# Deep Learning

## CS 435/635

Course Instructor:  Chandresh
AI Lab Coordinator @IIT Indore

# Course Content

**Module I:** History of Deep Learning, Perceptrons, and learning algorithms. Multilayer Perceptrons (MLPs), Representation Power of MLPs, Sigmoid Neurons.

**Module II:** Feedforward Neural Networks. Backpropagation. first and second-order training methods. NN Training tricks.

**Module III:** Introduction to Autoencoders and their characteristics, relation to PCA, Regularization in autoencoders, and Types of autoencoders.

**Module IV:** Architecture of Convolutional Neural Networks (CNN), types of CNNs.

**Module V:** Architecture of Recurrent Neural Networks (RNN), Backpropagation through time. Encoder-Decoder Models, Attention Mechanism. Advanced Topics: Transformers and BERT.

# Books

- Ian Goodfellow,Yoshua Bengio, Aaron Courville : *Deep Learning* : MIT Press : US : 2016 : 978-0262035613
- Deep Learning for NLP and Speech Recognition by Uday Kamath, John Liu, and James Whitaker
- Li Deng and Dong Yu : *Deep Learning Methods and Applications* : NOW Publishers : NA : 2014 : 978-1601988140

# Grading

- MSE- 30%
- ESE- 30%
- Project-20%
- Quiz-20%

# Acknowledgement


- Neural Networks and Deep Learning course by Danna Gurari University of Colorado Boulder

# Today’s Topics

- Applications
- History of neural networks and deep learning
- How does a machine learn?
- Course logistics

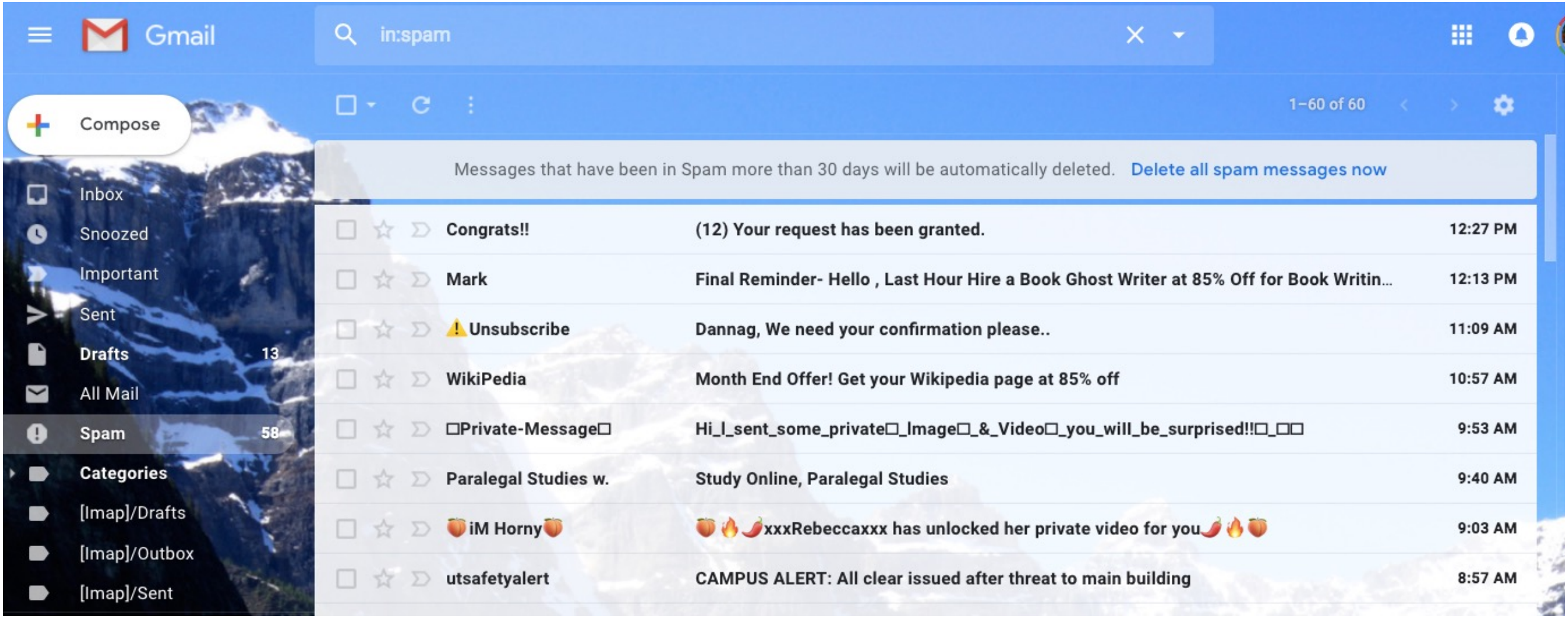
# Today’s Topics

- Applications
- History of neural networks and deep learning
- How does a machine learn?
- Course logistics

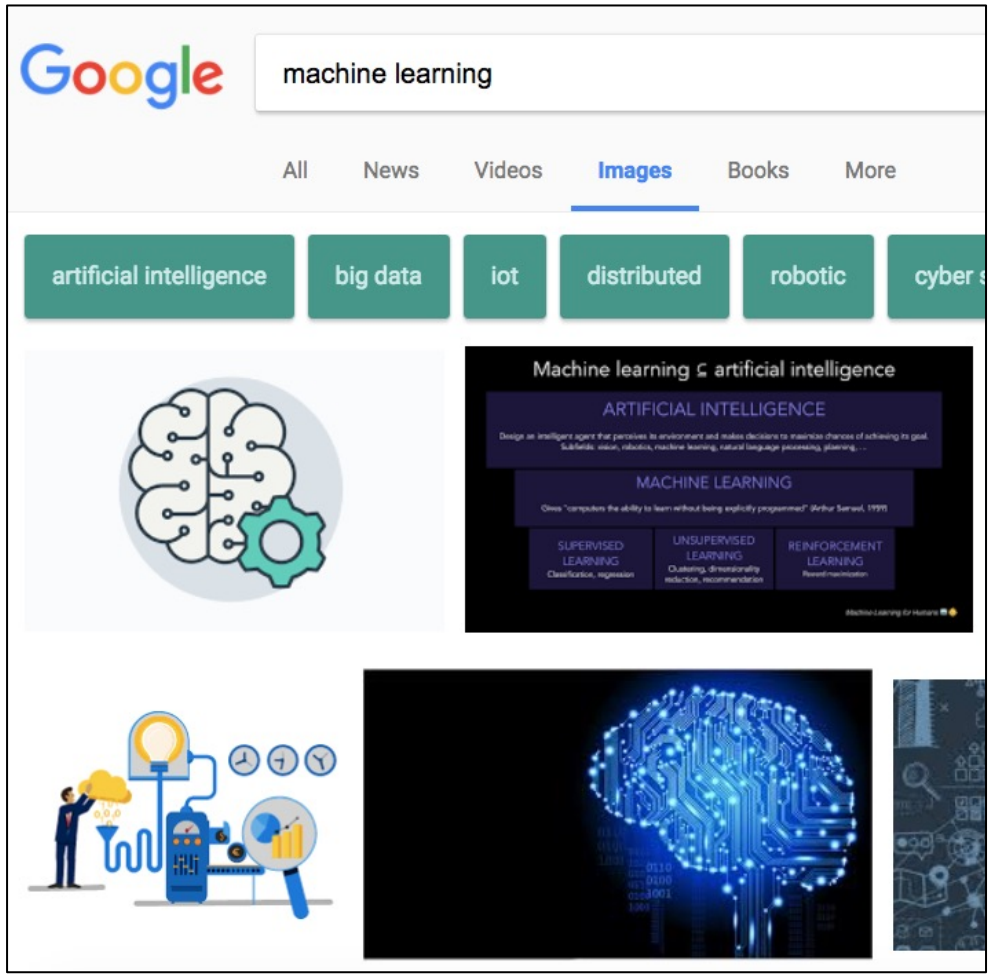
# Key Motivation

Systems that support humans by either
***improving upon existing human capabilities***
or ***providing new capabilities***

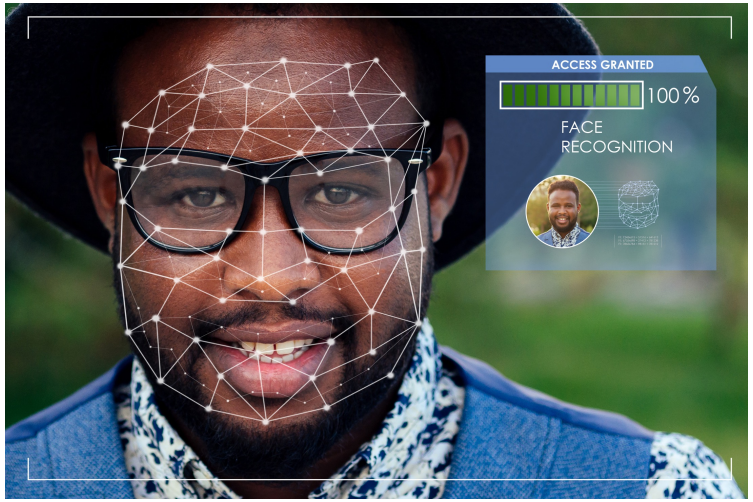
# Solutions – Spam Detection



# Solutions – Information Retrieval

# Solutions – Recognition




(Face)


(Speech)


(Fraud)

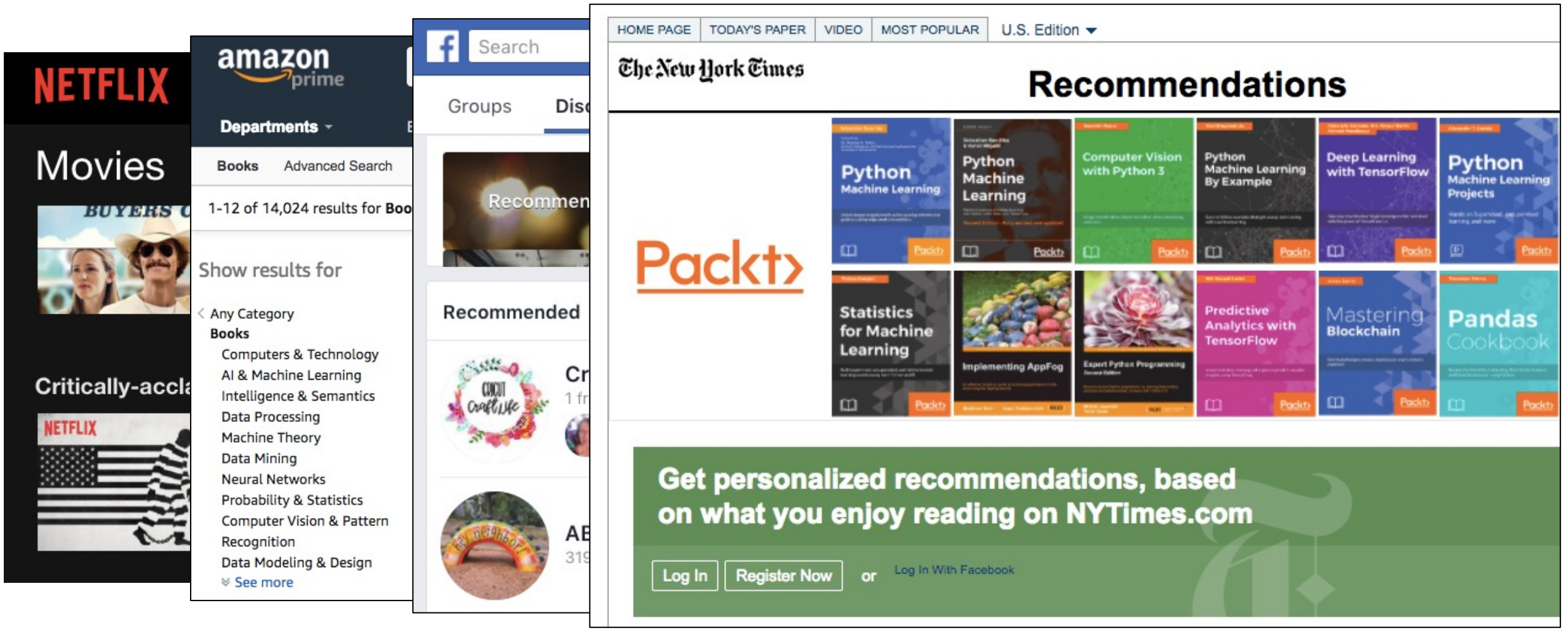
# Solutions – Robotics


(Self-driving Vehicles)

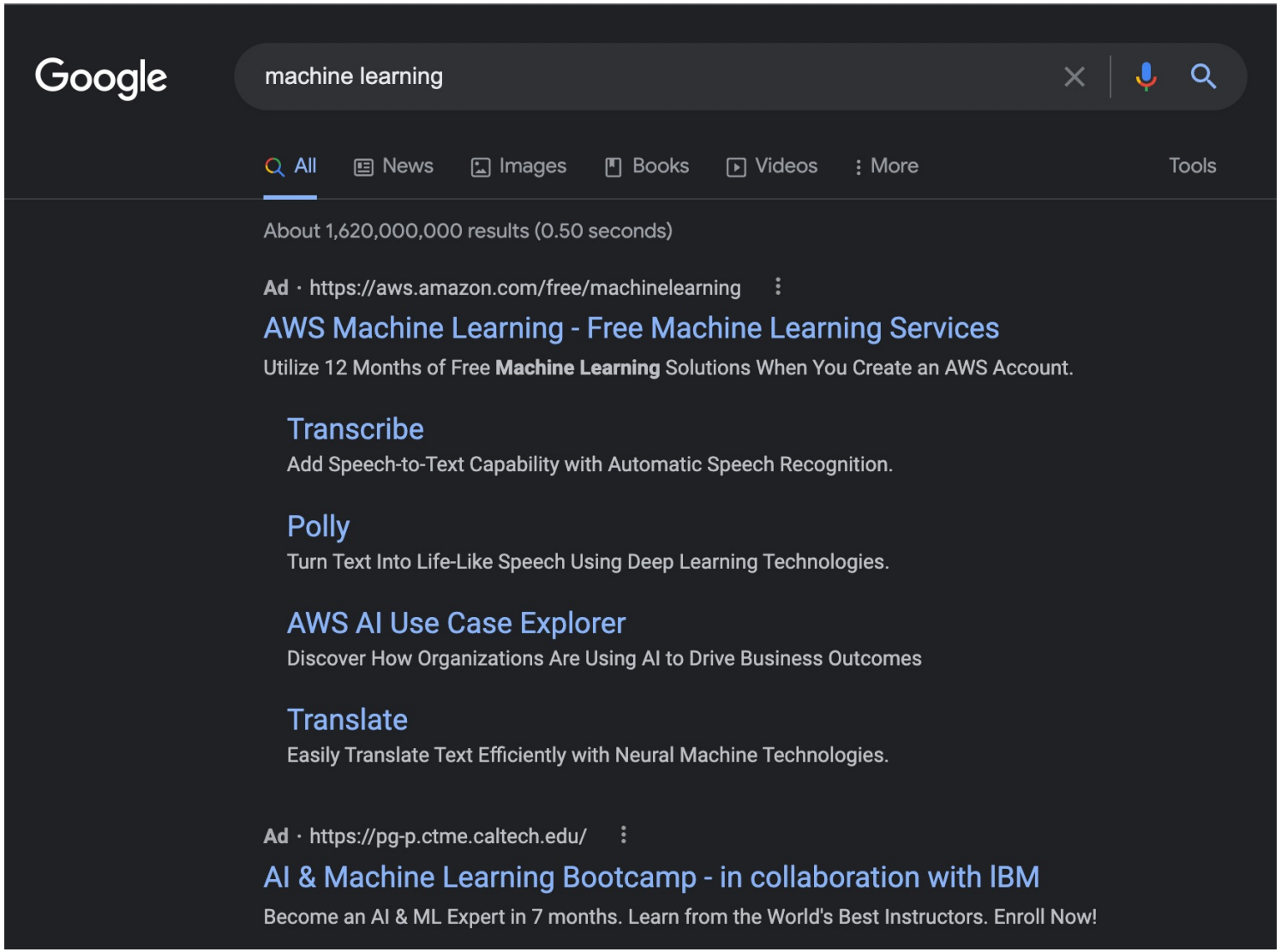
(Medical Surgery)

(Manufacturing)

# Solutions – Recommendation Systems



# Solutions – Advertising



# Solutions – Home Virtual Assistants


e.g., Amazon’s Echo with Alexa

e.g., Google Home

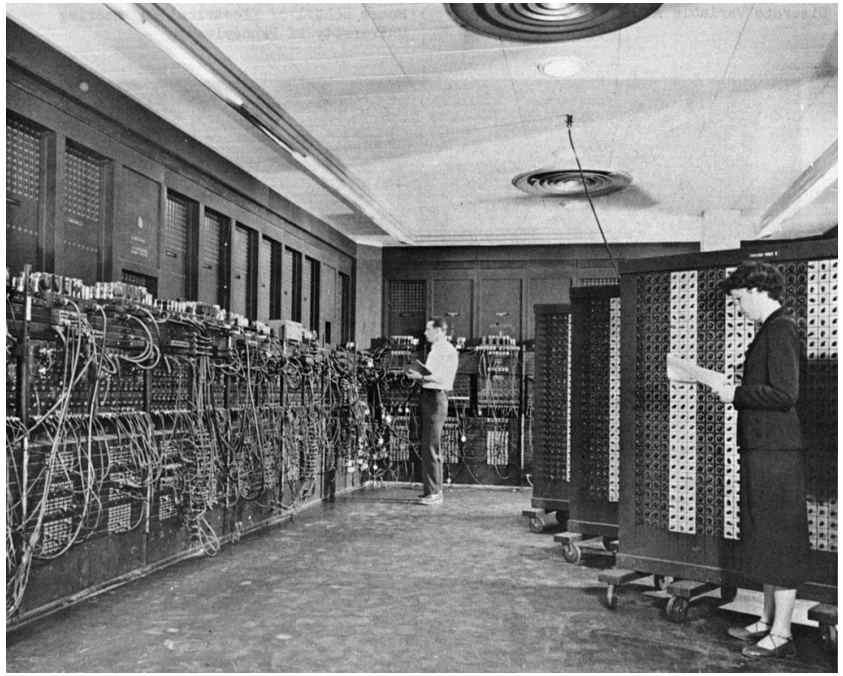
# Today’s Topics

- Applications
- History of neural networks and deep learning
- How does a machine learn?
- Course logistics

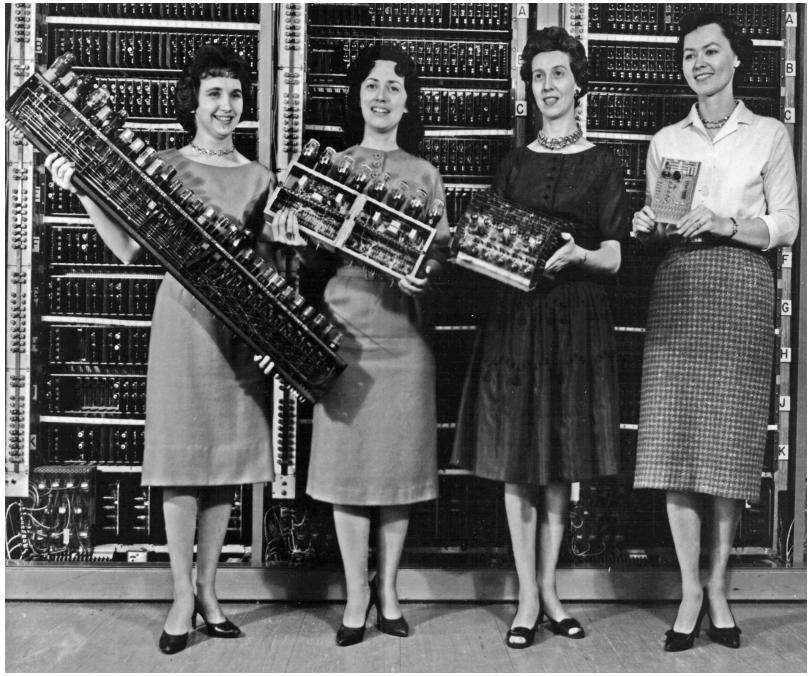
# Origins: Computers

1945

First programmable machine



ENIAC (Electronic Numerical Integrator and Computer) created during World War II
(could compute 5,000 additions in one second)



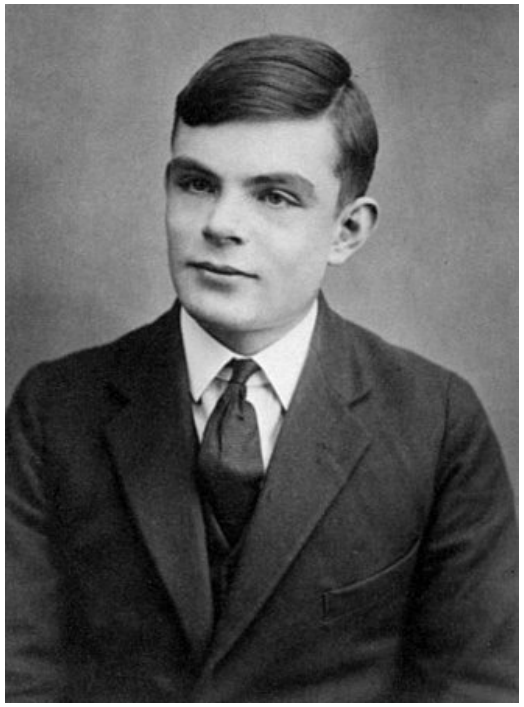
First programmers

# Origins: Conceptual Framework

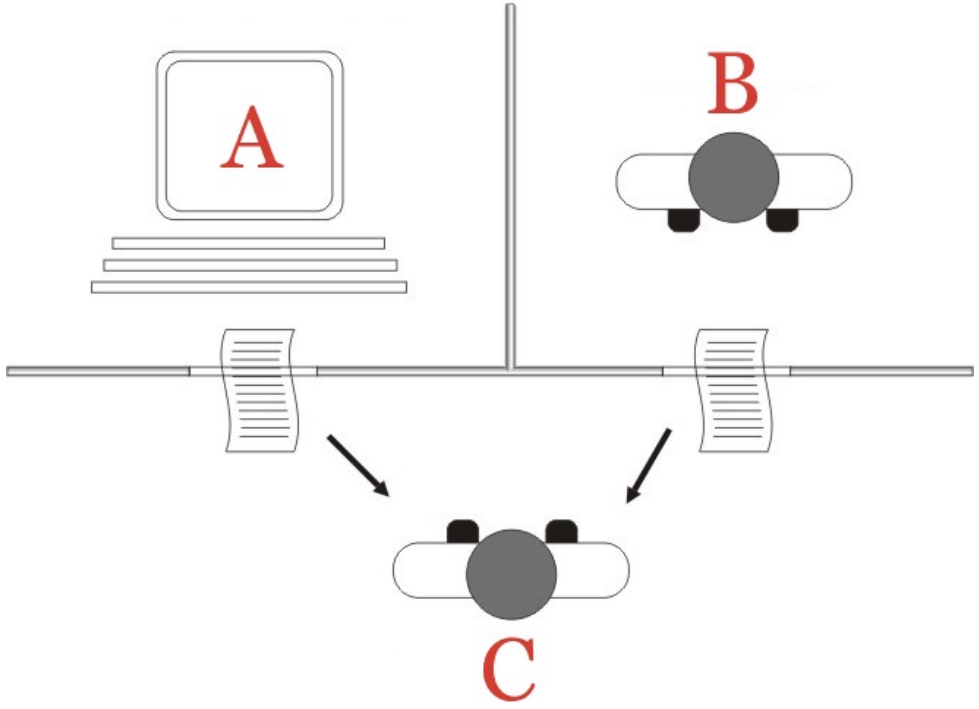
1945 1950

First programmable machine

Turing test

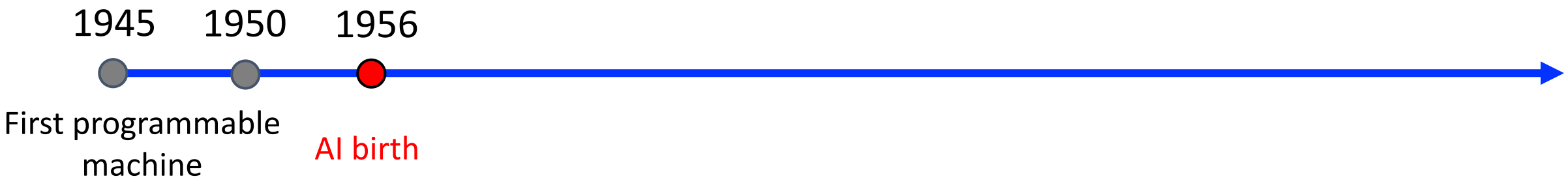


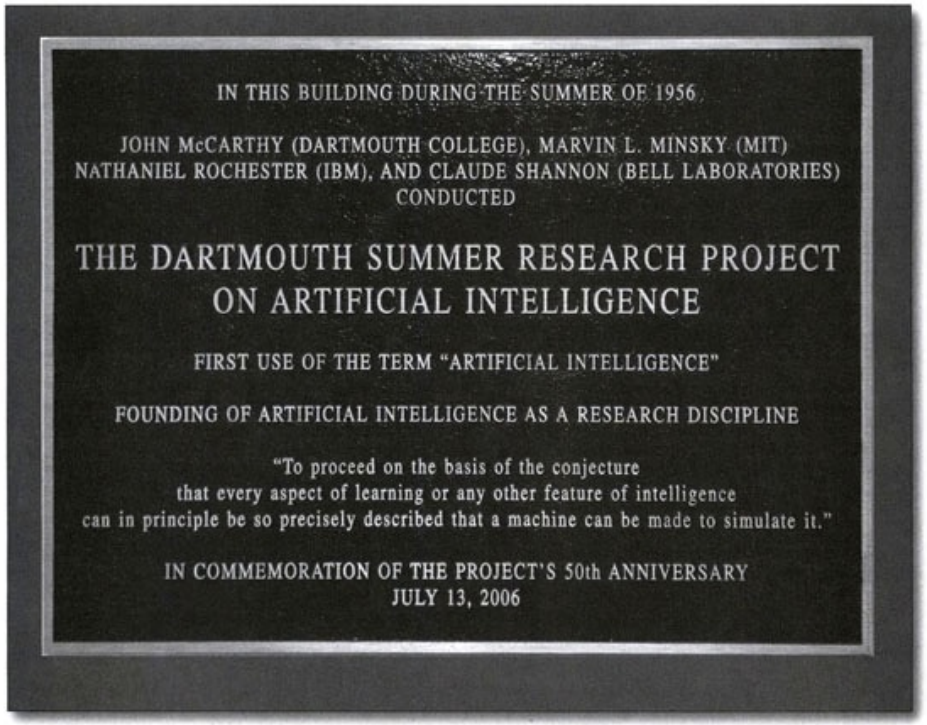
Alan Turing
(1912-1954)




Turing Test: can ”C” decide whether text responses come from a machine or human

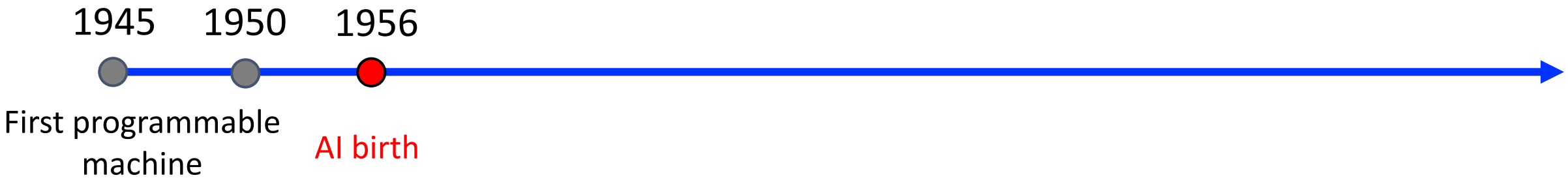
# Origins: Conceptual Framework

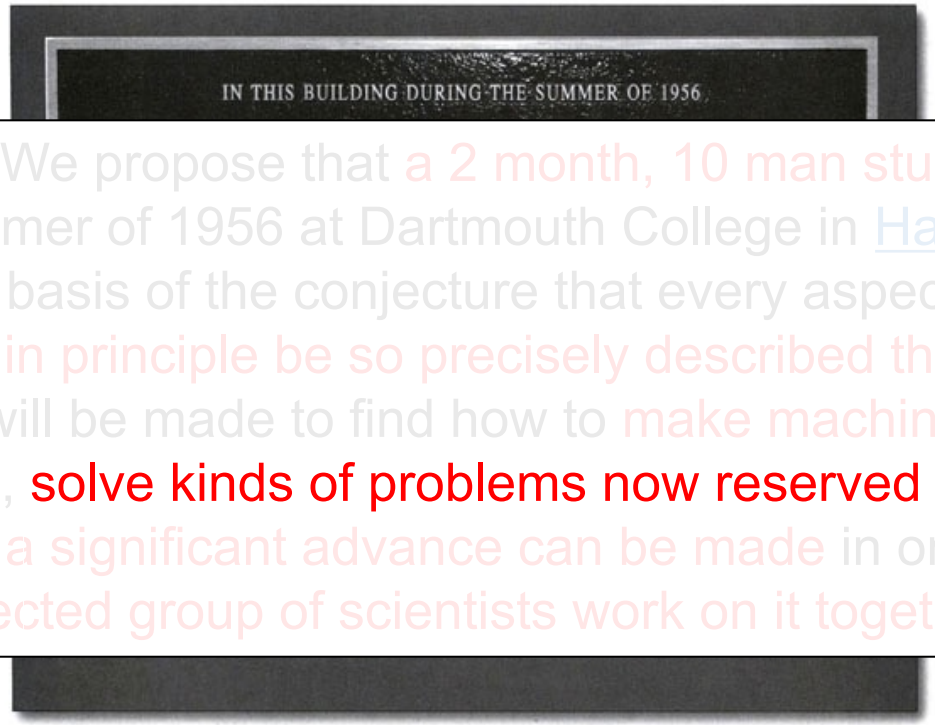



"Artificial intelligence" established as a field at a workshop

# Origins: Conceptual Framework

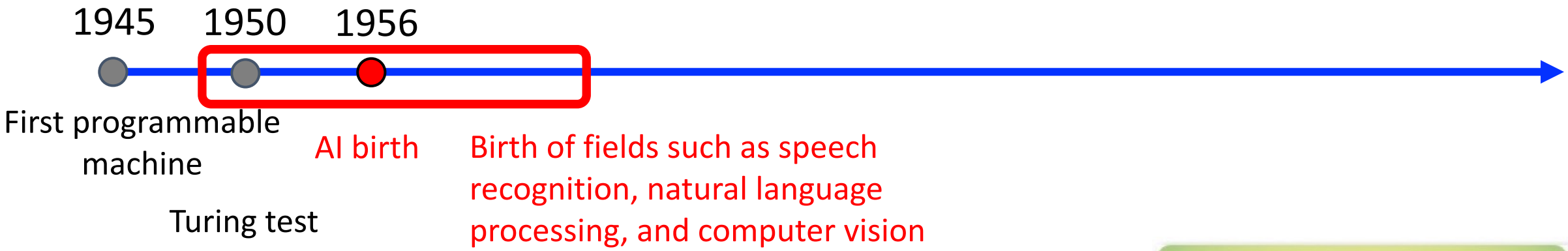



**Workshop Proposal**: "… We propose that a 2 month, 10 man study of artificial intelligence be carried out during the summer of 1956 at Dartmouth College in Hanover, New Hampshire. The study is to proceed on the basis of the conjecture that every aspect of learning or any other feature of intelligence 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. We think that a significant advance can be made in one or more of these problems if a carefully selected group of scientists work on it together for a summer…"

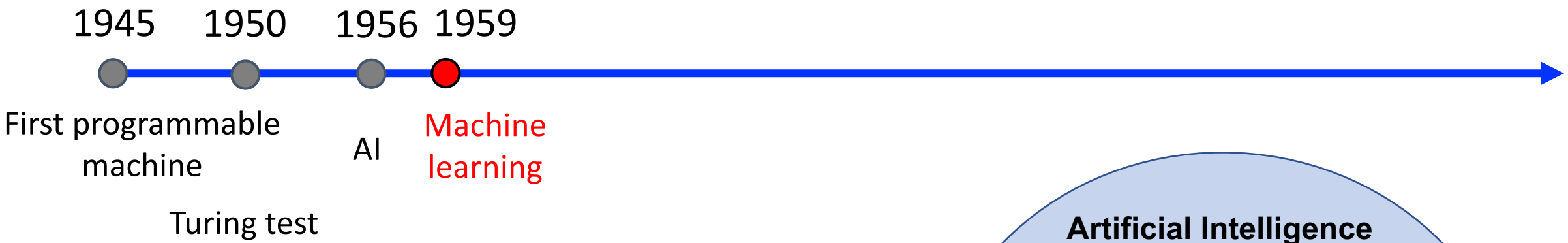
"Artificial intelligence" established as a field at a workshop

# Origins: Conceptual Framework



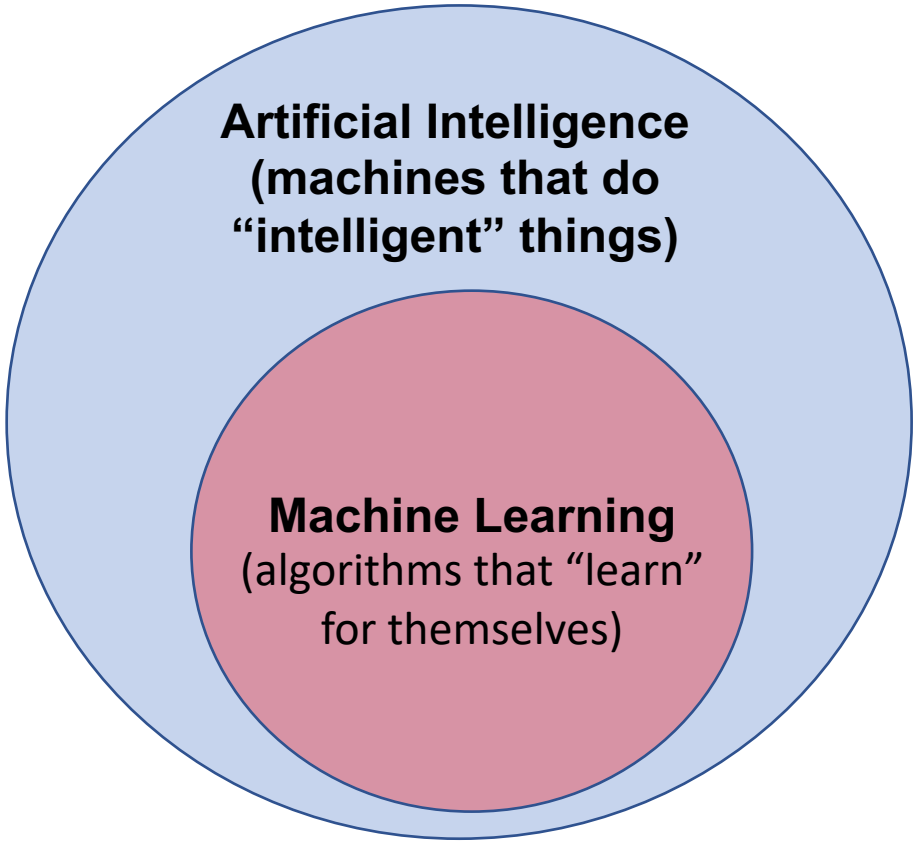

What human intelligence might computers imitate?

# Origins: Conceptual Framework



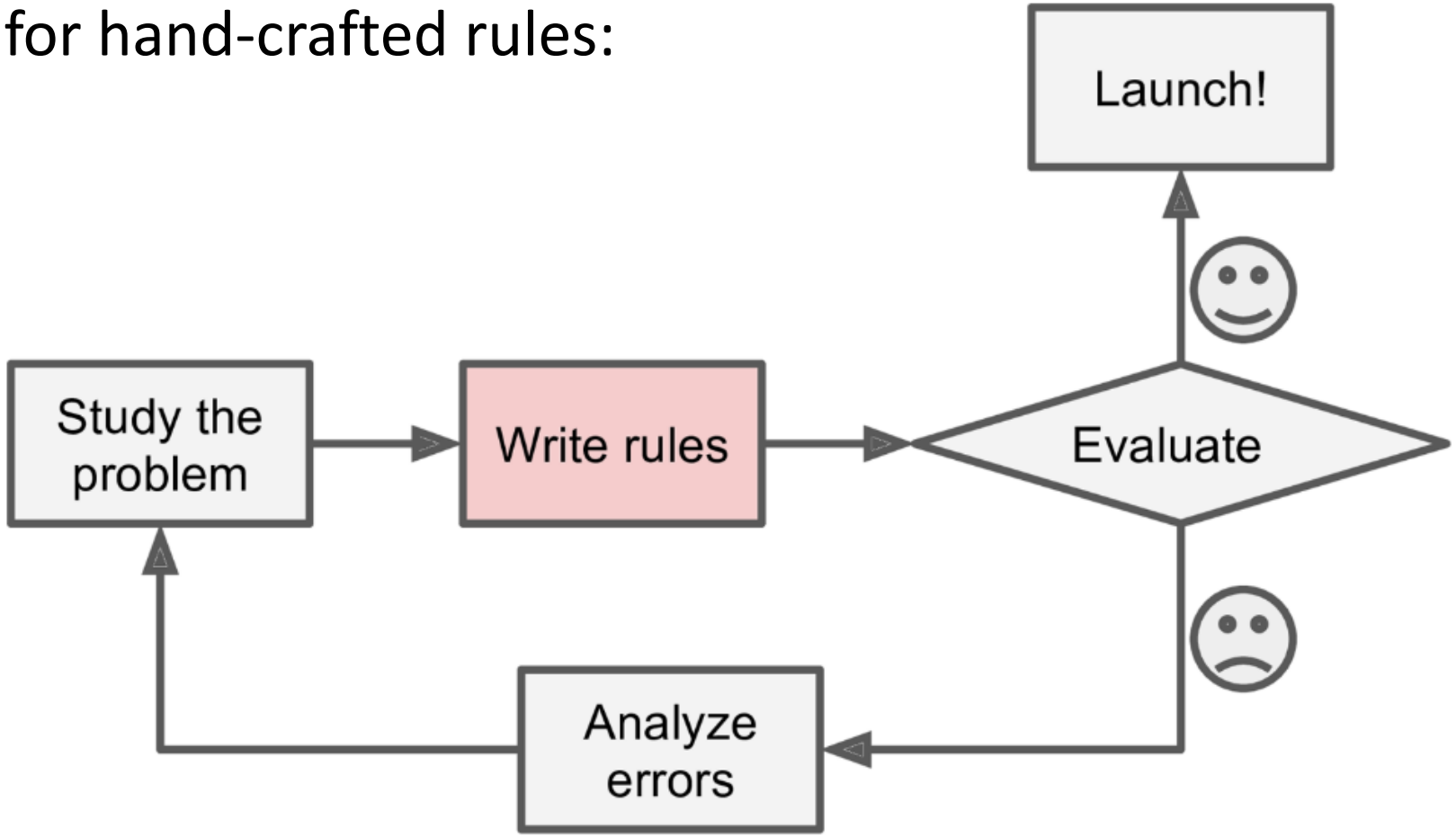

AI researcher Arthur Samuel coins the term "machine learning" as:

"Field of study that gives computers the ability to learn without being explicitly programmed."



# Motivation for Machines that “Learn”

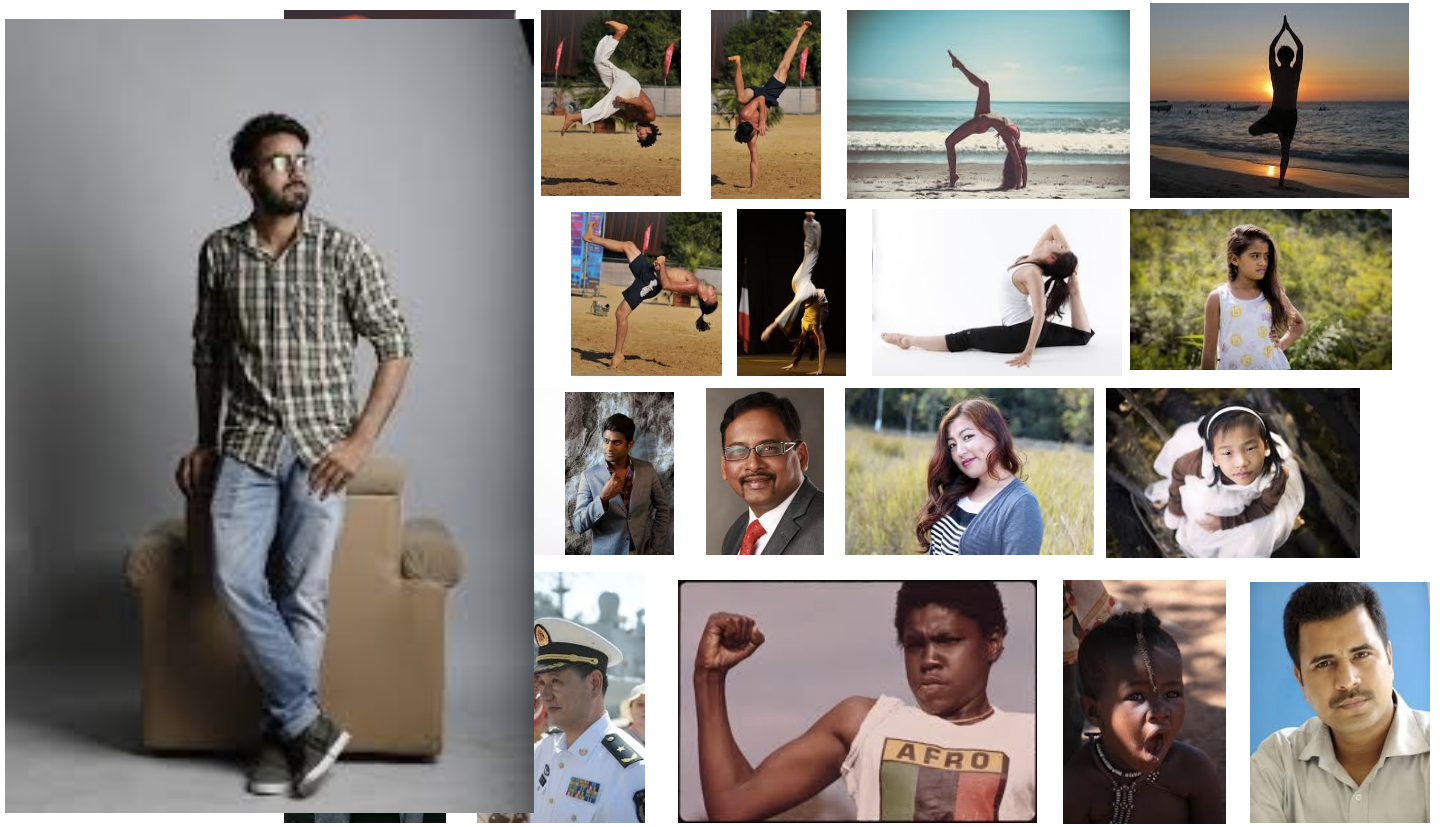
- Process for hand-crafted rules:




https://www.oreilly.com/library/view/hands-on-machine-learning/9781491962282/ch01.html

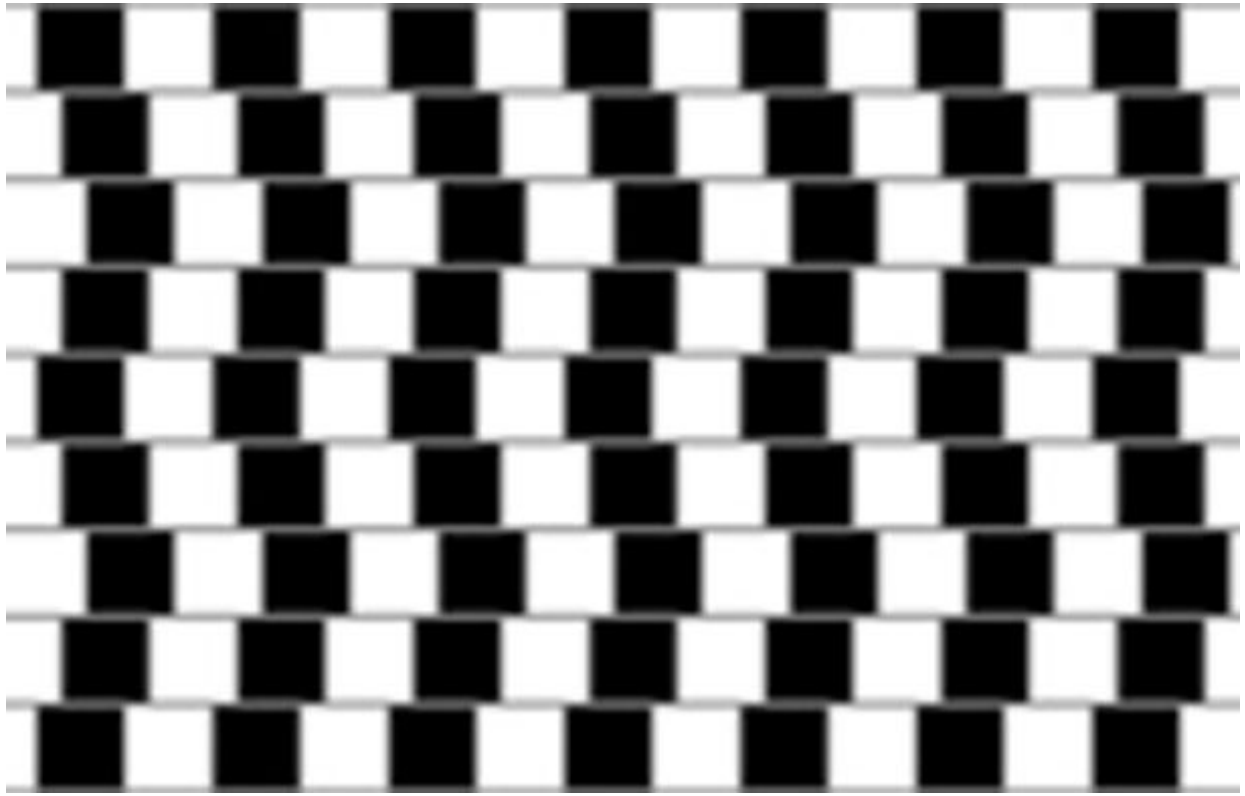
# Motivation for Machines that “Learn”: Class Task

e.g., What rules would you use to answer: “Is a person in the image?”



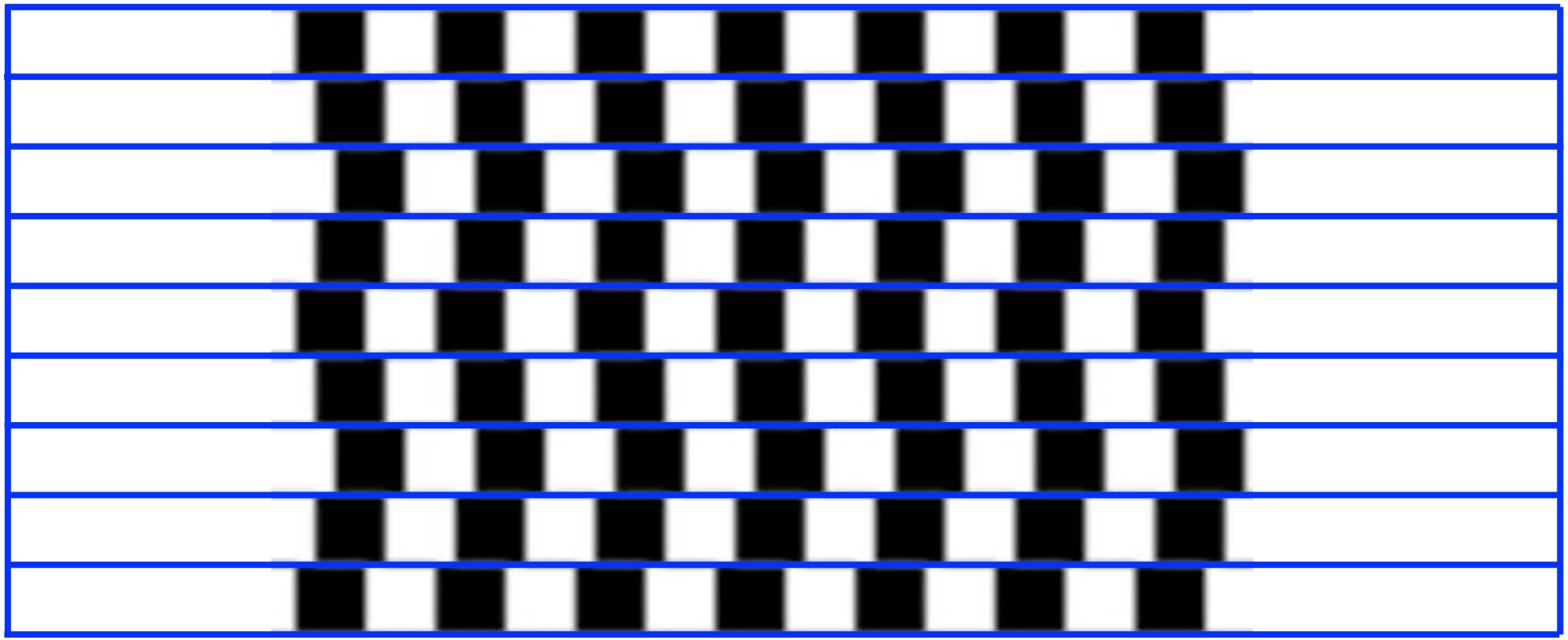
# Motivation for Machines that “Learn”

e.g., are these lines parallel?



# Motivation for Machines that “Learn”

e.g., are these lines parallel?

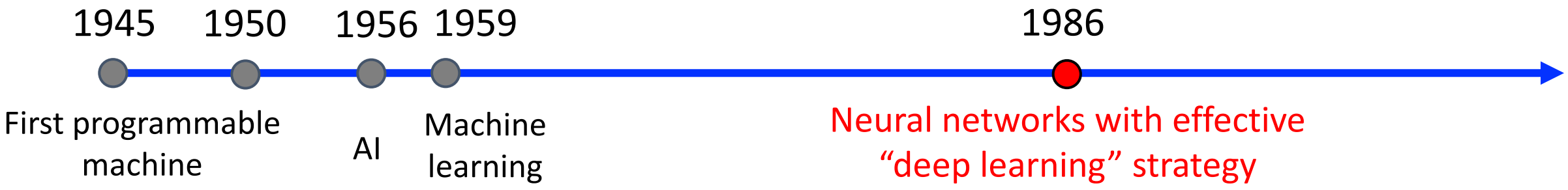


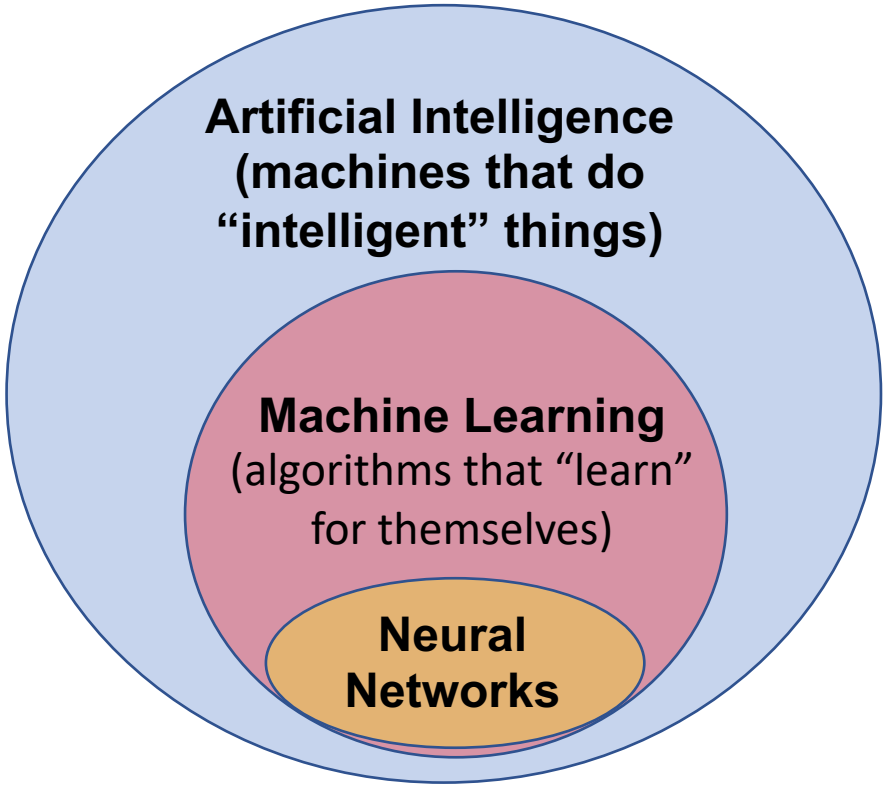
# Motivation for Machines that “Learn”

1. It is hard to hand-craft a complete set of rules

2. We, as humans, may not devise the best rules for a machine since our brains (unconsciously) pre-process the data we sense

# Origins: Neural Networks with Deep Learning



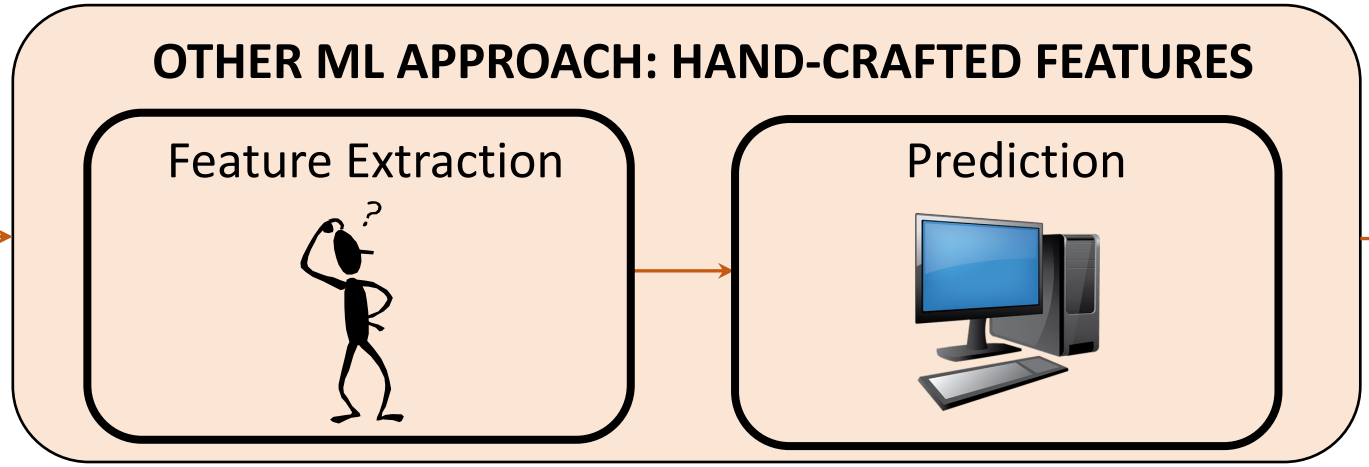



# Motivation for Neural Networks (NNs) Over Other Machine Learning (ML) Approaches

INPUT

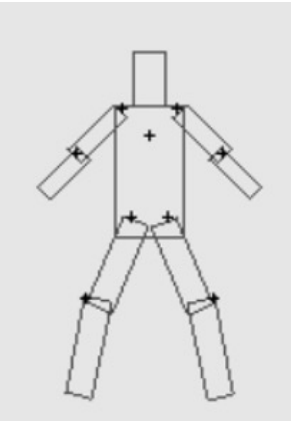
e.g., Is a person present?

OUTPUT



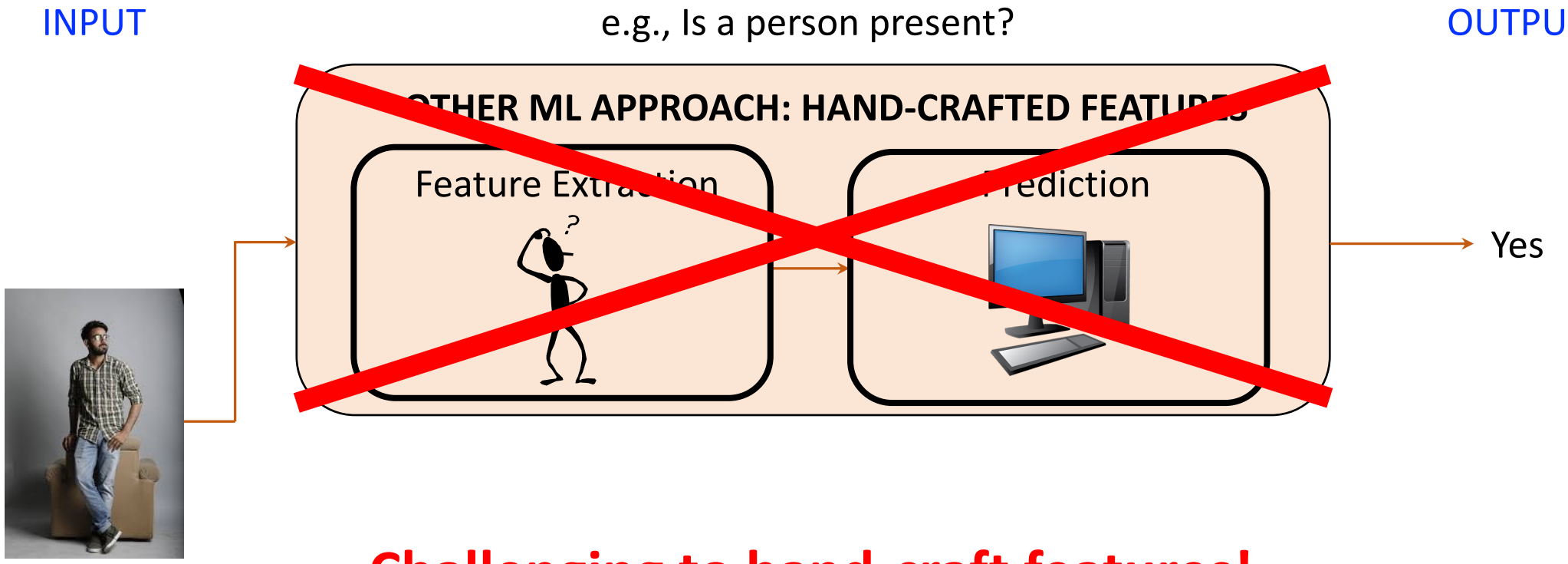

**What features would help predict yes/no?**

**e.g., corners, lines, and model of expected body parts as connected shapes**



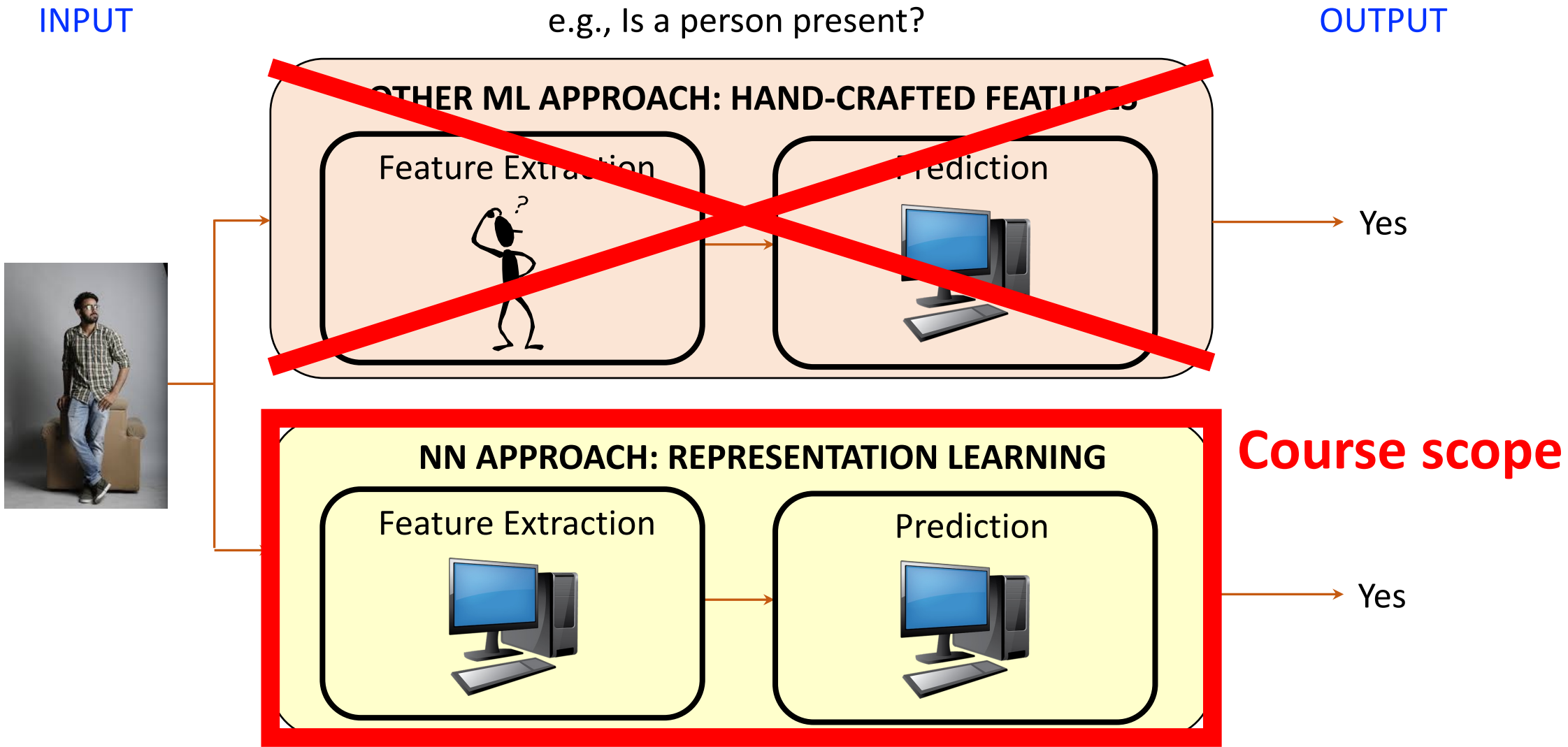
e.g., Pedro F Felzenszwalb and Daniel P Huttenlocher, IJCV 2004

# Motivation for Neural Networks (NNs) Over Other Machine Learning (ML) Approaches




**Challenging to hand-craft features!**

# Motivation for Neural Networks (NNs) Over Other Machine Learning (ML) Approaches



# Origins: Rises/Falls of Neural Network Popularity

1945 1950 1956 1959 1986

First programmable machine

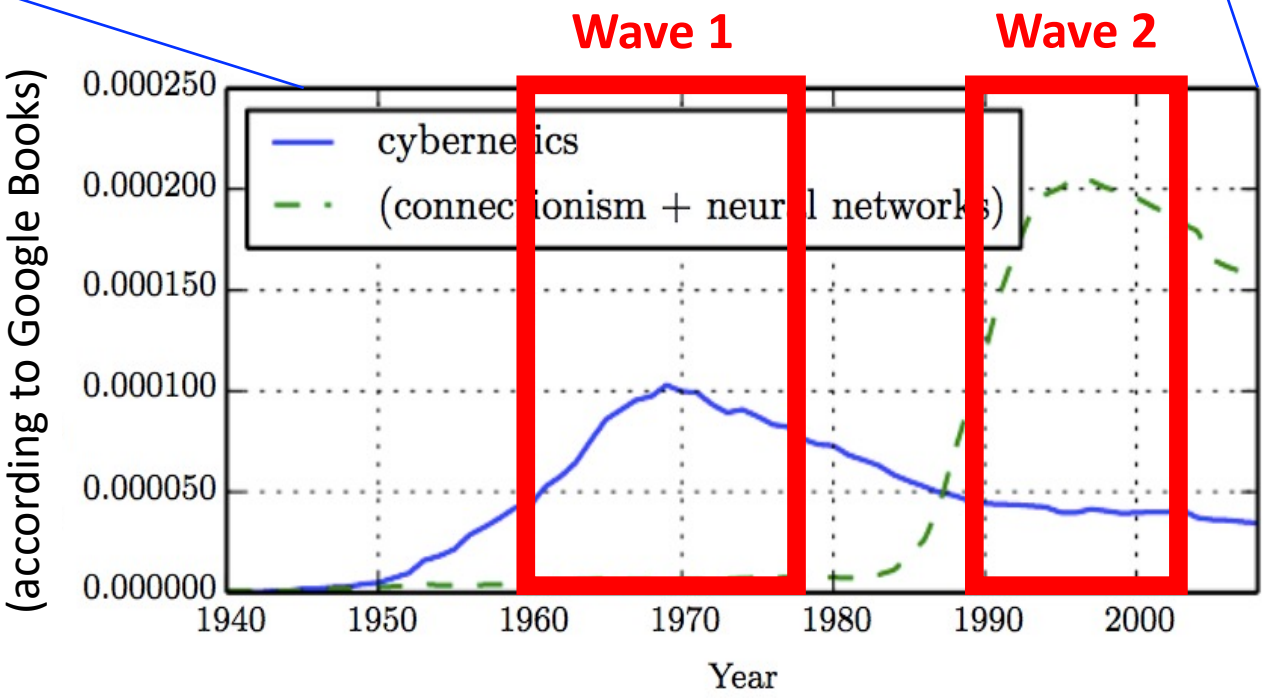
Turing test

AI

Machine learning

Neural networks with effective "deep learning" strategy

Neural networks are not new and have been called many names:




Ian Goodfellow, Yoshua Bengio, and Aaron Courville; Deep Learning, 2016

# Origins: Rises/Falls of Neural Network Popularity

1945 First programmable machine

1950 Turing test

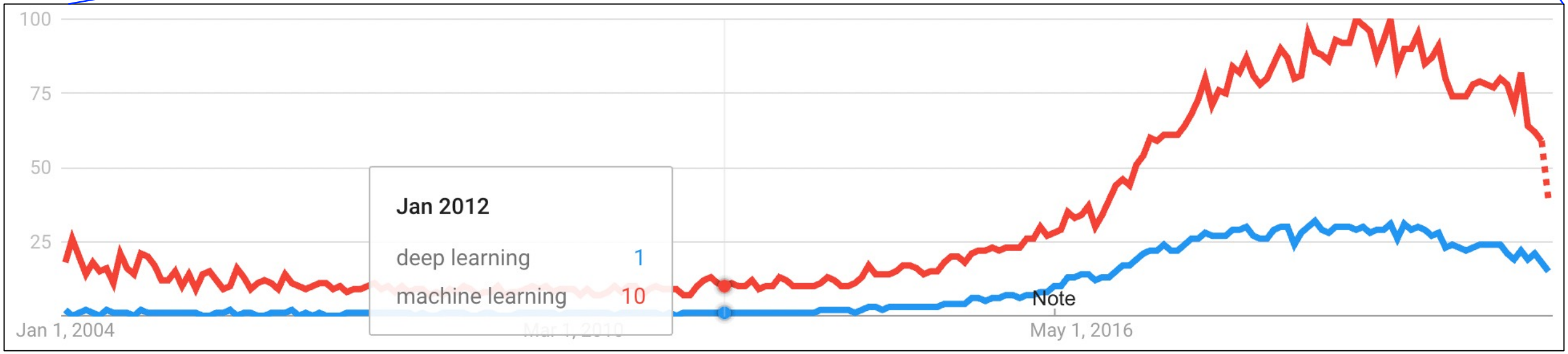
1956 AI

1959 Machine learning

1986 Neural networks with effective "deep learning" strategy

2012 Wave 3: rise of "deep learning"

(Google Trends)




**Machine learning popularity has paralleled rise of deep learning popularity**

# Today’s Topics

- Applications
- History of neural networks and deep learning
- How does a machine learn?
- Course logistics

# General Idea

An **algorithm** learns from **data** patterns that will be used to make a prediction

# General Idea

An **algorithm** learns from data patterns that will be used to make a prediction

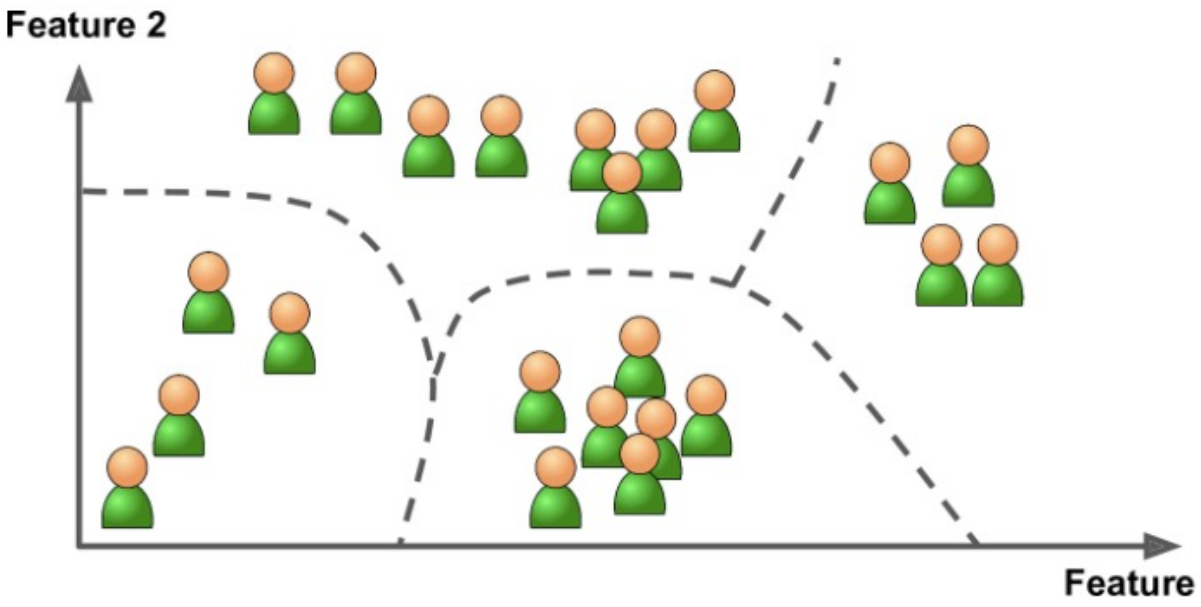
# Typical Algorithm Design

- Unsupervised Learning
  - Identify patterns by observing *unstructured* data

- Supervised Learning
  - Identify patterns by studying *structured* data with labels of expected outputs

# Types of “Unsupervised” Learning Tasks

Clustering

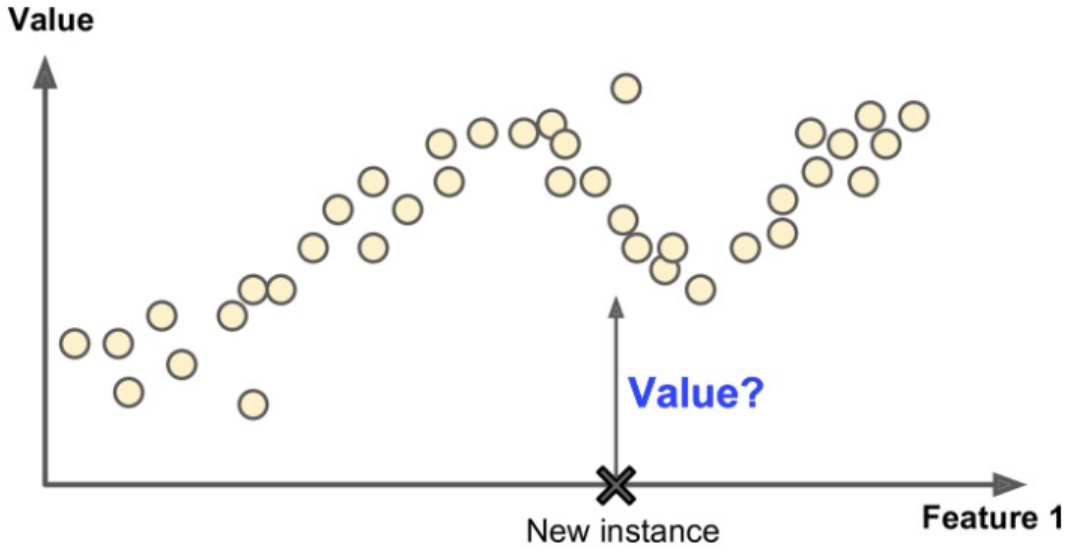



Anomaly Detection

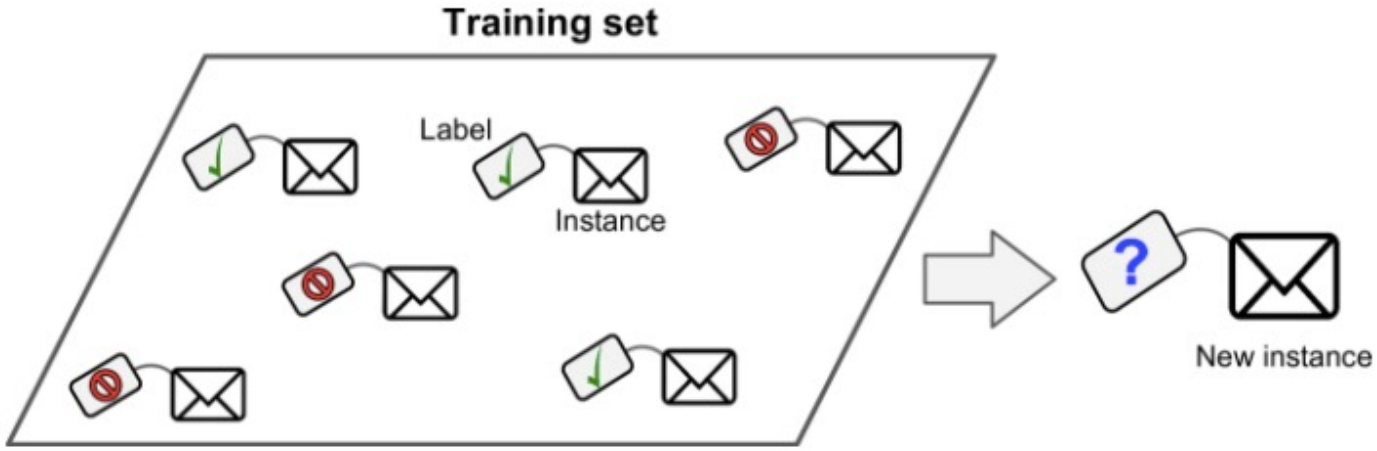

Hands-on Machine Learning with Scikit-Learn & TensorFlow, Aurelien Geron

# Types of “Supervised” Learning Tasks

Regression
(predict **continuous** value)



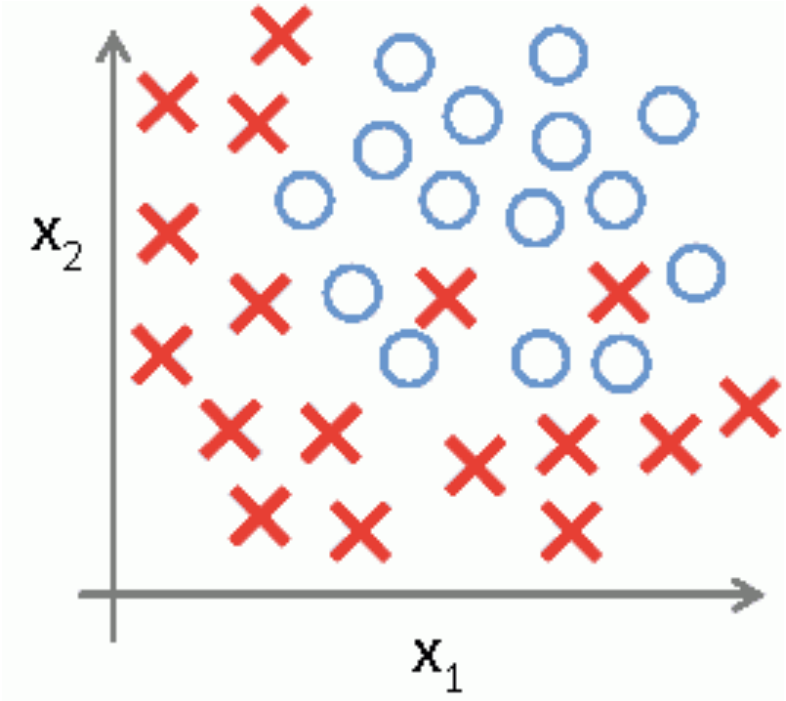

Classification
(predict **discrete** value)




Hands-on Machine Learning with Scikit-Learn & TensorFlow, Aurelien Geron

# Typical Supervised Learning Algorithm Design

- Model-based classification approach
  - e.g., create model to separate x from o

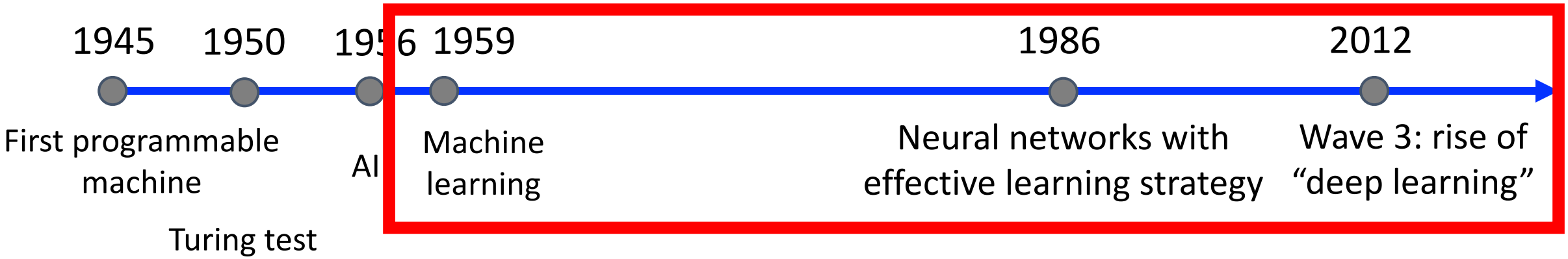



Class volunteer:
1) Draw a straight line (linear equation)
2) Draw a parabola (quadratic equation)
3) Draw any curve

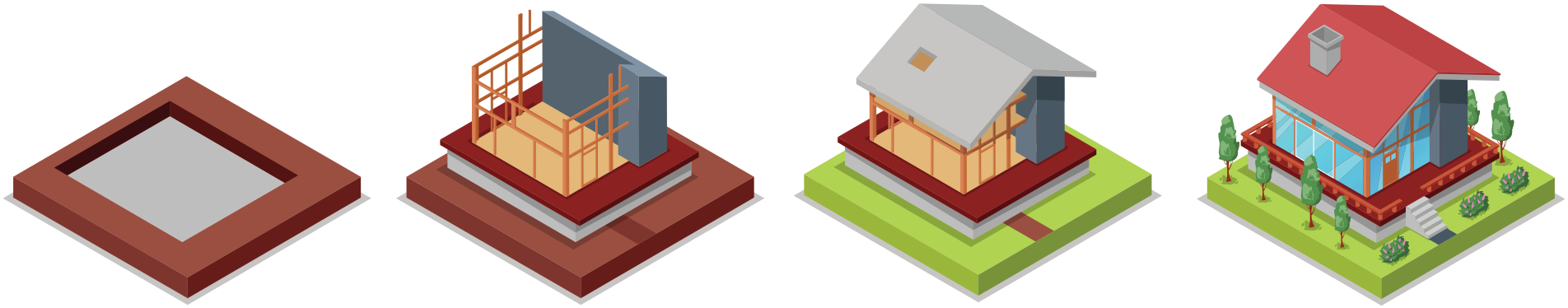
Models with increasing representational capacity

Figure source: https://medium.com/greyatom/what-is-underfitting-and-overfitting-in-machine-learning-and-how-to-deal-with-it-6803a989c76

# Algorithm Scope for Course: Last 65 Years

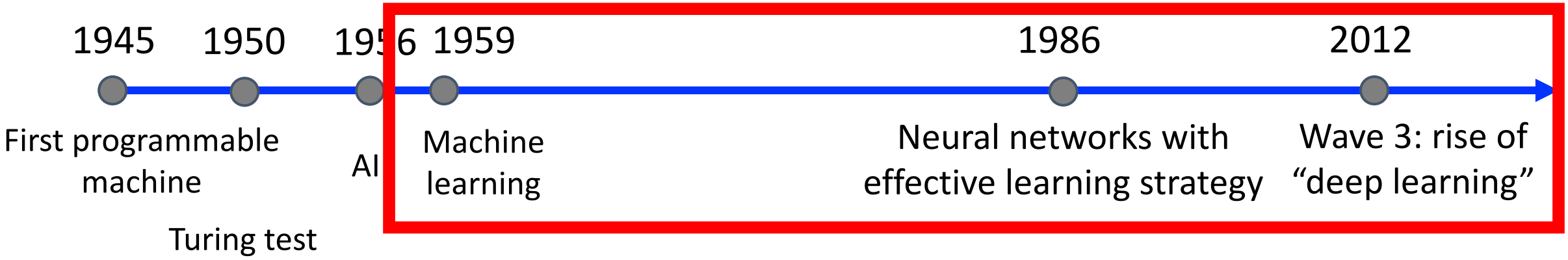



Analogous to understanding how houses we live-in work:



**We study older algorithms because modern deep learning algorithms rely on techniques developed over the past 65 years.**

# Algorithm Scope for Course: Last 65 Years




| Week | Topic(s) |
|---|---|
| 1 | Introduction, Artificial neurons |
| 2 | Feedforward neural networks (NN), NN training |
| 3 | NN training |
| 4 | Convolutional neural networks (CNN), Introduction to CV |
| 5 | Training CNN algorithms |
| 6 | Regularization, Pretrained CNN features, Fine-tuning |
| 7 | Object detection, Semantic segmentation, Recurrent neural networks |
| 8 | Introduction to natural language proecssing, Neural word embeddings, Attention |

| Week | Topic(s) |
|---|---|
| 9 | Transformers |
| 10 | Multimodal NN (vision + language) |
| 11 | Multimodal NN, Self-supervised learning, GANs |
| 12 | Few/zero-shot learning, Responsible/ethical learning |
| 13 | Deep learning in industry (guest speakers) |
| 14 | Model compression, Efficient learning |
| 15 | NNs for speech processing & reinforcement learning |
| 16 | NN for information retrieval & course summary |

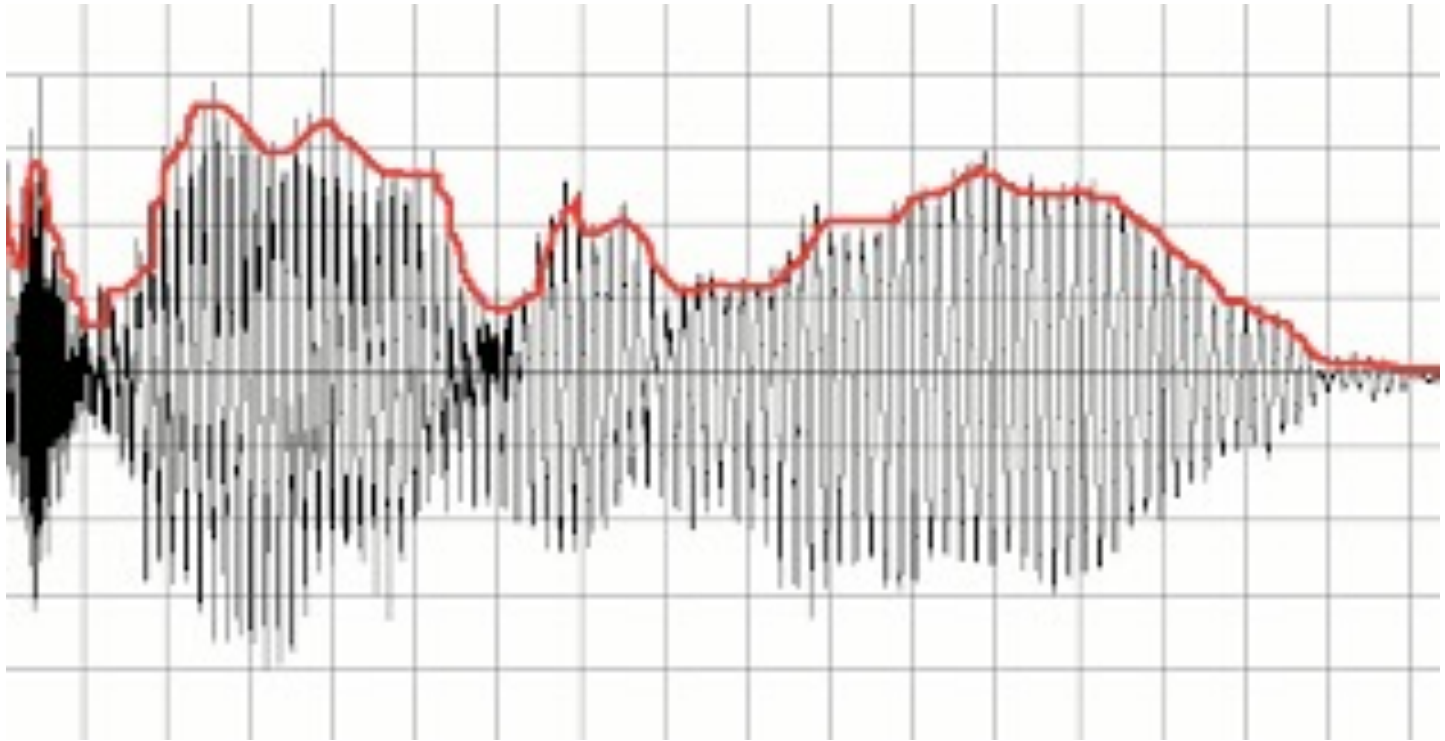
# General Idea

An algorithm learns from **data** patterns that will be used to make a prediction

# Data Types: What a Machine Learns From?

- Audio
  - Input?

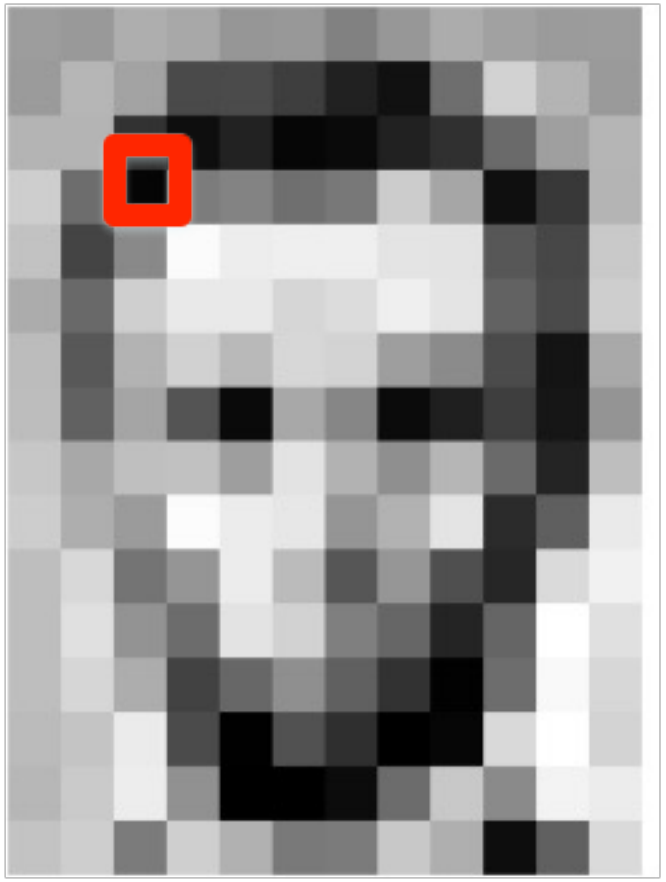

e.g.,



# Data Types: What a Machine Learns From?

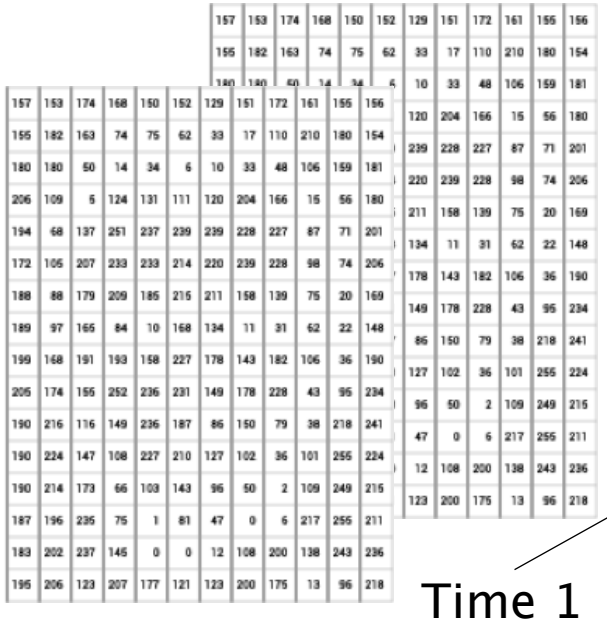
- Audio
  - Input?
- Images
  - Input?

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 157 | 153 | 174 | 168 | 150 | 152 | 129 | 151 | 172 | 161 | 155 | 156 |
| 155 | 182 | 163 | 74 | 75 | 62 | 33 | 17 | 110 | 210 | 180 | 154 |
| 180 | 180 | 50 | 14 | 34 | 6 | 10 | 33 | 48 | 106 | 159 | 181 |
| 206 | 109 | 5 | 24 | 131 | 111 | 120 | 204 | 166 | 15 | 56 | 180 |
| 194 | 68 | 137 | 251 | 237 | 239 | 239 | 228 | 227 | 87 | 71 | 201 |
| 172 | 105 | 207 | 233 | 233 | 214 | 220 | 239 | 228 | 98 | 74 | 206 |
| 188 | 88 | 179 | 209 | 185 | 215 | 211 | 158 | 139 | 75 | 20 | 169 |
| 189 | 97 | 165 | 84 | 10 | 168 | 134 | 11 | 31 | 62 | 22 | 148 |
| 199 | 168 | 191 | 193 | 158 | 227 | 178 | 143 | 182 | 106 | 36 | 190 |
| 205 | 174 | 155 | 252 | 236 | 231 | 149 | 178 | 228 | 43 | 95 | 234 |
| 190 | 216 | 116 | 149 | 236 | 187 | 86 | 150 | 79 | 38 | 218 | 241 |
| 190 | 224 | 147 | 108 | 227 | 210 | 127 | 102 | 36 | 101 | 255 | 224 |
| 190 | 214 | 173 | 66 | 103 | 143 | 96 | 50 | 2 | 109 | 249 | 215 |
| 187 | 196 | 235 | 75 | 1 | 81 | 47 | 0 | 6 | 217 | 255 | 211 |
| 183 | 202 | 237 | 145 | 0 | 0 | 12 | 108 | 200 | 138 | 243 | 236 |
| 195 | 206 | 123 | 207 | 177 | 121 | 123 | 200 | 175 | 13 | 96 | 218 |

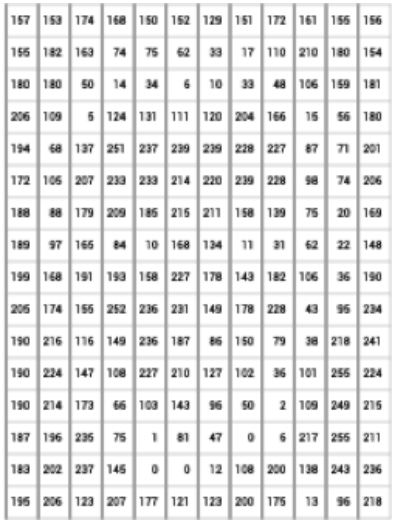


# Data Types: What a Machine Learns From?

- Audio
  - Input?
- Images
  - Input?
- Video
  - Input?

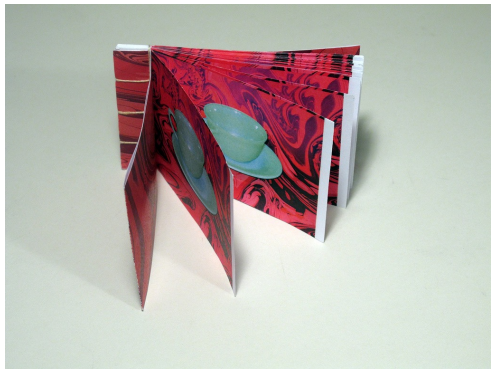


Time 1



1 hour

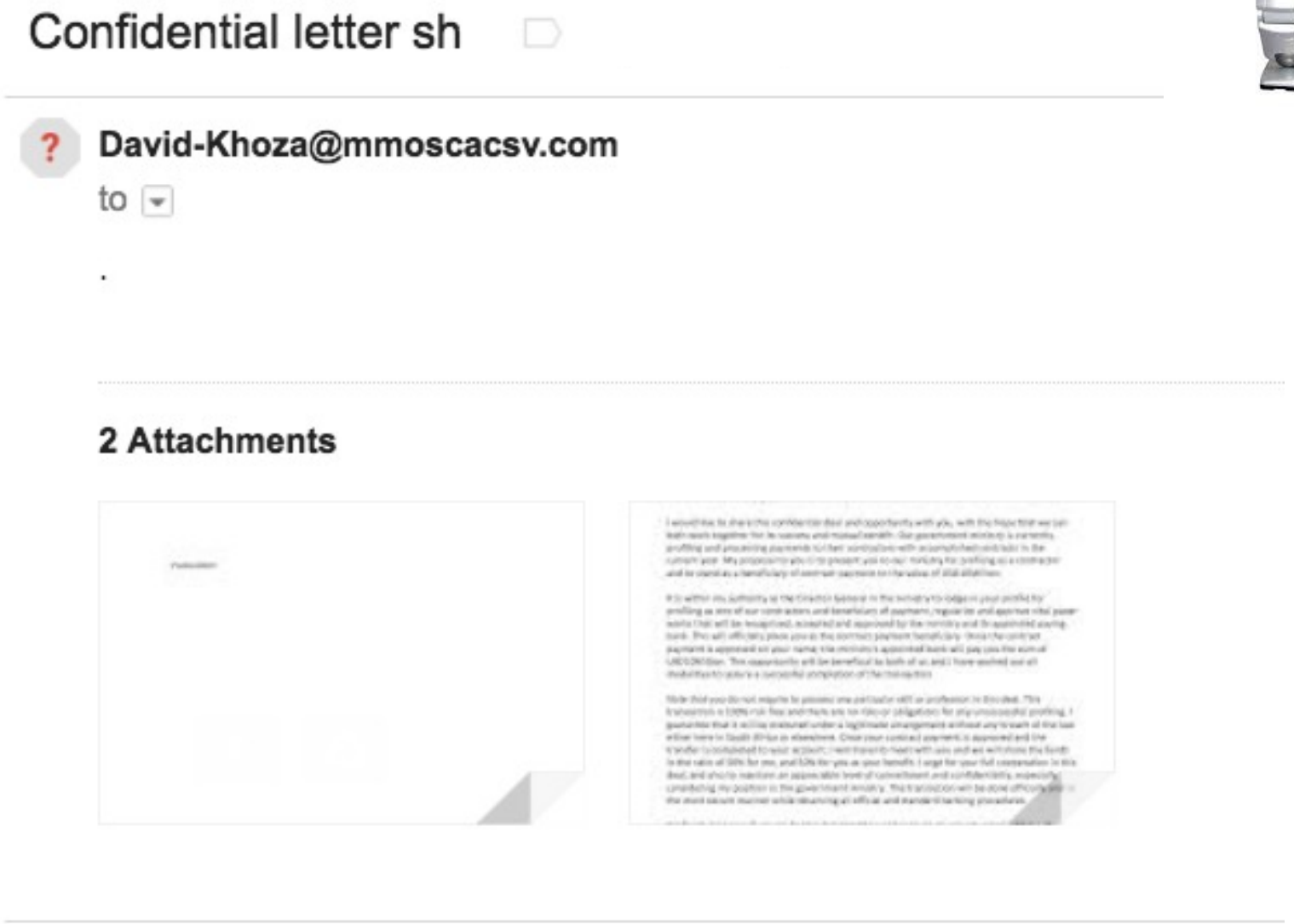
Analogous to:



# Data Types: What a Machine Learns From?

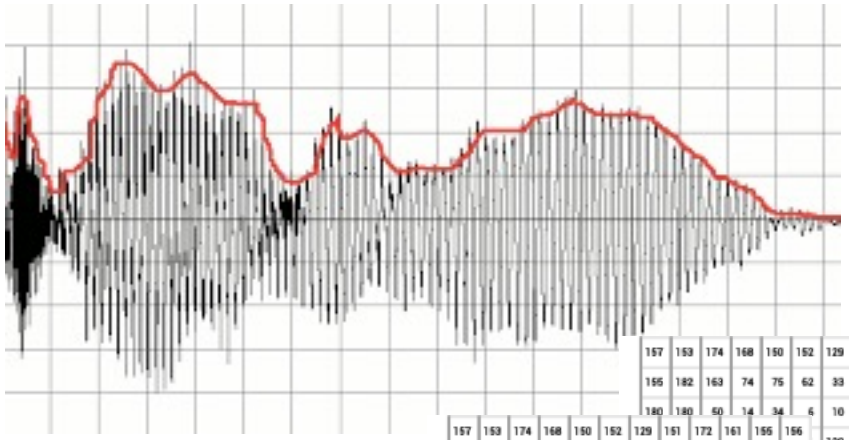
- Audio
  - Input?
- Images
  - Input?
- Video
  - Input?
- Text
  - Input?

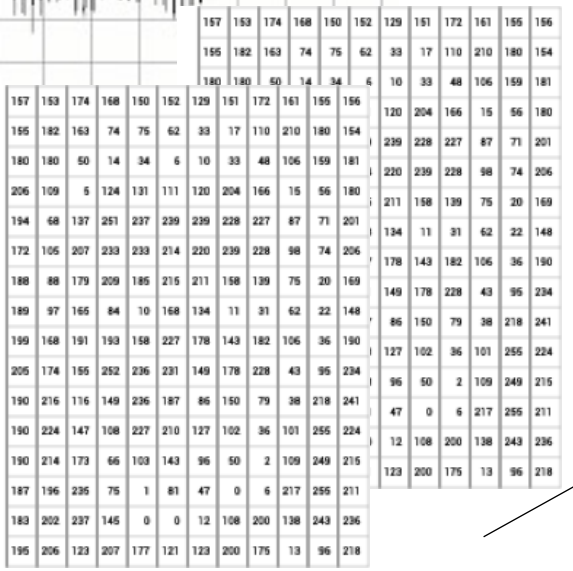
e.g.,

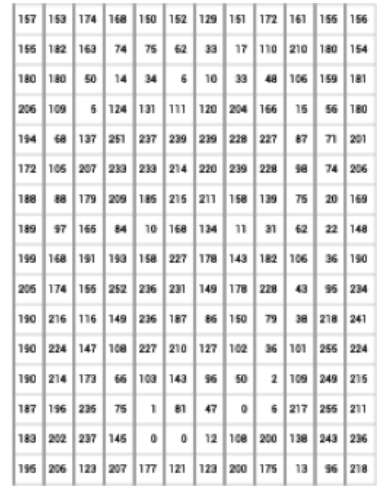


# Data Types: What a Machine Learns From?

- Audio
  - Input?
- Images
  - Input?
- Video
  - Input?
- Text
  - Input?
- Multi-modal
  - Input? - combination of the above







# Data Types: Many Public Datasets Available

- Dataset creation is beyond the scope of this class
- We will benefit from other people's efforts:
  - Google Dataset Search
  - Amazon's AWS datasets
  - Kaggle datasets
  - Wikipedia's list
  - UC Irvine Machine Learning Repository
  - Quora.com
  - Reddit
  - Dataportals.org
  - Opendatamonitor.eu
  - Quandl.com

# General Idea

An **algorithm** learns from **data** patterns that will be used to make a prediction

# Why Are Neural Networks and Deep Learning So Popular? – Its Success in Practice!

It's success was realized with the relatively recent onset of:

1. **Big data**: originally, often from the Internet
2. **Better hardware**: faster hardware and more storage enabled practically fast "deep learning"

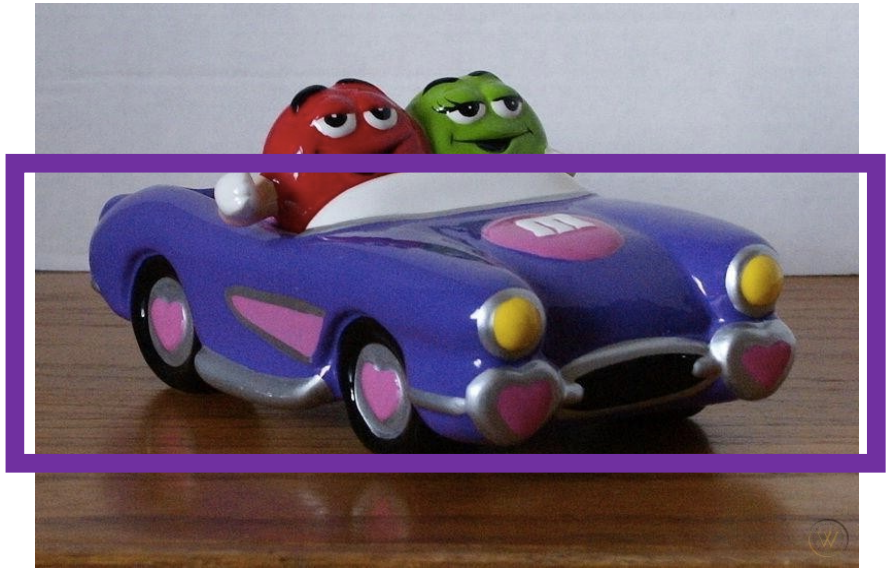
# Neural Networks: Key Ingredients for Success

An **algorithm** learns from **data**
on a **processor** the patterns that
will be used to make a prediction

Analogous to a Love Story of Partnering Up and Road Tripping Somewhere

# Key Challenge 1: How Long Does Learning Take?

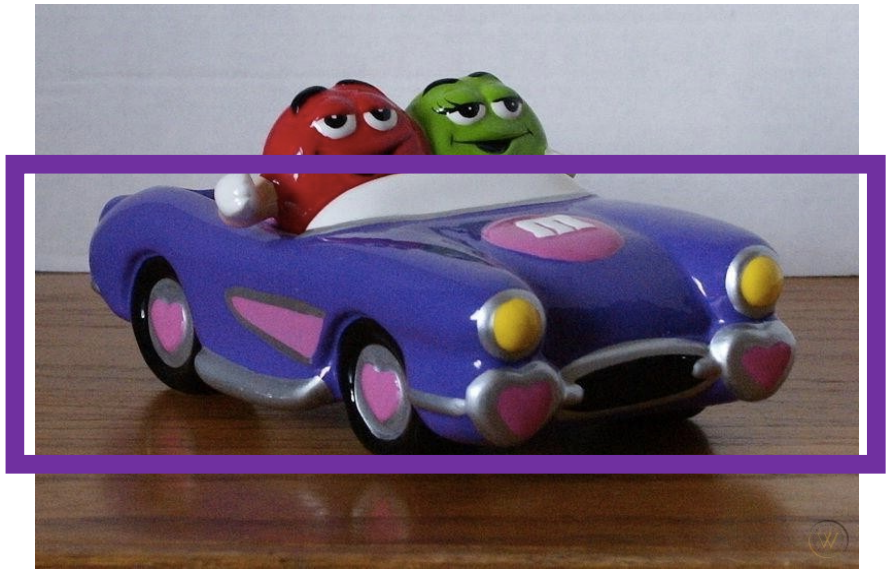
An **algorithm** learns from **data**
on a **processor** the patterns that
will be used to make a prediction



Analogous to a Love Story of Partnering Up and Road Tripping Somewhere

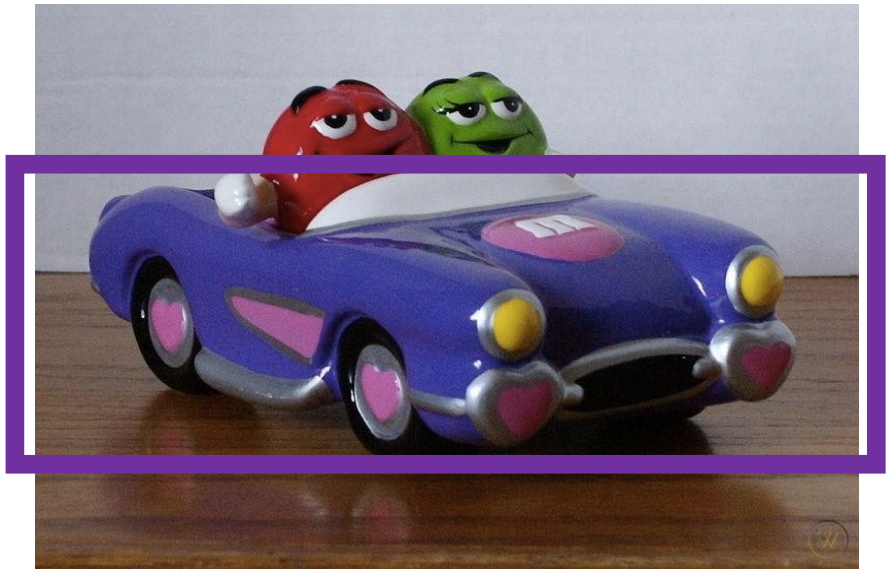
# Key Challenge 1: How Long Does Learning Take?

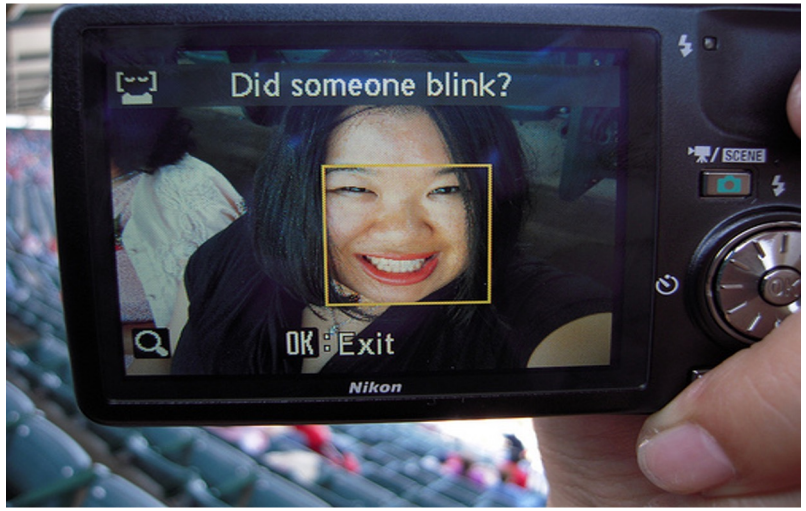
**e.g., Train Algorithms Using**
**GPUs (think Porsche) Instead of CPUs (think Golf Cart)**



# Key Challenge 2: Where Will You Go?


https://www.theverge.com/2015/7/1/8880363/google-apologizes-photos-app-tags-two-black-people-gorillas






Two kids bought their mom a camera for Mother's Day… when they took portrait pictures of each other, a message flashed across the screen asking, "Did someone blink?"

http://content.time.com/time/business/article/0,8599,1954643,00.html

# Course Objectives

- Understand the key concepts for designing deep learning models:
  1. Characterize the process to train and test deep learning algorithms
  2. Identify the challenges for designing modern deep learning algorithms that can harness today's 'big' data
  3. Recognize strengths and weaknesses of different deep learning algorithms

- Apply deep learning models to perform various AI tasks:
  1. Experiment with deep learning libraries, including scikit-learn and Keras
  2. Evaluate deep learning algorithms for tasks in various application domains, including for analyzing text and images

# Course Objectives

- Conduct and communicate a novel project:
  1. Propose a novel project idea (this will be an iterative process)
  2. Design and execute experiments to support the proposed idea
  3. Create a presentation about the project
  4. Write a report about the project

# Q&A: “Do I have the appropriate pre-requisites/background?”

- You are expected to have programming competency as well as experience with probability/statistics and linear algebra.


The End