AI: Strategy + Marketing (MGT 853)

Introduction (Session 1)

Vineet Kumar

Yale School of Management

Spring 2025

Agenda for Today's Session

Course Logistics

- Course Introduction

Agenda for Today's Session

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- Content: What we will cover and what we will not

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- What is AI? A brief history
- AI, ML, Data Science

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- AI, ML, Data Science
- Why AI now?
- What AI priorities do firms have?
- Types of ML
- AI stakeholders: consumers, firms, regulators and more

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- Develop a perspective regarding new emerging AI technologies and how they could reshape markets and firms
- Evaluate the broader societal implications of AI, and how different stakeholders (consumers, employees, firms, regulators, investors and others) are impacted by AI.

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  - No pressure to read the optional stuff before class! Whenever you get time...

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- Advising startups and established organizations in AI
- If you're working on your own business idea, happy to talk

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YSOM Policy: No electronic device use

Grading & Assessment

- Grading involves both group and individual assessment

Component	Details	Points
Assignments	1 Pairs and 3 individual (Due Tuesdays 9 am)	50
Participation & Attendance	Individual	30
Project	Group	25

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Please form groups for Project (Max group size: 4 for now).
$\Longrightarrow$ We can help with this. We may add to smaller groups.

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- *Think of the LLM's "answer" as a baseline, you should aim to do better than that.*

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Your goal should be to educate everyone in this class

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You will NOT:

- Understand the math behind how algorithms work
- Understand the best way to implement specific ML algorithms
- Develop new AI / ML algorithms and tools (Take CS courses for that)

Course Content

Course Outline

Can Change Significantly! See Canvas for Latest

#	Date	Topic	Assignment Due (9 am)
Module A: AI Foundations			
1	Mar 25 (Tue)	Course Introduction and Supervised and Unsupervised Algorithms	
2	Mar 27 (Thu)	ML Essentials	
3	April 1 (Tue)	Deep Learning, Reinforcement Learning and Generative Models	**A1 (Individual / Pairs)**
Module B: AI Decision Making Framework			
4	April 3 (Thu)	Economics of AI $\Longleftrightarrow$ Business Strategy	
5	April 8 (Tue)	Decision Making with AI / Interpretable and Explainable AI	**A2 (Individual)**
6	April 10 (Thu)	Ethical Issues in AI	**Group Project Proposal (one paragraph)**
Module C: AI in Business + Society			
7	April 15 (Tue)	Uber (CASE)	**A3 (Individual)**
8	April 17 (Thu)	Zebra Medical (CASE)	
9	April 22 (Tue)	Generative AI in practice	**A4 (Individual)**
10	April 24 (Thu)	Miroglio Fashion (CASE)	
11	April 29 (Thu)	Capstone: Human Capital	
Module D: Project Presentations and Course Wrap			
12	May 1 (Thu)	Presentations	**Presentation Slides Due for ALL groups on May 1**
13	May 6 (Tue)	Presentations and Course Wrap	

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ML Models Practicum in Class

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- Predictions $\Longrightarrow$ Decisions

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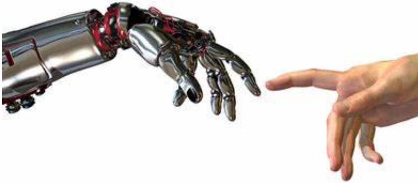
- How do human stakeholders view AI and decisions made by AI?



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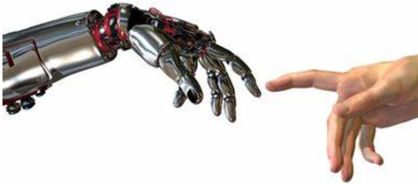

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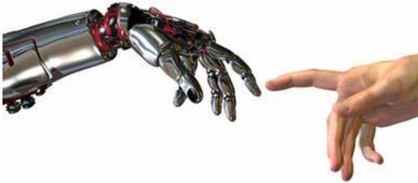

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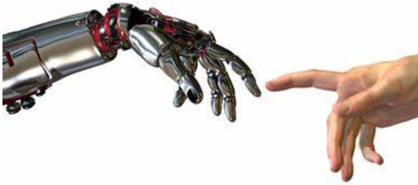

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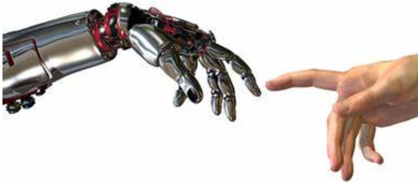
- What is the role of industry bodies and regulators?



Module C: AI in Business + Society

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- What are the biggest challenges and risks firms face in deploying AI?

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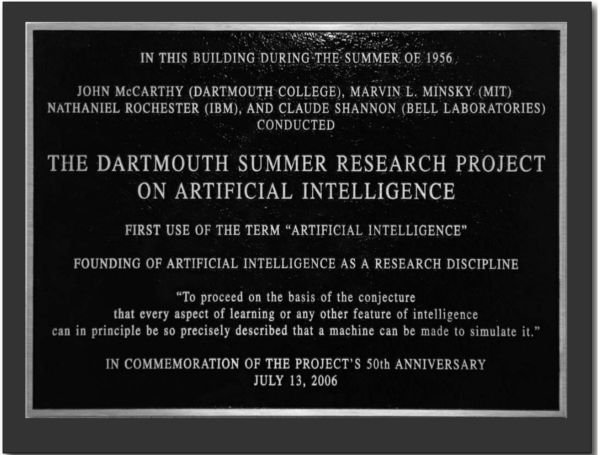
Historical Overview

History of AI

Dartmouth College Conference

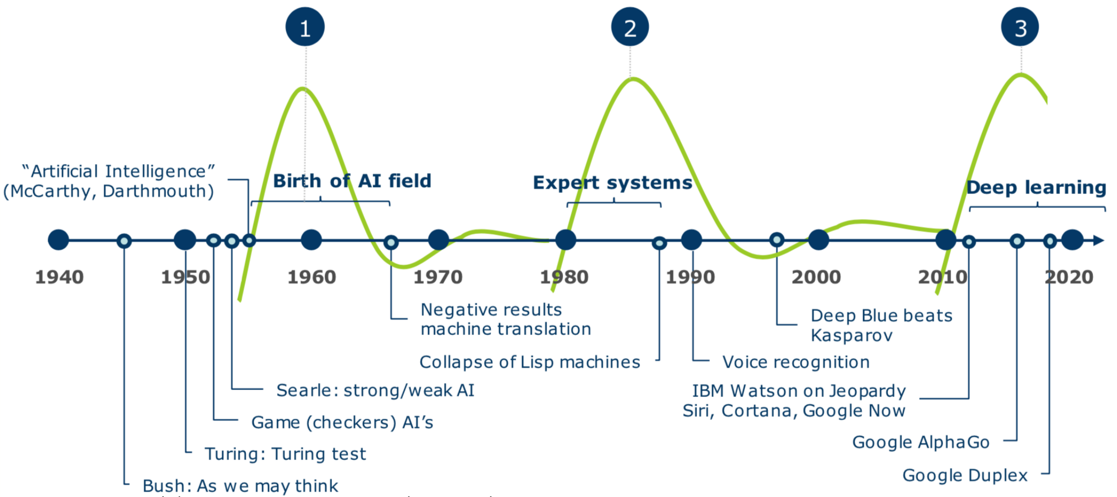


Photographer: Joe Mehling

Source: https://ojs.aaai.org/index.php/aimagazine/article/view/1911/1809

History of AI

Three waves of AI



Source: https://pixelspark.nl/2019/

Humans and Machines

Context for Turing

- Machines are very good at specific things, and can do things that humans cannot do
- A simple "machine" the wheel can go much faster than humans.
- But for a very long time, it was thought that there was one thing that humans could do that machines cannot do.
- Humans Can Think. Machines Cannot.

What exactly does it mean – "to think" ? Can Machines Think?

Turing's View of AI

https://www.csee.umbc.edu/courses/471/papers/turing.pdf

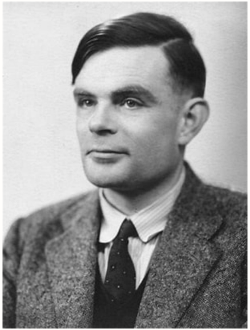
A. M. Turing (1950) Computing Machinery and Intelligence. *Mind 49:* 433-460.

COMPUTING MACHINERY AND INTELLIGENCE

By A. M. Turing

1. The Imitation Game

I propose to consider the question, "Can machines think?" This should begin with definitions of the meaning of the terms "machine" and "think." The definitions might be framed so as to reflect so far as possible the normal use of the words, but this attitude is dangerous, If the meaning of the words "machine" and "think" are to be found by examining how they are commonly used it is difficult to escape the conclusion that the meaning and the answer to the question, "Can machines think?" is to be sought in a statistical survey such as a Gallup poll. But this is absurd. Instead of attempting such a definition I shall replace the question by another, which is closely related to it and is expressed in relatively unambiguous words.



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Turing asks:

If a computer (C) replaces human (M), will human interrogator (Q) know?

`https://www.bbc.com/news/technology-18475646`

(Simplified) Turing's Test

Turing suggests:

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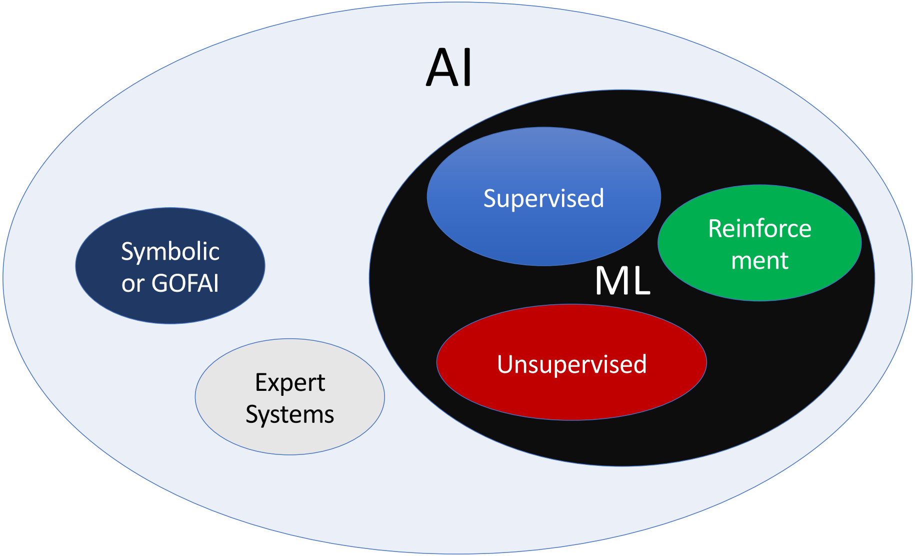
General idea for AI is to achieve human-level intelligence

Types of AI



AI
Symbolic or GOFAI
Expert Systems
ML
Supervised
Reinforce ment
Unsupervised

GOFAI

Good Old Fashioned AI

- Classical / Symbolic AI (Newell & Simon, 1970s)

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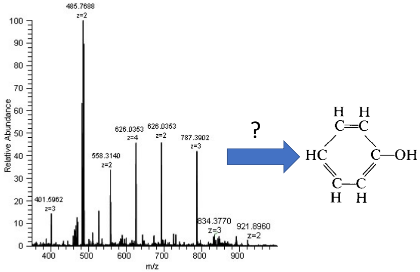
- Intelligence is encoded using symbols
- Idea: Thoughts might be similar to language (which can be encoded)
- Formal representation of what people know in symbols and computer code
- (-) Typically suitable for small or toy problems

Expert Systems

- "Solve problems within a specialized domain that ordinarily requires human expertise"



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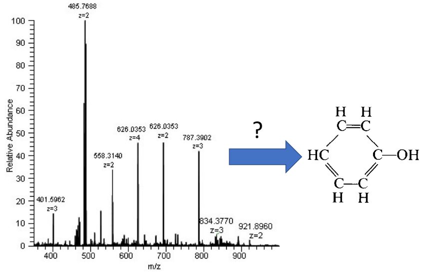

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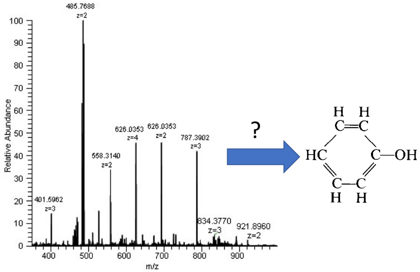

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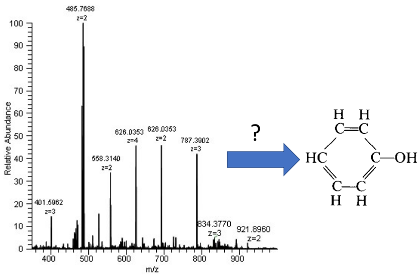

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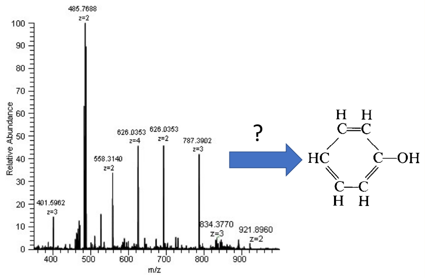
- Other applications in disease diagnosis (e.g. glaucoma), fraud detection etc.



Definitions: AI and ML

Artificial Intelligence

"...Intelligence can in principle be so precisely described that a machine can be made to simulate it." (John McCarthy)

Machine Learning

- "The field of study that gives computers the ability to learn without explicitly being programmed" (Arthur Samuel)

What's the difference?

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Machine Learning

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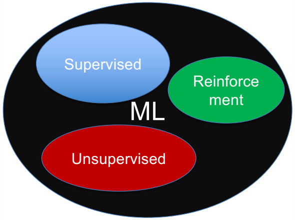
- "Improve over Task T with resect to some performance measure P based on experience E" (Tom Mitchell)

What's the difference?

Differences between ML and other AI approaches

- ML primarily is "learning from data"



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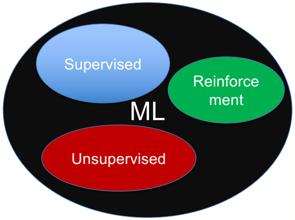

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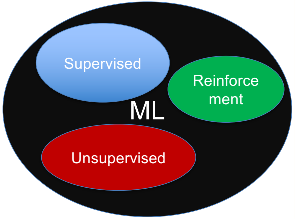

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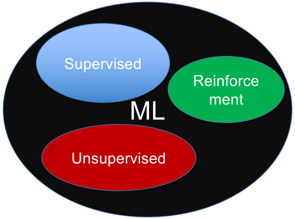

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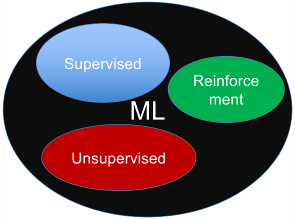

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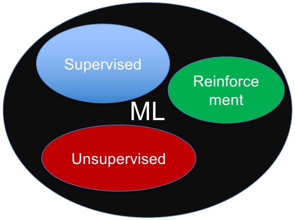

Rest of the course will focus on ML (use interchangeably with AI)

Supervised Learning

- Trying to predict some variable y based on other data X

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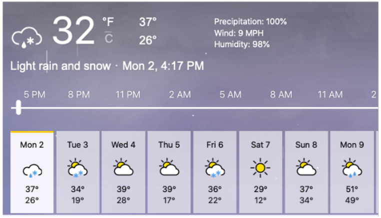
Most commonly used form of ML in practice



Logistic Regression
Polynomial Regression
Support Vector Machines
Decision Trees
Deep Neural Nets

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Can use for exploratory analysis and segmentation even when question is unclear

Cluster Analysis
K-means
K-Nearest Neighbor
Association Rule Mining
Principal Components Analysis

Reinforcement Learning

Q-learning

- Learn how to make good "sequence of decisions" under uncertainty

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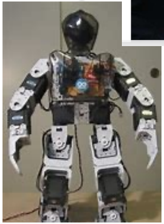
No data required

Former Go champion beaten by DeepMind retires after declaring AI invincible

James Vincent 5 days ago

The South Korean Go champion Lee Se-dol has retired from professional play, telling Yonhap news agency that his decision was motivated by the ascendancy of AI.



Why AI Now?

AI has been around for decades, so why has it become popular now?

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    - What's the connection between ML and Graphics?

Impact of AI / ML

AI Drives Change in Firm Strategy

Google Products and Services · Artificial Intelligence · Companies · Google (company)

What does it mean for Google to become an "AI-first" (quoting Sundar) company? How will this affect prioritization and product development?

https://googleblog.blogspot.com/2016/04/this-years-founders-letter.html

Google sees huge value in moving from 80% accuracy in search to 99.x% accuracy

Willing to de-prioritize everything else (before this, Google was "Mobile First")

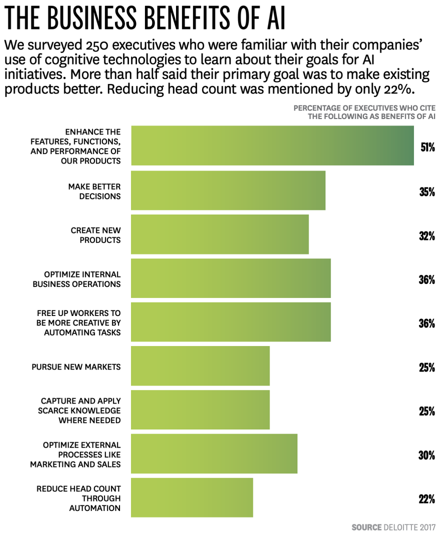
Peter Norvig, Research Director at Google
Answered May 16 2016 · Upvoted by Pål Bergerskogen, M.Sc Artificial Intelligence, Norwegian University of Science and Technology (2018) and Ken Fishkin, former Software Engineering Manager at Google (2013-2018)

"Classic" Google was an information retrieval company: you give a query, we quickly respond with ten suggestions of relevant pages, and it is your job to make sense of the suggestions. "Modern" Google, as Sundar has set out the vision, is based not just on suggestions of relevant information, but on informing and assisting. Informing, meaning that we give you the information you need, when you need it. For example, Google Now telling you it is time to leave for an appointment, or that you are now at the grocery store and previously you asked to be reminded to buy milk. And assisting means helping you to actually carry out actions—planning a trip, booking reservations; anything you can do on the internet, Google should be able to assist you in doing.

With information retrieval, anything over 80% recall and precision is pretty good—not every suggestion has to be perfect, since the user can ignore the bad suggestions. With assistance, there is a much higher barrier. You wouldn't use a service that booked the wrong reservation 20% of the time, or even 2% of the time. So an assistant needs to be much more accurate, and thus more intelligent, more aware of the situation. That's what we call "AI-first."

What are CEO priorities in AI?

- Both external market-facing and internal
- Top external: product
- Top internal: enable employees to do higher-value jobs
- *Not so much about reducing labor costs*



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- Integrating Prediction with decision making can be challenging (Module 2)
- AI has important societal and ethical implications (Module 2)

Next: Supervised and Unsupervised Learning

- Familiarize yourselves with using **Google Colab** using Python:
- More practice will help you understand the next class better
- URL: `https://drive.google.com/drive/folders/1L8LZvM-nEDhbUnZQzcnAv2Zo7cfwQViR`
- Start with the **Welcome To Colaboratory.ipynb** notebook if you're not familiar with Colab.
- **Practicum:** We will walk through code using these datasets
- Assignment 1 involves understanding and exploring the code. *You will not have to write your own code.*