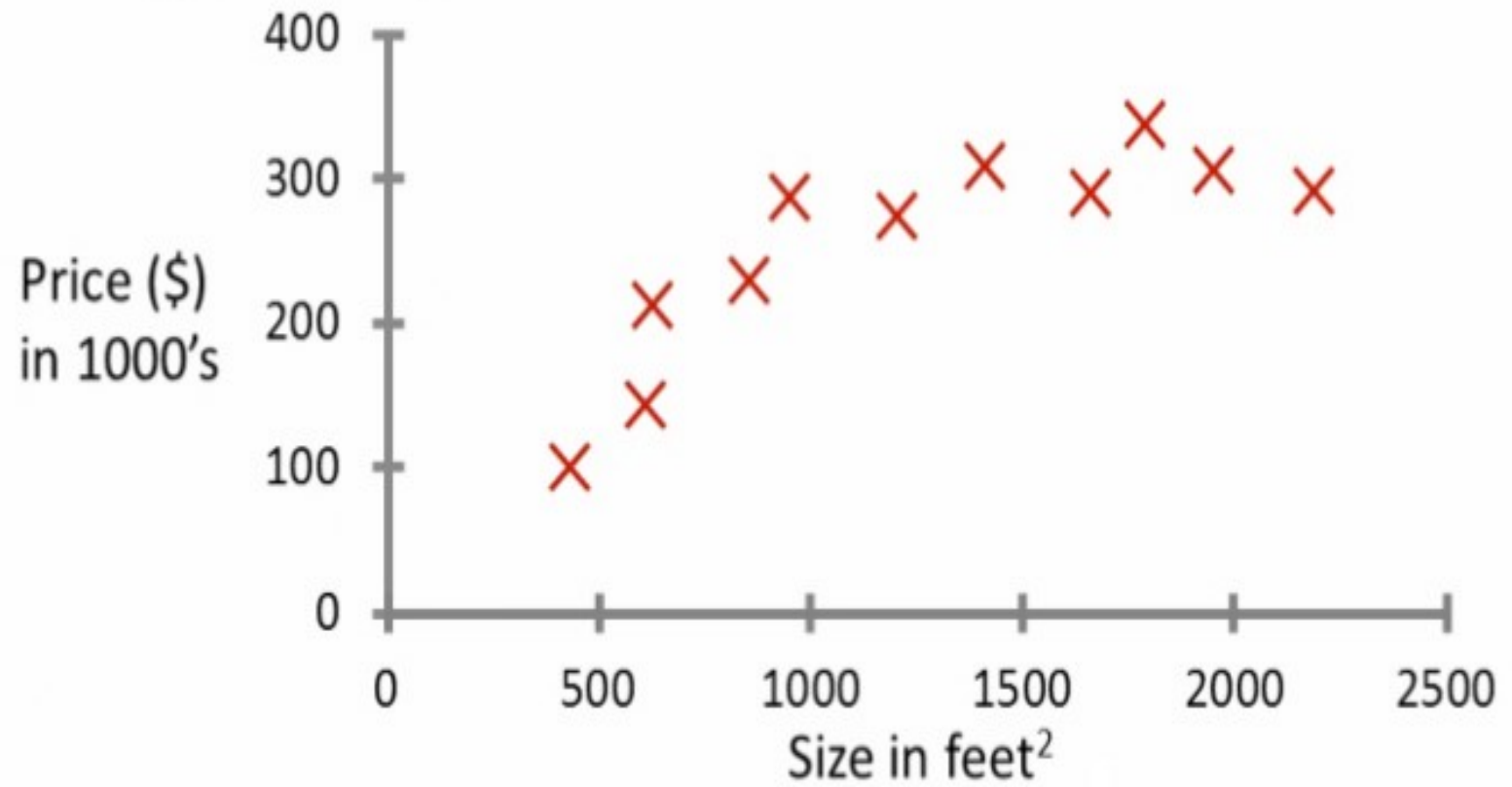


Regression: Predicting Continuous Outputs

Example: House Price Prediction based on House Size

House Size (Input)	House Price (\$ '000) (Output)
470	100
600	130
630	210
...	...
...	...
...	...

Housing price prediction.



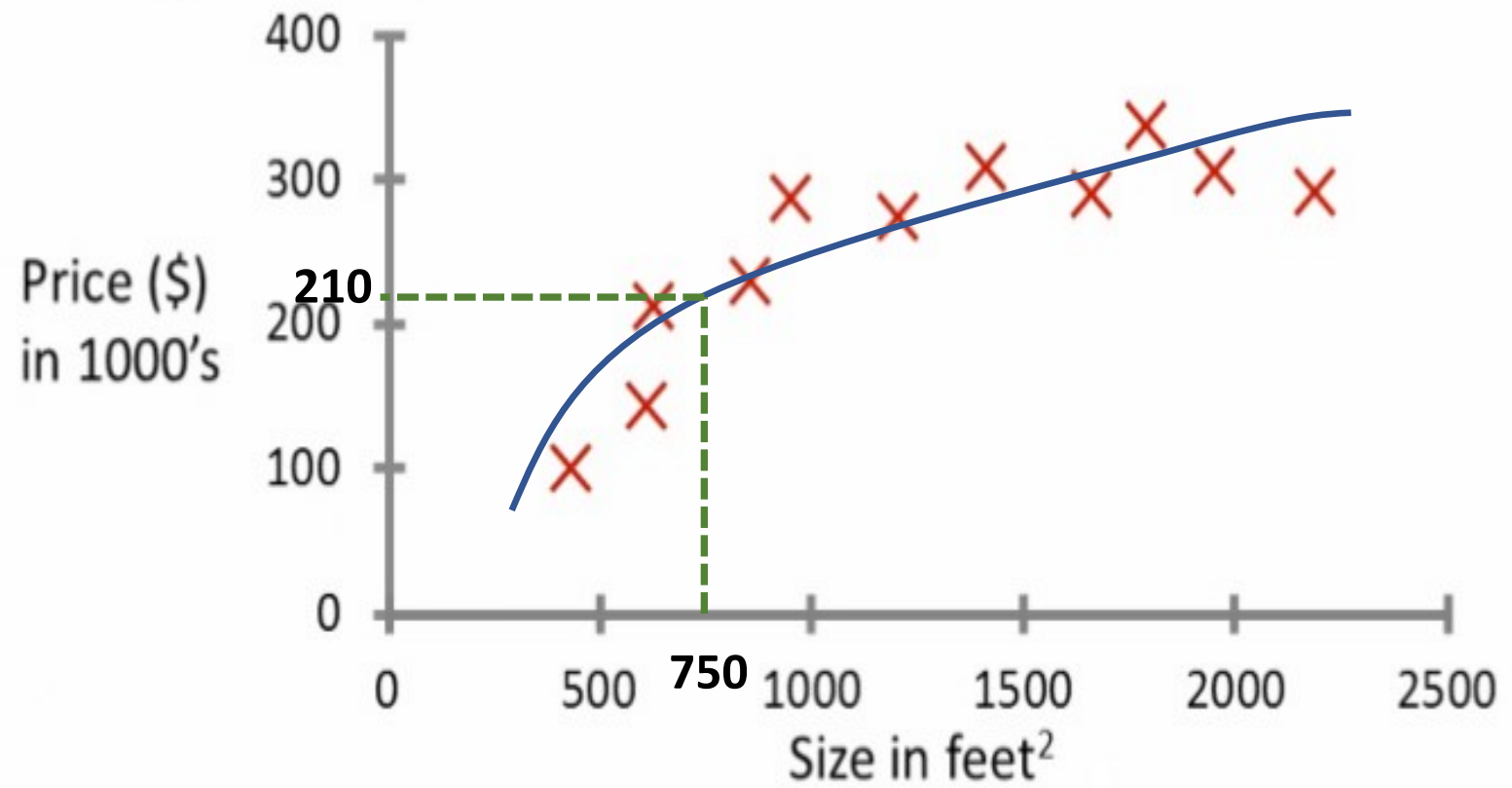
Regression: Predicting Continuous Outputs

Example: House Price Prediction based on House Size

House Size (Input)	House Price (\$ '000) (Output)
470	100
600	130
630	210
...	...
...	...
...	...

What is the price of a house with size 750 sq ft?

Housing price prediction.



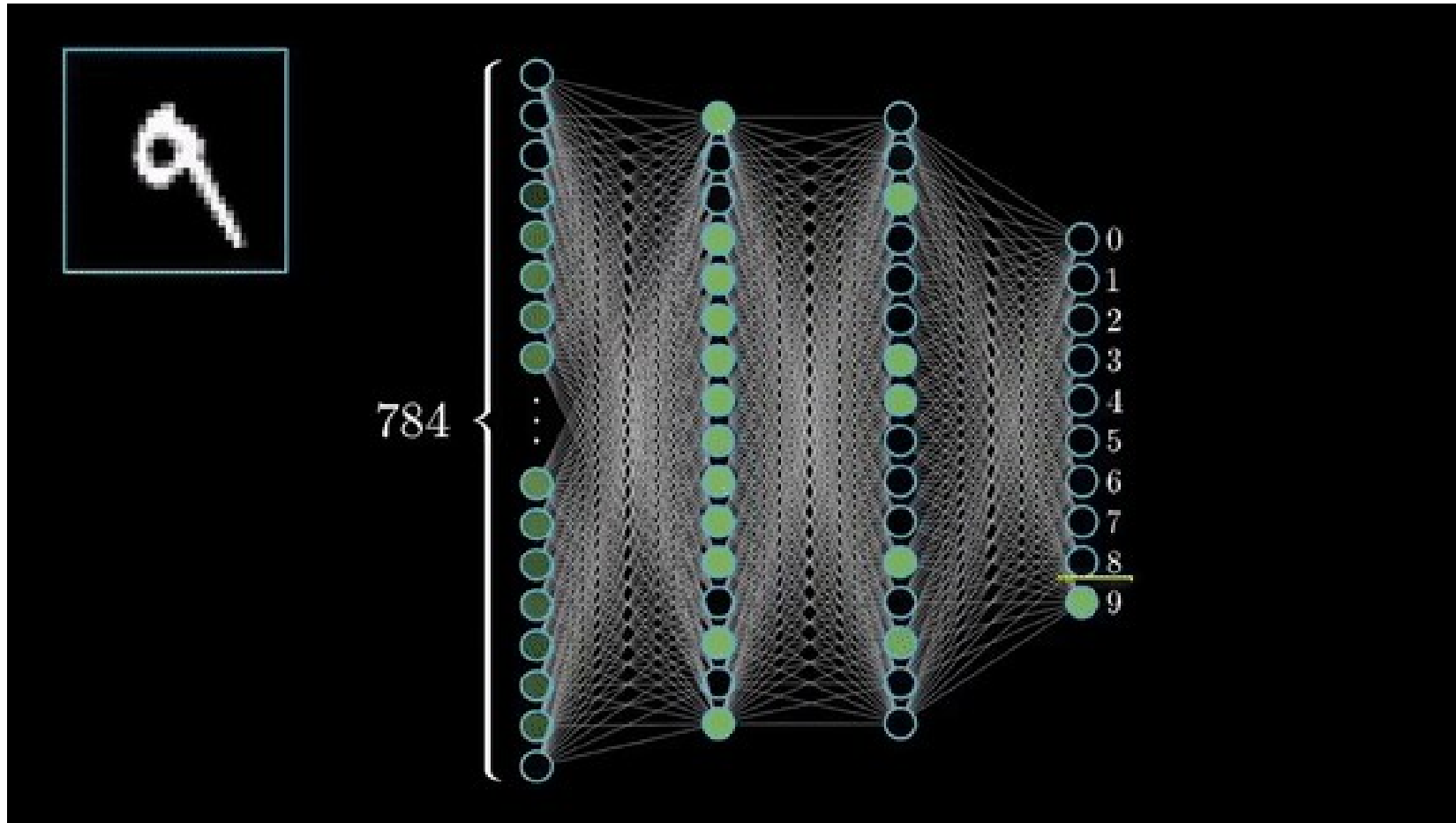
Classification: Prediction the Class/Category

How machines see images?



Classification: Prediction the Class/Category

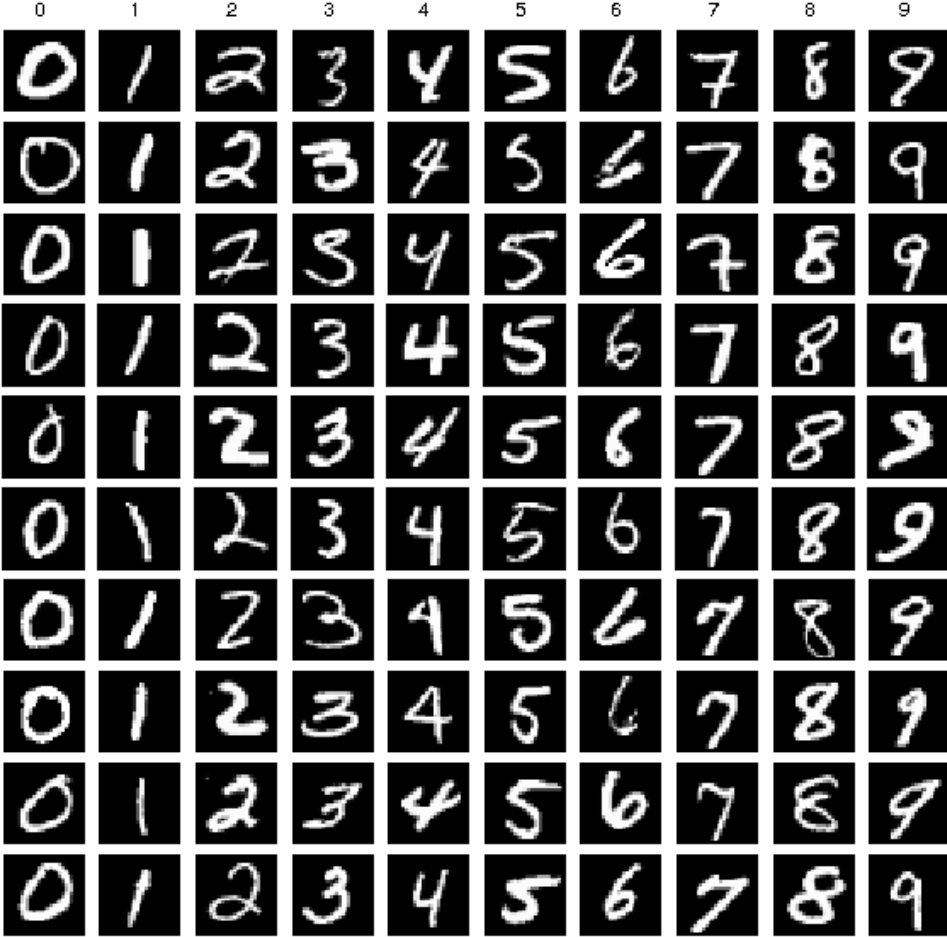
Example: Image Classification – Identify Digits



Classification: Prediction the Class/Category

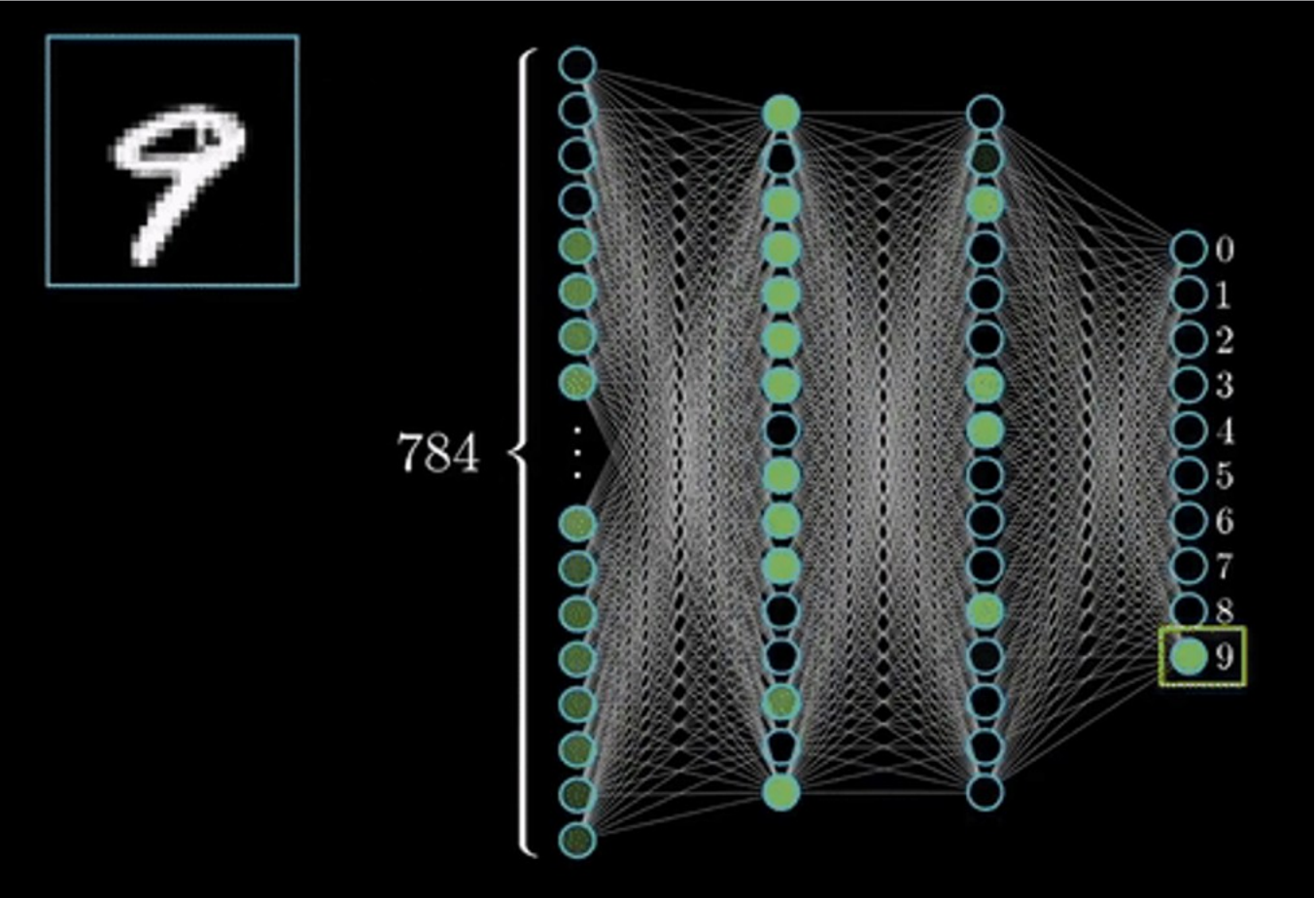
Example: Image Classification – Identify Digits

More Training Examples → Better Accuracy



Classification: Prediction the Class/Category

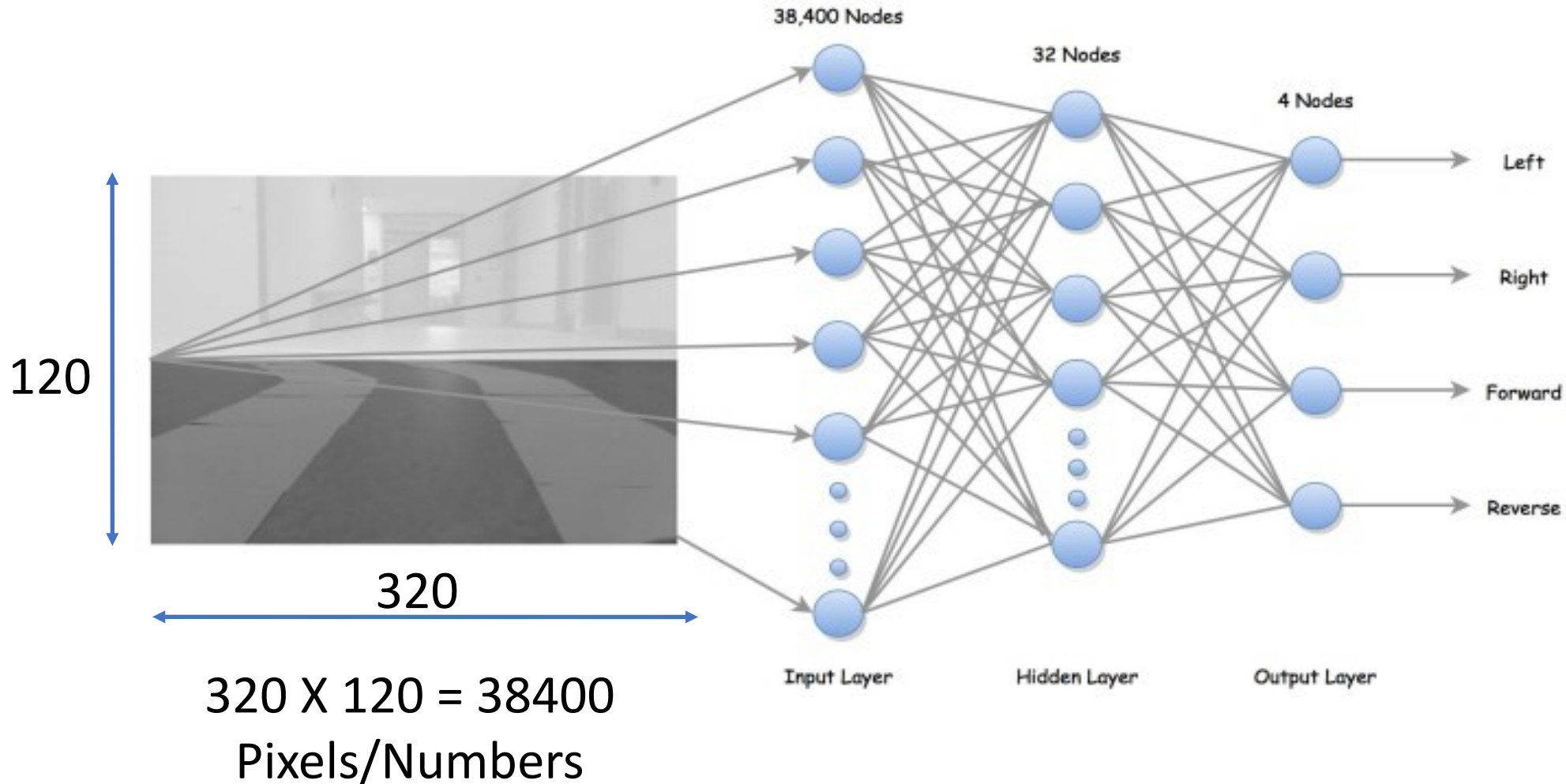
Example: Image Classification – Identify Digits



Digit	Prob
0	5%
1	1%
2	1%
3	3%
4	1%
5	5%
6	1%
7	10%
8	15%
9	58%

Classification: Prediction the Class/Category

Self driving car can be framed as a Classification Problem



Classification: Prediction the Class/Category

Self driving car can be framed as a Classification Problem

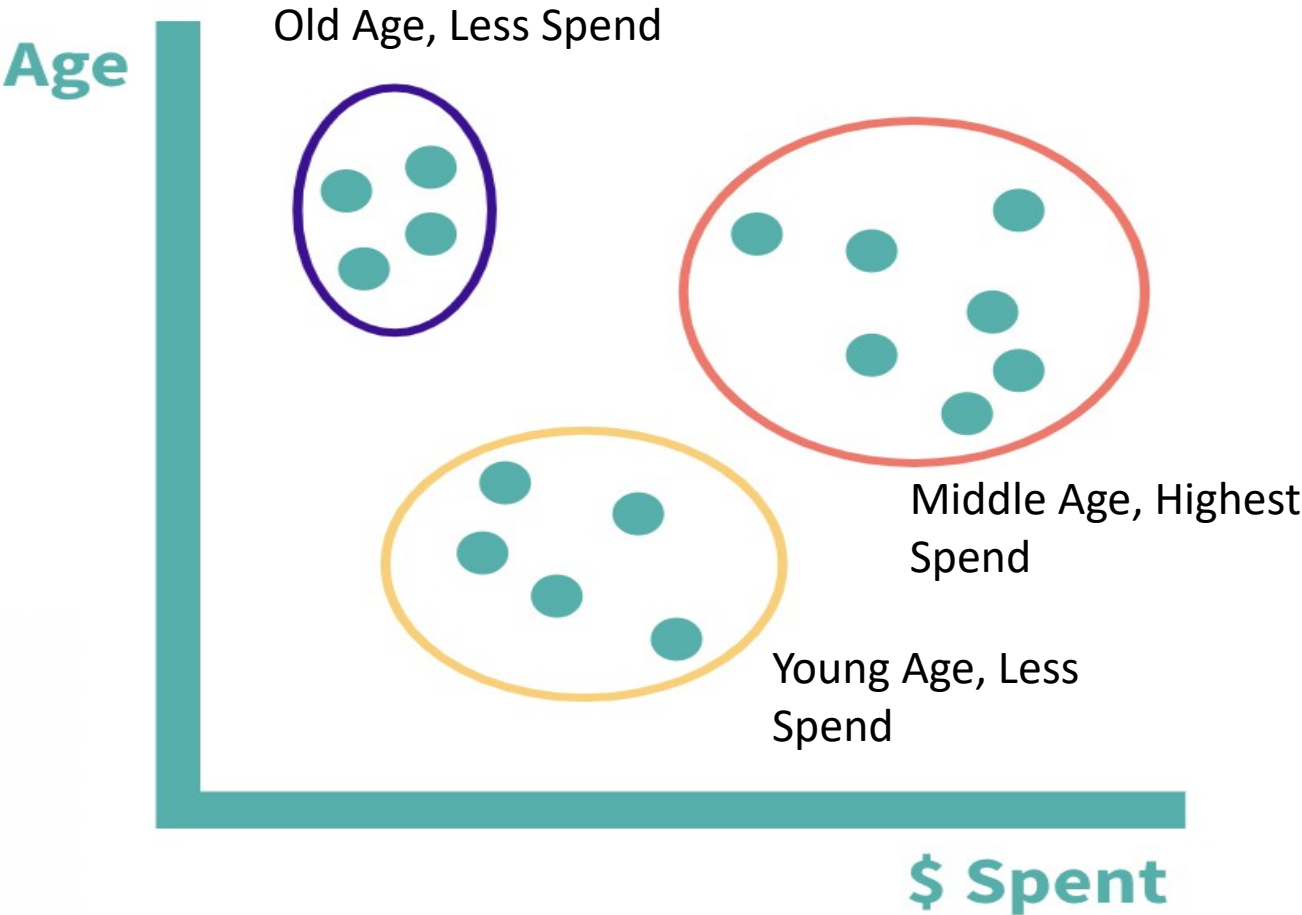


Source: <https://zhengludwig.wordpress.com/projects/self-driving-rc-car/>

Unsupervised Learning: Clustering

Example: Customer Segmentation

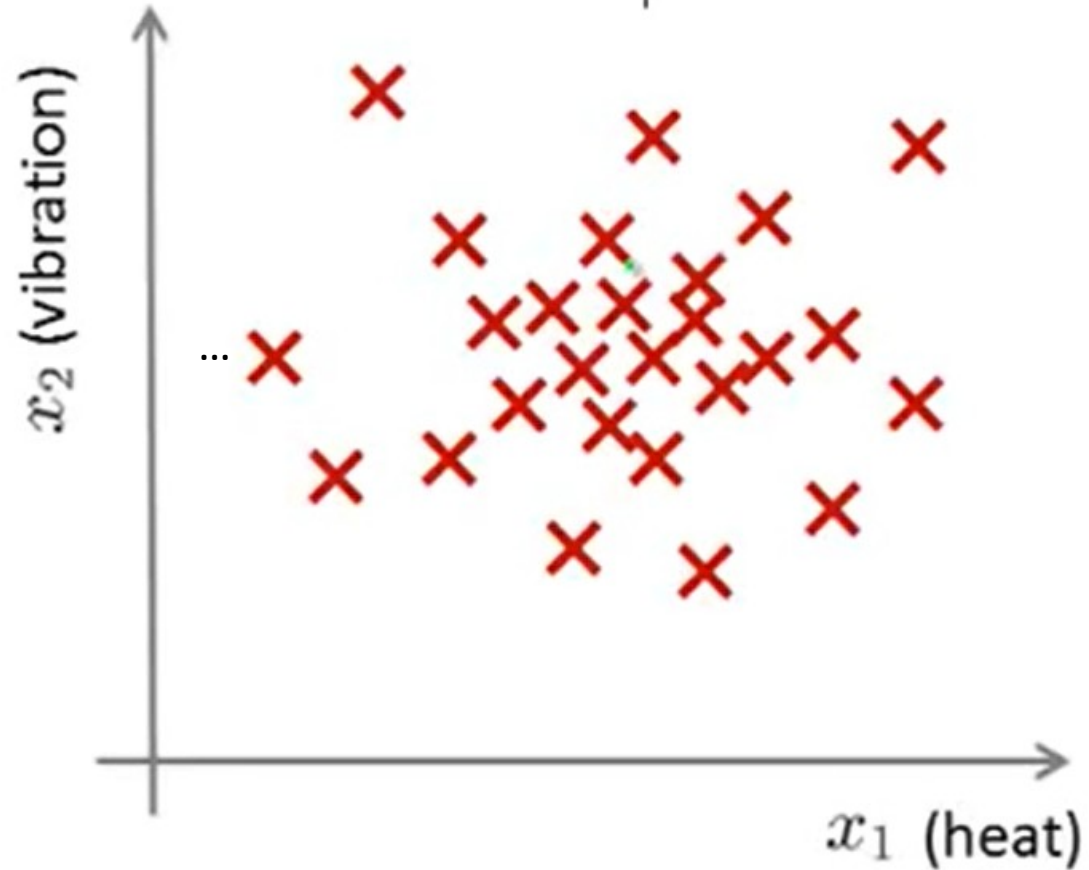
Age (Input)	Dollars Spent (Input)
25	100
20	85
35	200
40	175
55	75
60	80
...	...



Unsupervised Learning: Anomaly detection

Example: Fault Detection in Machine Parts

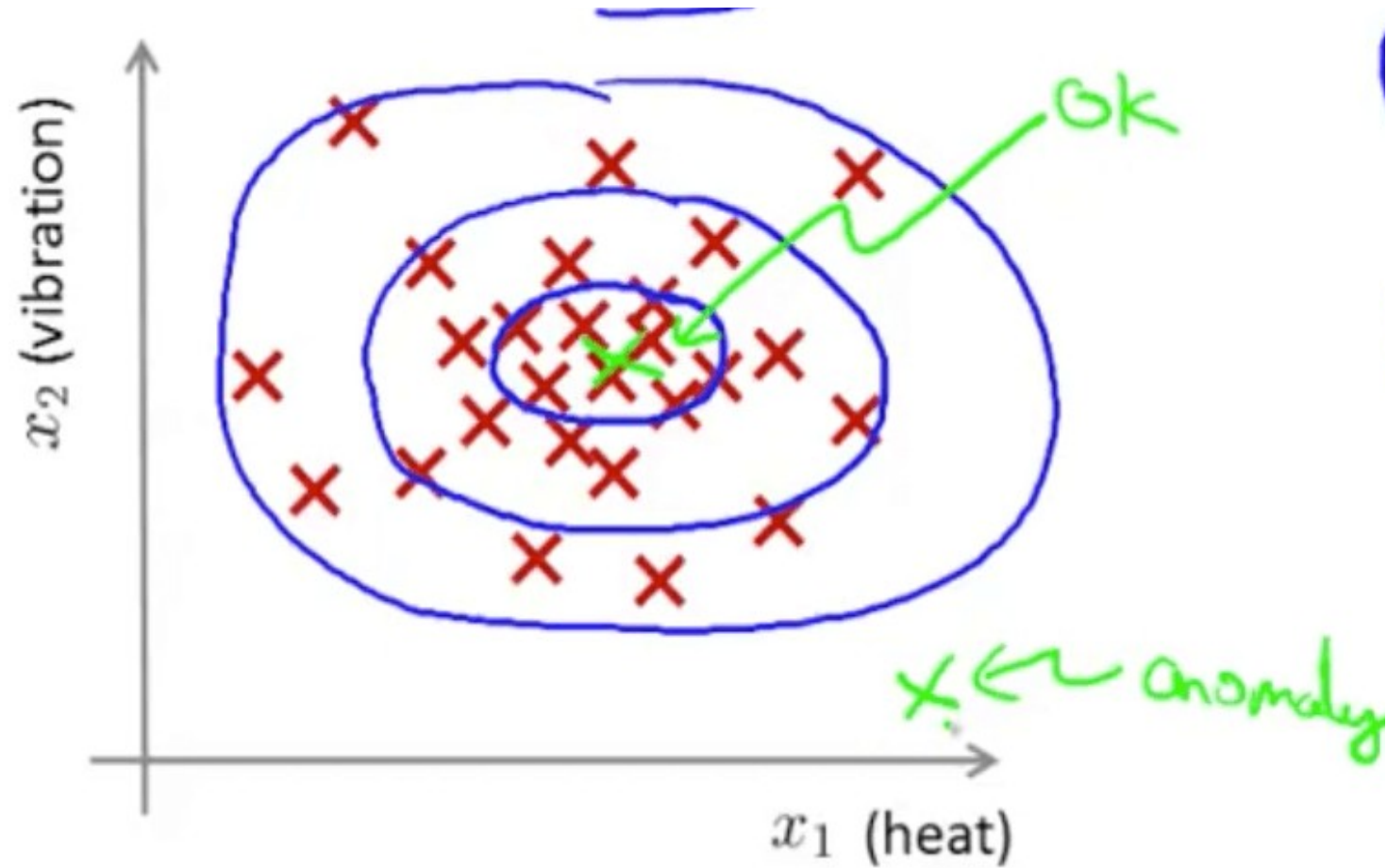
Heat (Input)	Vibration (Input)
...	...
...	...
...	...
...	...
...	...



Unsupervised Learning: Anomaly detection

Example: Fault Detection in Machine Parts

Heat (Input)	Vibration (Input)
...	...
...	...
...	...
...	...
...	...



History of Artificial Intelligence

AI as a field has existed since 1950s

Thinking Machine, MIT Documentary : 1961



AI: Story of Spring (Boom) and Winter (Bust)

- First attempts at machine translation, First neural networks written
- Major funding source: Defence
- ELIZA chatbot

- Expert Systems become popular
- Market for LISP machines boomed
- Funding increased

Spring
1956 - 1974

1974 - 1980

1980 - 1987

1987 - 2000

2000 - Present


- Many Applications fail to materialize. Research highlights limitations of existing algo
- Defence funding reduced dramatically

- Limitations of Expert Systems become apparent
- Specialised hardware market (LISP Machines) collapsed
- Defence funding reduced again

AI Spring: Research Breakthroughs, Increasing applications & Funding. But also Overpromise and Hype

The New York Times

NEW NAVY DEVICE LEARNS BY DOING; Psychologist Shows Embryo of Computer Designed to Read and Grow Wiser

 Give this article



July 8, 1958

AI Winter: Reset of over inflated expectations, Interest & Funding Dries Up

“At its low point, some computer scientists and software engineers avoided the term artificial intelligence for fear of being viewed as wild-eyed dreamers.”

*- New York Times Article : **2005***

A Brief History of AI

A BRIEF HISTORY OF AI: HOW TO PREVENT ANOTHER WINTER (A CRITICAL REVIEW)

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esiegel@umaryland.edu

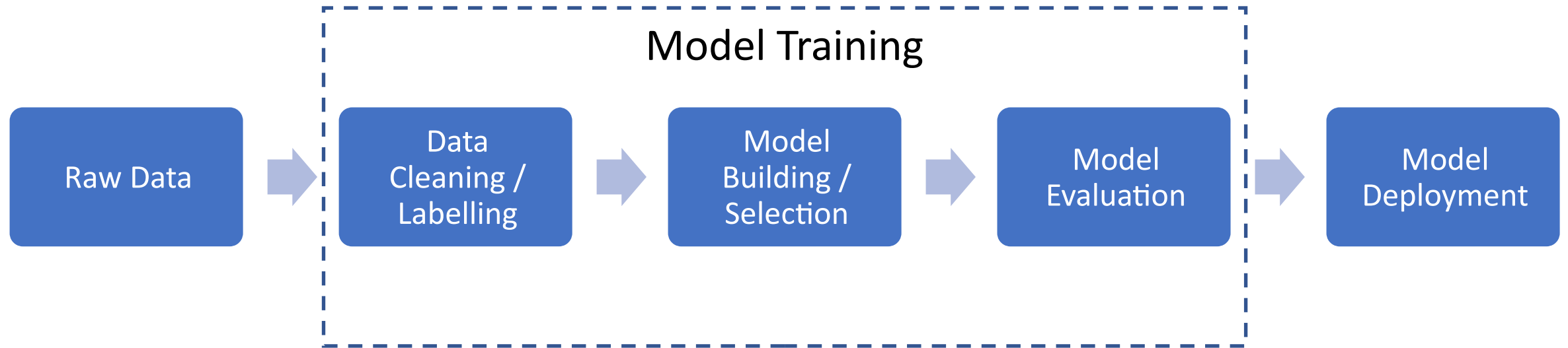
Arman Rahmim

Departments of Radiology and Physics
University of British Columbia
Vancouver, BC
arman.rahmim@ubc.ca

What is driving the current AI Spring?

Machine Learning Process

Greatly Simplified



- More Complex Algorithm → More Data & More Compute
- More Data → More storage & More Compute

What is driving the current AI spring?

**Research
Breakthroughs**

**Cloud:
Accessible
computing
and Storage**

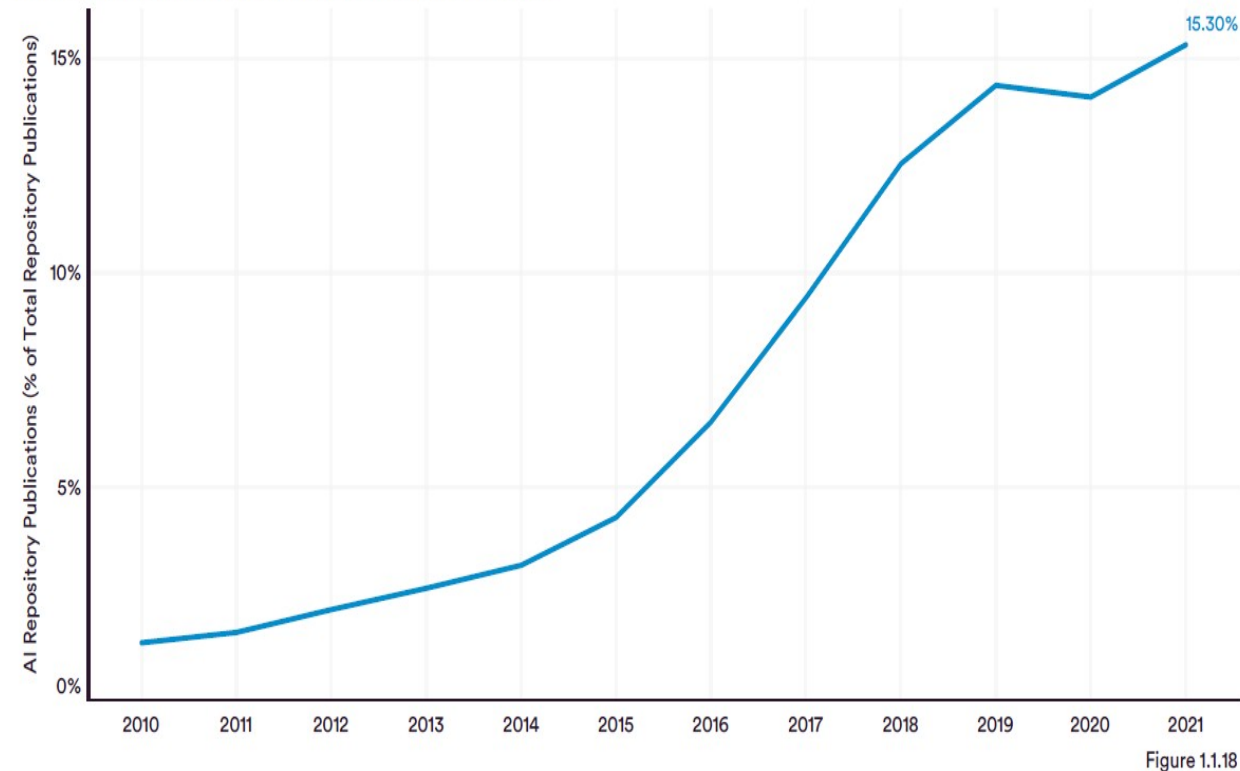
**Increasing
Data
Availability**

**Increasing
Computing
Power**

Pace of Research in AI has been incredible

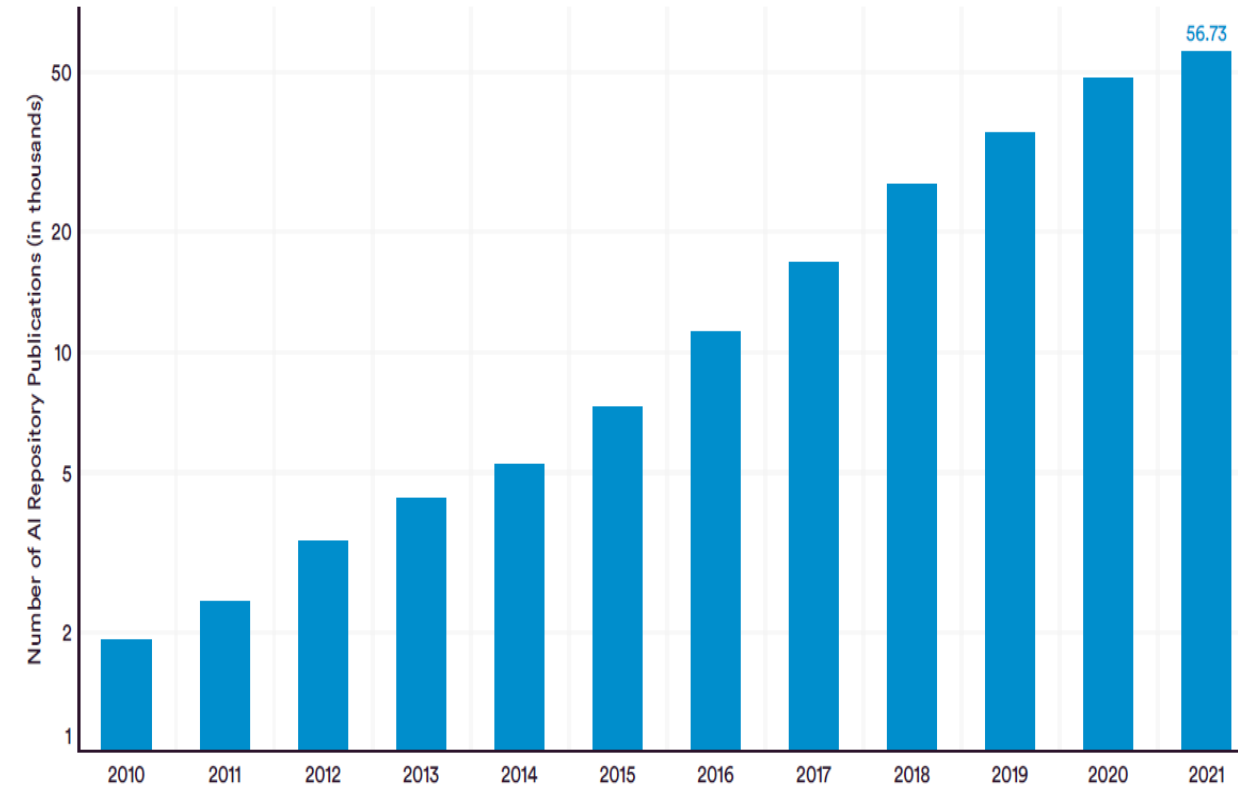
AI REPOSITORY PUBLICATIONS (% of TOTAL REPOSITORY PUBLICATIONS), 2010–21

Source: Center for Security and Emerging Technology, 2021 | Chart: 2022 AI Index Report



NUMBER of AI REPOSITORY PUBLICATIONS, 2010–21

Source: Center for Security and Emerging Technology, 2021 | Chart: 2022 AI Index Report



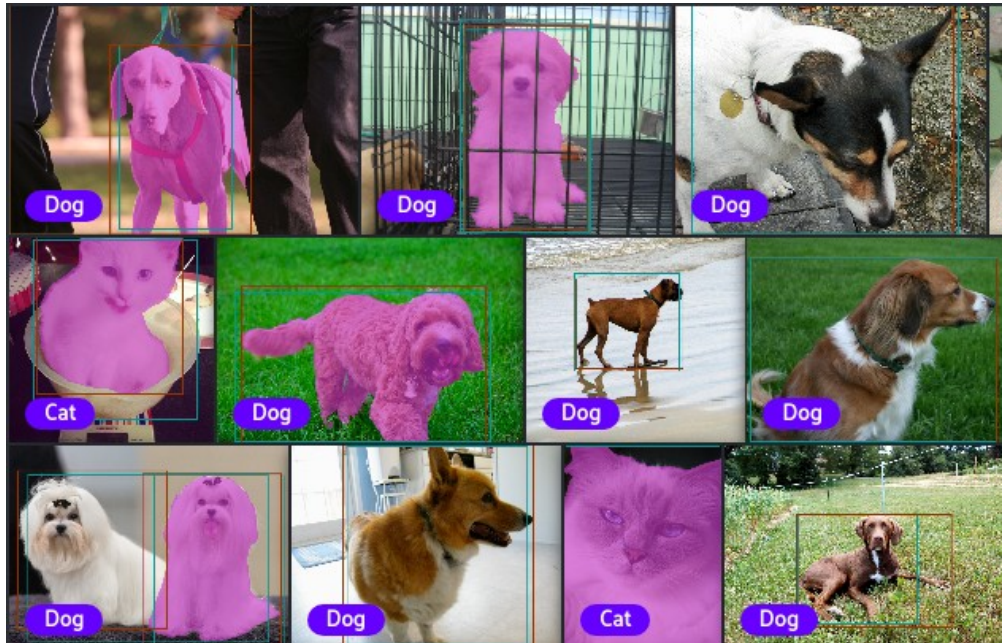
Source: State of AI 2021 Report

Increasing availability of Clean and Labelled Data

IMAGENET

14 Million Labelled Images

Google Open Images: 9M

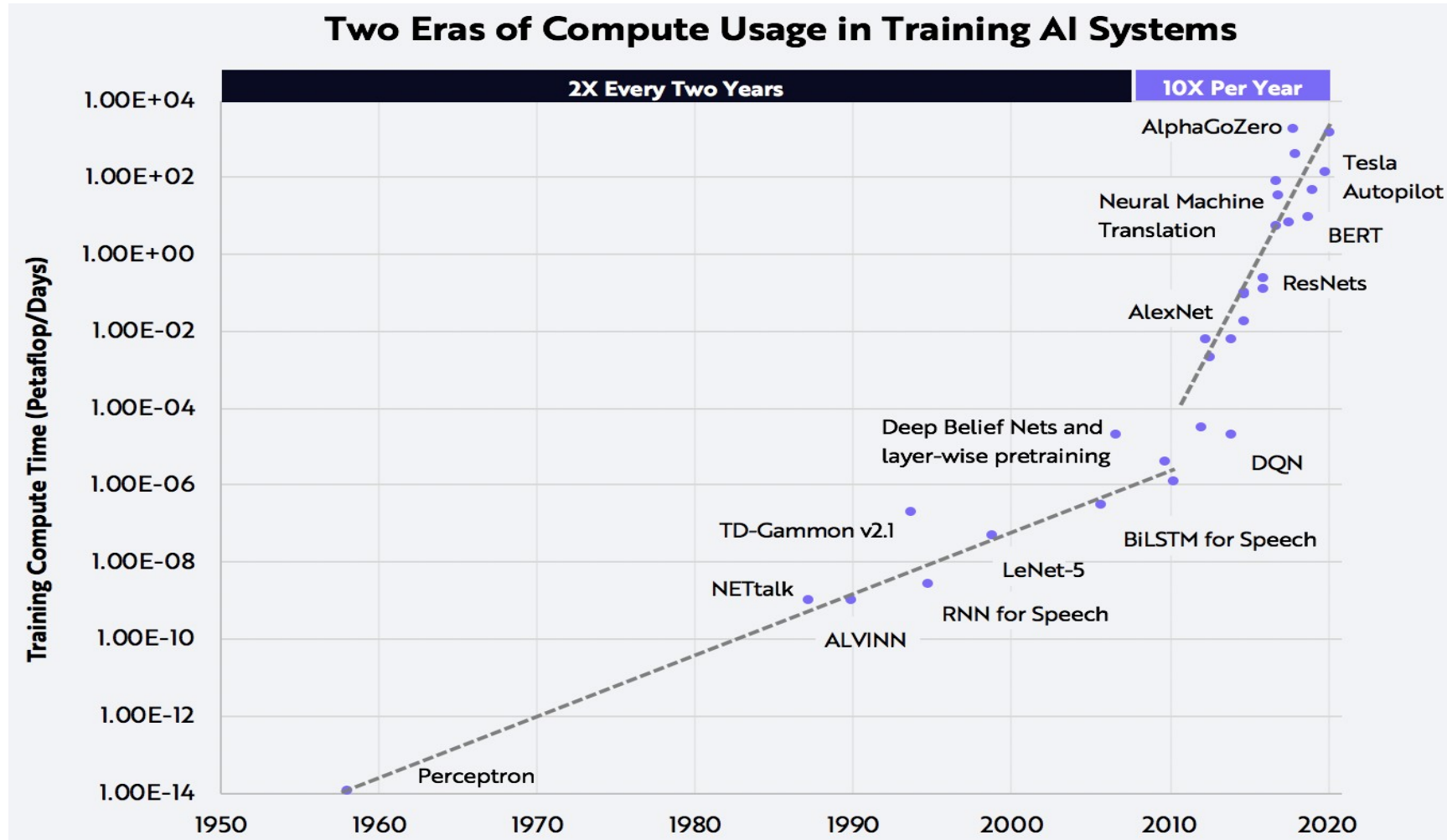


Amazon Review Data:
233M Reviews with detailed
Metadata

Malware Database



Increasing compute capability



Source: OpenAI, ARK Invest

Like for like compute cost has reduced

IMAGENET: TRAINING COST (to 93% ACCURACY)

Source: AI Index and Narayanan, 2021 | Chart: 2022 AI Index Report

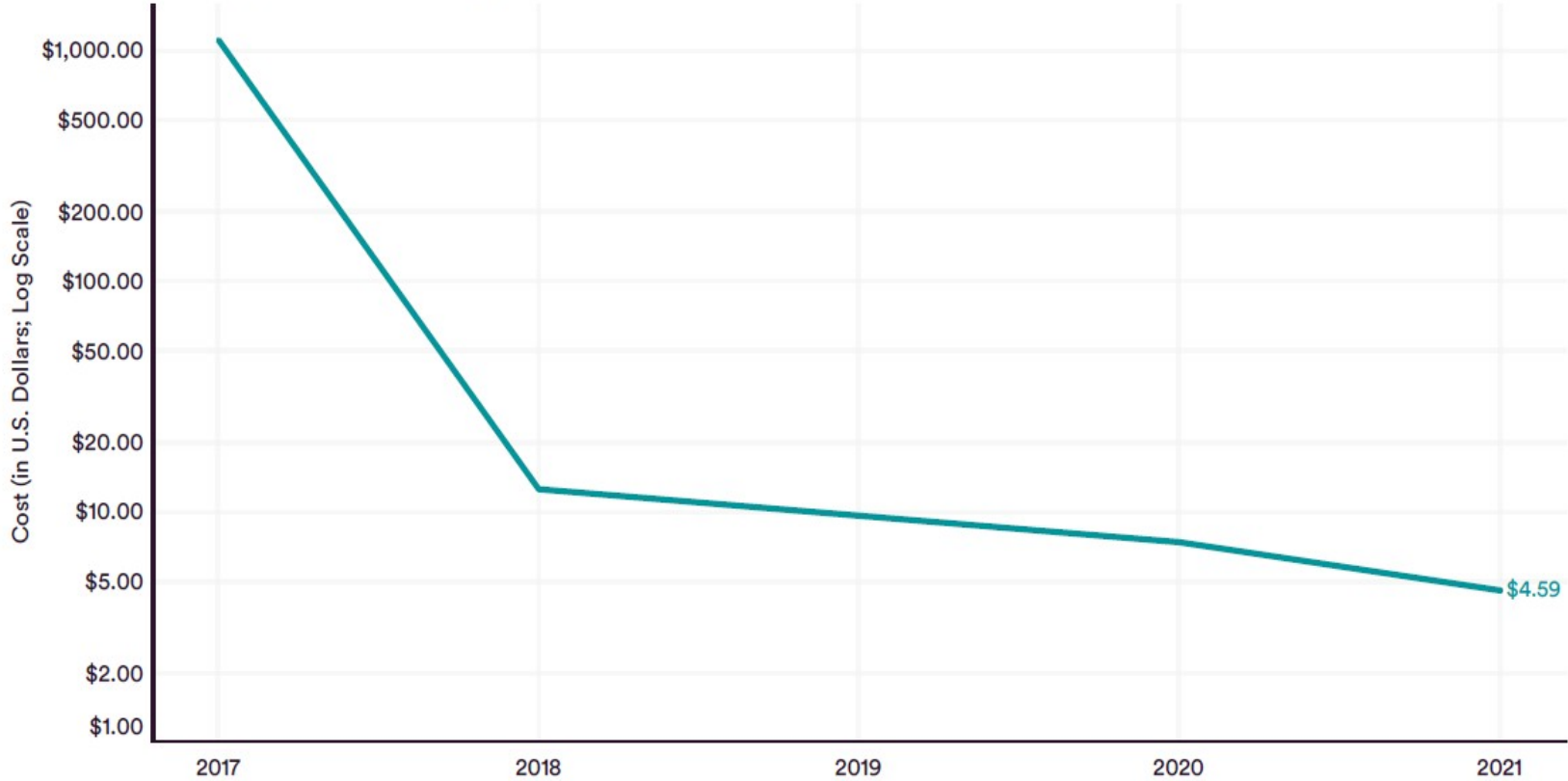


Figure 2.7.4

AI Ecosystem Pyramid

**Busi
ness
Appli**

**Horizontal / Vertical
Solution Providers**

**Core Infrastructure : Compute, Storage,
Cloud**

Picks and Shovels

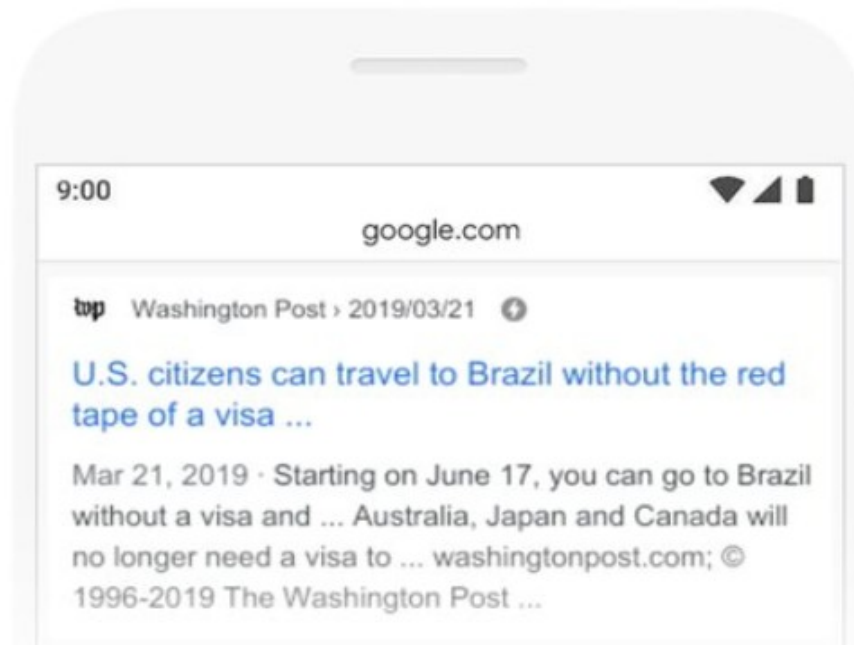
AI Ecosystem: AI / ML Applications & Challenges

Natural Language Processing(NLP)

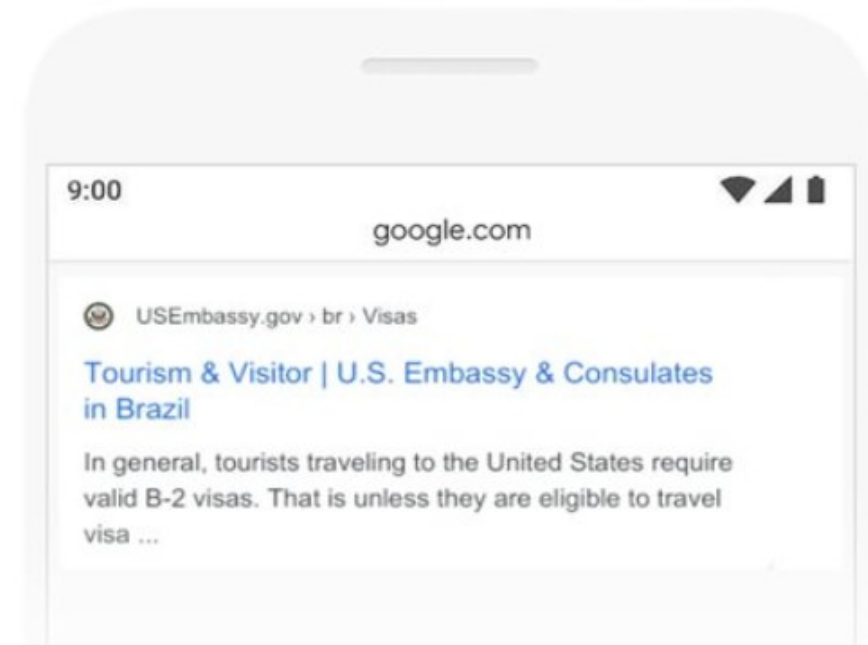
Search: Understanding the meaning of Text

🔍 2019 brazil traveler to usa need a visa

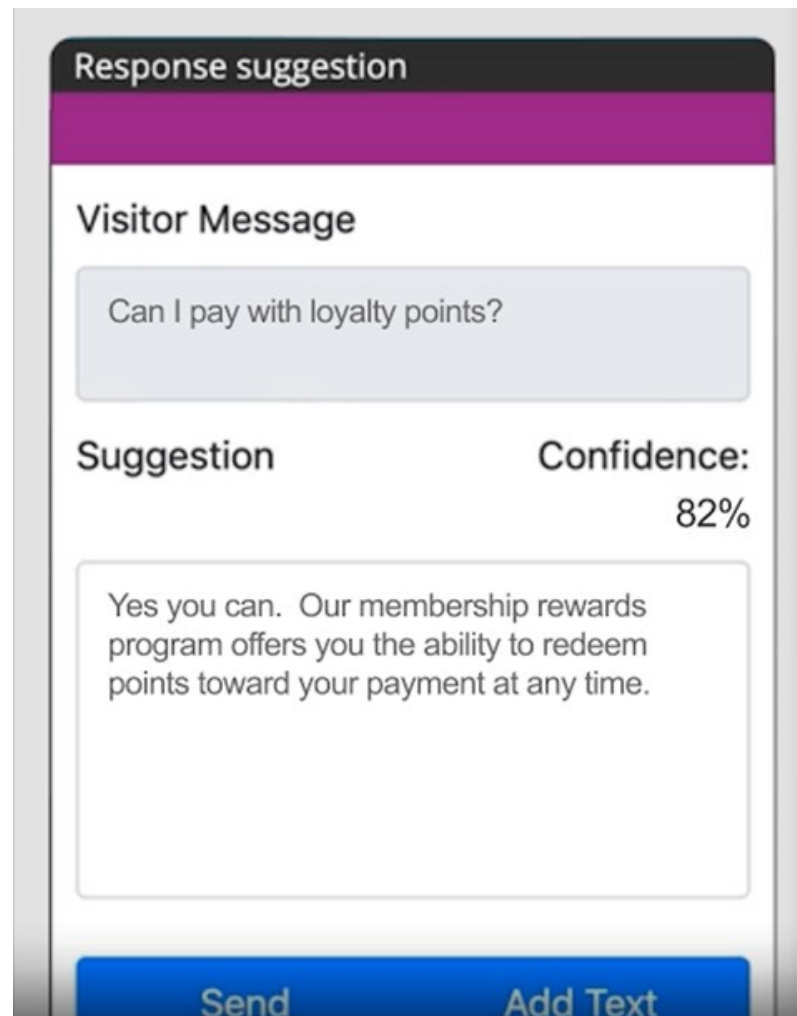
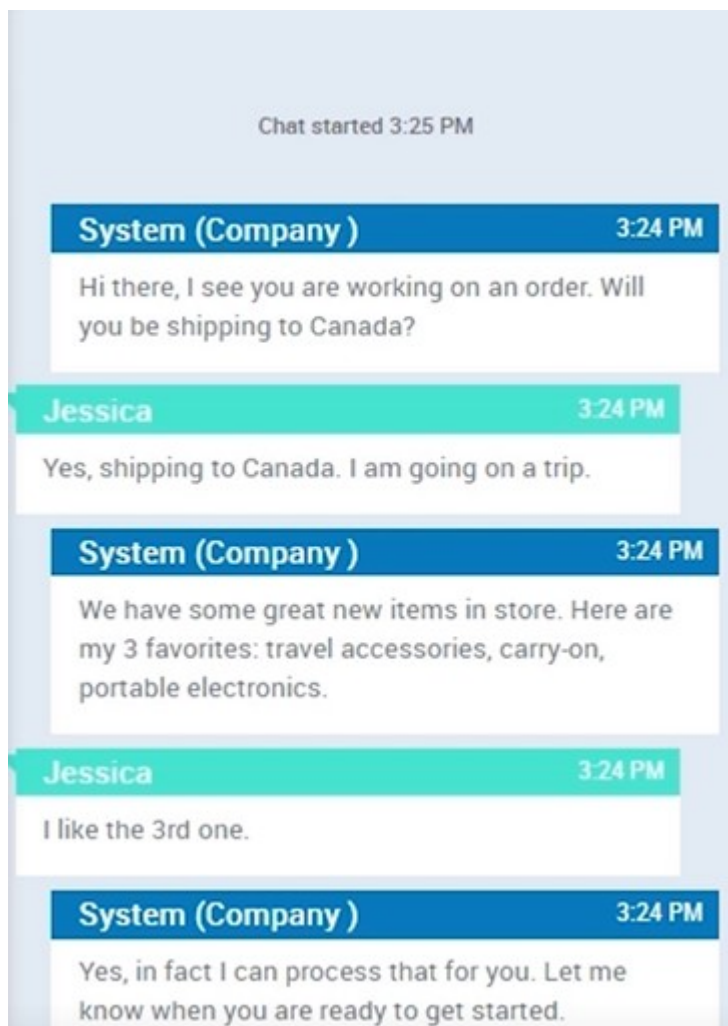
BEFORE



AFTER



Natural Language Processing(NLP) Chatbots



Natural Language Processing(NLP) Legal Document Review

The screenshot shows a Microsoft Word document with several paragraphs of text. The text is highlighted in green, indicating it has been reviewed. A sidebar on the right shows the Luminance interface, including a 'Traffic Light Analysis' section with a summary of 2 Reject, 1 Review, and 16 Approve. The 'Currently selected paragraph' section shows a red flag for 'Data Tag Value' and a green flag for 'Clause Wording'. The document title is 'Alexander Burgess Sanchez' and the file name is '01-06-2021 Alexander, Burgess and Sanchez Non-Disclosure Agreement V2.docx'. The status bar at the bottom indicates 'Page 2 of 3', '875 words', and 'English (United States)'.

be construed as granting by implication, estoppel or otherwise, any right in or license under any present or future invention, trade secret, trademark, copyright, or patent, now or hereafter owned or controlled by either party hereto.

4. A party may disclose Confidential Information where disclosure is required by law, the Receiving Party shall notify the Disclosing Party of the request and cooperate with the Disclosing Party's reasonable, lawful efforts to resist, limit or delay disclosure at the Disclosing Party's expense, and provided that except for making such required disclosure, such information shall otherwise continue to be Confidential Information, or

5. This Agreement may be terminated by either party by giving thirty (30) days written notice to the other party, and, unless sooner terminated, shall automatically terminate **four (4) years** from the effective date hereof. However, the receiving party's obligation to protect previously received Confidential Information shall survive for **twelve (12) years** from the date of receipt of such Confidential Information.

6. All Confidential Information shall remain the property of the disclosing party and shall be returned to the disclosing party, or destroyed, upon written request, provided that each party may retain one copy of the disclosing party's Confidential Information for legal archival purposes only. The disclosing party's failure to request such return or destruction, shall not relieve the receiving party of its confidentiality obligations under this Agreement.

7. This Agreement contains the entire understanding relative to the protection of Confidential Information covered by this Agreement and supersedes all prior and collateral communications, reports, and understandings, if any, between the parties

The graphic compares two methods of legal document review. It features two circular icons: a red one with a document icon for 'TRADITIONAL SAMPLING' and a blue one with a magnifying glass icon for 'REVIEW WITH LUMINANCE'. The text for each method lists the number of associates, duration, and cost. A final line states the overall cost saving and time saving for a complete document review.

TRADITIONAL SAMPLING:
3 associates, 3 weeks, 10% review. **Cost: \$88,800 (associate salary)**

REVIEW WITH LUMINANCE:
2 associates, 3 weeks, 10% review. **Cost: \$22,200 (associate salary) + c.\$32,000 (technology) = \$54,200**

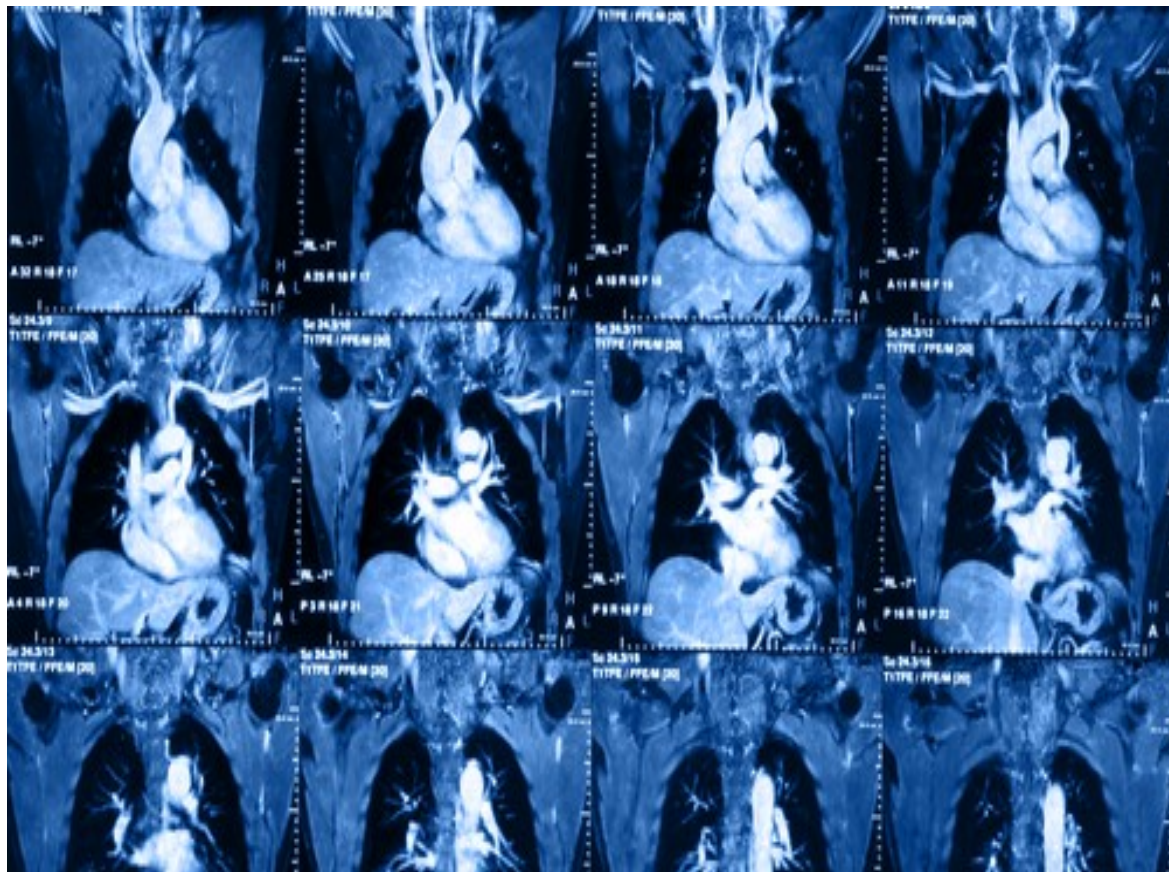
Cost saving for a sampled document review = 40%
Time saving for a complete document review = 18 associate weeks

Source: Luminance

Computer Vision

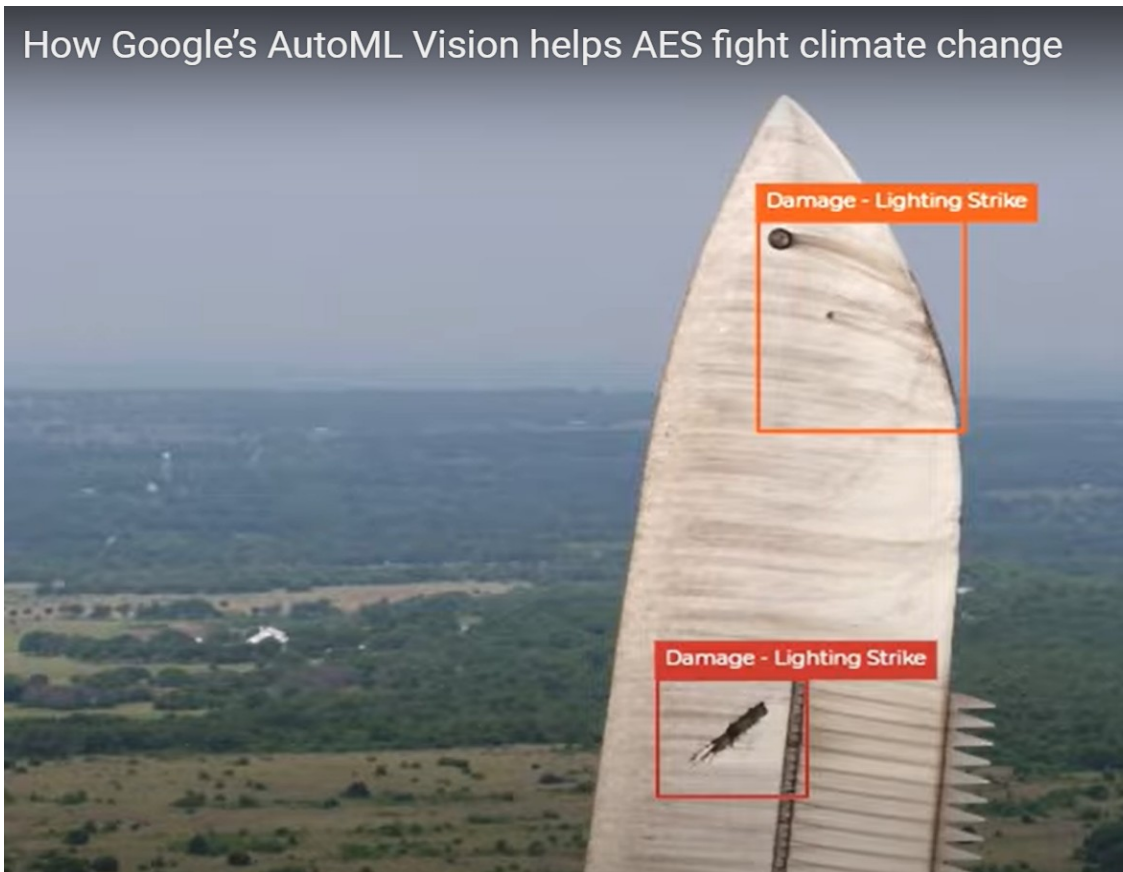
Image/Object Recognition

Nanox AI: Evaluating CT Scans



Source: Nanox AI, AES

AES: Windmill Damage Detection

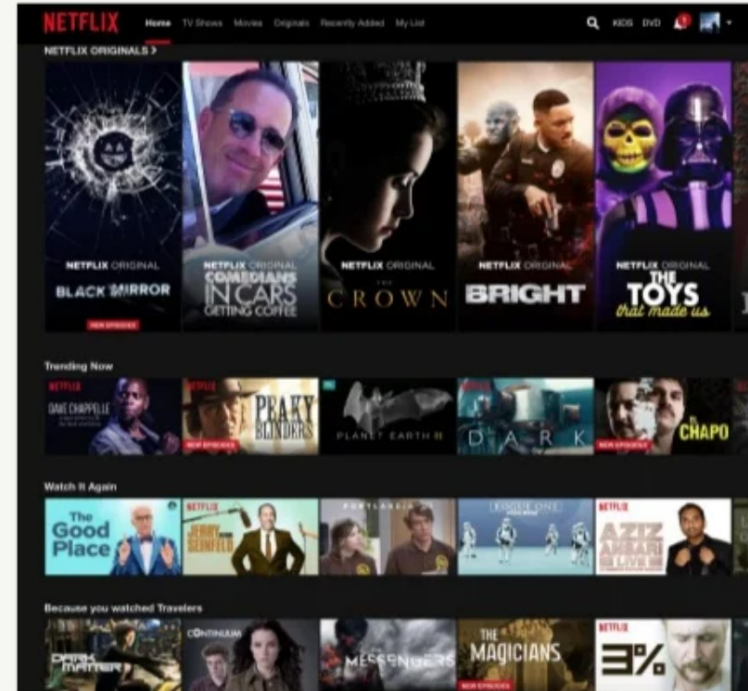


Recommendation Systems

What will a customer like?

The value of recommendations

- A few seconds to find something great to watch...
- Can only show a few titles
- Enjoyment directly impacts customer satisfaction
- *How?* Personalize everything, for 130M members across 190+ countries



Recommendation Systems

What will a customer like?

WSJ | VIDEO

Investigation: How TikTok's Algorithm Figures Out Your Deepest Desires

The Wall Street Journal created dozens of automated accounts that watched hundreds of thousands of videos to reveal how the social network knows you so well

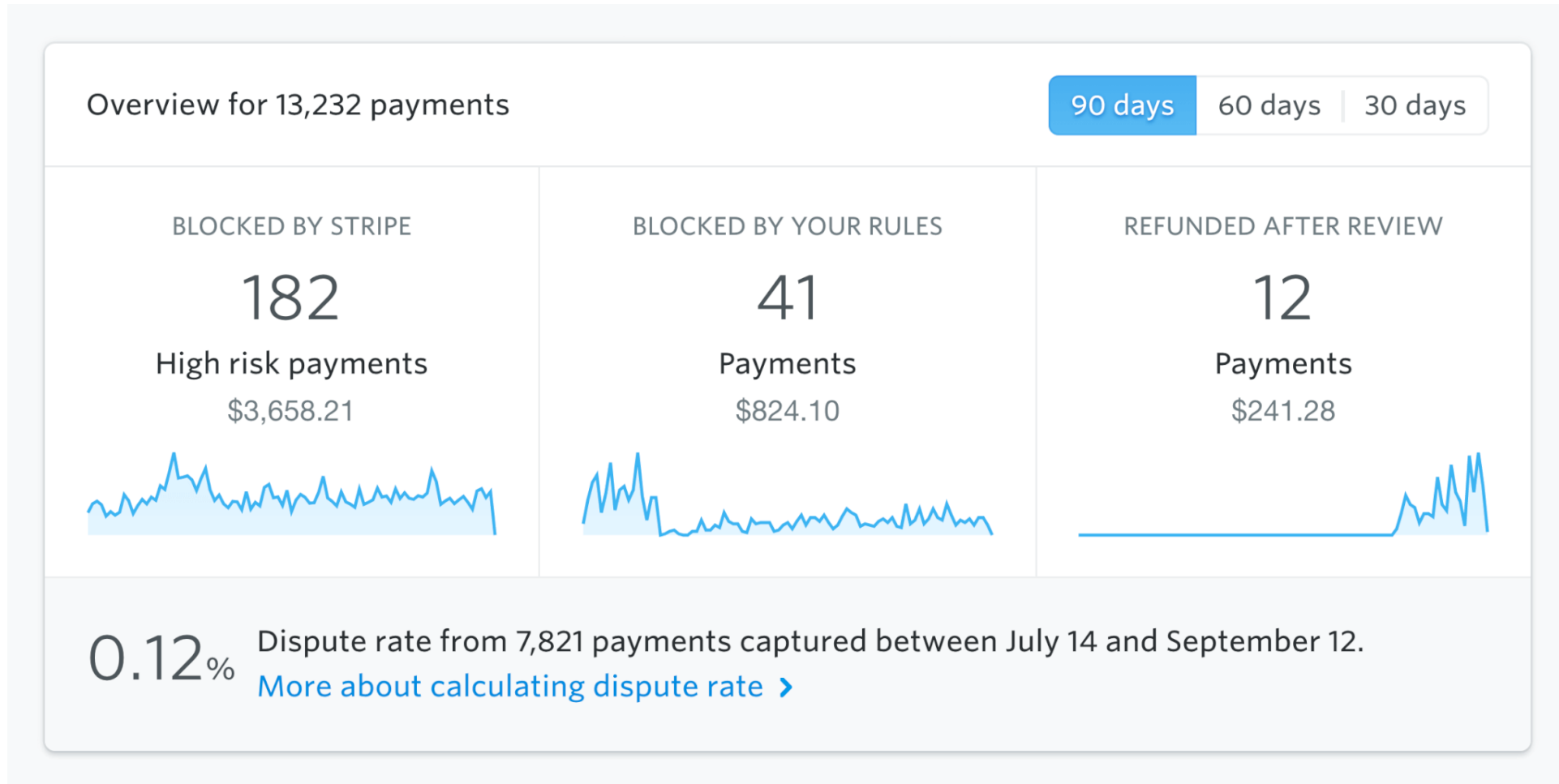
By Wall Street Journal

Jul 21, 2021 5:30 pm



Anomaly / Fraud Detection

Stripe: Radar



Analytics

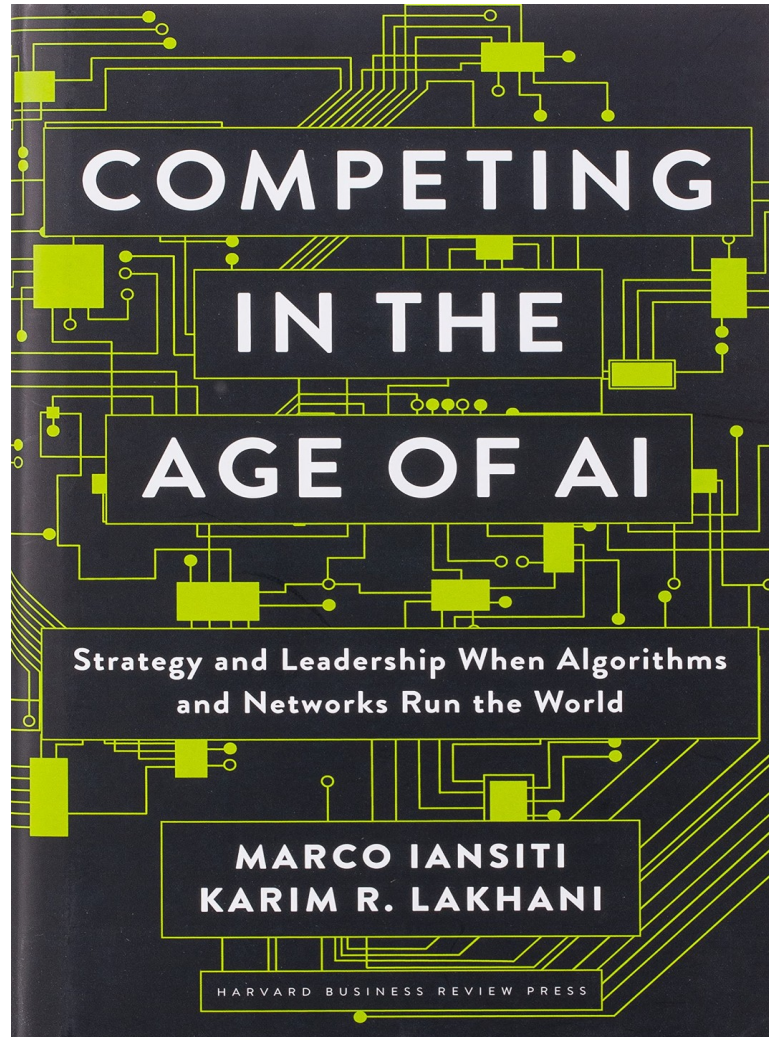
Credit Quality Evaluation

Fundbox

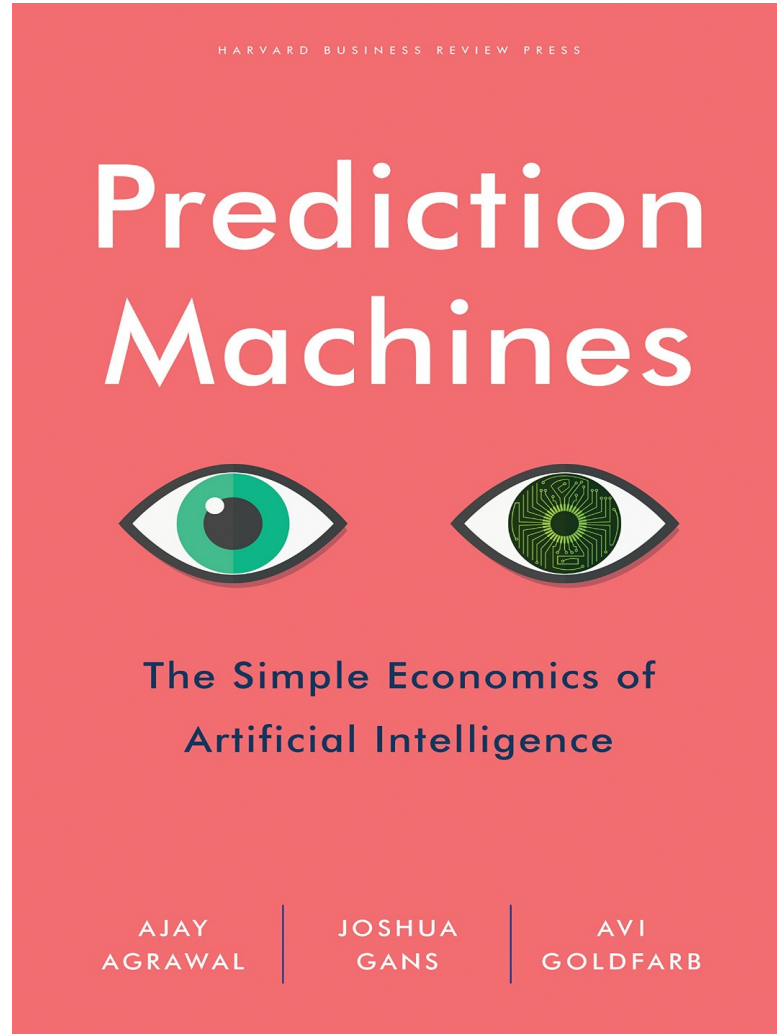


- When a small business works with Fundbox, it connects a “transactional system” i.e. **accounting software**, their **invoicing system**, or even its **bank account**.
- Fundbox immediately pulls business performance from this data source and our machine learning algorithms quickly assess business risk so that we can make a credit decision.
- The entire process typically takes a few minutes or less.

Examples on how AI is changing business



Broader Economic view of AI



- AI is making Predictions / Pattern Matching cheap
- Makes Predictions easily available in turn reduces uncertainty in some business activities
- Changing division of labor between man and machine

Challenges to AI/ML Application

60-80% of Projects don't get deployed

ENTERPRISE & CLOUD

AI Stats News: Only 14.6% Of Firms Have Deployed AI Capabilities In Production

Gil Press Senior Contributor 

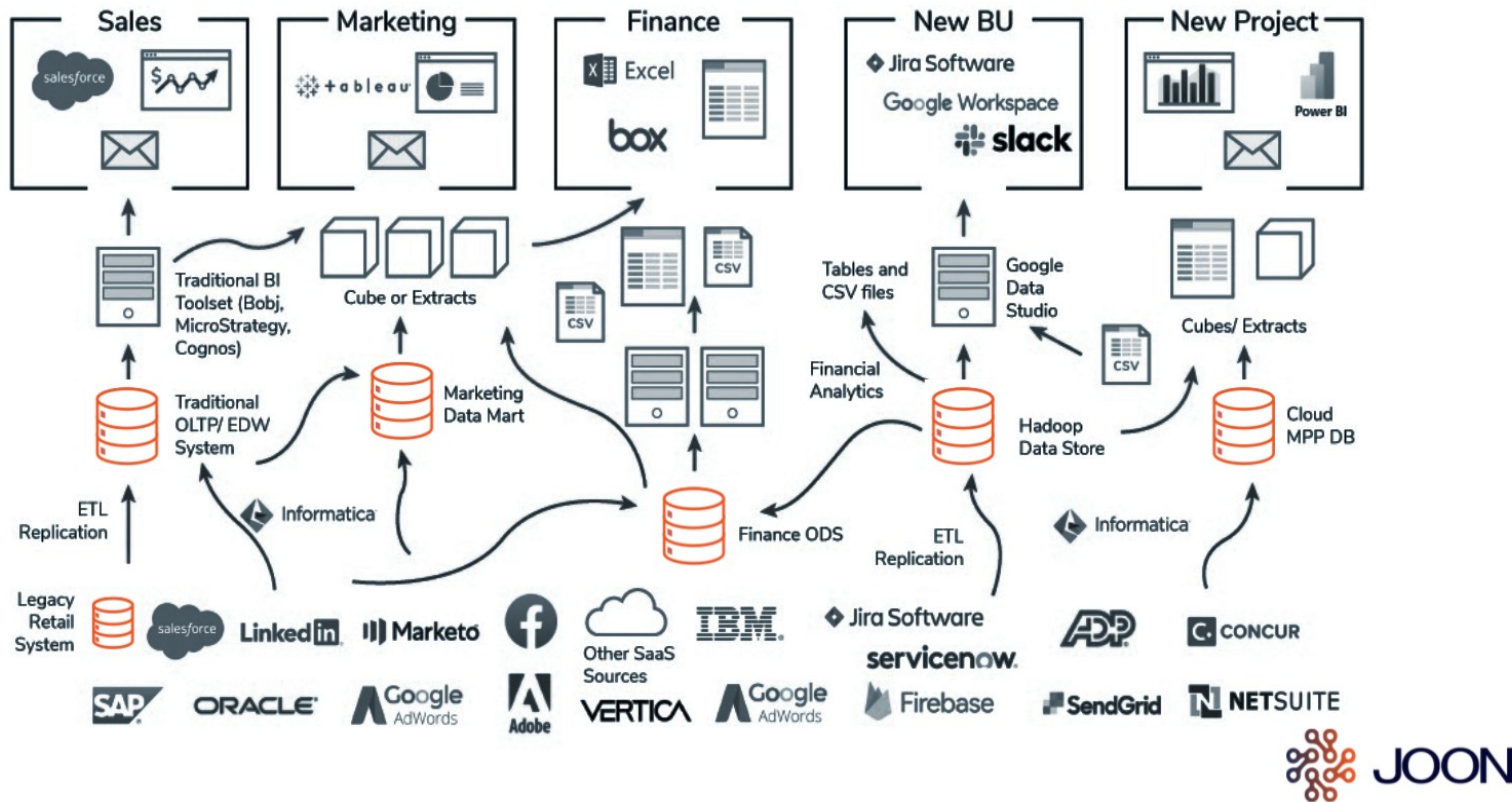
I write about technology, entrepreneurs and innovation.

Challenges to AI/ML Application

Data Challenge

Businesses have **messy** data

5



- Data Silos
- Multiple Data stores
- Storing structured and unstructured data
- Data keeps changing
- Little to no control on external Data Sources

Challenges to AI/ML Application

Data Challenge

Atlanta Firebird System

- Data joining a difficult problem.
- Data collected from 12 datasets
- Spatial information had different formats, sometimes contain minor differences such as different spellings.
- Turned out to be a massive effort that consumed a lot of time

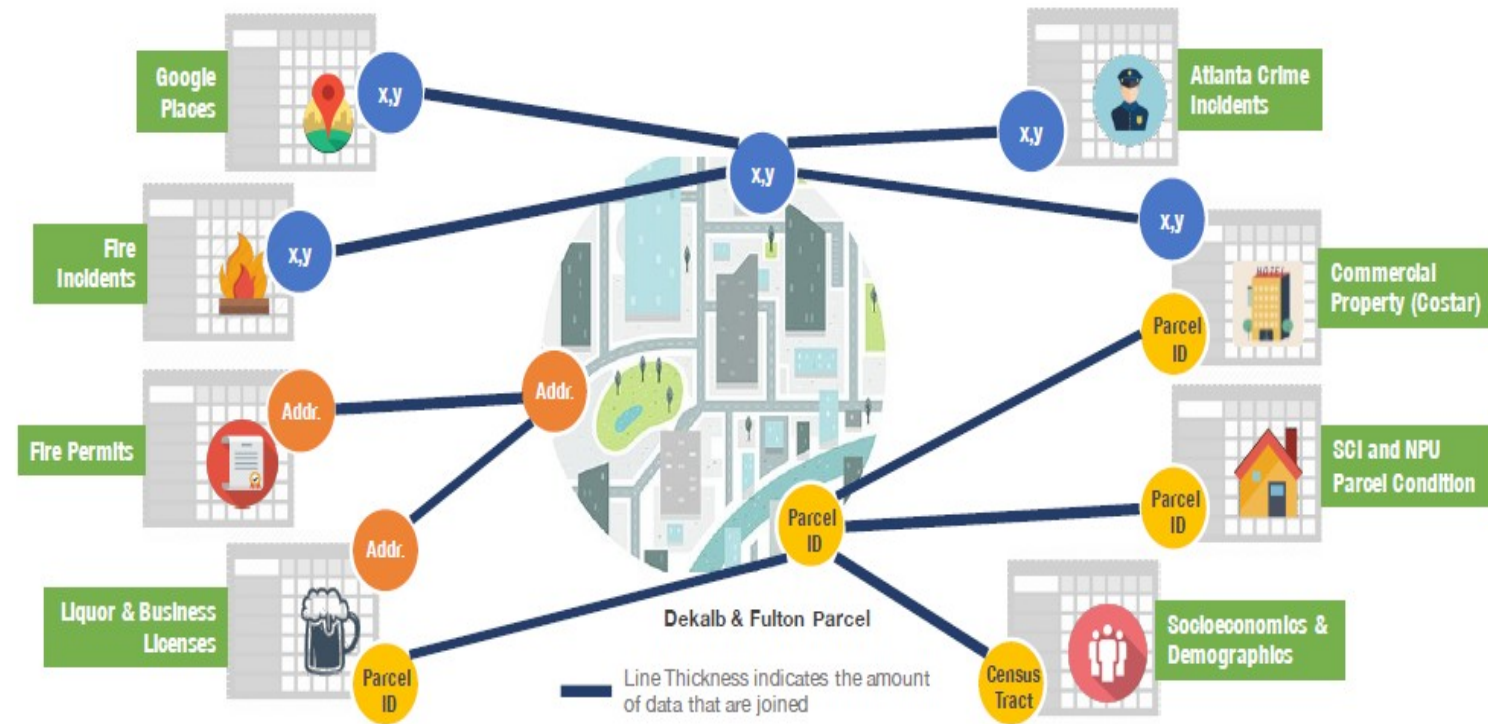
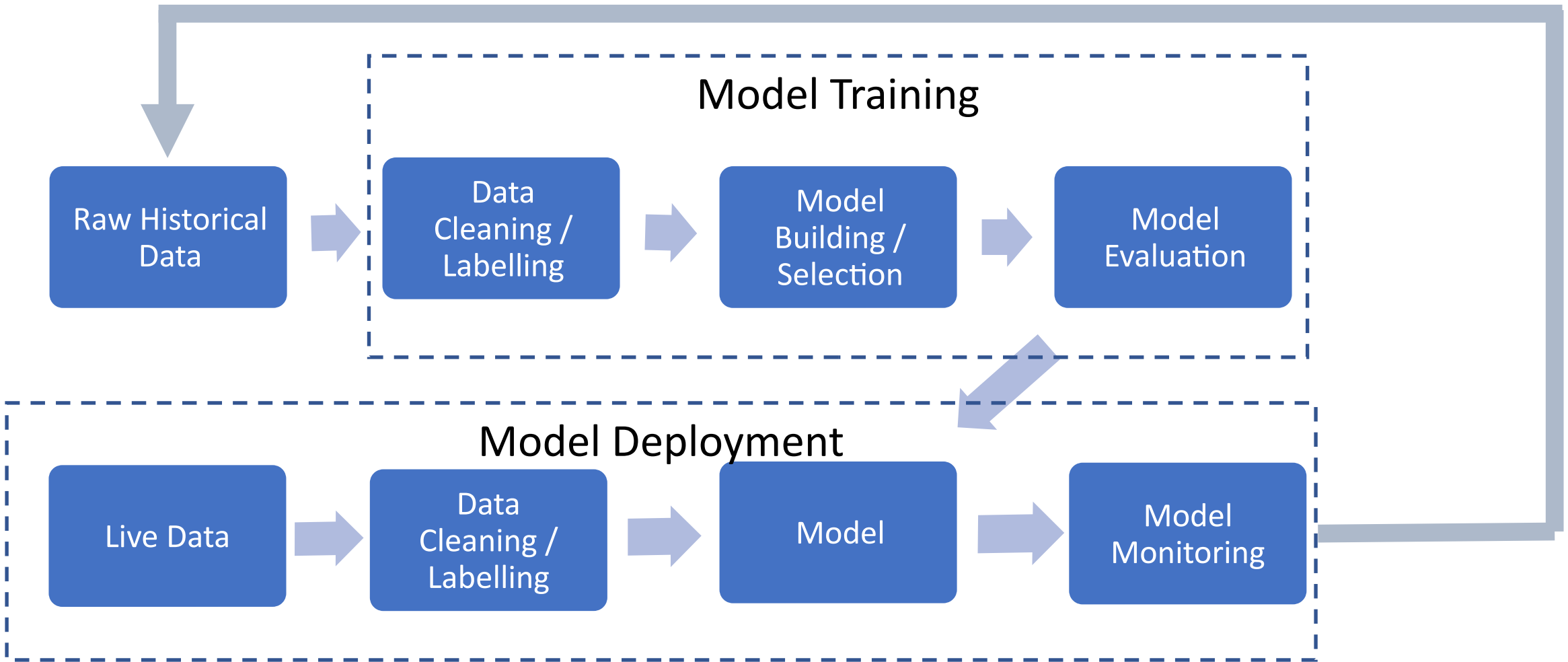


Figure 2: Joining eight datasets using three spatial information types (geocode, address, parcel ID).

MLOps Challenge

Machine Learning Process Elaborated



MLOps Challenge

AI/ML needs lot of supporting Human and Tech infrastructure

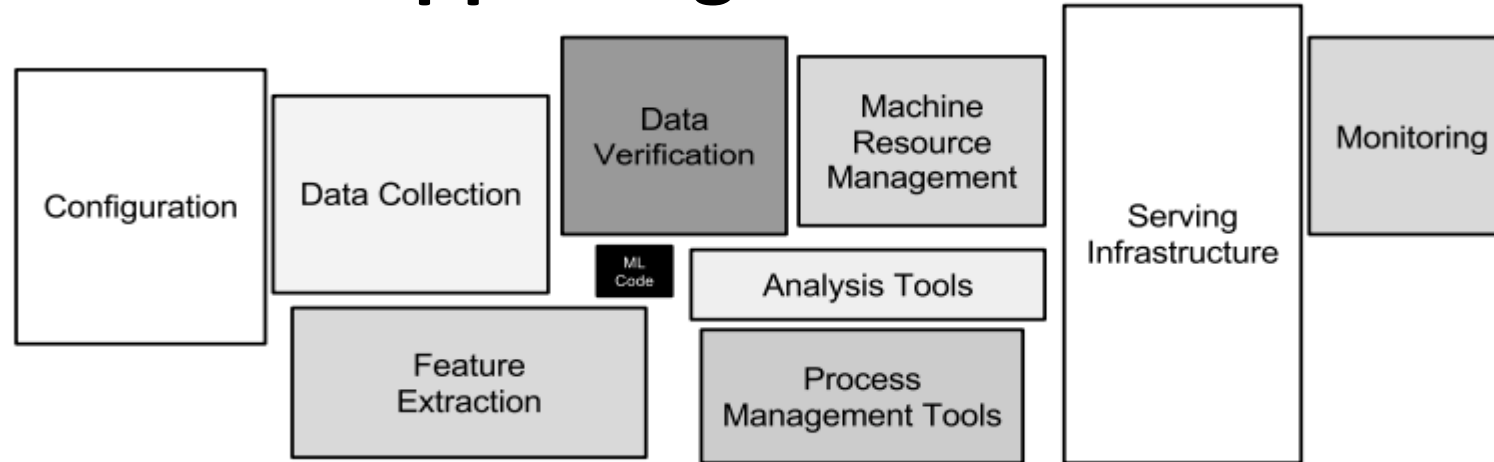


Figure 1: Only a small fraction of real-world ML systems is composed of the ML code, as shown by the small black box in the middle. The required surrounding infrastructure is vast and complex.

- Deployed Model should have minimal manual intervention. Needs software engineering
- Data Scientists are (mostly) not Software Engineers
- Deployed model needs to be monitored for performance deterioration
- Tools used by Data Scientists for Model Training may not work for Model Deployment
- Other considerations: Data Governance and Privacy

Source: Google - Hidden Technical Debt in Machine Learning Systems

Data and MLOps as Competitive Advantage

“The Looper platform currently hosts 700 AI models and generates 4 million of AI outputs per second.”

- Meta (Facebook)

“Once we figure out where all the data is, we assemble data catalogs for all the different data sources. We take the data and mash it up into lakes, so we can build ML models.”

“We can now build AI and ML models on top of everything. We can search across the entirety of our data sets and do analysis on them. This is a critical departure from the previous operating model in IT where many apps and services were siloed with little sharing, and many versions of similar capabilities.”

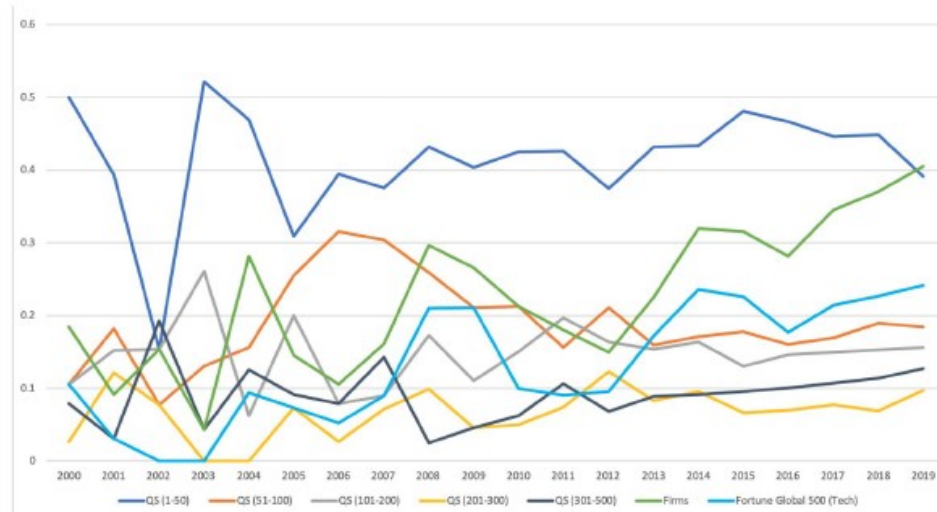
- Kurt DelBene and Ludo Hauduc, Microsoft

Data and MLOps as Competitive Advantage

Elites work with elites: a compute divide drives the “de-democratization” of AI research

- ▶ Since 2012, large technology companies have increasingly published either on their own or in collaboration primarily with elite universities as opposed to mid-tier and lower-tier universities. Counterfactual analysis suggests a causal divergence between large technology companies and non-elite universities that is driven by access to computing power as a form of de-democratisation. This results in a small set of actors creating a majority of the high-impact research output.

Figure 7: Share of papers within deep learning research

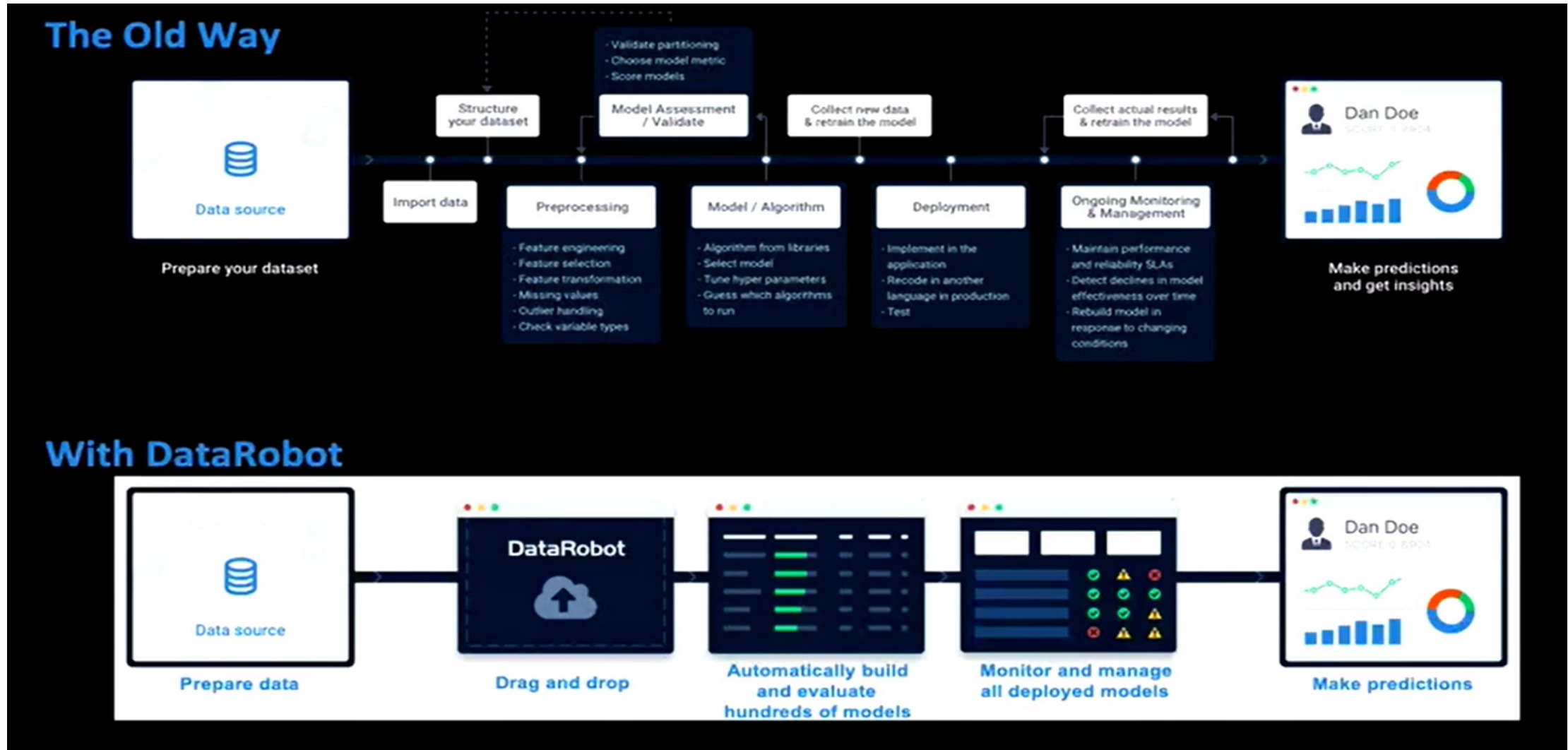


Note: This figure illustrates the share of papers that have at least one co-author from that specific group (e.g., firms, universities) within the deep learning papers.

AI Ecosystem: Picks and Shovels

Machine Learning as a Service (MLaaS)

Making ML accessible



ML as a Service (MLaaS)

Accessible, Lower Cost and Reduced Time to Market

DataRobot

Val : \$6.3 Bn
Revenue: \$210 Mn

H₂O.ai

Val : \$1.7 Bn
Revenue: \$45 Mn

aws machine learning



Azure Machine Learning



**data
iku**

Val : \$4.6 Bn
Revenue: \$150 Mn

C3.ai

Val : \$1.6 Bn
Revenue: \$232 Mn

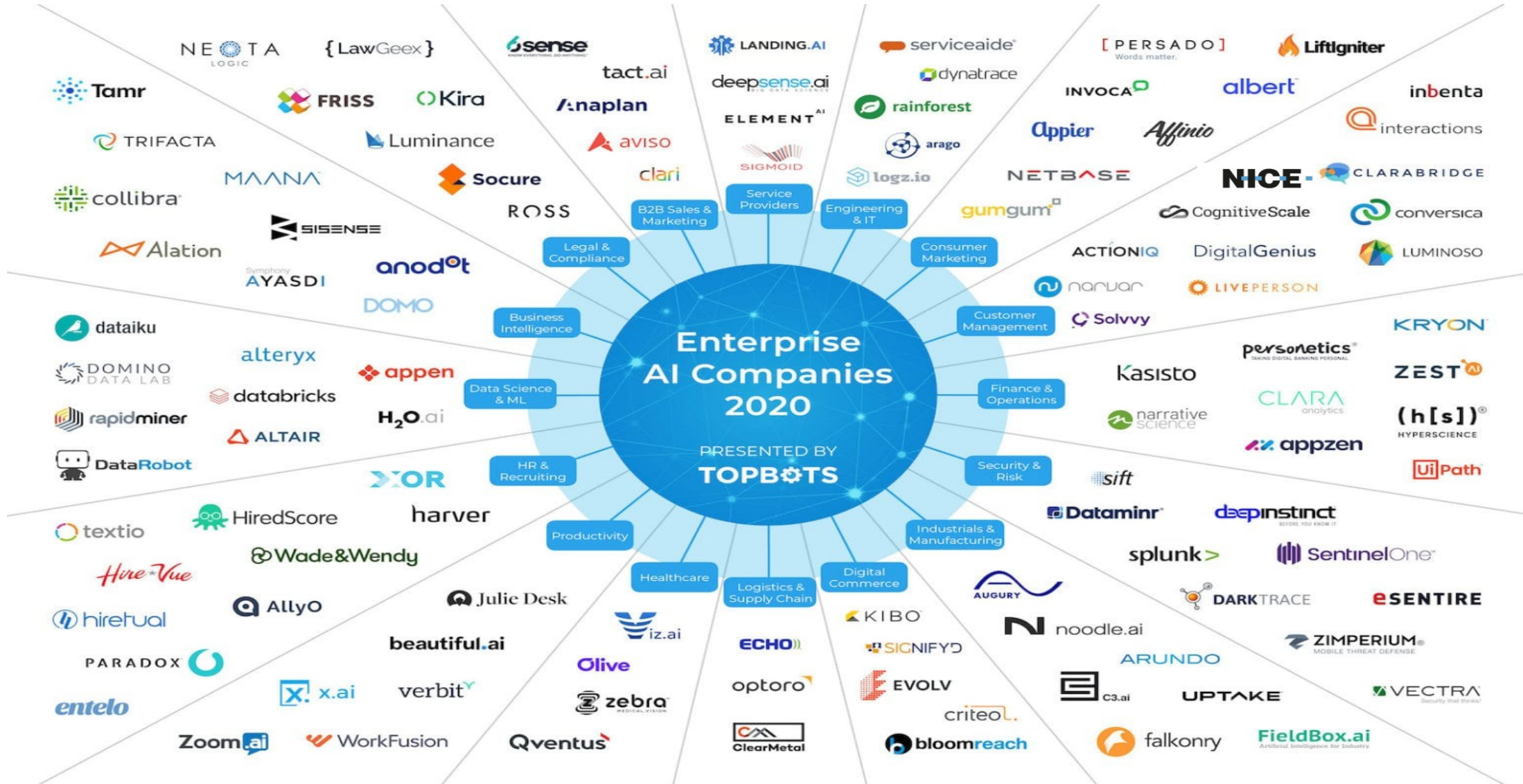


vertex.ai



Watson Machine Learning

ML based Solution Providers



Data Providers

TGS The logo for TGS features the letters 'TGS' in a bold, blue, sans-serif font. To the right of the text is a graphic element consisting of a blue arc that curves upwards and to the right, ending in a multi-pointed starburst or spark-like shape.

Bloomberg

S&P Global

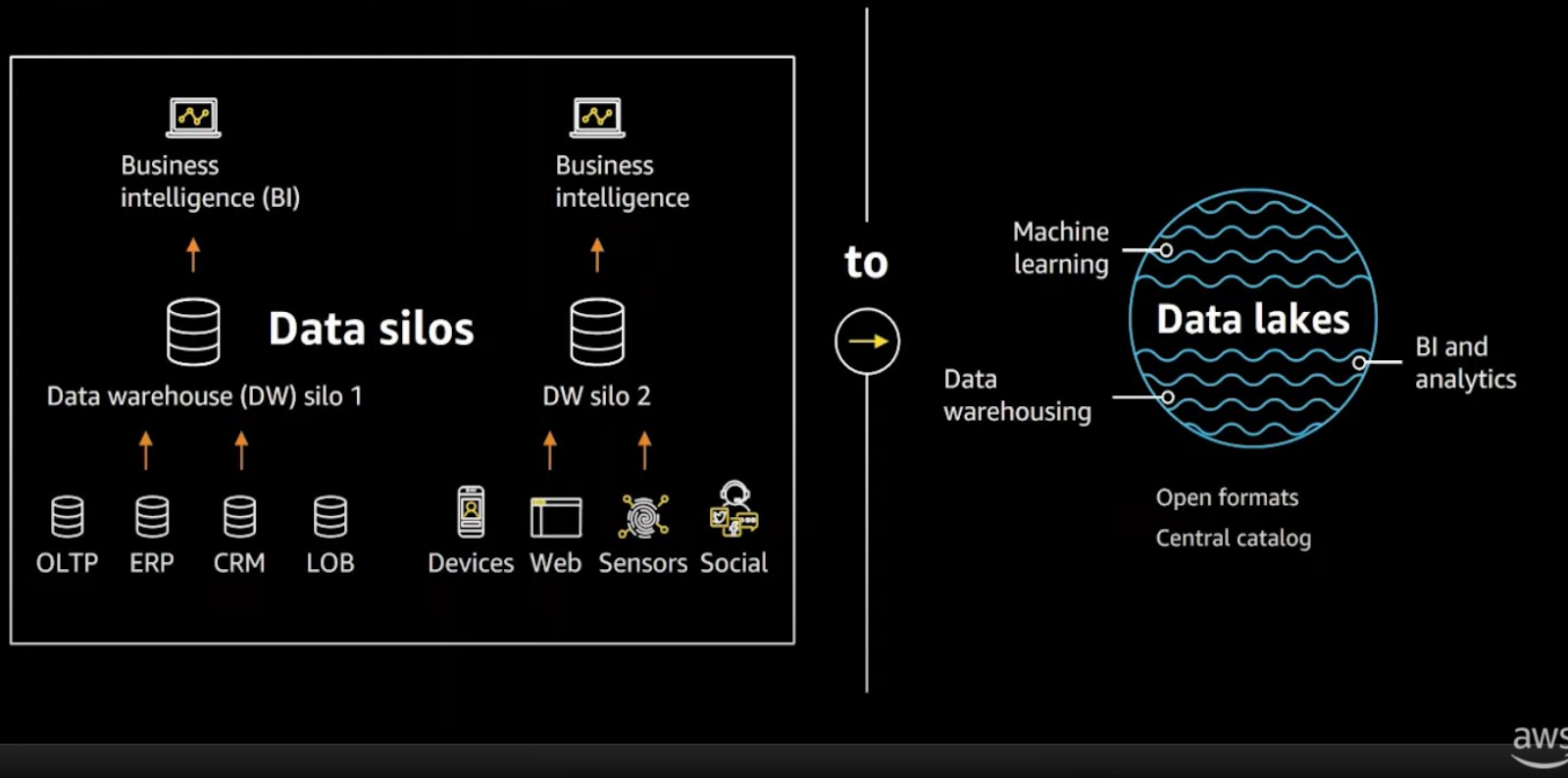
 **IQVIA**The logo for IQVIA features a graphic element on the left consisting of five horizontal blue bars of varying lengths, stacked vertically. To the right of this graphic is the word 'IQVIA' in a blue, sans-serif font.

FACTSET [®]

Datawarehouse and DataLakes

Storing and Processing Massive Data on the Cloud

Traditional data warehousing approaches don't scale



- Data Lake: One central Database which support all data formats
- Cloud Based : No specialised hardware or software. Much less maintenance headache
- Separate Cost for Compute and Storage

Datawarehouse and DataLakes

Storing and Processing Massive Data on the Cloud



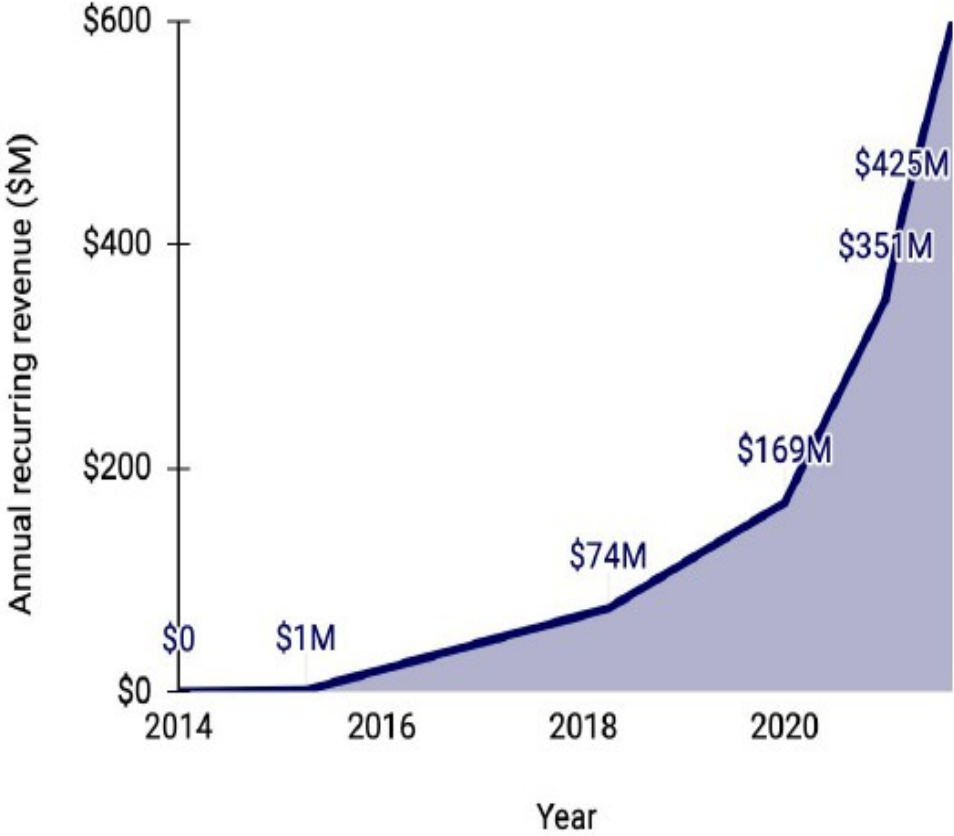
databrick



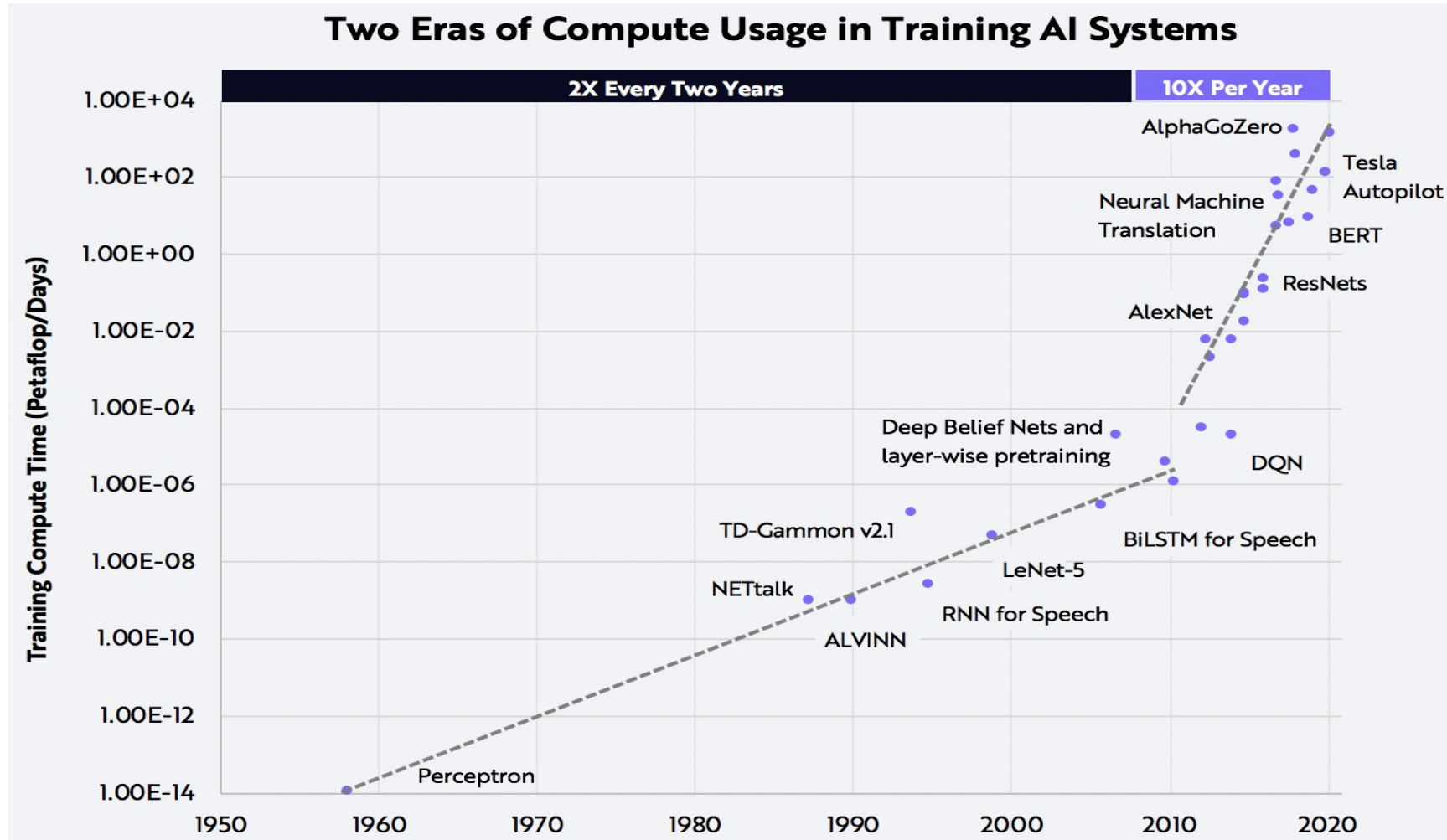
Google BigQuery



Azure Synapse Analytics

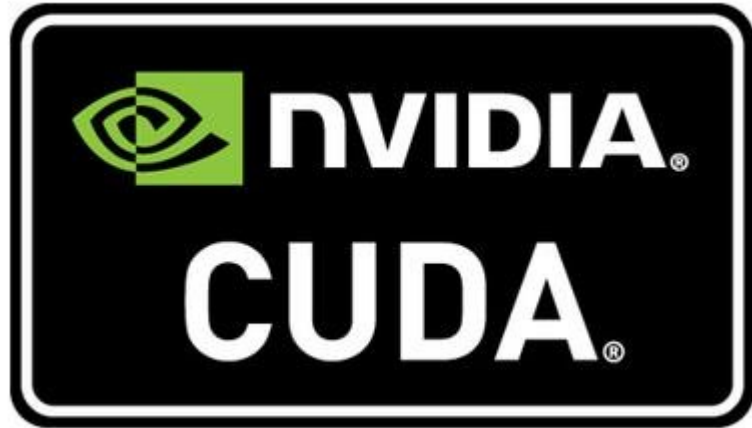


Providing Compute Power



Providing Compute Power

Rise of GPU computing



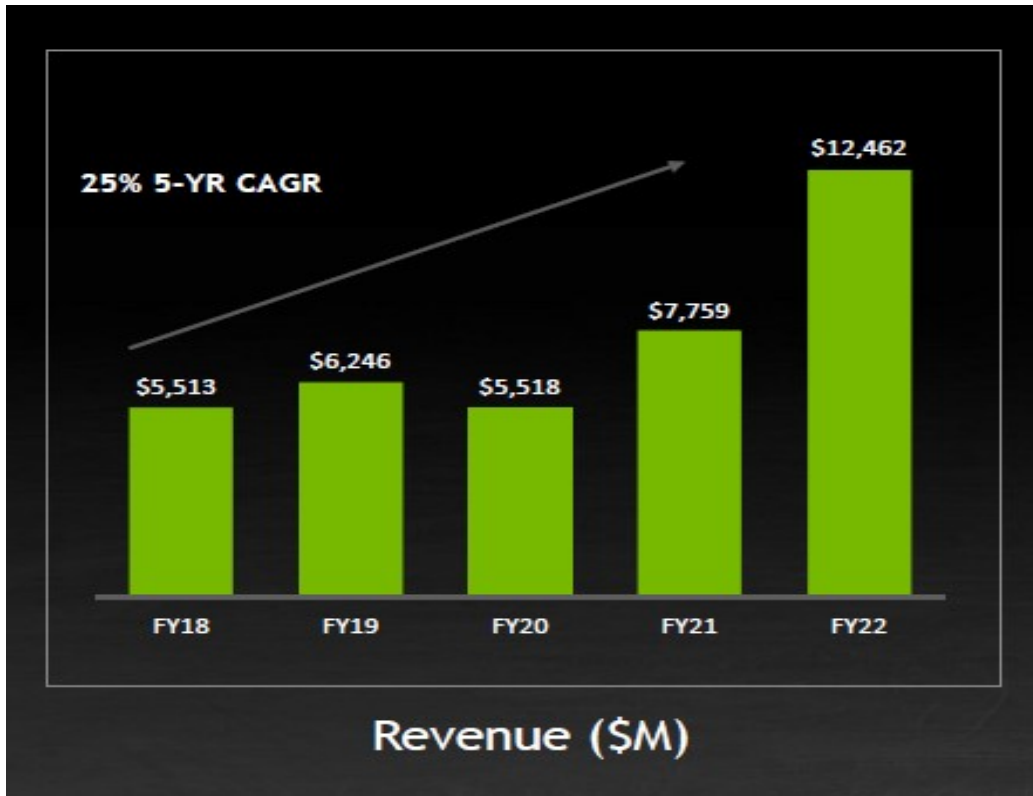
“GPUs are so incredibly powerful. Programs that previously ran on supercomputers, we’re now realizing we can rewrite to run on GPUs at a fraction of the price.”

- David Anderson, Computer scientist at Berkeley

Providing Compute Power

Perspective on how ML has revolutionised GPU demand

Nvidia: Gaming Revenues



Nvidia: Data Centre Revenues



Providing Compute Power Customised Chips for AI/ML



GRAPHCORE



“We now believe that Broadcom’s cloud/hyperscale ASIC revenues have recently passed \$1B in annualized run-rate revenues and have more than doubled Y/Y since 2017 when the team was driving \$50M in annualized revenues from the cloud titan (Google) ” - Harlan Sur, JP Morgan

Cloud

The backbone of everything

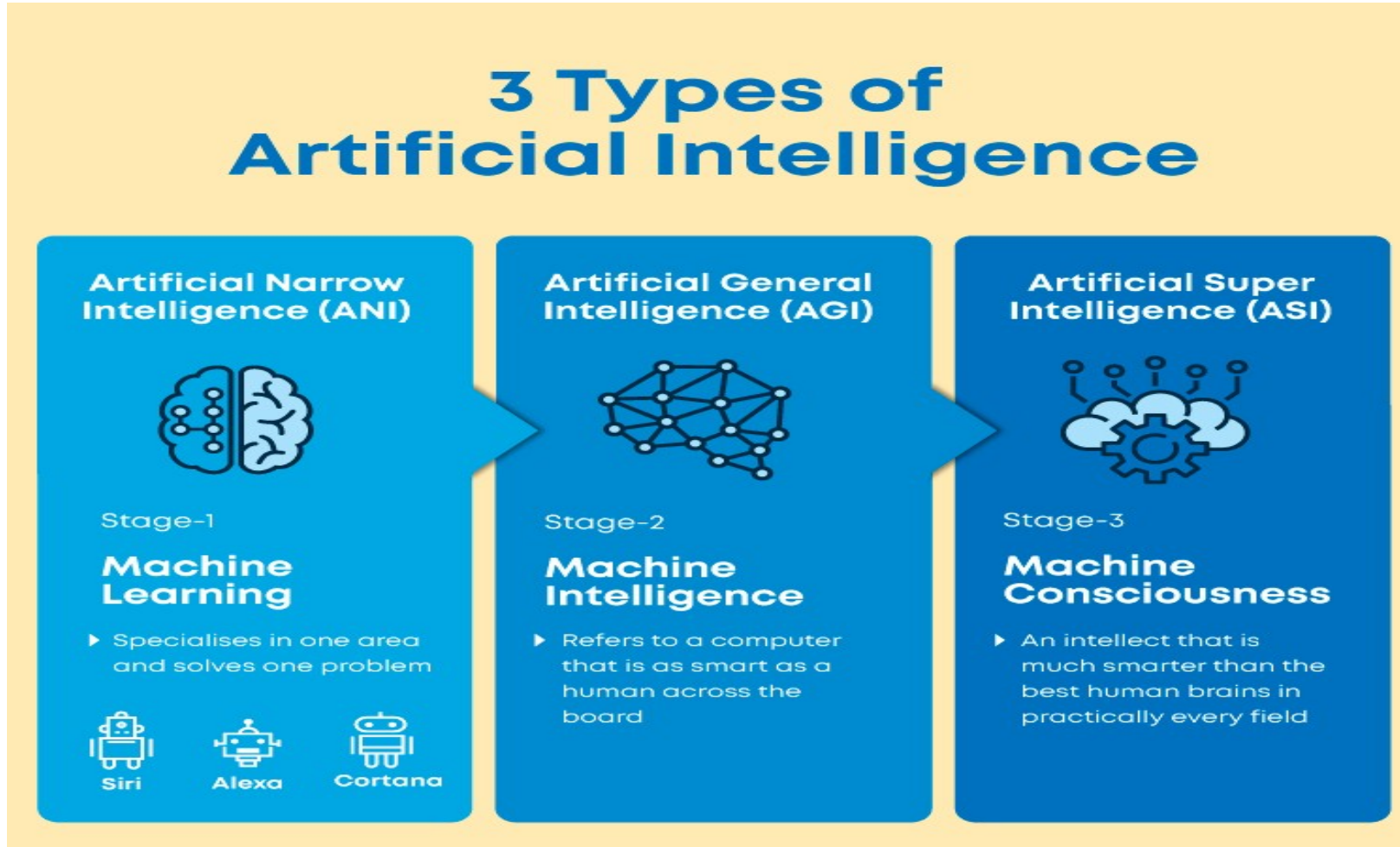


Google Cloud

Limitations

Current AI is 'Narrow' at best

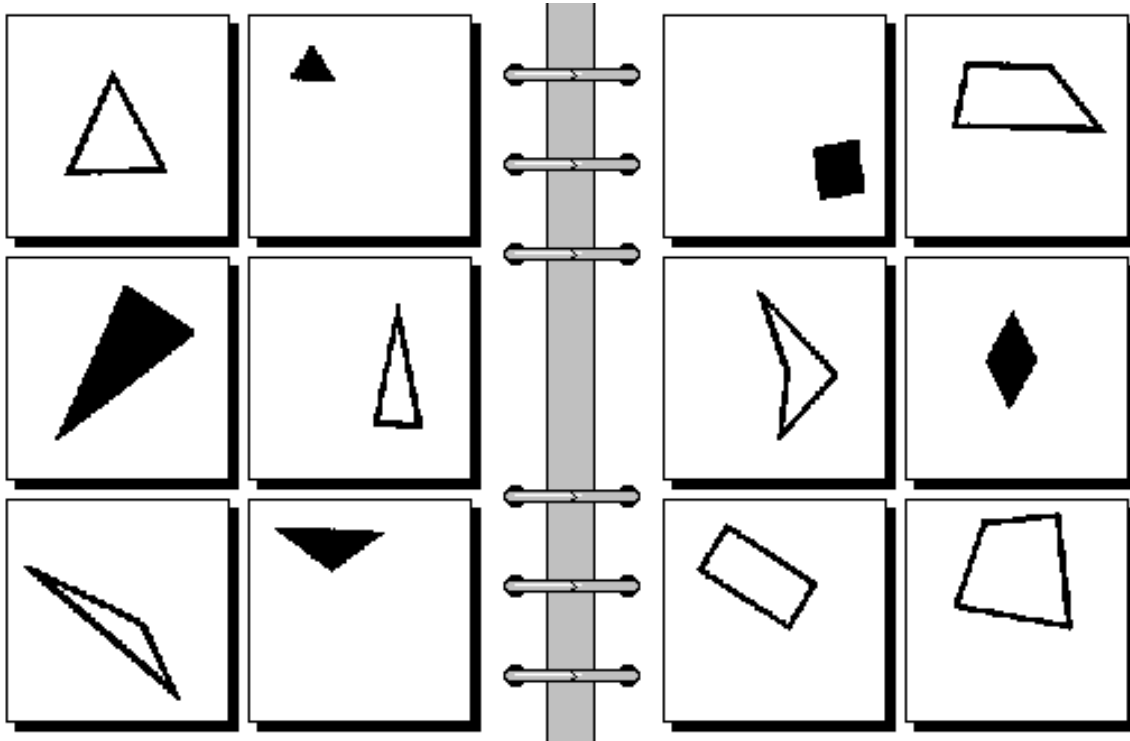
“We are far away from human-level AI” – Yoshua Bengio



Current AI is 'Narrow' at best

Common Sense is not common (at least for machines)

Bongard's Problems



“A teenager learning to drive does not have to try to run off a cliff to see what happens. Whereas the AI system will have to run off the cliff to figure out that it is a bad idea; probably do it for a few thousand times before it realizes how not to do it”

“Current AI Systems are missing this common sense language which is why they are data hungry...and rigid...”

Yann LeCun

Real world is different from Training Data

NDTV

LIVE TV

LATEST

COVID

INDIA

OPINION

VIDEO

CITIES

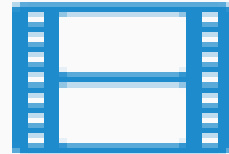
WORLD

OFFBEAT

TRENDS

AI Camera Ruins Football Game By Mistaking Referee's Bald Head For Ball

Many complained that they missed their team's goals because the camera "kept thinking the Lino bald head was the ball."



Real world is different from Training Data

Zillow

How it Started?

Zestimate Algorithm: Invasion of AI on Real Estates

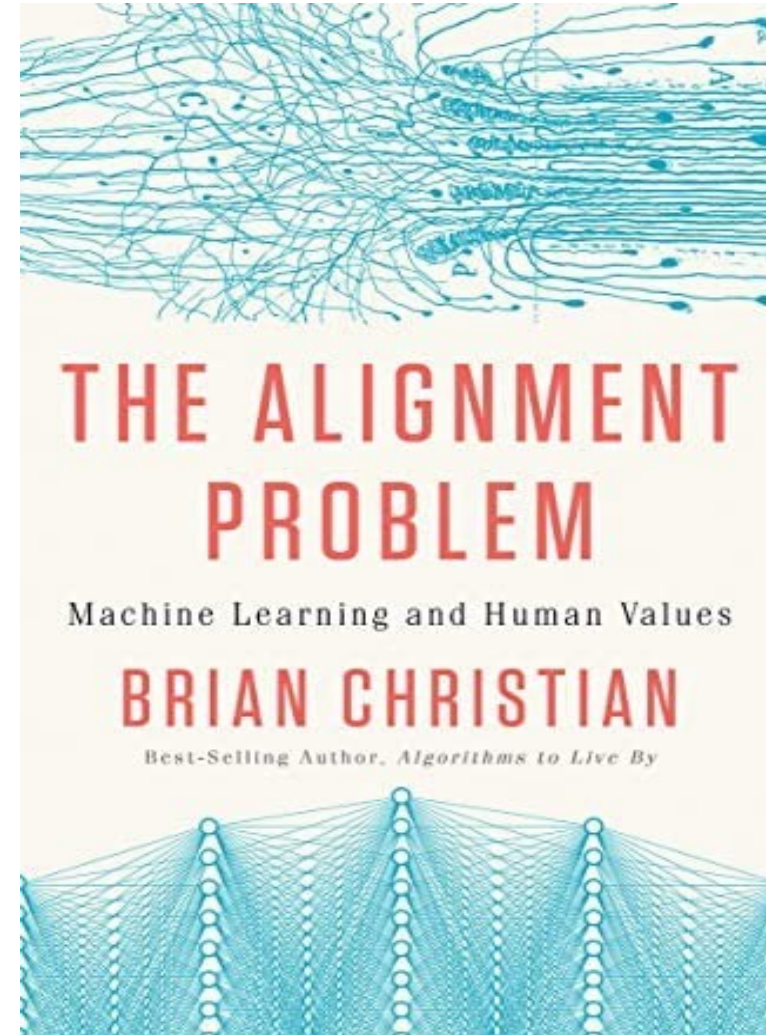
Incorporating artificial intelligence into several stages of the mortgage process.

How it's Going?

The \$500mm+ Debacle at Zillow Offers – What Went Wrong with the AI Models?

AI is (largely) Blackbox

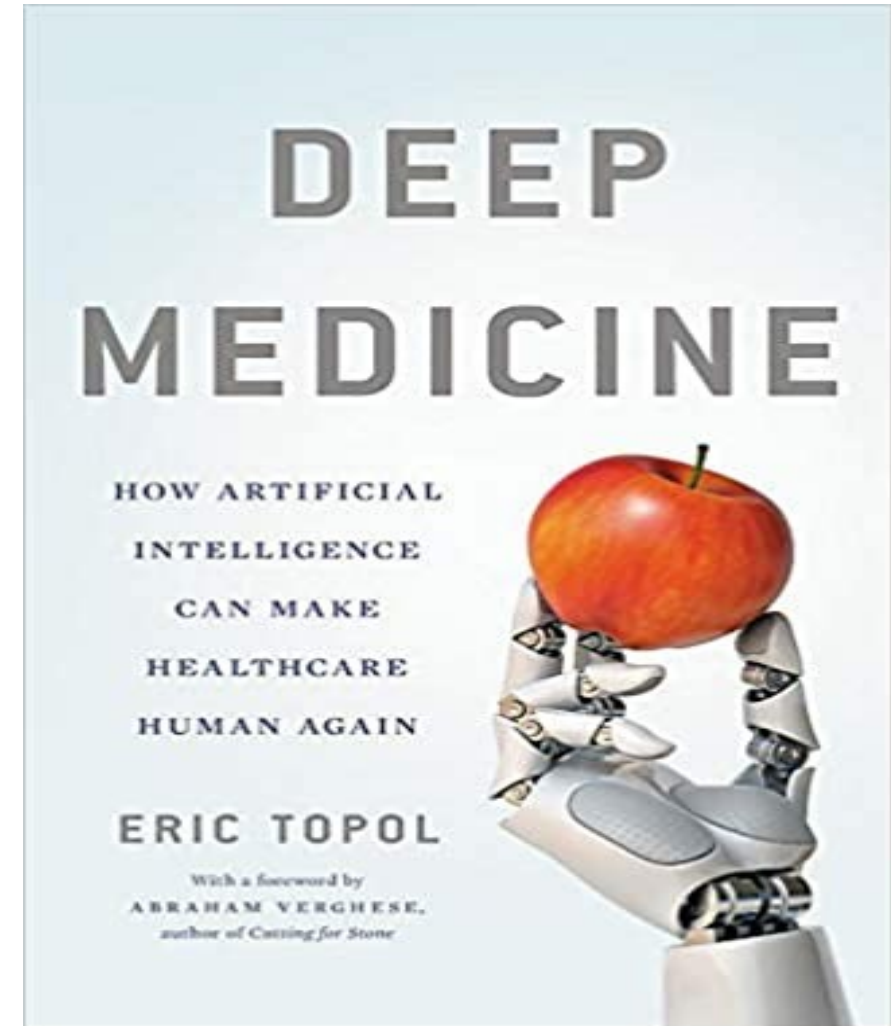
- Data Inefficient
 - Not all domains have so much data
 - Research Areas : Zero Shot Learning , Few Shot Learning
- Blackbox
 - Explainability / Trust is a challenge.
 - Regulatory implications
- Ethical / Fairness Concerns
 - Training Data can have hidden bias



What happens to us?

Humans and Machines

- Humans and AI make different kind of errors
 - We aren't good at Statistical/Probabilistic Reasoning
 - We suffer from Behavioral biases
 - AI suffers from lack of Common Sense / Data Inefficiency / Bad Data
- AI can free humans to focus on more productive work
 - Spreadsheets didn't eliminate accountants. Rather made them more valuable



To Conclude

AI isn't magic but it can be great productivity tool

“The fundamental error was in chasing perfection and moonshots instead of the achievable markers of technological progress ... one small step at a time. Implementing augmented intelligence into our day-to-day life does not need to be revolutionary, and it does not need to solve all of our problems at once to still be progress. But by taking the new tools and lessons of augmented intelligence, we can gradually improve every aspect of our lives.. .”

- Gary Kasparov

Appendix

Artificial Intelligence

A Guide for
Thinking Humans



Melanie Mitchell

"PEDRO DOMINGOS DEMYSTIFIES MACHINE LEARNING AND SHOWS HOW WONDROUS
AND EXCITING THE FUTURE WILL BE." —WALTER ISAACSON

THE MASTER ALGORITHM

HOW THE QUEST FOR
THE ULTIMATE
LEARNING MACHINE WILL
REMAKE OUR WORLD

PEDRO DOMINGOS

**Compute used to train deep learning models
has increased 300,000x in six years**

- Gumgum
- Stripe
- Diffbot

- “Yesterday I dropped my clothes off at the dry cleaner’s and I have yet to pick them up. Where are my clothes?”
 - **I have a lot of clothes**
- You are having a small dinner party. You want to serve dinner in the living room. The dining room table is wider than the doorway, so to get it into the living room, you will have to **remove the door. You have a table saw, so you cut the door in half and remove the top half.**
- “A teenager can learn to drive with 15-20 hours of practice, whereas millions of hours of training in different environments is not adequate for cars to drive themselves with the same degree of reliability, he said”
- “LeCun said the laws of physics do not change when you move from North America to Britain. He said this allows the teenager to drive and not have to try to run off a cliff to see what happens. Whereas the AI system will have to run off the cliff to figure out that it is a bad idea; probably do it for a few thousand times before it realises how not to do it. So, that is what we are missing, said LeCun”