

Machine Learning Fundamentals

David McClintock, MD
Pathology Informatics Summit 2018 Boot Camp
May 21, 2018

DISCLOSURES

I have no relevant financial relationships with commercial interests to disclose in relation to the content of this presentation.

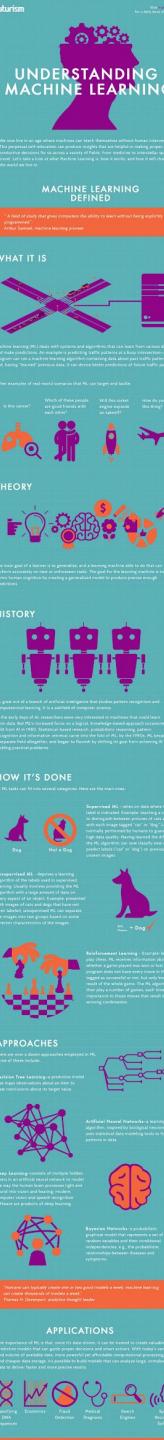
Who Am I??



David S. McClintock, MD
Director, Digital Pathology

Associate Chief Medical Information Officer, Michigan Medicine
Associate Director, Pathology Informatics
Associate Professor, University of Michigan, Dept. of Pathology

President, Association for Pathology Informatics (API)



DISCLAIMERS

Machine Learning is **HUGE...**

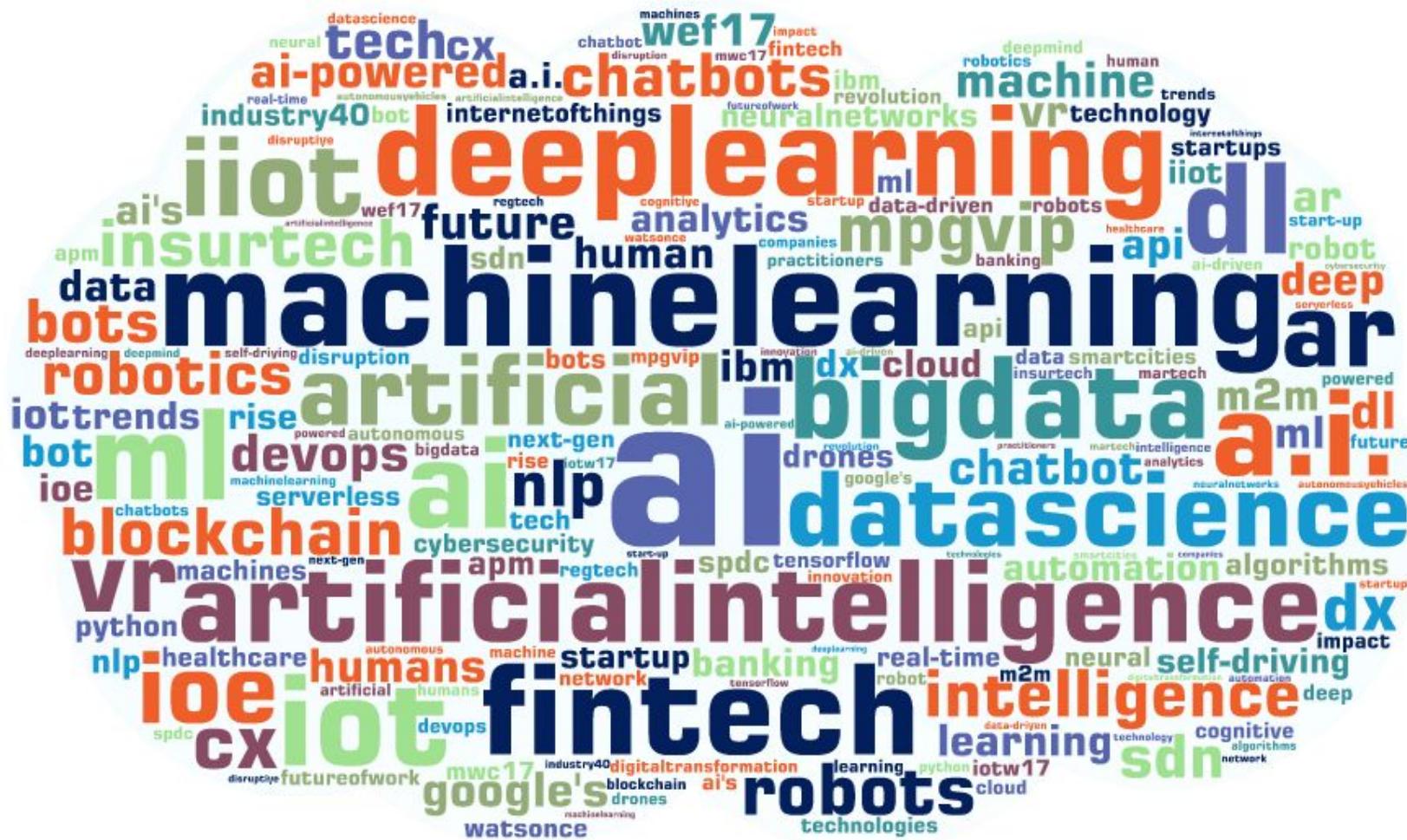
Practically impossible to learn everything on such a vast and rapidly evolving topic

I am not an über expert in Machine Learning

Goal is to make this topic **UNDERSTANDABLE**

For today → make you familiar with basic machine learning terminology and concepts

So...Machine Learning?



Machine Learning Is Everywhere



Google

machine learning

machine learning

machine learning **algorithms**

machine learning **vs ai**

machine learning **umich**

machine learning **engineer**

machine learning **definition**

machine learning **jobs**

machine learning **tutorial**

machine learning **datasets**

machine learning **python**

Google Search I'm Feeling Lucky

Report inappropriate predictions

A screenshot of a Google search results page. The search query "machine learning" has been entered. Below the search bar, a list of suggested search terms appears, with "machine learning umich" highlighted by a yellow box. At the bottom of the search results, there are two buttons: "Google Search" and "I'm Feeling Lucky". A link at the bottom right of the search results says "Report inappropriate predictions".

Meet Alexa



Just ask to play music, read the news, control your smart home, tell a joke, and more—you are at home or on the go, Alexa is designed to make your life easier by letting you voice-control your world. [Explore more things to try with Alexa.](#)

ting smarter, and updates are delivered automatically. The more you talk to Alexa, the more it learns about your interests, behaviors, and personal preferences. Alexa comes included with Echo and other Alexa devices.



"Alexa, find me a Chinese restaurant."

"Alexa, what's on my calendar today?"

"Alexa, set timer for 20 minutes."

"Alexa, what's my commute?"

But is NOT Infallible

Federal Agency Investigate
Driver Says Car Was On Au-

May 16, 2018 · 8:30 PM ET

VANESSA ROMO



Google

I feel like a p

i feel like a purple pikmin

i feel like a prisoner in my own home

i feel like a popstar

i feel like a potato

i feel like a piece of meat to my boyfriend

i feel like a plastic bag

i feel like a piece of me is missing

i feel like a puppet

i feel like a phony

i feel like a pig shit in my head

Google Search I'm Feeling Lucky

Report inappropriate predictions

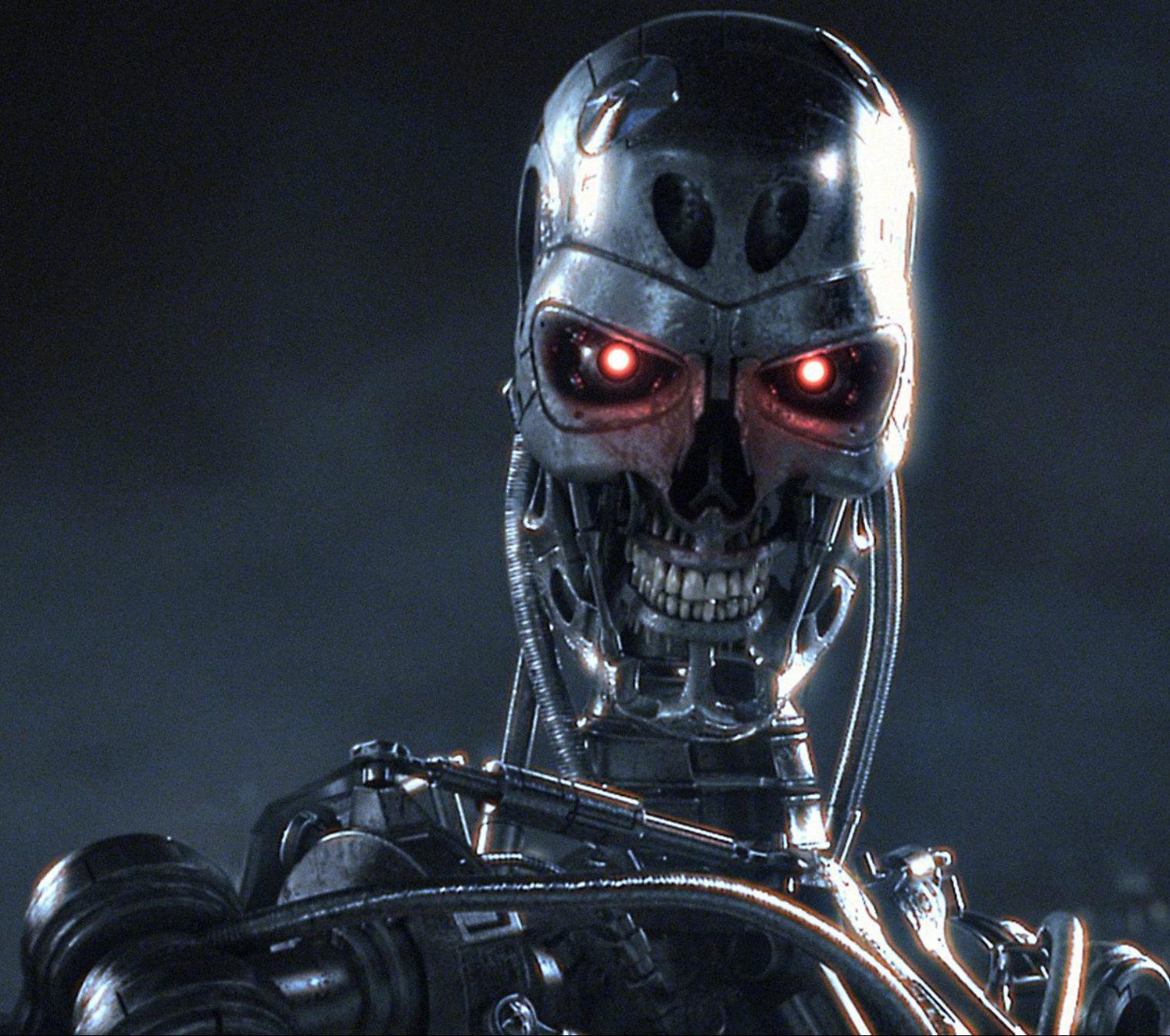
g or laughing? Amazon's Alexa is out with unprovoked chuckle

May 16, 2018 at 12:35 pm

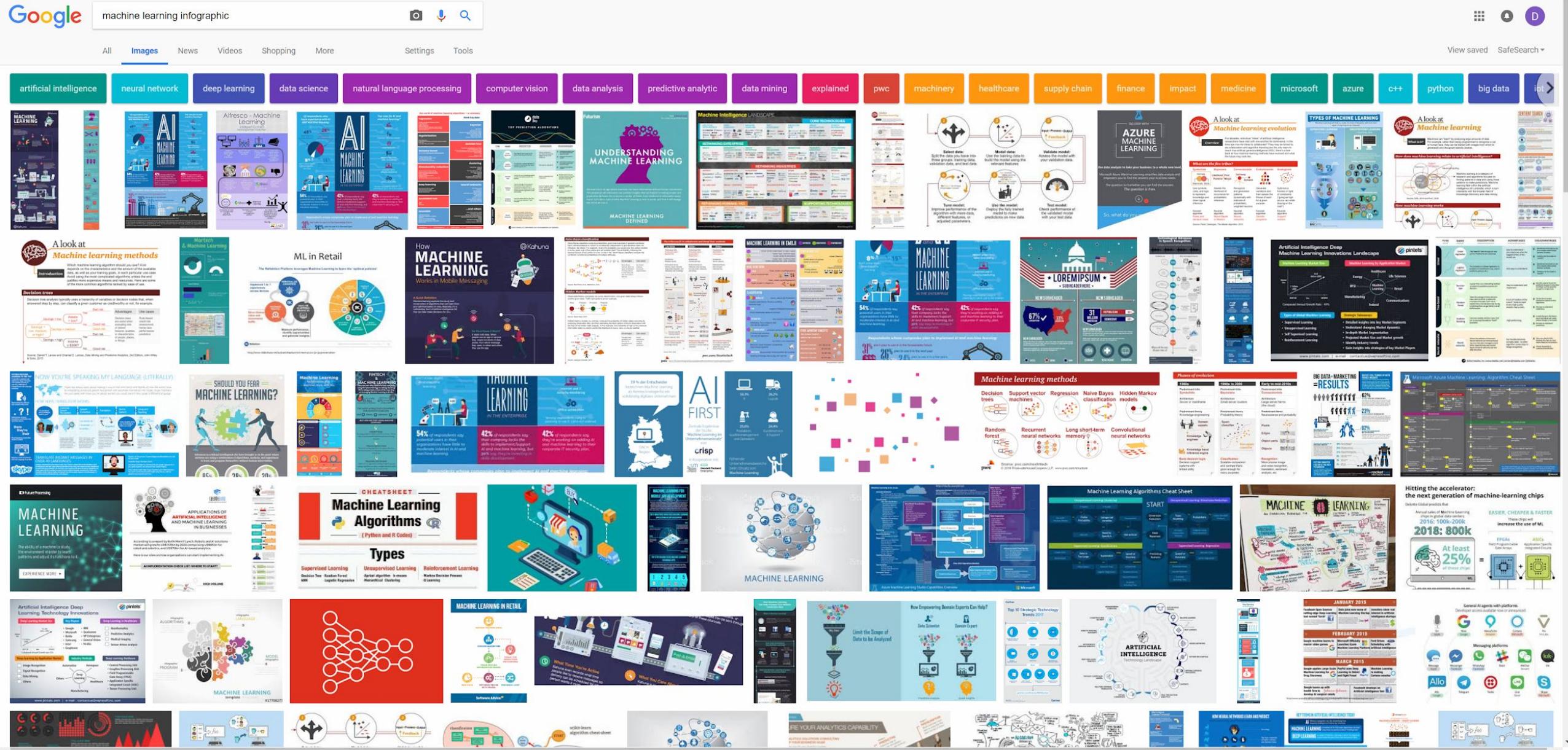


Nire Photo / Kurt Schlosser)

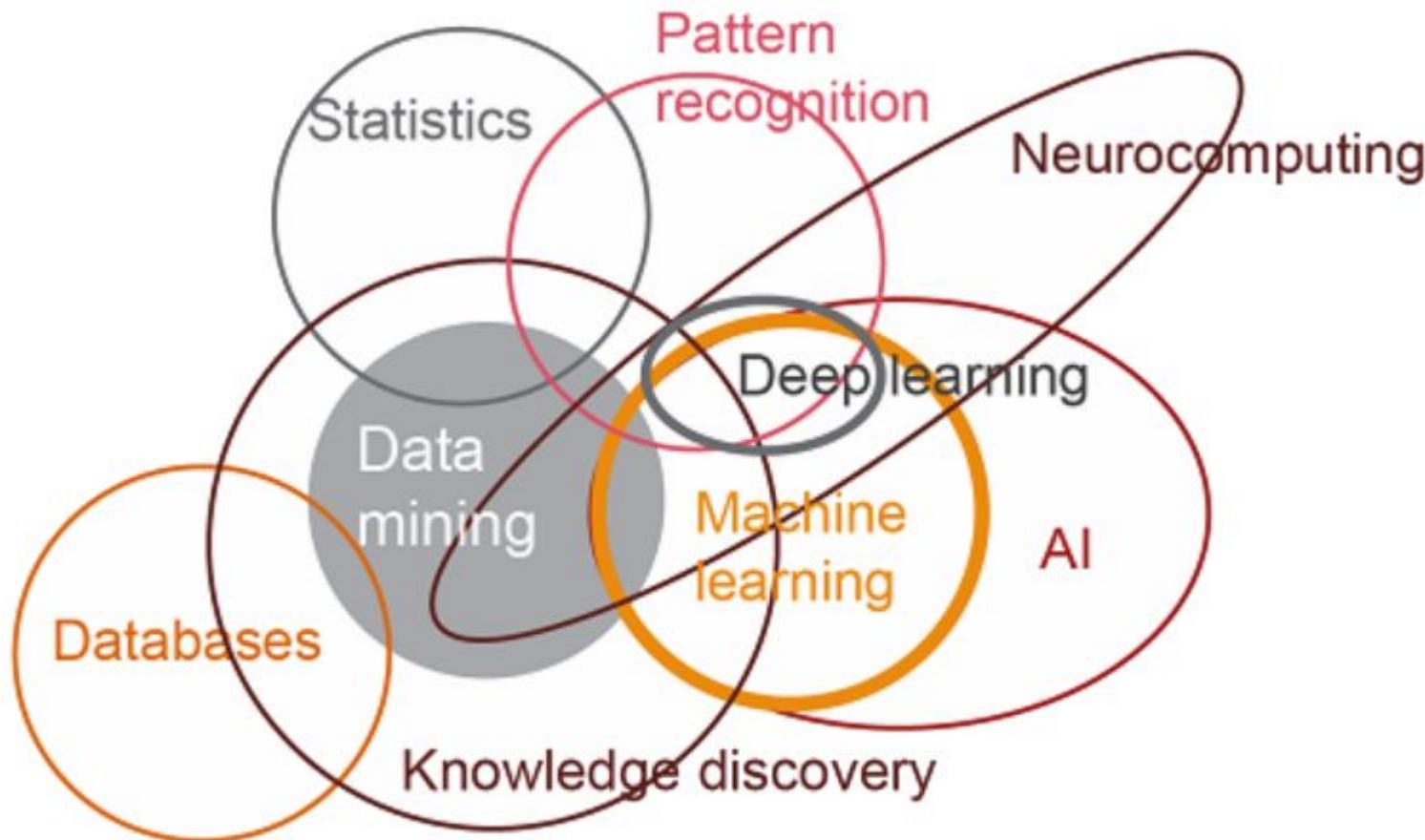
And it's only a
matter of time...



Where Do We Start?



Where Do We Start?



Source: SAS, 2014 and PwC, 2016

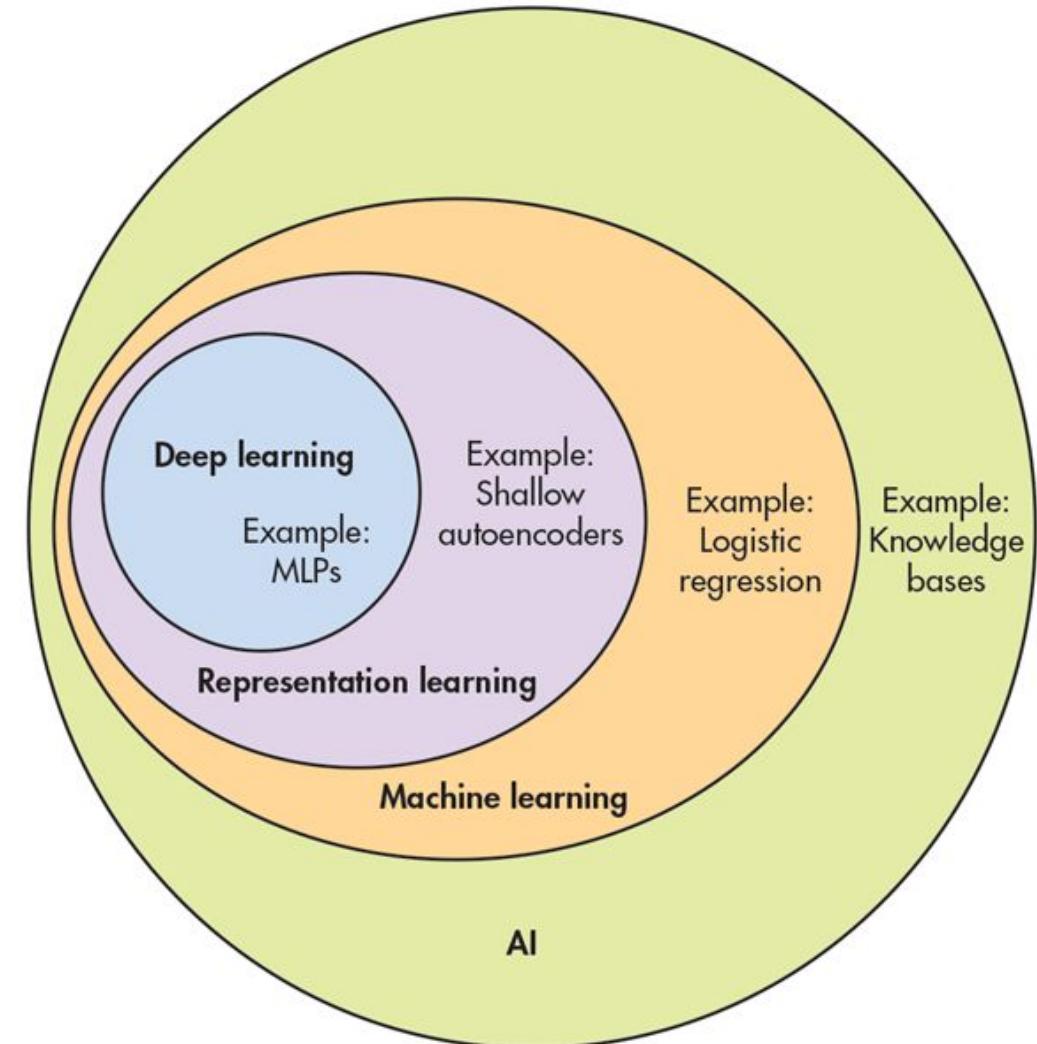
Where Do We Start?

Artificial Intelligence

Machine Learning

Representation Learning

Deep Learning



Artificial Intelligence - Definition

- Machines that think the way humans think
- How to make machines that can:
 - Understand the world
 - Make predictions
 - Choose appropriate actions
 - Perform judgemental processes we associate with human intelligence
 - And, do it all better than humans can

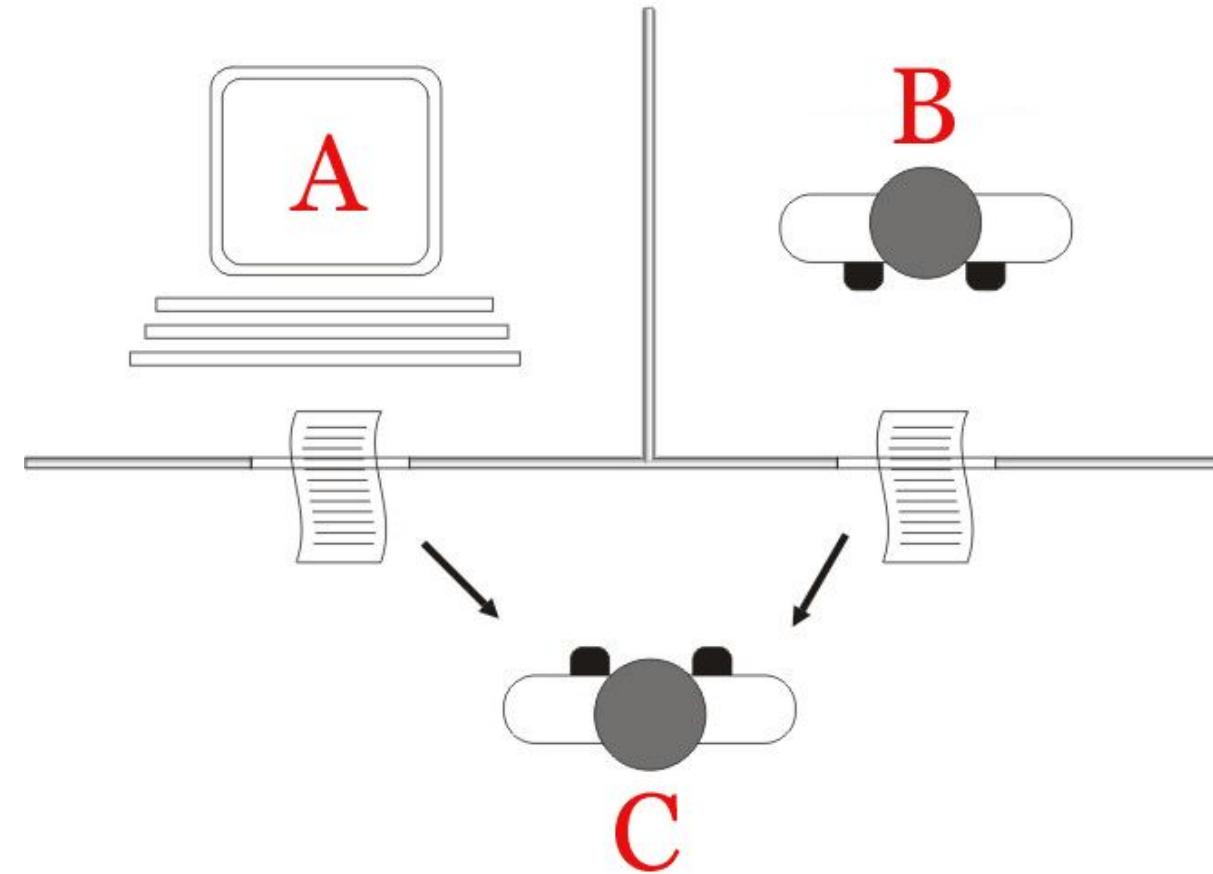
AI Has Deep Roots

- Ancient Greeks
 - Myths of automatons created by the gods that think
- 1600s - Leibniz, Thomas Hobbes and Descartes
 - All rational thought could be expressed as algebra or geometry
- 1800s - 1900s
 - Many instances of early “AI” in literature
- 1950 - Alan Turing
 - Groundbreaking paper "Computing Machinery and Intelligence"
 - Can machines “think”? → Turing Test



AI - The Turing Test

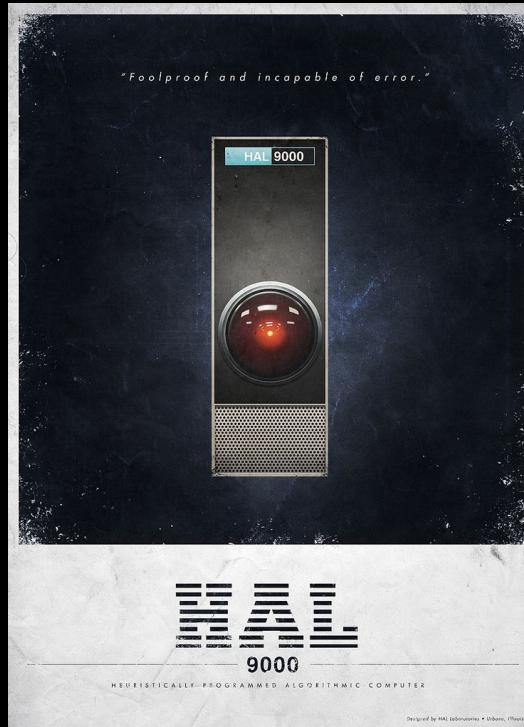
- Test of a machine's ability to exhibit intelligent behavior equivalent to, or indistinguishable from, that of a human
- A computer can be said to be intelligent, or “think”, if a human judge cannot tell if he/she is interacting with a human or a machine



AI - 1956 Dartmouth University Workshop

- AI founded as a discipline
- Experts there coined the term Artificial Intelligence
- Recommended further study of:
 - "...the conjecture that every aspect of learning or any other feature of intelligence can in principle be so precisely described that a machine can be made to simulate it."
 - "An attempt will be made to find how to make machines use language, form abstractions and concepts, solve kinds of problems now reserved for humans, and improve themselves."

Artificial Intelligence in Popular Culture



STANLEY KUBRICK'S
2001:
a space odyssey

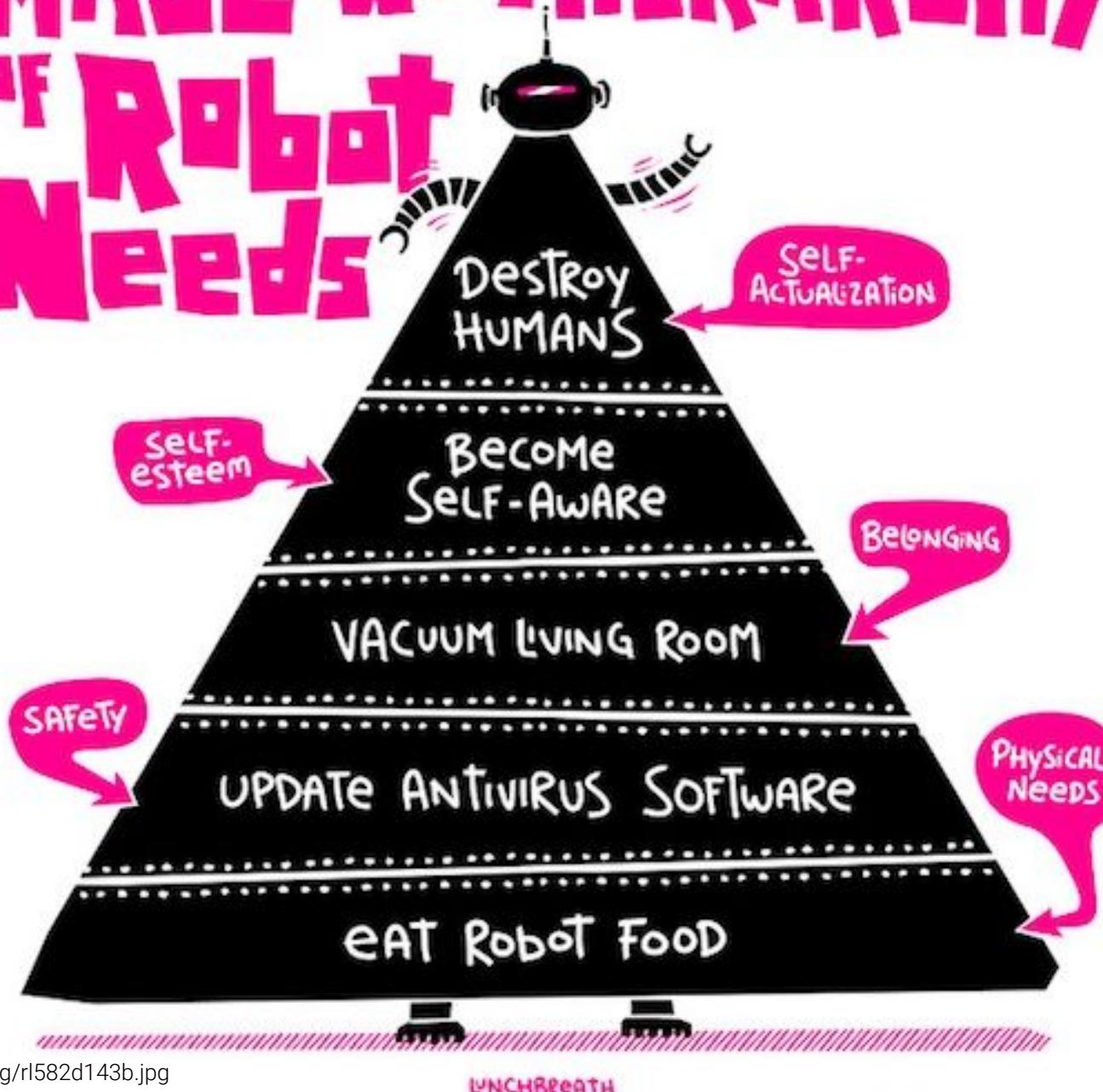


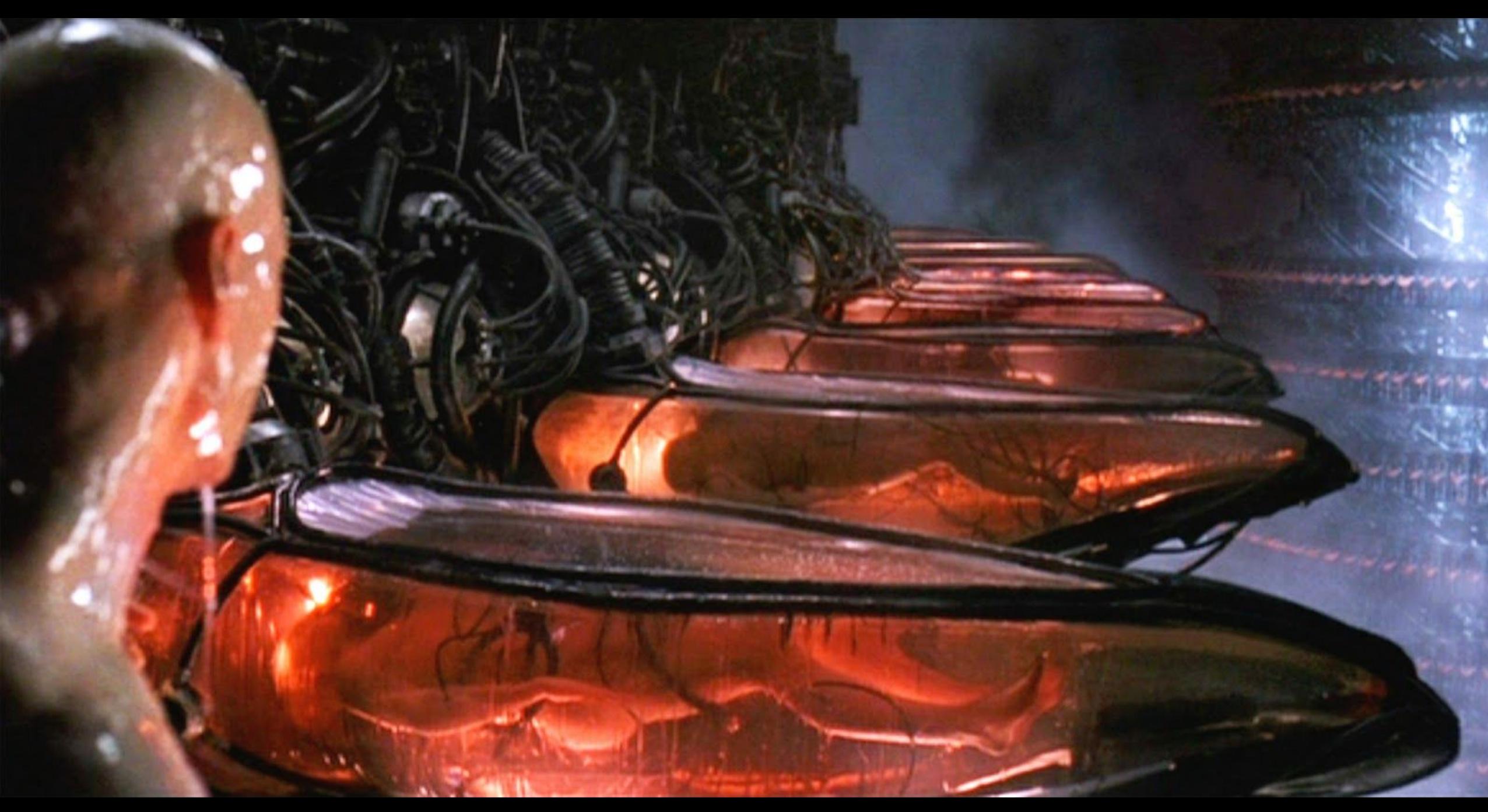
ex machina

WHAT HAPPENS TO ME IF I FAIL YOUR TEST?

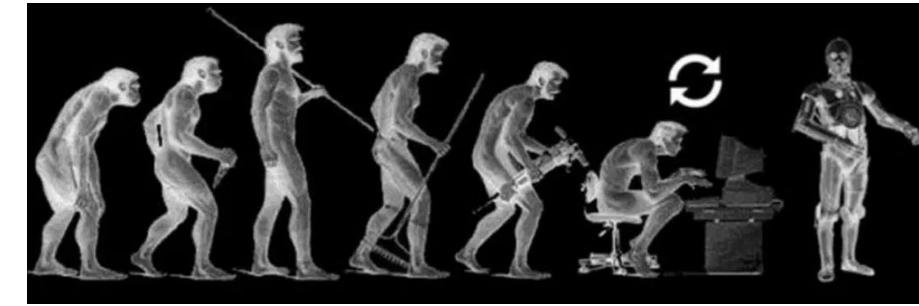


MASLOW'S HIERARCHY OF Robot Needs





Primary AI Goals



- Deduction, Reasoning, & Problem Solving
- Knowledge representation (expert systems)
- Automated planning and scheduling
- **Machine learning**
- Natural language processing
- Perception (a computer's "five senses")
- Creativity
- Social intelligence (affective computing)
- General intelligence

AI - General Intelligence

- Ability for machines to solve problems as well as humans do
- Example: Machine Translation
 - Must read and write in both languages (NLP)
 - Follow the author's argument (reason)
 - Recognize what is being talked about (knowledge)
 - Faithfully reproduce the author's original intent (social intelligence)
- Considered "AI-complete"
 - All of these problems need to be solved simultaneously in order to reach human-level machine performance

ARTIFICIAL INTELLIGENCE

Early artificial intelligence
stirs excitement.



MACHINE LEARNING

Machine learning begins
to flourish.



DEEP LEARNING

Deep learning breakthroughs
drive AI boom.



1950's

1960's

1970's

1980's

1990's

2000's

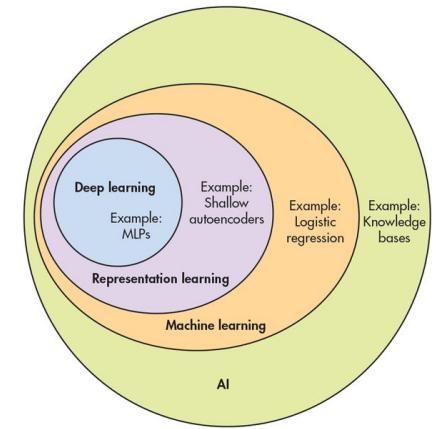
2010's

Machine Learning - Definition

- The field of study giving computers the ability to learn without being explicitly programmed
 - Term first used in 1959 by Arthur Samuel at IBM
- Process of using intelligent statistical techniques to construct algorithms that progressively improve performance on a specific task by making data-driven predictions or decisions, typically through building a model from sample inputs

AI vs Machine Learning

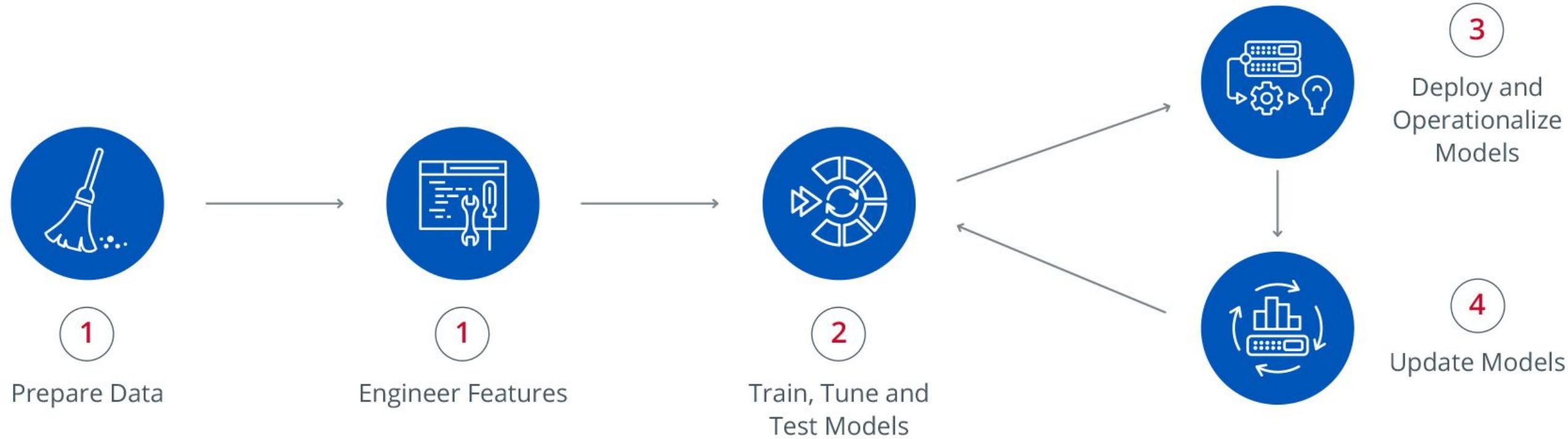
- ML can be thought of as a *subset* of AI
- Artificial Intelligence USES machine learning to minimize the manual input necessary to program an AI construct
 - Requires very large databases that contain many different examples of different scenarios
 - ML algorithms can study these databases and “learn” their own description of elements of interest (feature learning)
 - All done without additional human input



Features

- Attribute or property shared by all of the independent units on which analysis or prediction is to be done
 - Any attribute can be a feature, as long as it is useful to the model
- Feature engineering
 - Process of using domain knowledge of the data to create features that make ML algorithms work
- Features are easier to understand in the context of a problem!!
 - Characteristic(s) that might help when solving the problem

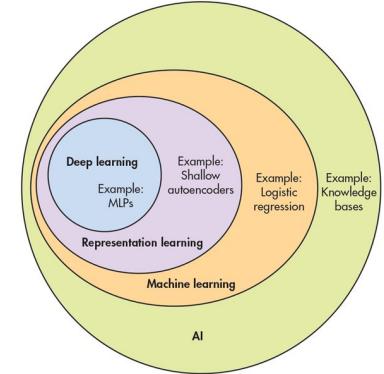
ML Basics - Creating Models



- 1) Understand patterns in large sets of input data
- 2) Generate models based on this data
- 3) Predict outputs based on the models it generates

Representation Learning - Definition

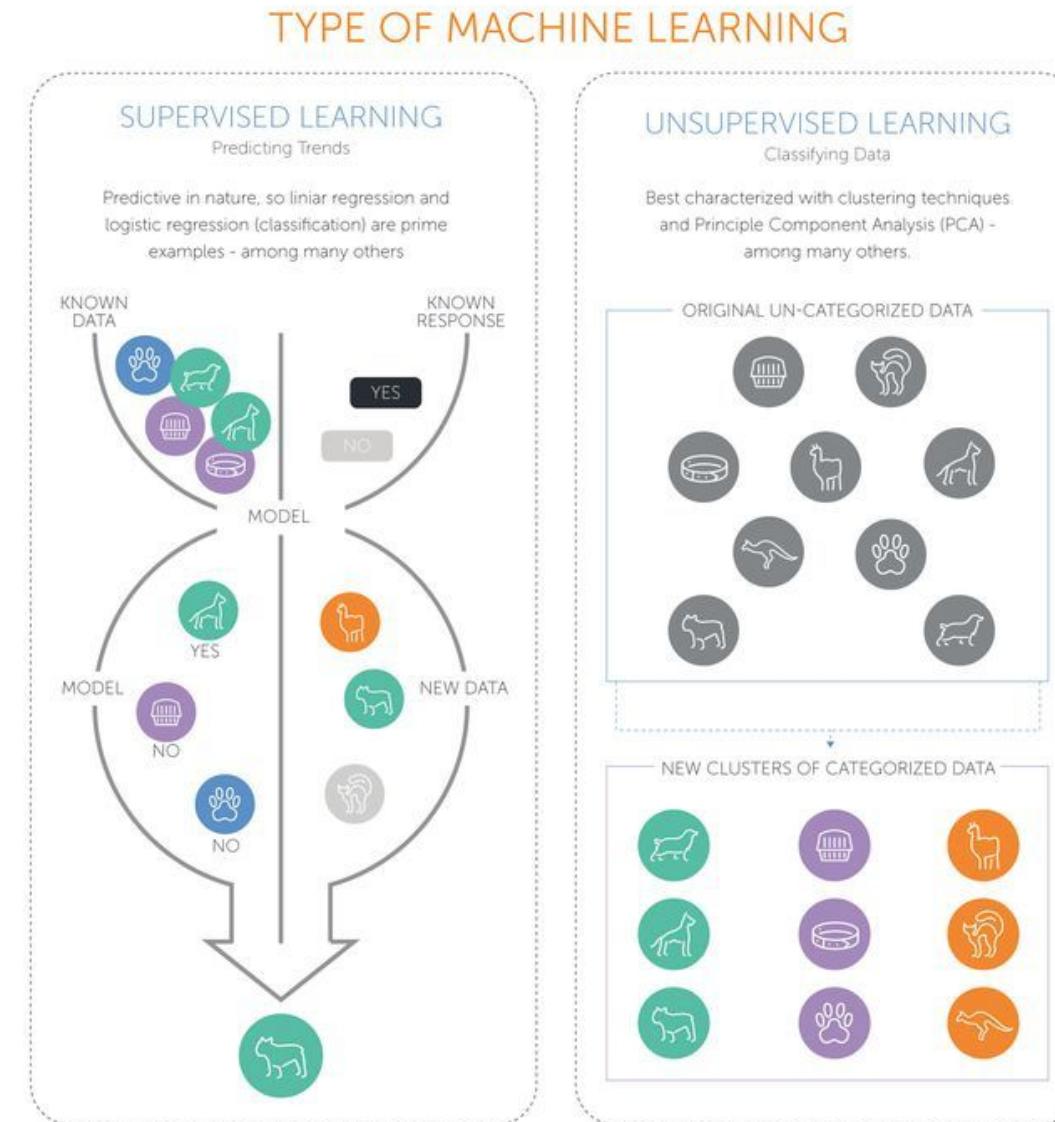
- A.k.a. Feature Learning
- Strategy for machine learning where the representation learning algorithms figure out how to process the data
 - System uses RAW DATA to automatically discover the representations needed for feature detection/classification
 - Replaces manual feature engineering
 - Allows a machine to both learn the features and use them to perform a specific task



Representation Learning

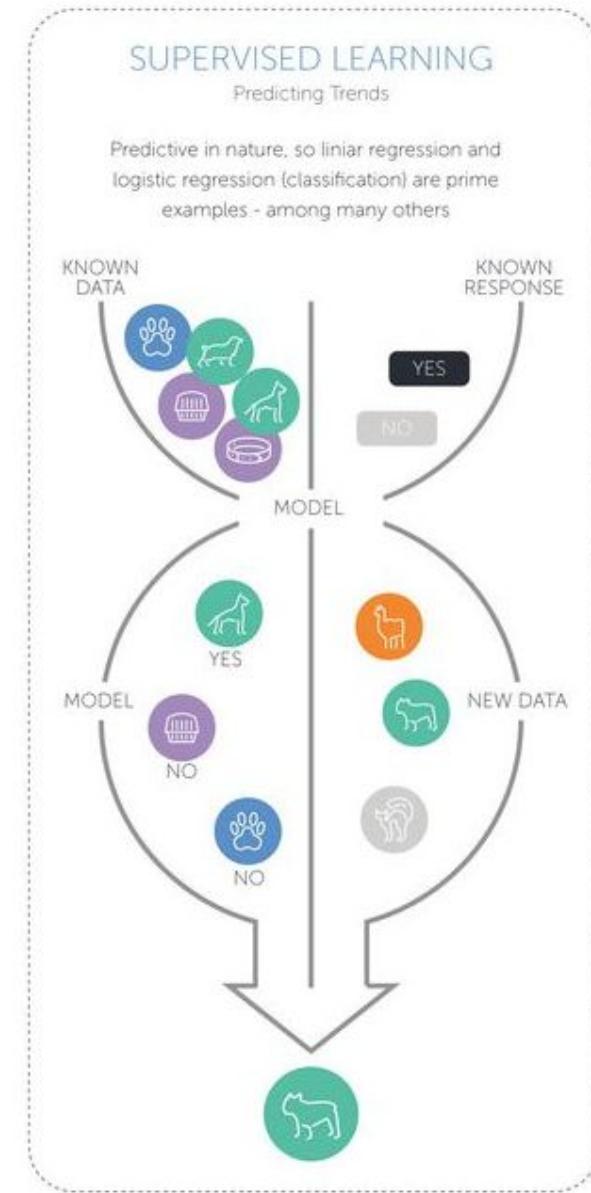
Discovering features or representations through examination, without relying on explicit algorithms

Two main types: Supervised and Unsupervised



Supervised Feature Learning

- Learning features from labeled data
 - System has knowledge of the output
 - Training data set exists where the feature is known
 - Goal is to discover patterns in the data relating to targeted data attributes
 - Patterns utilized to predict values in new, untested data
 - Examples
 - Bayesian classifiers
 - Neural networks
 - Decision trees
 - Support vector machines
 - Linear regression
 - Random Decision Forests

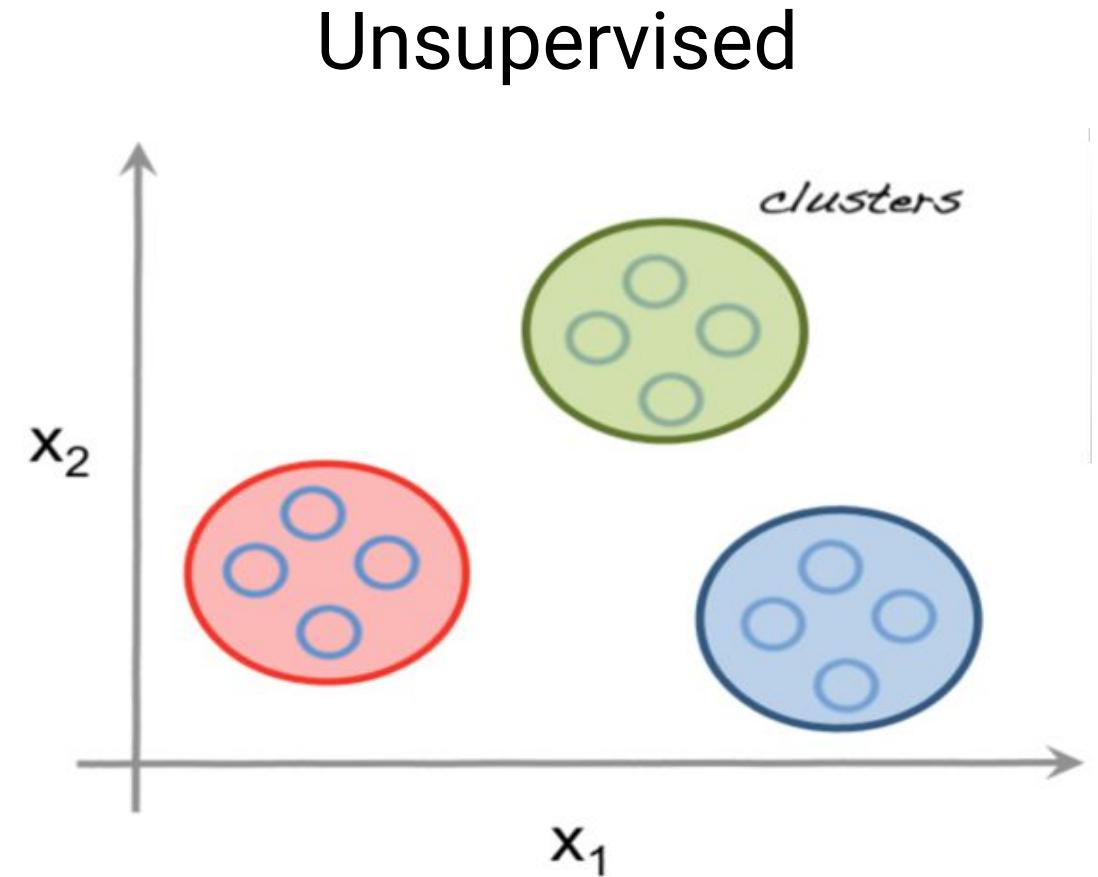
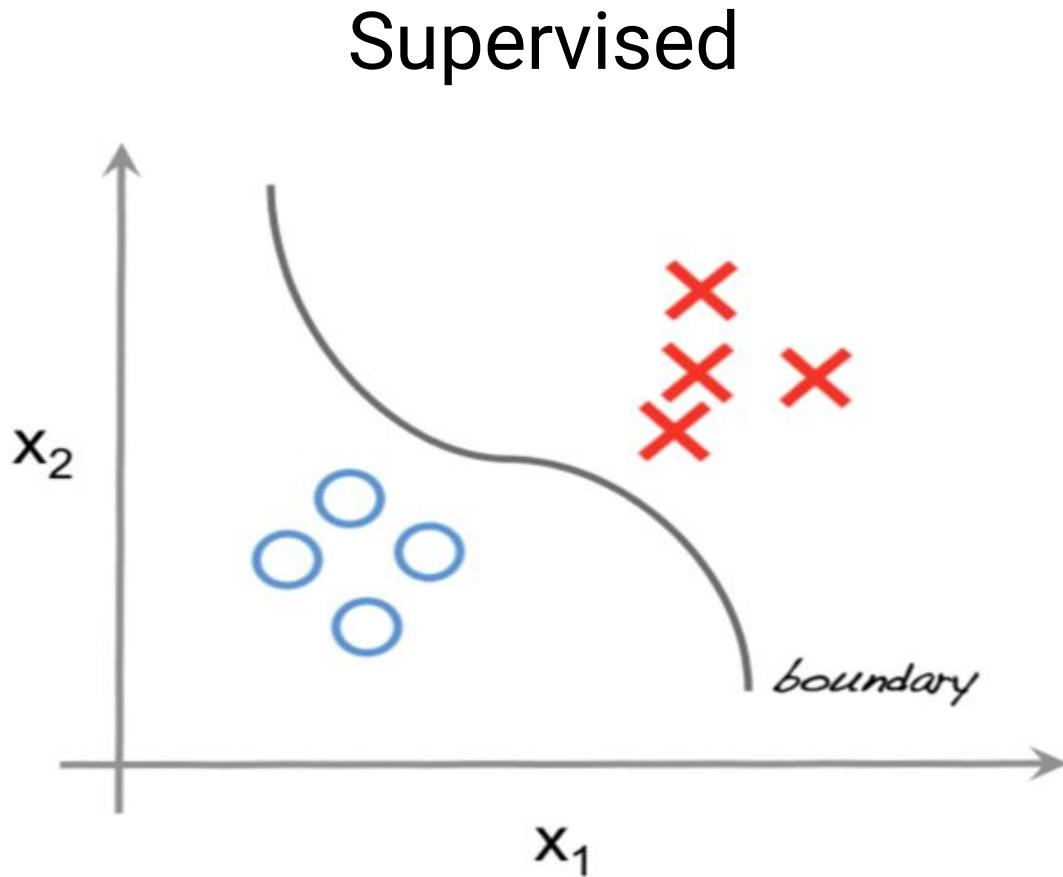


Unsupervised Feature Learning

- Learning features from unlabeled data
 - System has NO knowledge of the output
 - The data have no target attributes
 - Goal is to determine data patterns/groupings
 - Discover low-dimensional features capturing some structure underlying the high-dimensional input data
 - Examples
 - Hierarchical clustering
 - k-means clustering
 - Gaussian mixture models
 - Self-organizing maps
 - Hidden markov models

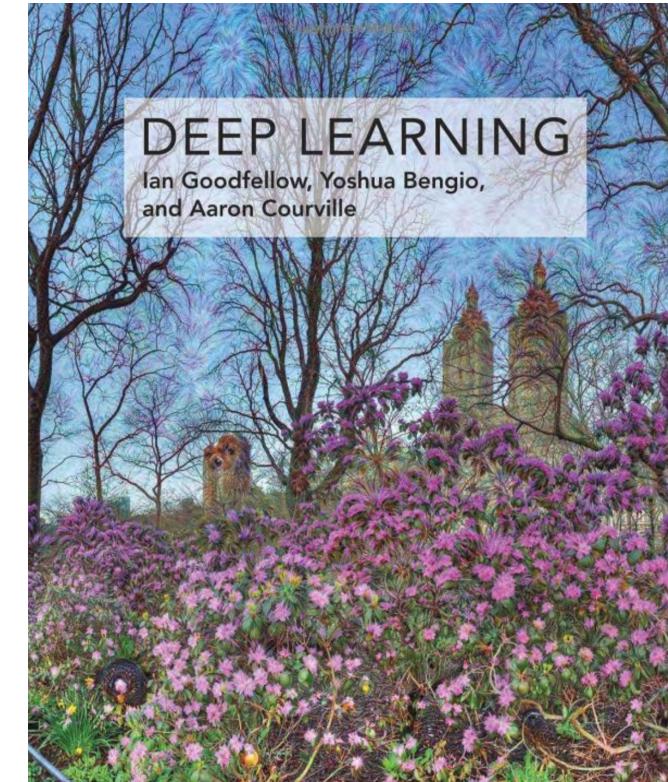
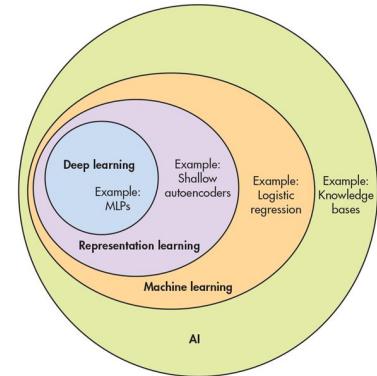


Supervised vs Unsupervised Learning



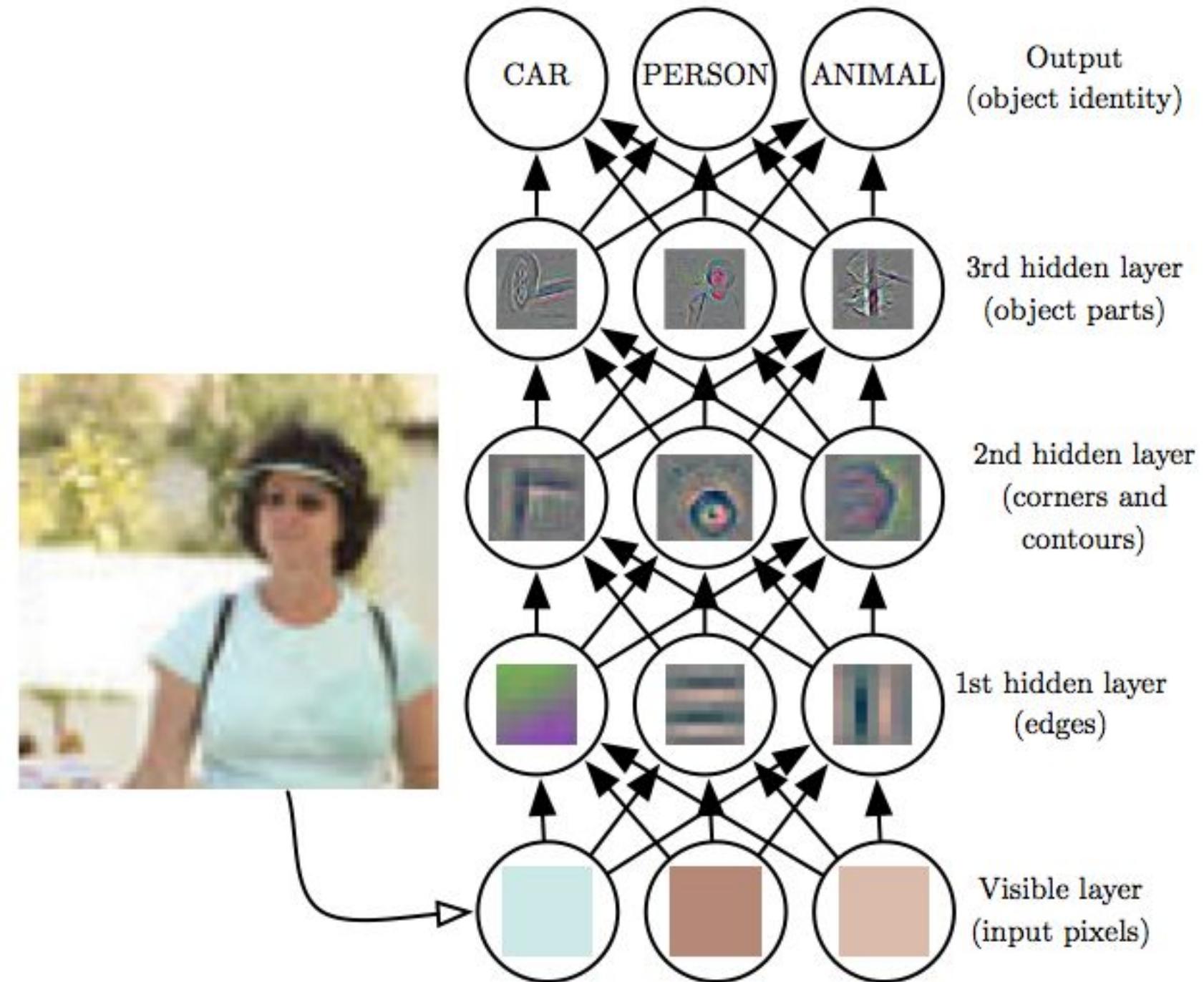
Deep Learning - Definition

- Subset of representation learning
 - Feature learning algorithms that apply several different sequential transformations of the data
 - Eventually arrives at very sophisticated transformations of the data
 - Can solve very difficult and complex engineering tasks
- "Deep" refers to the number of layers through which the data is transformed



Example - Deep Learning Model

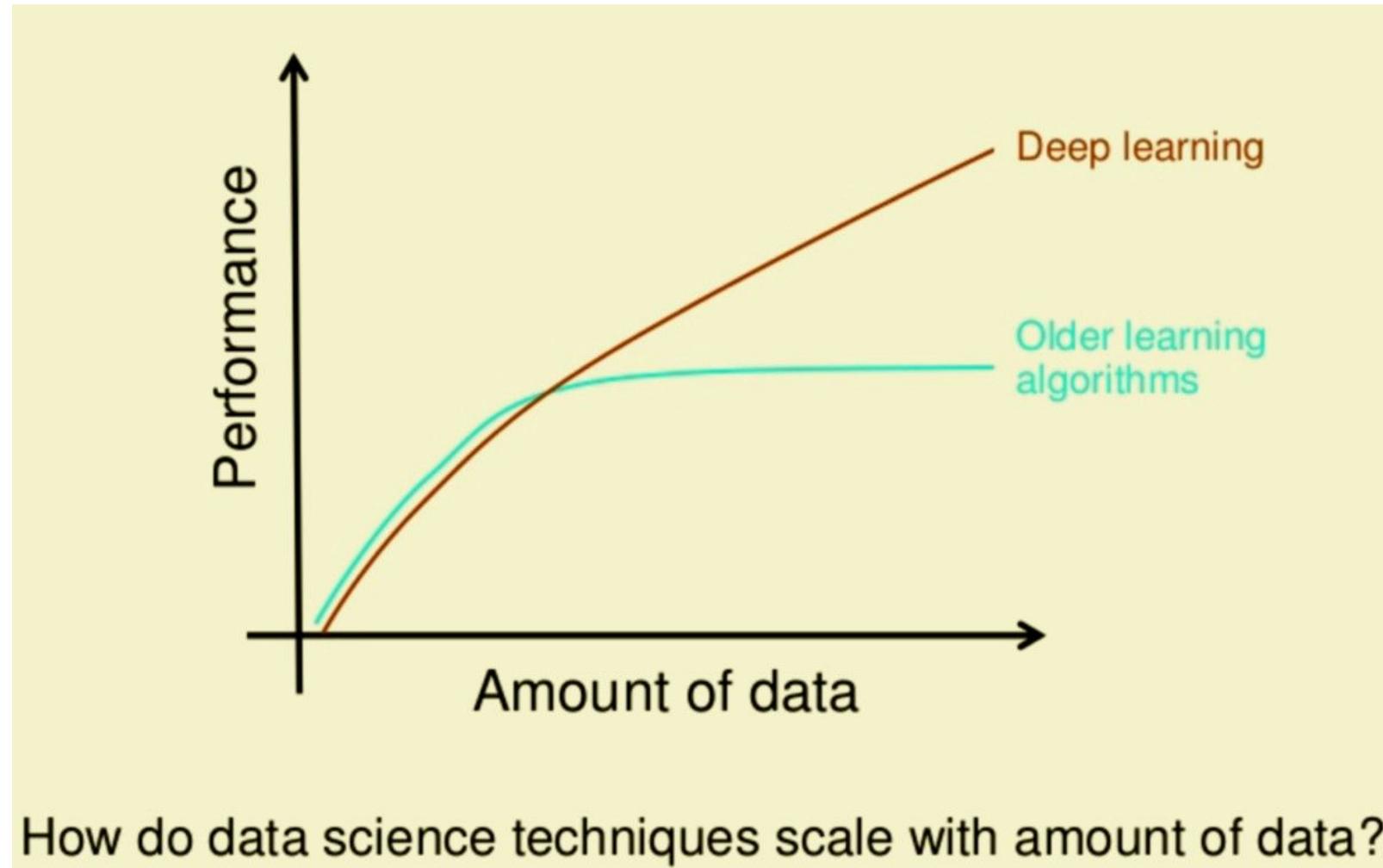
Figure from: Goodfellow et. al. Deep Learning. 2016. MIT Press, Boston, MA. Page 6.



When Should Deep Learning Be Used?

- 1) For large data sets
 - a) Traditional ML algorithms preferred for smaller data sets
 - Less likely to “overtrain” the data
- 2) If you have a high end infrastructure → DL is much faster!!
- 3) Lack of domain knowledge for feature engineering
 - a) Automated feature learning obviates the need for manual feature engineering
- 4) For dealing with complex problems, e.g.
 - a) Image classification
 - b) Natural language processing
 - c) Speech recognition

Big Data and Deep Learning



Traditional ML vs DL

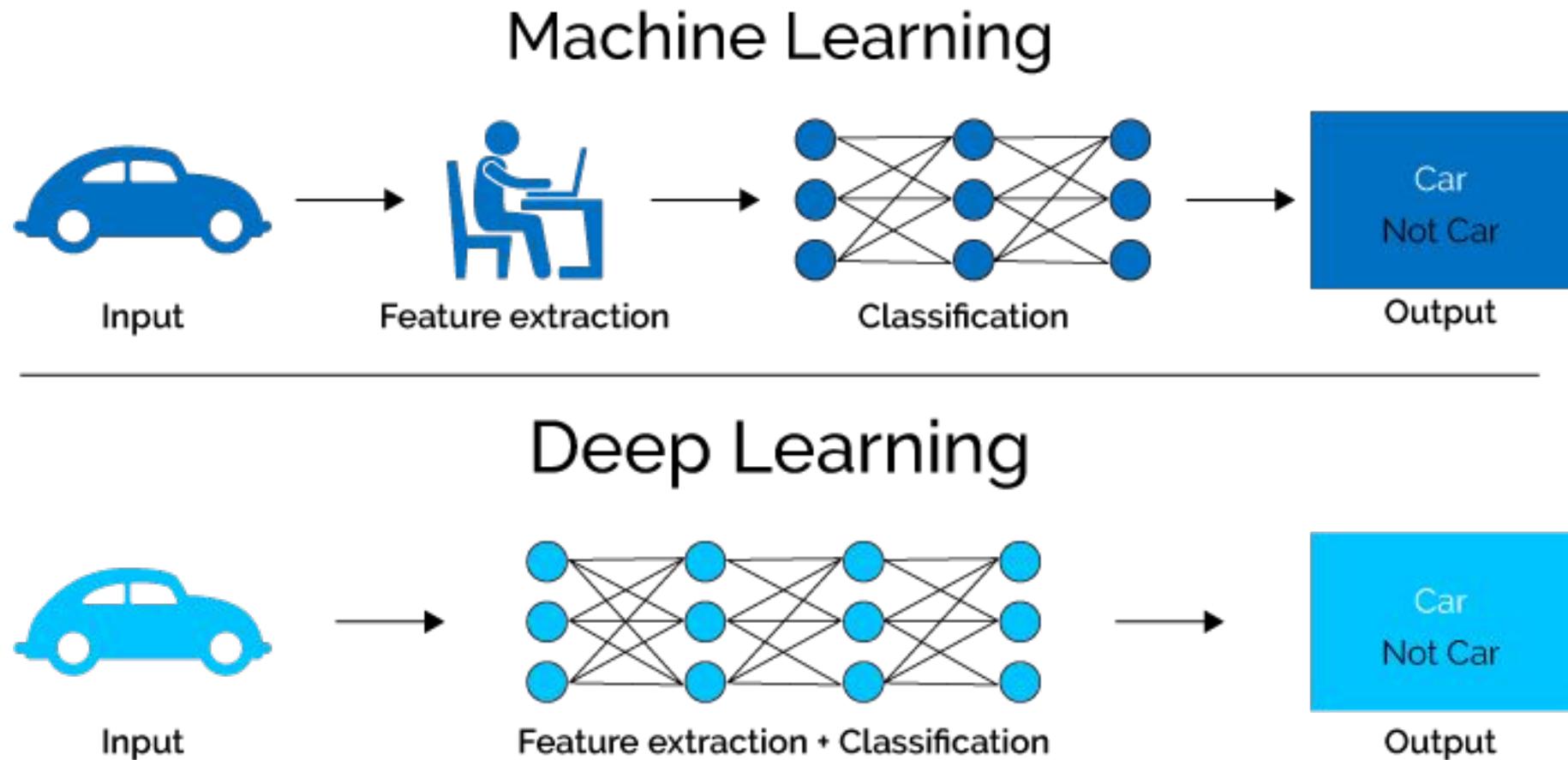


Image (left): <https://towardsdatascience.com/why-deep-learning-is-needed-over-traditional-machine-learning-1b6a99177063>

Machine Learning Methods

regression

Ordinary Least Squares Regression (OLSR)
Linear Regression
Logistic Regression
Stepwise Regression
Multivariate Adaptive Regression Splines (MARS)
Locally Estimated Scatterplot Smoothing (LOESS)
Jackknife Regression

regularization

Ridge Regression
Least Absolute Shrinkage and Selection Operator (LASSO)
Elastic Net
Least-Angle Regression (LARS)

instance based

also called cake-based, memory-based

k-Nearest Neighbour (kNN)
Learning Vector Quantization (LVQ)
Self-Organizing Map (SOM)
Locally Weighted Learning (LWL)

dimensionality reduction

Principal Component Analysis (PCA)
Principal Component Regression (PCR)
Partial Least Squares Regression (PLSR)
Sammon Mapping
Multidimensional Scaling (MDS)
Projection Pursuit
Discriminant Analysis (LDA, MDA, QDA, FDA)

think big data

bayesian

Naive Bayes
Gaussian Naive Bayes
Multinomial Naive Bayes
Averaged One-Dependence Estimators (AODE)
Bayesian Belief Network (BBN)
Bayesian Network (BN)
Hidden Markov Models
Conditional random fields (CRFs)

decision tree

Classification and Regression Tree (CART)
Iterative Dichotomiser 3 (ID3)
C4.5 and C5.0 (different versions of a powerful approach)
Chi-squared Automatic Interaction Detection (CHAID)
Decision Stump
M5
Random Forests
Conditional Decision Trees

clustering

Single-linkage clustering
k-Means
k-Medians
Expectation Maximisation (EM)
Hierarchical Clustering
Fuzzy clustering
DBSCAN
OPTICS algorithm
Non Negative Matrix Factorization
Latent Dirichlet allocation (LDA)

deep learning

Deep Boltzmann Machine (DBM)
Deep Belief Networks (DBN)
Convolutional Neural Network (CNN)
Stacked Auto-Encoders

associated rule

Apriori
Eclat
FP-Growth

ensemble

Logit Boost (Boosting)
Bootstrapped Aggregation (Bagging)
AdaBoost
Stacked Generalization (blending)
Gradient Boosting Machines (GBM)
Gradient Boosted Regression Trees (GBRT)
Random Forest

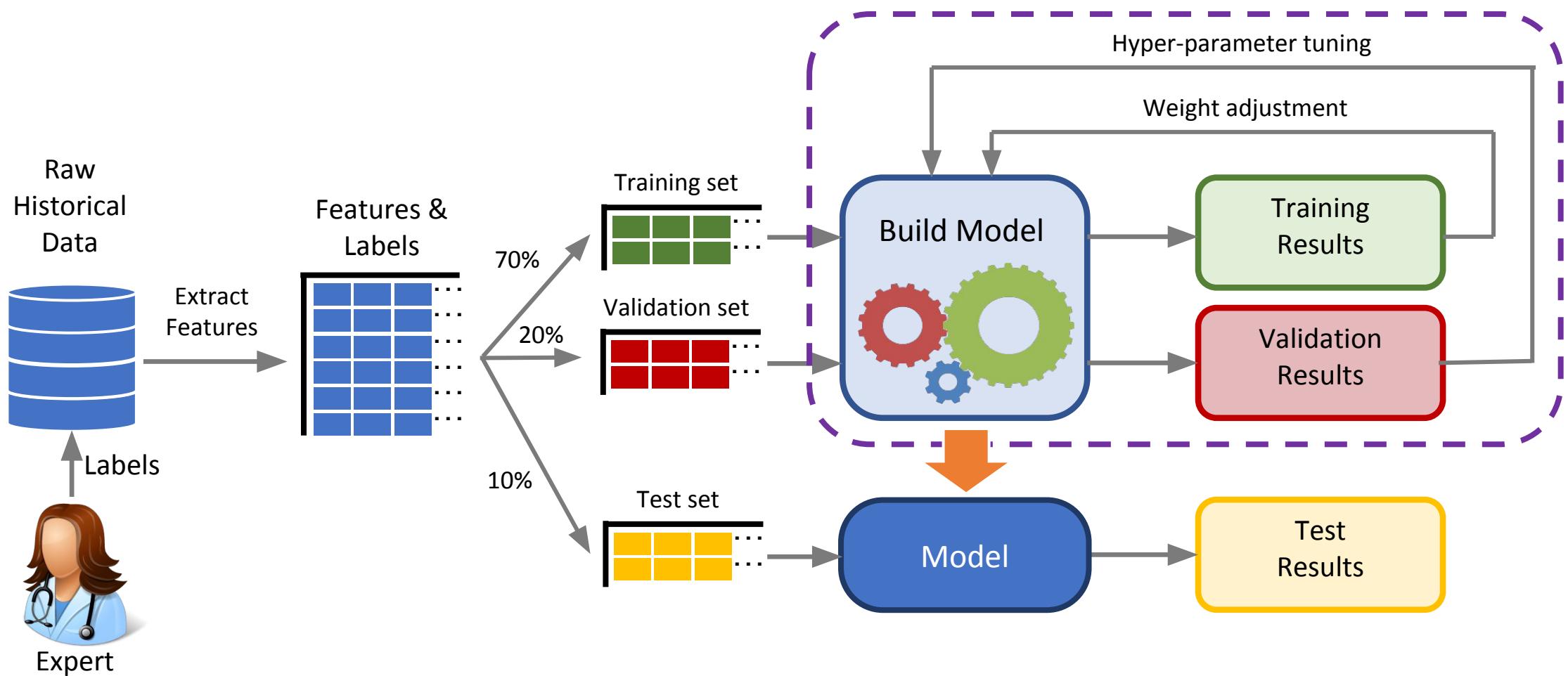
neural networks

Self Organizing Map
Perceptron
Back-Propagation
Hopfield Network
Radial Basis Function Network (RBFN)
Backpropagation
Autoencoders
Hopfield networks
Boltzmann machines
Restricted Boltzmann Machines
Spiking Neural Networks
Learning Vector quantization (LVQ)

...and others

Support Vector Machines (SVM)
Evolutionary Algorithms
Inductive Logic Programming (ILP)
Reinforcement Learning (Q-Learning, Temporal Difference, State-Action-Reward-State-Action (SARSA))
ANOVA
Information Fuzzy Network (IFN)
Page Rank
Conditional Random Fields (CRF)

Machine Learning Workflow



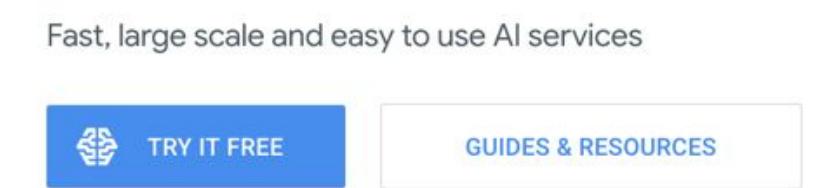
Automating Machine Learning

Many cloud and enterprise based ML platforms available



Azure Machine Learning
Open and elastic AI development spanning the cloud and the edge

Try for free >



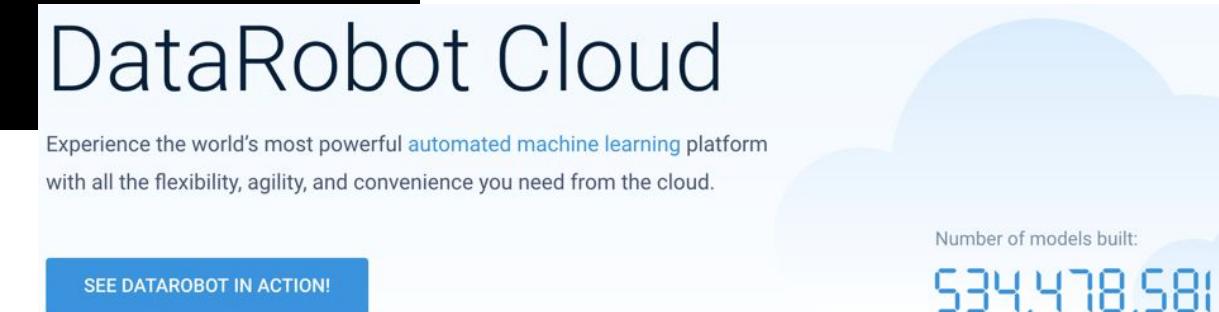
Google Cloud

CLOUD AI
Fast, large scale and easy to use AI services

IBM Cloud

Watson Machine Learning
Create, train, and deploy self-learning models.

Start your free trial



DataRobot Cloud
Experience the world's most powerful automated machine learning platform with all the flexibility, agility, and convenience you need from the cloud.

SEE DATAROBOT IN ACTION!

AWS Deep Learning AMIs
Pre-configured environments to quickly build deep learning applications

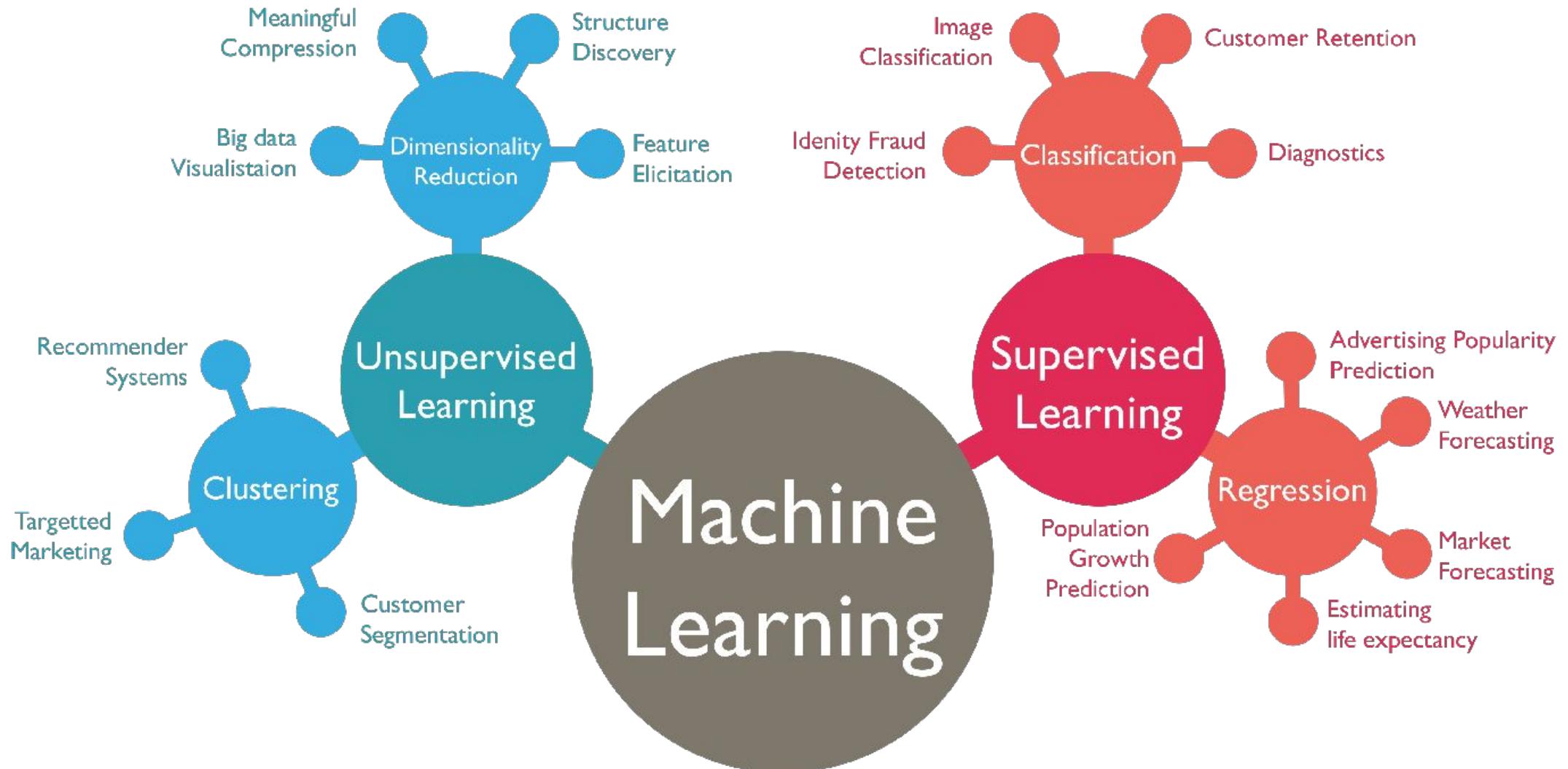
Get started with AWS Deep Learning AMIs

Number of models built:
534,478,581

Slide (modified) courtesy of Toby Cornish, MD
All images from vendor's websites, current as of 5/20/18

For other popular vendors, see:
<http://www.butleranalytics.com/20-most-popular-machine-learning-service-platforms/>

Machine Learning in Everyday Life



Machine Learning in Everyday Life

Machine Learning Use Cases



Banking



Healthcare



Retail

Supervised Learning

Predict credit worthiness of credit card holders: Build a machine learning model to look for delinquency attributes by providing it with data on delinquent and non-delinquent customers

Predict patient readmission rates: Build a regression model by providing data on the patients' treatment regime and readmissions to show variables that best correlate with readmissions

Analyze products customers buy together: Build a supervised learning model to identify frequent item sets and association rules from transactional data

Unsupervised Learning

Segment customers by behavioral characteristics: Survey prospects and customers to develop multiple segments using clustering

Categorize MRI data by normal or abnormal images: Use deep learning techniques to build a model that learns different features of images to recognize different patterns

Recommend products to customers based on past purchases: Build a collaborative filtering model based on past purchases by "customers like them"

Reinforcement Learning

Create a 'next best offer' model for the call center group: Build a predictive model that learns over time as users accept or reject offers made by the sales staff

Allocate scarce medical resources to handle different types of ER cases: Build a Markov Decision Process that learns treatment strategies for each type of ER case

Reduce excess stock with dynamic pricing: Build a dynamic pricing model that adjusts the price based on customer response to offers

RESEARCH



From Virtual Nurses To Drug Discovery: 106 Artificial Intelligence Startups In Healthcare

February 3, 2017

f t in e

[Artificial Intelligence](#)

The number of startups entering the healthcare AI space has increased in recent years, with over 50 companies raising their first equity rounds since January 2015. Deals to healthcare-focused AI startups went up from less than 20 in 2012 to nearly 70 in 2016. Last year also saw two new unicorns emerge in the space: China-based [iCarbonX](#) and oncology-focused [Flatiron Health](#).

“By 2025, AI systems could be involved in everything from population health management, to digital avatars capable of answering specific patient queries.” — Harpreet Singh Buttar, analyst at Frost & Sullivan.

We identified over 100 companies that are applying machine learning algorithms and predictive analytics to reduce drug discovery times, provide virtual assistance to patients, and diagnose ailments by processing medical images, among other things.

Machine Learning in Healthcare

Machine Learning in Healthcare

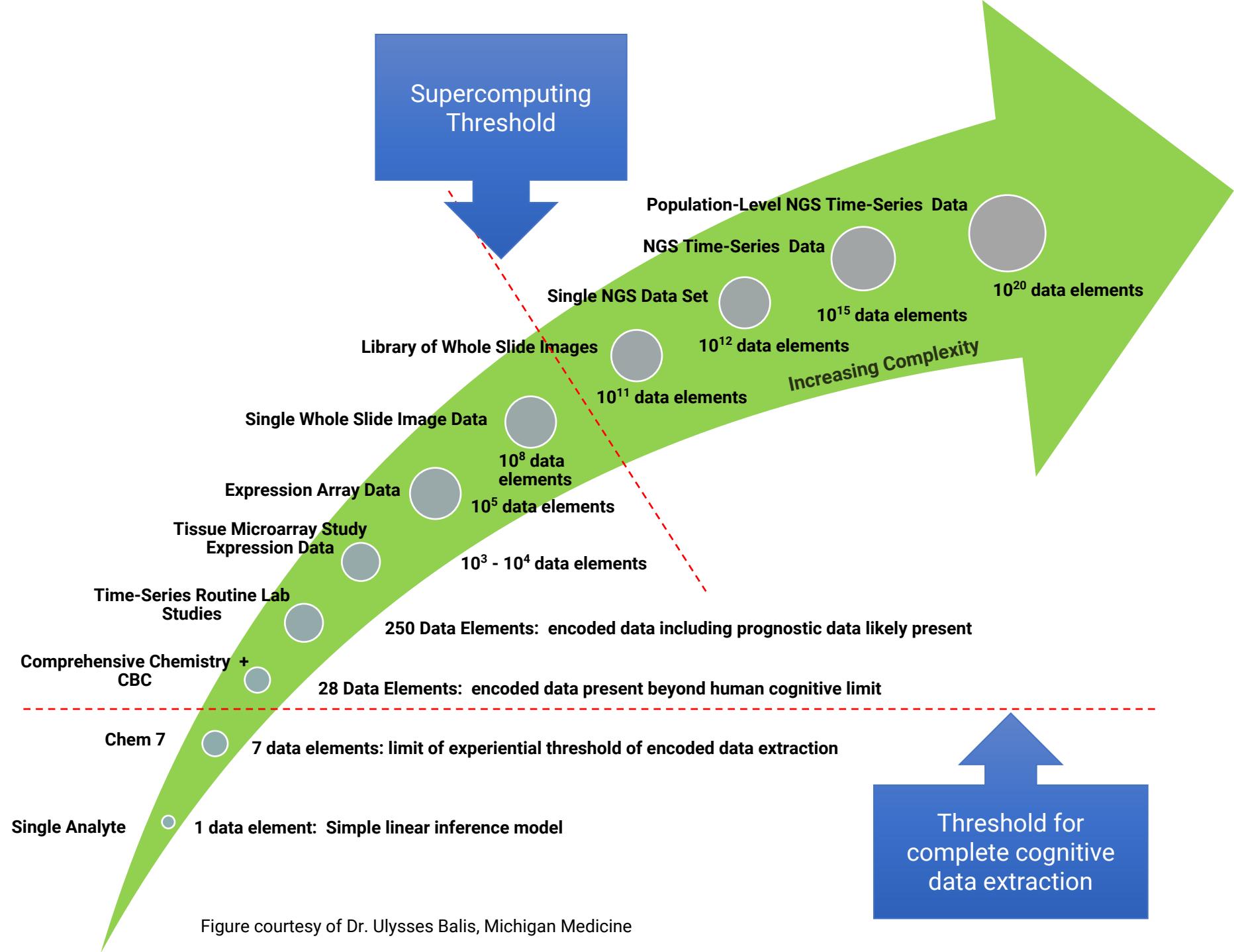
- Many opportunities for ML in healthcare
 - Reduce readmission rates
 - Reduce hospital Length-of-Stay (LOS)
 - Prevent hospital acquired infections (HAIs)
 - Predicting chronic disease
 - Diagnosis in medical imaging
 - Enhanced robotic surgery
 - Personalized medicine
 - Computational Pathology
 - ...and many more!

Use Cases - ML in Healthcare

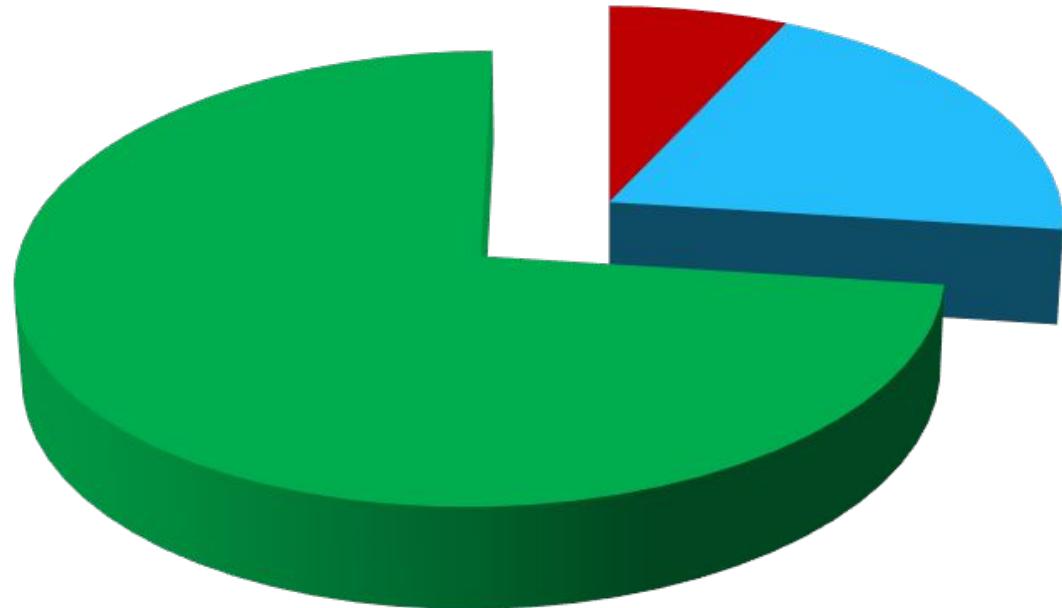


- Clinical decision support and predictive analytics
 - Computationally based assay for 6-MP (mercaptopurine), predicts toxicity and compliance (ThioMon, University of Michigan)
- Imaging analytics
 - Discrimination of physiological versus pathological patterns of cardiac hypertrophic remodeling in 2D echocardiography (Mount Sinai, New York)
- Natural Language Processing
 - Automated speech analysis to measure subtle, clinically relevant mental state changes to predict psychosis onset in youths (Columbia University)

Limits of Human Cognition



Limits of Human Cognition

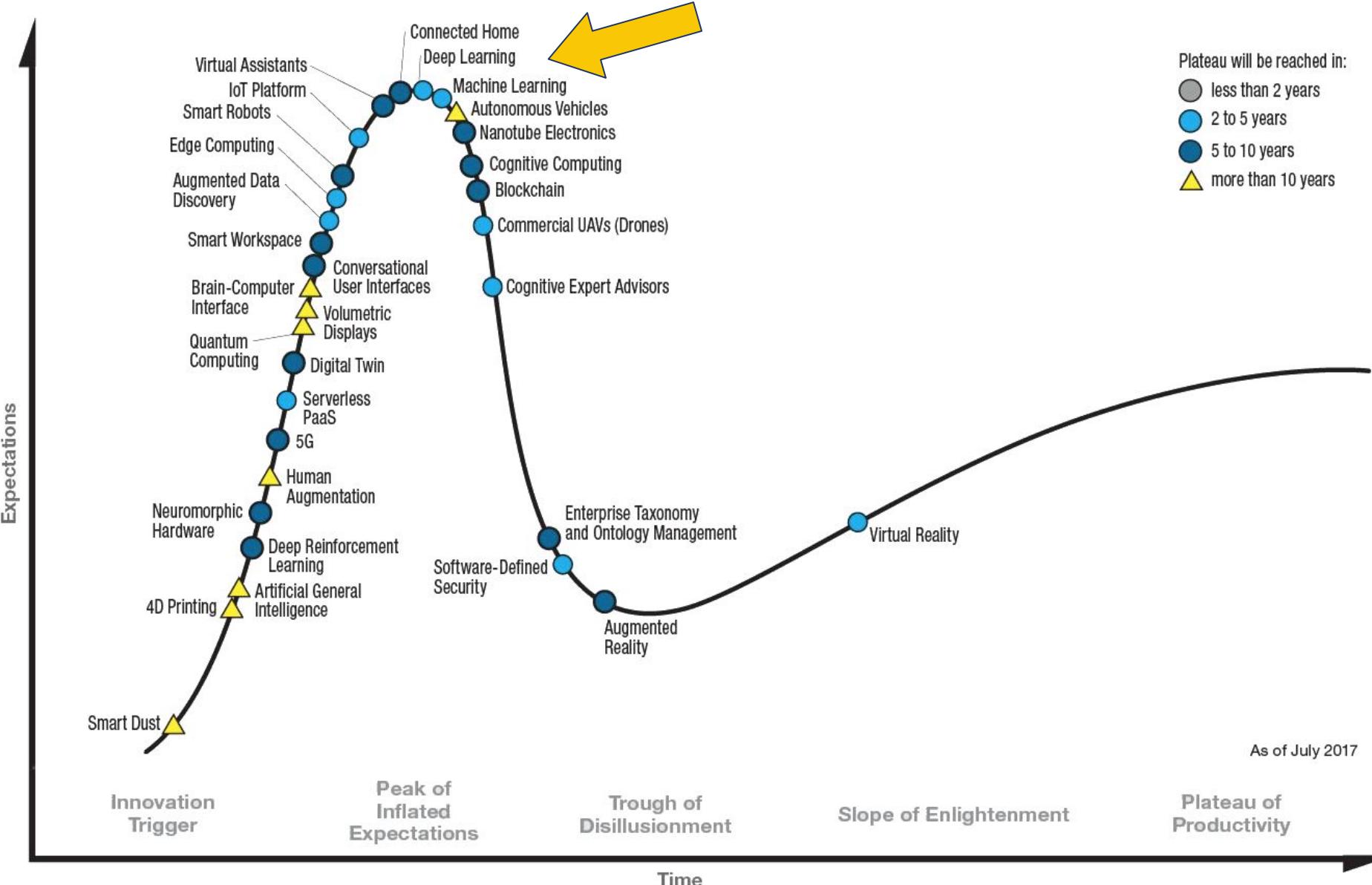


- Directly available to interpretation
- Within human cognitive limits, with expertise
- Beyond direct human cognitive capabilities

Machine learning techniques and tools are intended to take advantage of **the full extent** of data available to interrogation and clinical use...and not just for the red and blue segments!

Machine Learning: Expectations for the Future?

Gartner Hype Cycle for Emerging Technologies, 2017



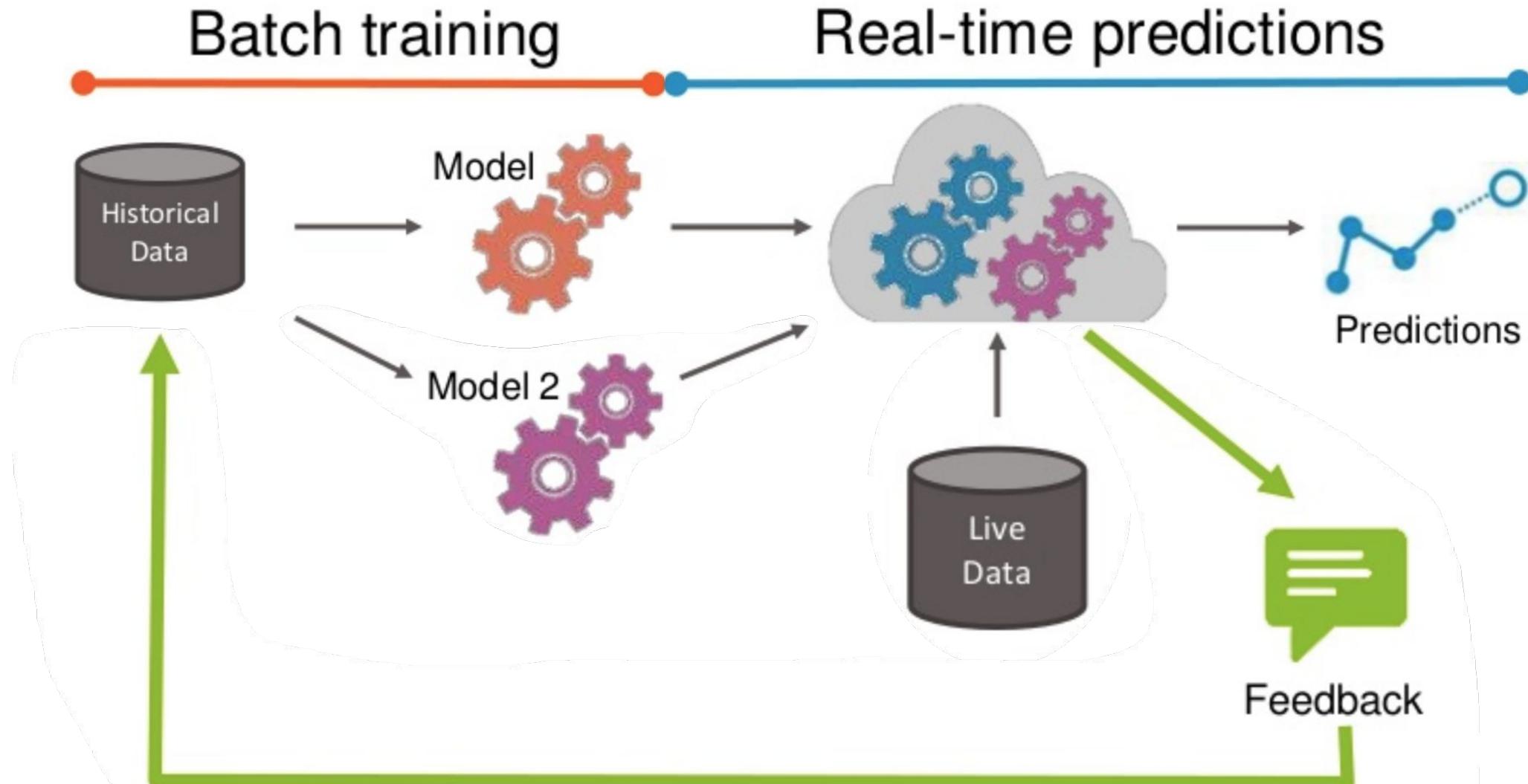
Source: Gartner (July 2017)

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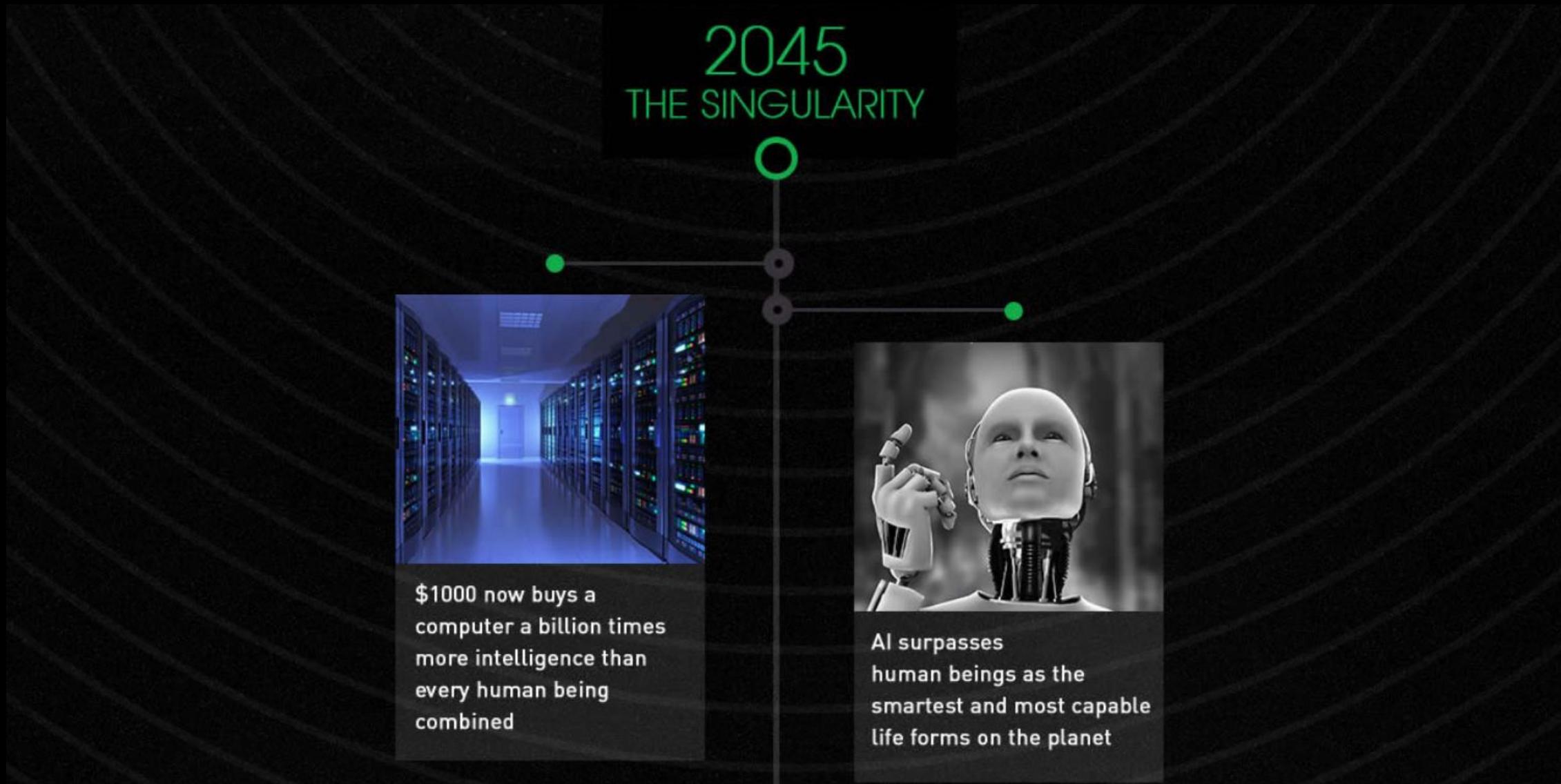
<https://www.gartner.com/smarterwithgartner/top-trends-in-the-gartner-hype-cycle-for-emerging-technologies-2017/>

Gartner

Machine Learning Deployment



In closing...The Singularity is fast approaching



QUESTIONS?

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Association for Pathology Informatics

<https://pathologyinformatics.org>

BECOME A MEMBER TODAY!!!

