Machine Learning

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Week 2

PH451 PH551

January 16, 2025

Announcements

- **Welcome Fermilab/LPC participants!**

- **So far**
  - **Course Introduction/Syllabus**
  - **Python Primer**
    - **course github**
  - **Please join Slack**

Outline

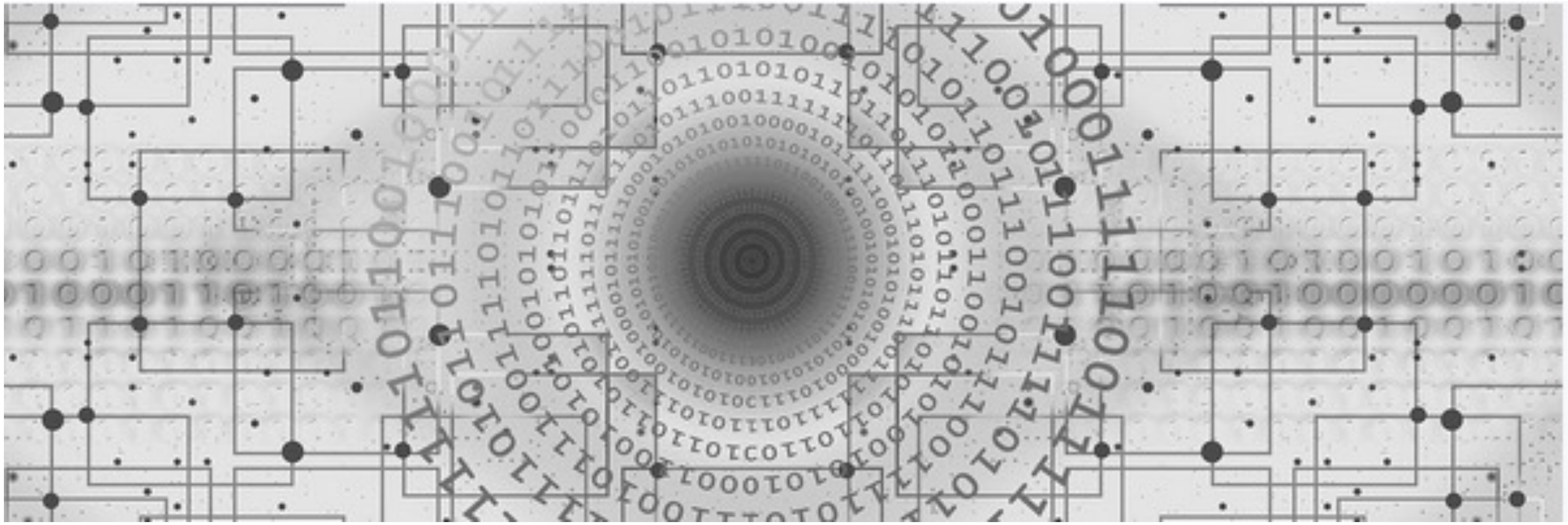
- **What is Machine Learning?**
  - **In Theory**
  - **In Practice**

Machine Learning Introduction

Machine Learning

"Learning is any process by which a system improves performance from experience."

- Herbert Simon



Machine Learning

What is Machine Learning?

- Study of algorithms that
  improve their performance **P**
  for a given task **T**
  with more experience **E**

Sample tasks: identifying faces, dark matter

Machine Learning

Is particularly useful when:

- Humans cannot explain their expertise or no good solution exists
- Models require significant fine-tuning
- There is a fluctuating environment
- Software is too complex to write by hand

Machine Learning

Excellent Tasks for Machine Learning:

- Recognizing patterns (Pattern Recognition)
- Generating patterns (Generative Modeling)
- Identifying anomalies (Anomaly detection)
- Making Predictions (Forecasting)

In Computer Science

Already the preferred approach to:

- Speech recognition, natural language processing
- Computer vision, Robot control
- Medical outcomes analysis

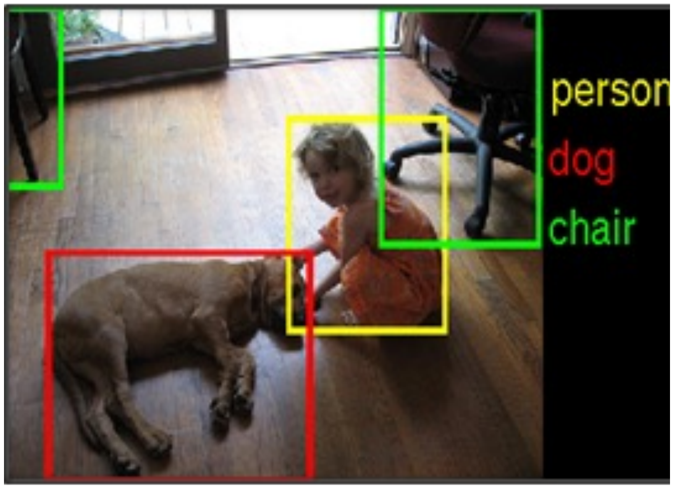
Growing fast

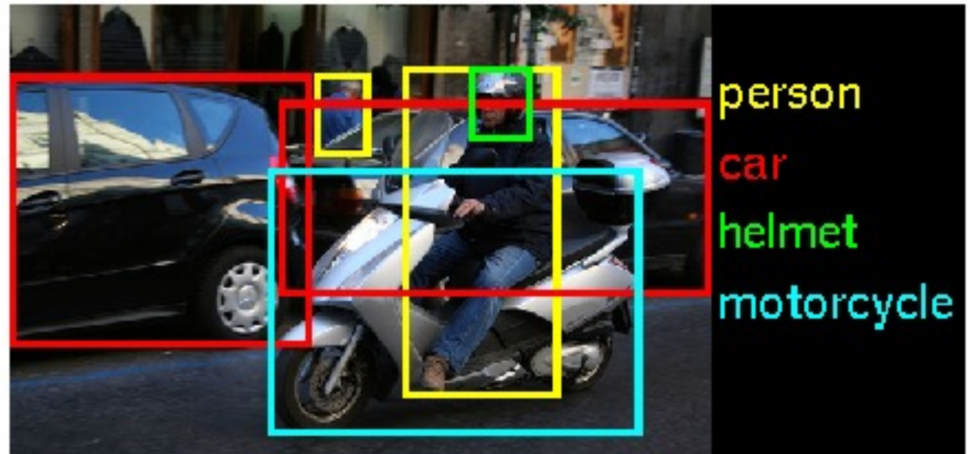
- Improved algorithms
- Increased data capture

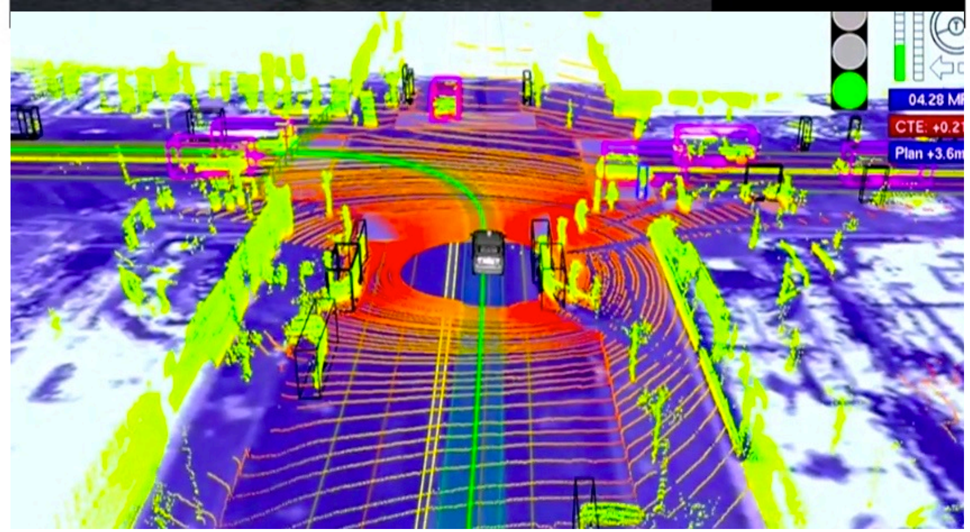
Sample Applications

- Spam detection
- Engineering
- Science
- Robotics
- Social Networks
- Finance
- Genetics
- Games
- Add Your Favorite Application

Examples

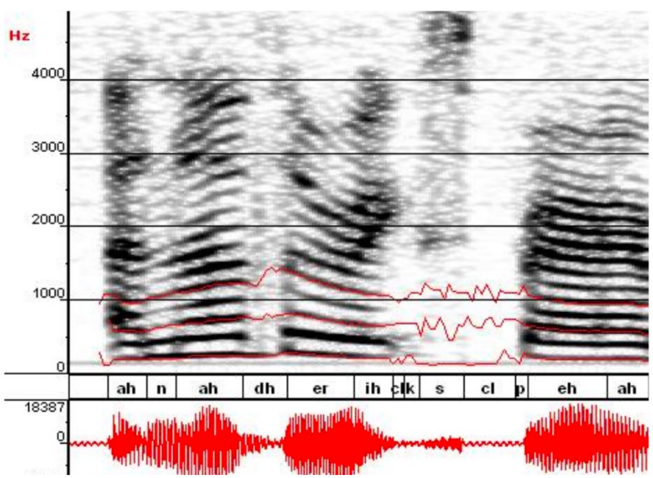






Examples

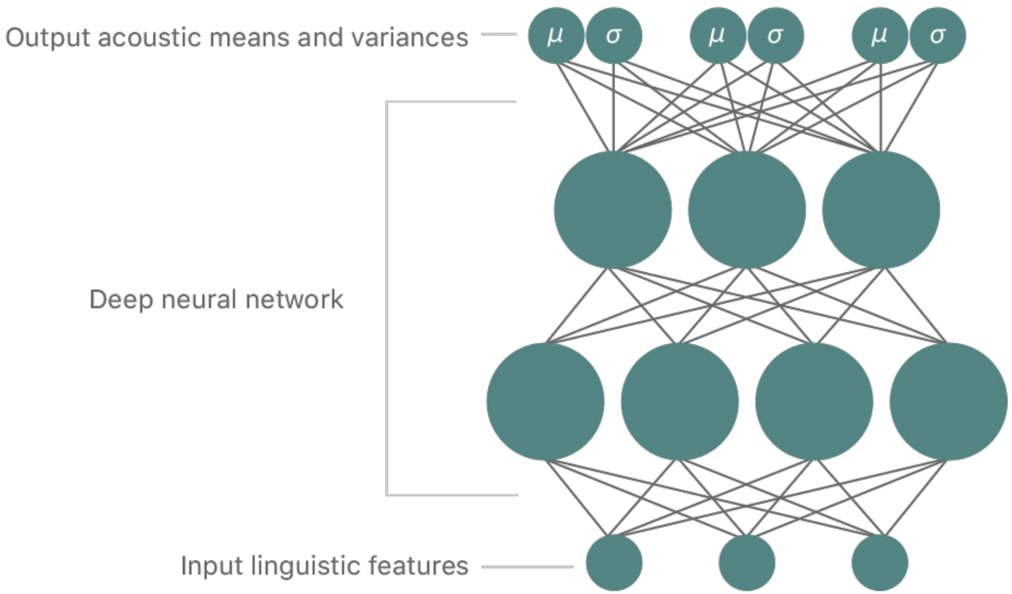
Examples



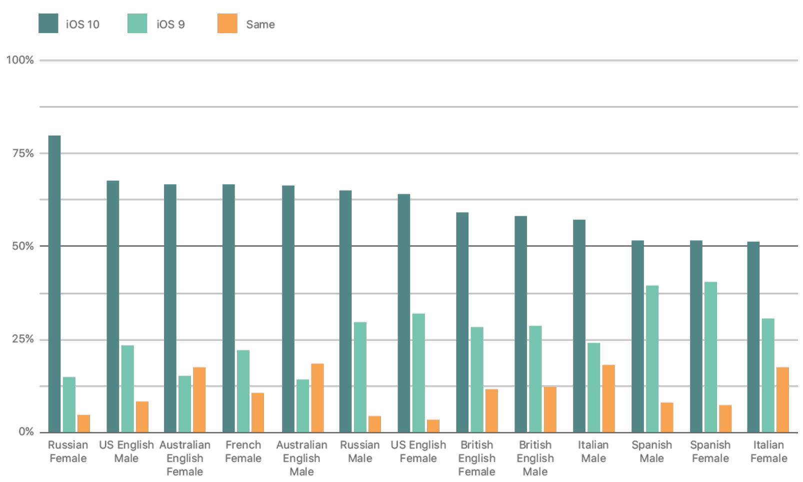
Typical Speech Recognition System

# Hidden Layers	1	2	4	8	10	12
Word Error Rate %	16.0	12.8	11.4	10.9	11.0	11.1

Examples

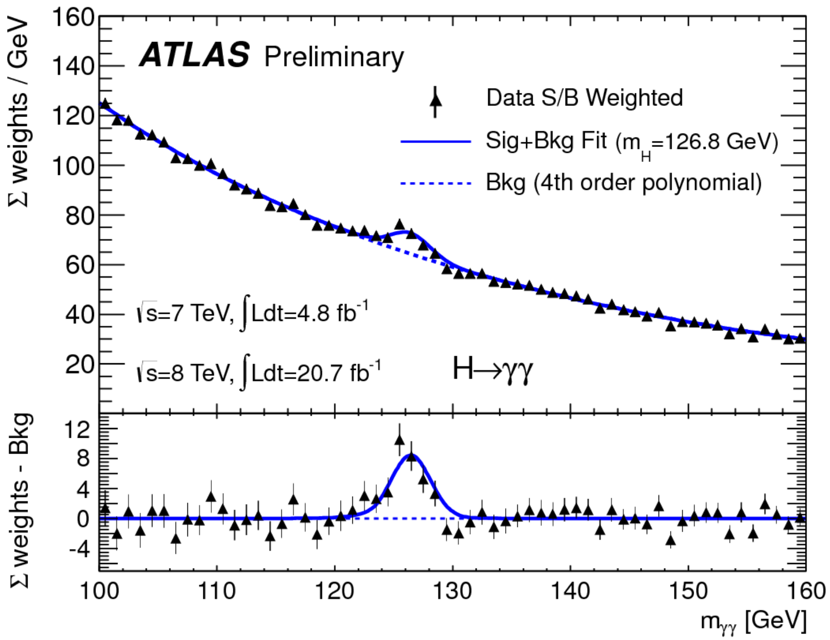


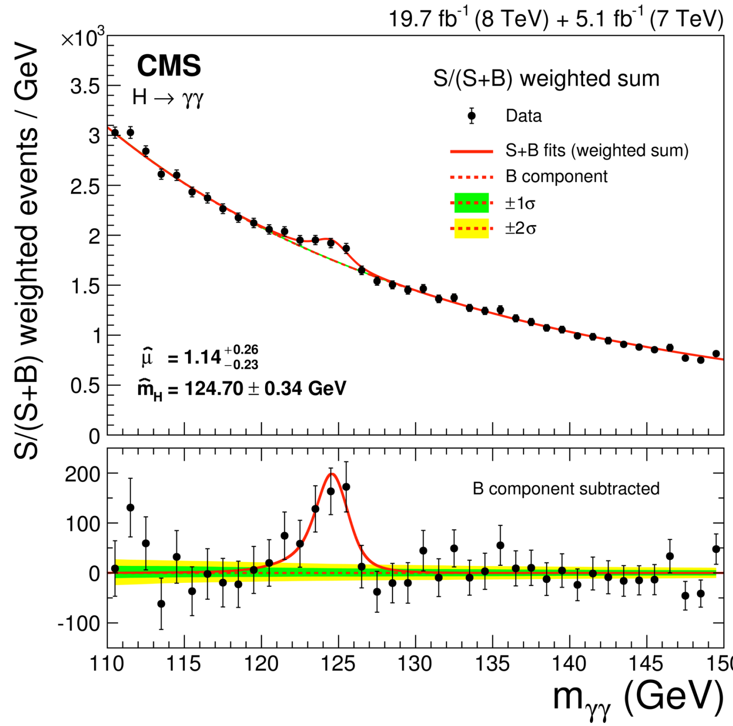
Deep Learning
Siri's voice



Higgs Boson Discovery

Higgs to di-photons

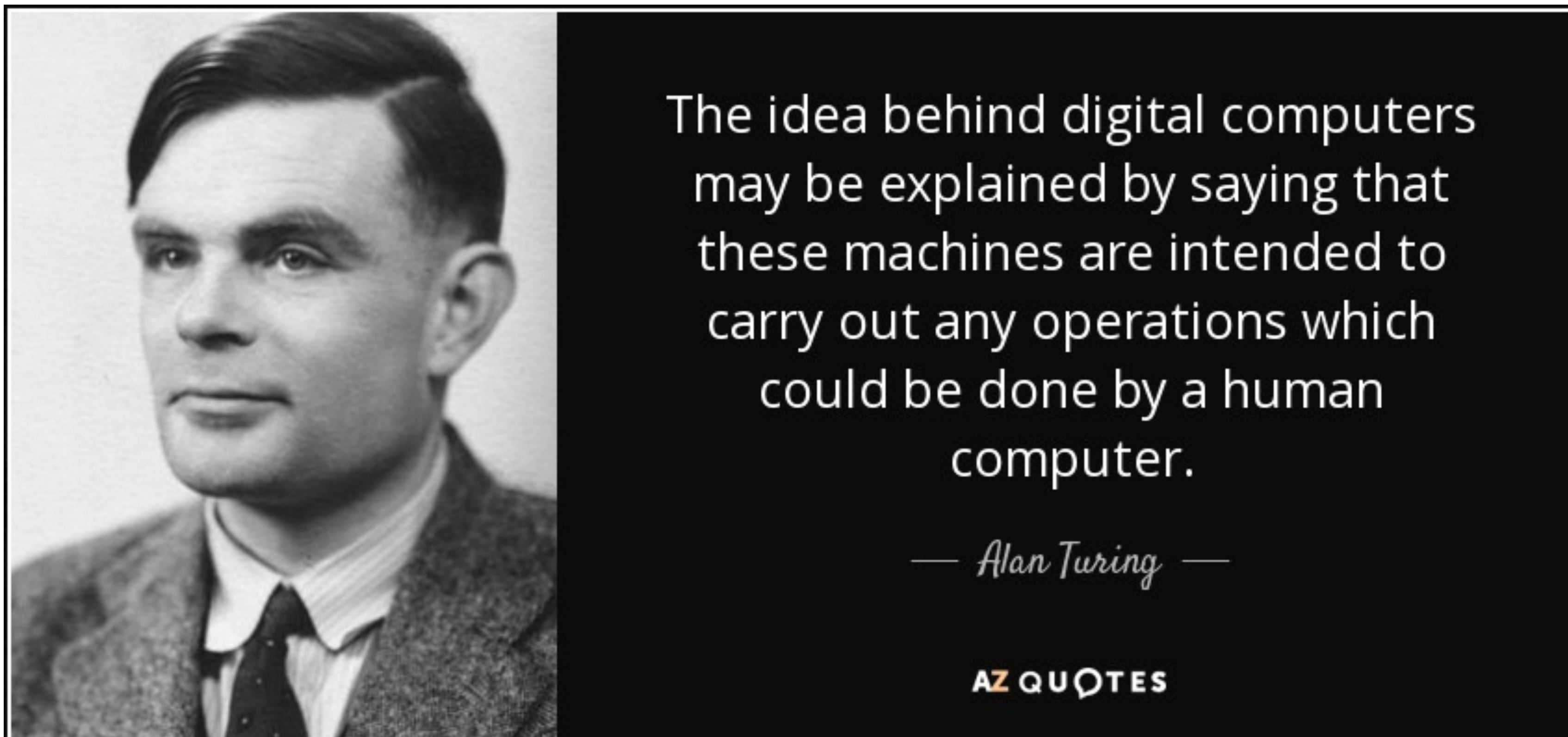




ATLAS **CMS**

History

Human Computers - people who perform calculations - first mentioned in 1613



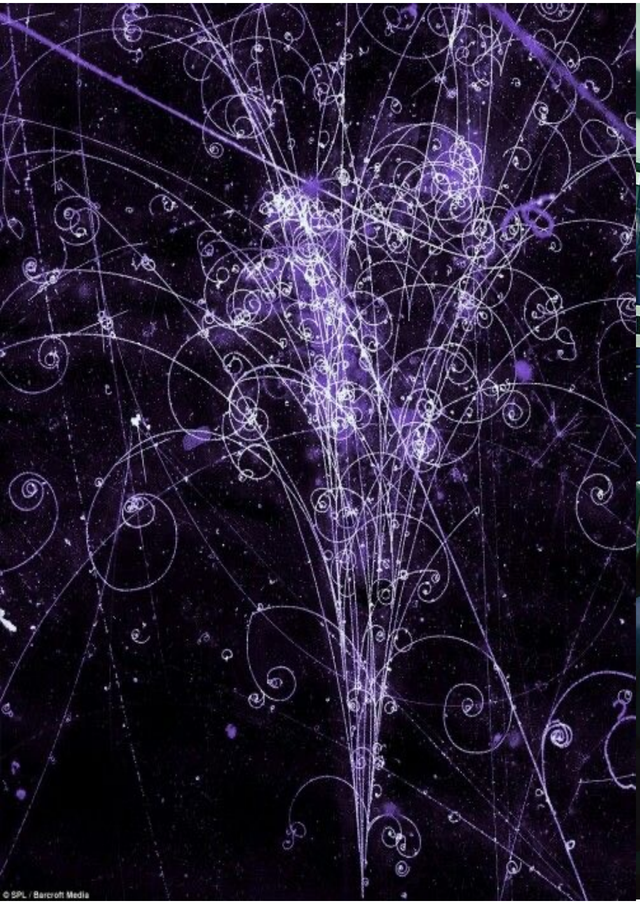
History

"Human Computers"

Human Computers

Dorothy Vaughan (left), Lessie Hunter (center)

Human Computers



Bubble Chamber Photographs and Human Scanners

Recent History

1950 Turing Test (Turing)

1950s: First ML methods invented

1956 AI coined as a field (Minsky, Shannon et al.)

1958 Invention of Perceptron (Frank Rosenblatt)

1959 Machine Learning term first used (Arthur Samuel)

1960-80s: Slow growth, focus on knowledge

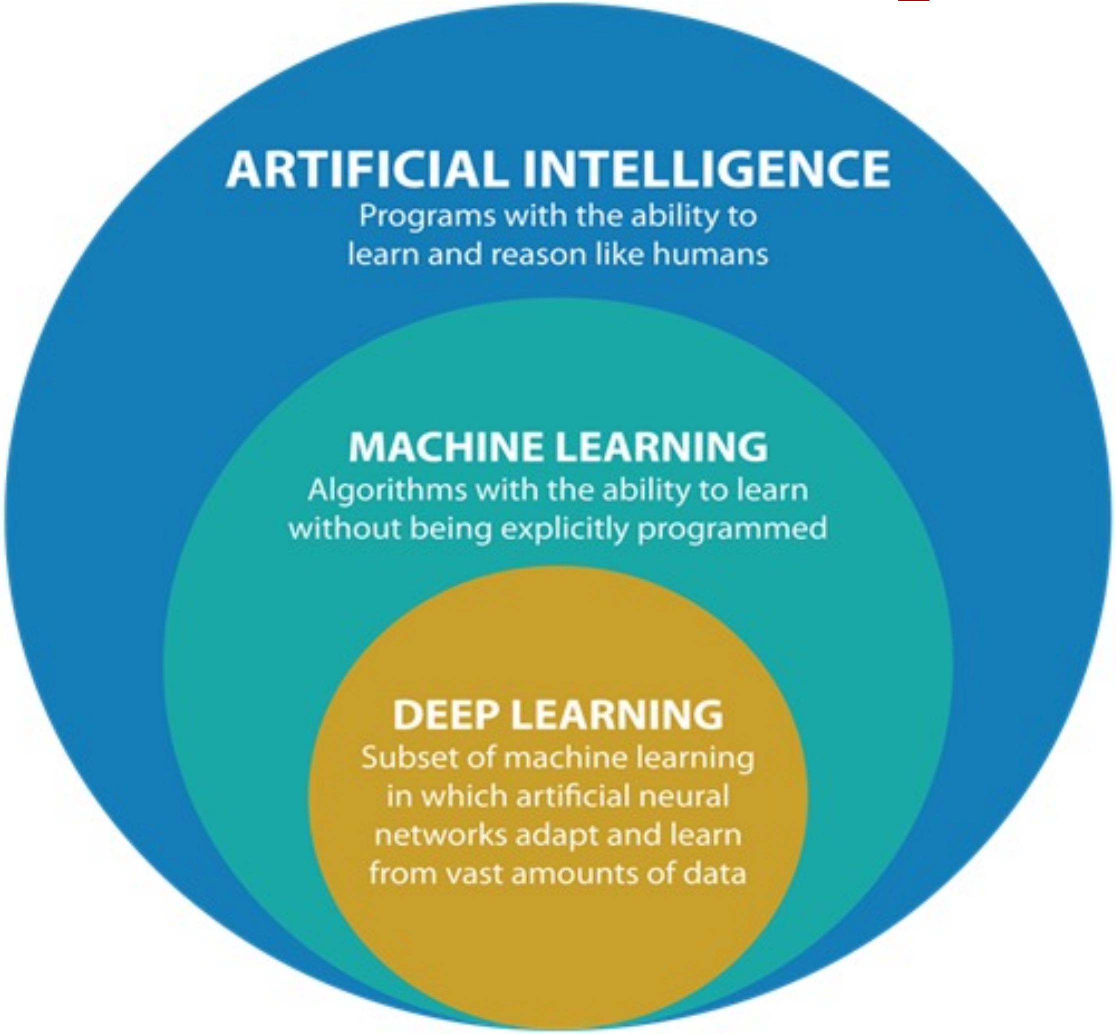
1990s: Growth of computing power, new learning methods, data-centric

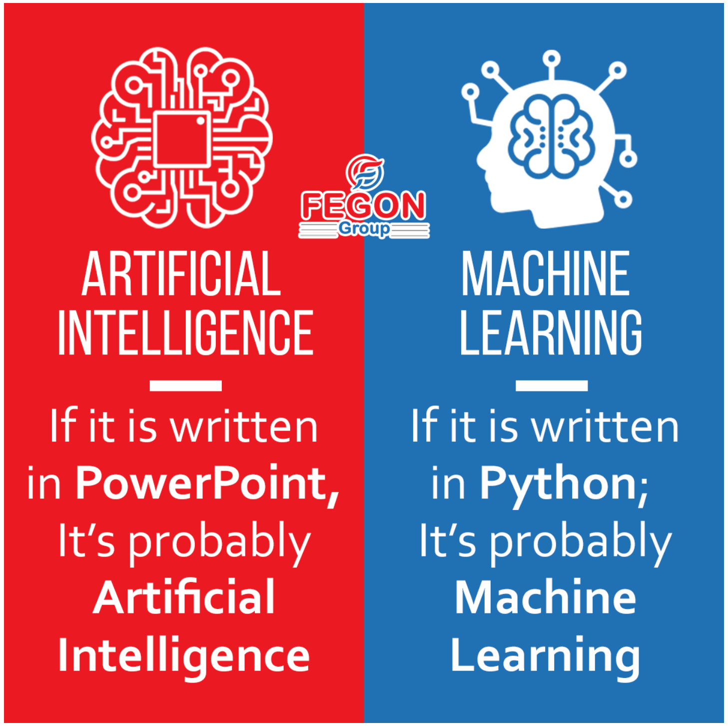
2000-10s: Wider use in research and industry

2010s: Deep learning improvement, dedicated hardware

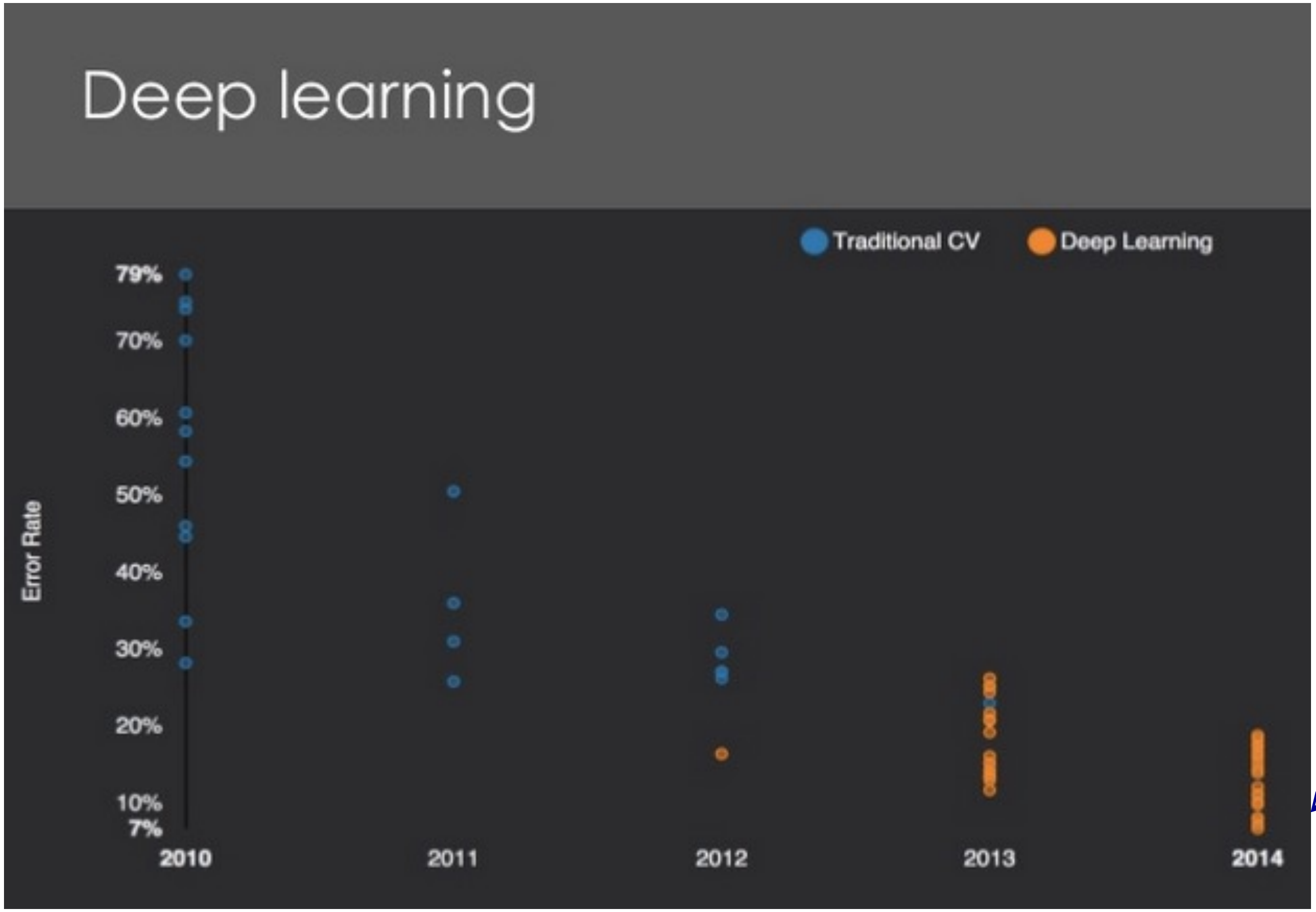
2020s: Scaling, transformers, mainstream

"AI" Taxonomy


ARTIFICIAL INTELLIGENCE
Programs with the ability to learn and reason like humans
MACHINE LEARNING
Algorithms with the ability to learn without being explicitly programmed
DEEP LEARNING
Subset of machine learning in which artificial neural networks adapt and learn from vast amounts of data


ARTIFICIAL INTELLIGENCE
If it is written in PowerPoint, It's probably Artificial Intelligence
FEGON Group
MACHINE LEARNING
If it is written in Python; It's probably Machine Learning

Diving Deeper



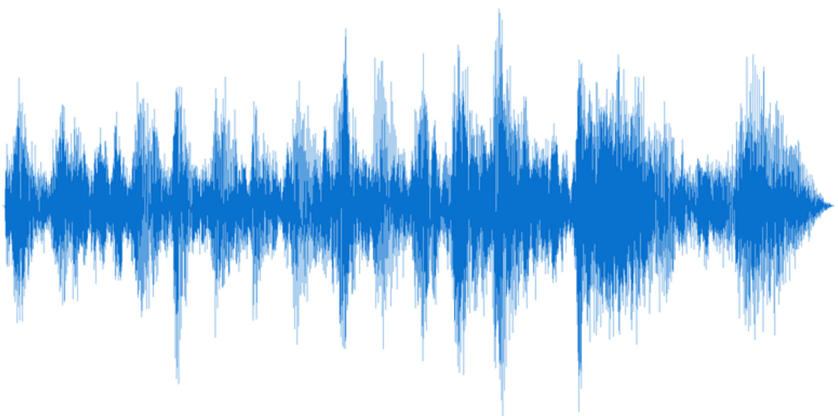
Huge Progress

ML Tools

C5.0

Data Types

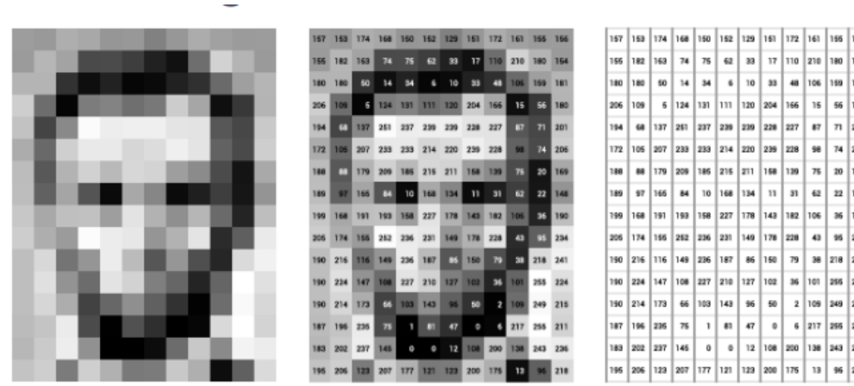
Audio:



$[x^1\ x^2\ x^3 \ldots x^i]^T$
waveform heights

Data Types

Images:

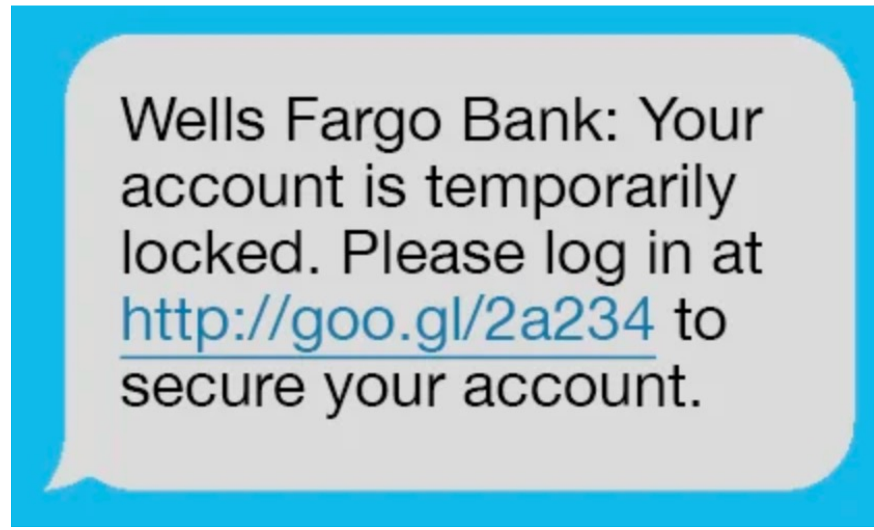


$[x^{11}\ x^{12}\ldots x^{1n}\ x^{21}\ x^{22}\ldots]^T$

pixel intensities

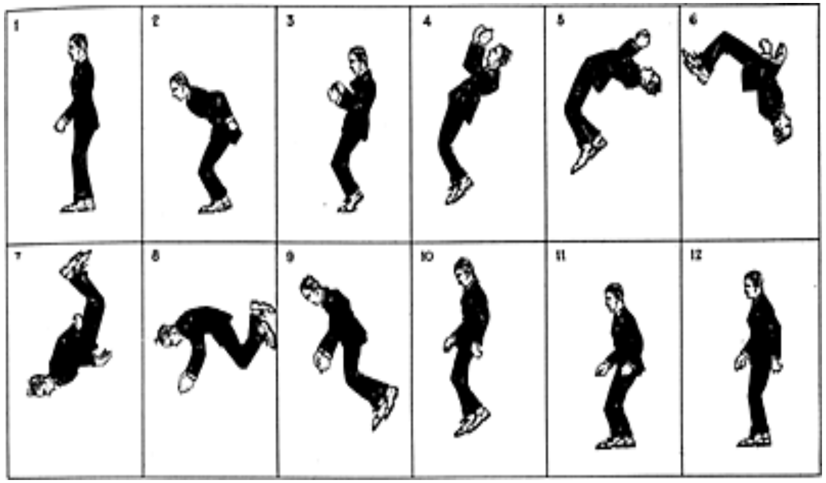
Data Types

Text:



Data Types

Video:



Machine Learning

General Approach:

Given **training** data $T_D = \{y, \mathbf{x}\} = (y,x)_1 \ldots (y,x)_N$,

function space $\{f\}$ and a
constraint on these functions

Teach a machine to learn the **mapping** $y = f(x)$

Machine Learning

Find hypothesis that minimizes the error

Function Space ***F*** = { f(x, **w**) }
possibly constrained
Loss Function L

Learn y = f(x)

- By minimizing empirical risk, computed from the loss function on a known set of training data
  - **How far are estimated values from true values?**

Machine Learning

Empirical because we can only access a subset of the domain (training data)

"inductive learning"

- How well does the solution **generalize** to instances the model has not seen during training

Machine Learning

What type of function is f?

- Neural networks, decision trees, etc. are part of a set of possible functions (Hypothesis Class H)

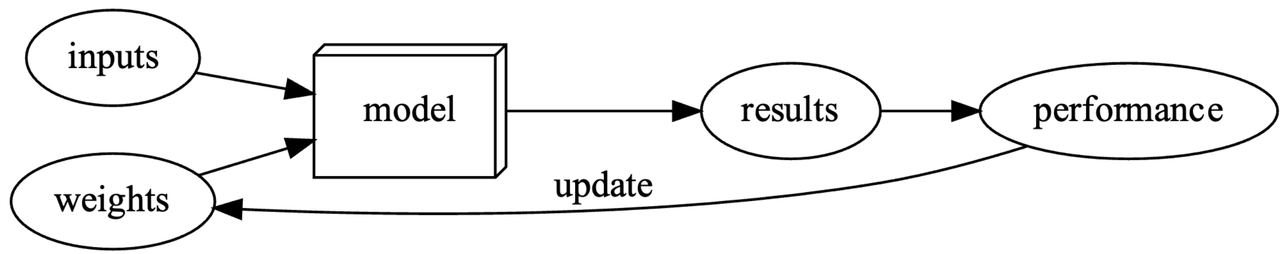
- Every good machine learning algorithm has to make assumptions in order to generalize
    - No Free Lunch Theorem
    - No single ML algorithm works for every setting
        - can't always "run the football"

Machine Learning

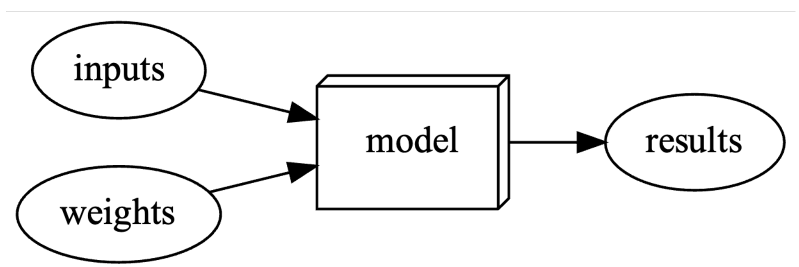
Loss function is something you can choose

- Many machine learning algorithms use a particular type of loss function
  - i.e. quadratic loss $[y - f(x, w)]^2$
    absolute loss $|y - f(x, w)|$
- Largely depends on what you are trying to accomplish
  - Classification, regression…
  - We will study types of **loss functions** in more detail next time

Pictorially



"training"



"inference"

Today's plan

- **Colab and Python Primer**
- **Hands-on exercise #0**
  - **Python basics**
  - **Due on Tue 01/22 at 1pm**