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

Course Logistics

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

Agenda for Today's Session

Course Logistics

- Course Introduction
- Content: What we will cover and what we will not
- Teaching Philosophy

Agenda for Today's Session

Course Logistics

- Course Introduction
- Content: What we will cover and what we will not
- Teaching Philosophy
- Course Expectations

Agenda for Today's Session

Course Logistics

- Course Introduction
- Content: What we will cover and what we will not
- Teaching Philosophy
- Course Expectations
- Grading / Assessment

Agenda for Today's Session

Course Logistics

- Course Introduction
- Content: What we will cover and what we will not
- Teaching Philosophy
- Course Expectations
- Grading / Assessment

Agenda for Today's Session

Course Logistics

- Course Introduction
- Content: What we will cover and what we will not
- Teaching Philosophy
- Course Expectations
- Grading / Assessment

Overview of AI

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

Agenda for Today's Session

Course Logistics

- Course Introduction
- Content: What we will cover and what we will not
- Teaching Philosophy
- Course Expectations
- Grading / Assessment

Overview of AI

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

Agenda for Today's Session

Course Logistics

- Course Introduction
- Content: What we will cover and what we will not
- Teaching Philosophy
- Course Expectations
- Grading / Assessment

Overview of AI

- What is AI? A brief history
- AI, ML, Data Science
- Why AI now?
- What AI priorities do firms have?

Agenda for Today's Session

Course Logistics

- Course Introduction
- Content: What we will cover and what we will not
- Teaching Philosophy
- Course Expectations
- Grading / Assessment

Overview of AI

- What is AI? A brief history
- AI, ML, Data Science
- Why AI now?
- What AI priorities do firms have?
- Types of ML

Agenda for Today's Session

Course Logistics

- Course Introduction
- Content: What we will cover and what we will not
- Teaching Philosophy
- Course Expectations
- Grading / Assessment

Overview of AI

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

Course Logistics

Course Objectives

- Understand the basics of AI and ML models

Course Objectives

- Understand the basics of AI and ML models
- Determine how AI objectives connect to business objectives and strategy

Course Objectives

- Understand the basics of AI and ML models

- Determine how AI objectives connect to business objectives and strategy

- Understand a framework for decisions on AI / ML and identify the major resources required to implement the chosen AI strategy

Course Objectives

- Understand the basics of AI and ML models

- Determine how AI objectives connect to business objectives and strategy

- Understand a framework for decisions on AI / ML and identify the major resources required to implement the chosen AI strategy

- Develop a perspective regarding new emerging AI technologies and how they could reshape markets and firms

Course Objectives

- Understand the basics of AI and ML models

- Determine how AI objectives connect to business objectives and strategy

- Understand a framework for decisions on AI / ML and identify the major resources required to implement the chosen AI strategy

- 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.

My Teaching Philosophy

- This is a **high-involvement** learning activity for all of us

My Teaching Philosophy

- This is a **high-involvement** learning activity for all of us
  - Not the right course if you want to be a passive observer

My Teaching Philosophy

- This is a **high-involvement** learning activity for all of us
  - Not the right course if you want to be a passive observer

- Instructor is part of the teaching plan

My Teaching Philosophy

- This is a **high-involvement** learning activity for all of us
  - Not the right course if you want to be a passive observer

- Instructor is part of the teaching plan

- Mastery comes from multiple sources: Self (Reflective study), Peers, Practice, Instructor

My Teaching Philosophy

- This is a **high-involvement** learning activity for all of us
  - Not the right course if you want to be a passive observer

- Instructor is part of the teaching plan

- Mastery comes from multiple sources: Self (Reflective study), Peers, Practice, Instructor

- Format: Lectures, Case Discussions, In-class discussions, Practica (kind of), Assignments, Project

My Teaching Philosophy

- This is a **high-involvement** learning activity for all of us
  - Not the right course if you want to be a passive observer

- Instructor is part of the teaching plan

- Mastery comes from multiple sources: Self (Reflective study), Peers, Practice, Instructor

- Format: Lectures, Case Discussions, In-class discussions, Practica (kind of), Assignments, Project

- By the end of the course, I will learn from you too...

My Teaching Philosophy

- This is a **high-involvement** learning activity for all of us
  - Not the right course if you want to be a passive observer

- Instructor is part of the teaching plan

- Mastery comes from multiple sources: Self (Reflective study), Peers, Practice, Instructor

- Format: Lectures, Case Discussions, In-class discussions, Practica (kind of), Assignments, Project

- By the end of the course, I will learn from you too...

- I have included a lot of material that is optional. Why?

My Teaching Philosophy

- This is a **high-involvement** learning activity for all of us
  - Not the right course if you want to be a passive observer

- Instructor is part of the teaching plan

- Mastery comes from multiple sources: Self (Reflective study), Peers, Practice, Instructor

- Format: Lectures, Case Discussions, In-class discussions, Practica (kind of), Assignments, Project

- By the end of the course, I will learn from you too...

- I have included a lot of material that is optional. Why?
  - No pressure to read the optional stuff before class! Whenever you get time...

About Myself (He / Him)

- Broadly interested in the intersection of Tech + Business / Society

About Myself (He / Him)

- Broadly interested in the intersection of Tech + Business / Society

- Research on ML algorithms and Human $\iff$ AI Interface

About Myself (He / Him)

- Broadly interested in the intersection of Tech $+$ Business / Society

- Research on ML algorithms and Human $\iff$ AI Interface

- Advising startups and established organizations in AI

About Myself (He / Him)

- Broadly interested in the intersection of Tech + Business / Society

- Research on ML algorithms and Human $\Longleftrightarrow$ AI Interface

- Advising startups and established organizations in AI

- If you're working on your own business idea, happy to talk

Class Participation

- Expect everyone to participate in class discussions

Class Participation

- Expect everyone to participate in class discussions
- Requires your presence (physical and cognitive) to engage

Class Participation

- Expect everyone to participate in class discussions
- Requires your presence (physical and cognitive) to engage
- Quantity and Quality are both important, latter more valued

Class Participation

- Expect everyone to participate in class discussions
- Requires your presence (physical and cognitive) to engage
- Quantity and Quality are both important, latter more valued
- You get points for adding value to our class discussion

Class Participation

- Expect everyone to participate in class discussions
- Requires your presence (physical and cognitive) to engage
- Quantity and Quality are both important, latter more valued
- You get points for adding value to our class discussion
  - Cannot enumerate these in advance so use your judgment

Class Participation

- Expect everyone to participate in class discussions

- Requires your presence (physical and cognitive) to engage

- Quantity and Quality are both important, latter more valued

- You get points for adding value to our class discussion
  - Cannot enumerate these in advance so use your judgment
  - Biased in favor of speaking up

Class Participation

- Expect everyone to participate in class discussions

- Requires your presence (physical and cognitive) to engage

- Quantity and Quality are both important, latter more valued

- You get points for adding value to our class discussion
  - Cannot enumerate these in advance so use your judgment
  - Biased in favor of speaking up
  - We often learn more from "mistakes" than "correct answers"

Class Participation

- Expect everyone to participate in class discussions

- Requires your presence (physical and cognitive) to engage

- Quantity and Quality are both important, latter more valued

- You get points for adding value to our class discussion
  - Cannot enumerate these in advance so use your judgment
  - Biased in favor of speaking up
  - We often learn more from "mistakes" than "correct answers"

- Can include good questions that make us think in a useful direction

Class Participation

- Expect everyone to participate in class discussions

- Requires your presence (physical and cognitive) to engage

- Quantity and Quality are both important, latter more valued

- You get points for adding value to our class discussion
  - Cannot enumerate these in advance so use your judgment
  - Biased in favor of speaking up
  - We often learn more from "mistakes" than "correct answers"

- Can include good questions that make us think in a useful direction

Class Participation

- Expect everyone to participate in class discussions

- Requires your presence (physical and cognitive) to engage

- Quantity and Quality are both important, latter more valued

- You get points for adding value to our class discussion
  - Cannot enumerate these in advance so use your judgment
  - Biased in favor of speaking up
  - We often learn more from "mistakes" than "correct answers"

- Can include good questions that make us think in a useful direction

YSOM and Course Policy
No electronic device use (only university-approved exceptions)

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

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

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

LLM Policy

- You can use LLMs to explore and ideate (no penalty)

LLM Policy

- You can use LLMs to explore and ideate (no penalty)
- Submissions must reflect your own view

LLM Policy

- You can use LLMs to explore and ideate (no penalty)
- Submissions must reflect your own view
- Acknowledge LLM use and include a couple of sentences about your experience with each submission

LLM Policy

- You can use LLMs to explore and ideate (no penalty)
- Submissions must reflect your own view
- Acknowledge LLM use and include a couple of sentences about your experience with each submission
- We will consider originality in determining grades.

LLM Policy

- You can use LLMs to explore and ideate (no penalty)

- Submissions must reflect your own view

- Acknowledge LLM use and include a couple of sentences about your experience with each submission

- We will consider originality in determining grades.
  - Ideas commonly generated by LLMs may not receive full points.

LLM Policy

- You can use LLMs to explore and ideate (no penalty)
- Submissions must reflect your own view
- Acknowledge LLM use and include a couple of sentences about your experience with each submission
- We will consider originality in determining grades.
  - Ideas commonly generated by LLMs may not receive full points.

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

Project: 3 Types

- AI / ML is a rapidly evolving field with lots of intellectual and research developments

Project: 3 Types

- AI / ML is a rapidly evolving field with lots of intellectual and research developments

  A: AI Business Case Development: Develop a business case for implementing AI in a specific function to solve a specific set of problems (e.g. marketing, finance, operations).

Project: 3 Types

- AI / ML is a rapidly evolving field with lots of intellectual and research developments

  A: AI Business Case Development: Develop a business case for implementing AI in a specific function to solve a specific set of problems (e.g. marketing, finance, operations).

  B: AI Regulation and Governance: Develop a framework for ensuring AI systems are transparent, explainable, and fair in a particular business or regulatory context.

Project: 3 Types

- AI / ML is a rapidly evolving field with lots of intellectual and research developments

  A: AI Business Case Development: Develop a business case for implementing AI in a specific function to solve a specific set of problems (e.g. marketing, finance, operations).

  B: AI Regulation and Governance: Develop a framework for ensuring AI systems are transparent, explainable, and fair in a particular business or regulatory context.

  C: Academic Paper: Present a research paper with thoughts on business applications. We will provide a curated list of academic papers.

Project: 3 Types

- AI / ML is a rapidly evolving field with lots of intellectual and research developments

    A: AI Business Case Development: Develop a business case for implementing AI in a specific function to solve a specific set of problems (e.g. marketing, finance, operations).

    B: AI Regulation and Governance: Develop a framework for ensuring AI systems are transparent, explainable, and fair in a particular business or regulatory context.

    C: Academic Paper: Present a research paper with thoughts on business applications. We will provide a curated list of academic papers.

Project: 3 Types

- AI / ML is a rapidly evolving field with lots of intellectual and research developments

  A: AI Business Case Development: Develop a business case for implementing AI in a specific function to solve a specific set of problems (e.g. marketing, finance, operations).

  B: AI Regulation and Governance: Develop a framework for ensuring AI systems are transparent, explainable, and fair in a particular business or regulatory context.

  C: Academic Paper: Present a research paper with thoughts on business applications. We will provide a curated list of academic papers.

Your goal should be to educate everyone in this class

Project & Groups

- Please form groups for Project

Project & Groups

- Please form groups for Project

- Max group size: **4** for now, we can help form groups.

Project & Groups

- Please form groups for Project

- Max group size: **4** for now, we can help form groups.

- We might add individuals to smaller groups.

Project & Groups

- Please form groups for Project

- Max group size: **4** for now, we can help form groups.

- We might add individuals to smaller groups.

- Important: Groups only within section, not across sections

Project & Groups

- Please form groups for Project

- Max group size: **4** for now, we can help form groups.

- We might add individuals to smaller groups.

- Important: Groups only within section, not across sections

- Plan on a 10 minute presentation $+$ Q&A

Project & Groups

- Please form groups for Project

- Max group size: **4** for now, we can help form groups.

- We might add individuals to smaller groups.

- Important: Groups only within section, not across sections

- Plan on a 10 minute presentation $+$ Q&A

- Might move one of the presentation dates to be earlier in the course

You will:

- Get a big-picture overview of AI / ML technology

Course Material Overview

You will:

- Get a big-picture overview of AI / ML technology

- Understand basic methods and algorithms that constitute ML

Course Material Overview

You will:

- Get a big-picture overview of AI / ML technology

- Understand basic methods and algorithms that constitute ML

- Learn and apply the AI decision framework to business problems (more on predictive AI)

Course Material Overview

You will:

- Get a big-picture overview of AI / ML technology

- Understand basic methods and algorithms that constitute ML

- Learn and apply the AI decision framework to business problems (more on predictive AI)

- Evaluate how AI impacts business and society

Course Material Overview

You will:

- Get a big-picture overview of AI / ML technology

- Understand basic methods and algorithms that constitute ML

- Learn and apply the AI decision framework to business problems (more on predictive AI)

- Evaluate how AI impacts business and society

Course Material Overview

You will:

- Get a big-picture overview of AI / ML technology

- Understand basic methods and algorithms that constitute ML

- Learn and apply the AI decision framework to business problems (more on predictive AI)

- Evaluate how AI impacts business and society

Course Material Overview

You will:

- Get a big-picture overview of AI / ML technology

- Understand basic methods and algorithms that constitute ML

- Learn and apply the AI decision framework to business problems (more on predictive AI)

- Evaluate how AI impacts business and society

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	

Is this a coding heavy class?

Module A: Introduction

- Difference between ML / AI

Module A: Introduction

- Difference between ML / AI
- Types of ML methods: Supervised, Unsupervised and Reinforcement Learning

ARTIFICIAL
INTELLIGE

Module A: Introduction

- Difference between ML / AI
- Types of ML methods: Supervised, Unsupervised and Reinforcement Learning
- Deep Learning

Module A: Introduction

- Difference between ML / AI
- Types of ML methods: Supervised, Unsupervised and Reinforcement Learning
- Deep Learning
- Elements of an ML model – ML Pipeline

Module A: Introduction

- Difference between ML / AI
- Types of ML methods: Supervised, Unsupervised and Reinforcement Learning
- Deep Learning
- Elements of an ML model – ML Pipeline
- Evaluating and Comparing ML models

Module A: Introduction

- Difference between ML / AI

- Types of ML methods: Supervised, Unsupervised and Reinforcement Learning

- Deep Learning

- Elements of an ML model – ML Pipeline

- Evaluating and Comparing ML models

- ML Models Practicum (over the next couple sessions)

ARTIFICIAL INTELLIGE

ML Models Practicum in Class

- Google Colab `https://drive.google.com/drive/folders/1L8LZvM-nEDhbUnZQzcnAv2Zo7cfwQViR`

ML Models Practicum in Class

- Google Colab `https://drive.google.com/drive/folders/1L8LZvM-nEDhbUnZQzcnAv2Zo7cfwQViR`
- Understanding even a bit of model ingredients will go a long way in helping make better decisions

ML Models Practicum in Class

- Google Colab `https://drive.google.com/drive/folders/1L8LZvM-nEDhbUnZQzcnAv2Zo7cfwQViR`
- Understanding even a bit of model ingredients will go a long way in helping make better decisions
- Next 2 classes we will go into ML models

ML Models Practicum in Class

- Google Colab `https://drive.google.com/drive/folders/1L8LZvM-nEDhbUnZQzcnAv2Zo7cfwQViR`
- Understanding even a bit of model ingredients will go a long way in helping make better decisions
- Next 2 classes we will go into ML models
- Code will be in Python / R

ML Models Practicum in Class

- Google Colab `https://drive.google.com/drive/folders/1L8LZvM-nEDhbUnZQzcnAv2Zo7cfwQViR`
- Understanding even a bit of model ingredients will go a long way in helping make better decisions
- Next 2 classes we will go into ML models
- Code will be in Python / R
- We will walk through code in class

ML Models Practicum in Class

- Google Colab `https://drive.google.com/drive/folders/1L8LZvM-nEDhbUnZQzcnAv2Zo7cfwQViR`
- Understanding even a bit of model ingredients will go a long way in helping make better decisions
- Next 2 classes we will go into ML models
- Code will be in Python / R
- We will walk through code in class
- You need to be comfortable making small changes and running code

colab

ML Models Practicum in Class

- Google Colab `https://drive.google.com/drive/folders/1L8LZvM-nEDhbUnZQzcnAv2Zo7cfwQViR`
- Understanding even a bit of model ingredients will go a long way in helping make better decisions
- Next 2 classes we will go into ML models
- Code will be in Python / R
- We will walk through code in class
- You need to be comfortable making small changes and running code
- You will NOT be required to write your own code from scratch

colab

Module B: AI Decision Making Framework

- How does ML connect to business strategy?

- How does ML connect to business strategy?
- What types of problems are suitable for ML? Are there problems that are *not* suitable?

Module B: AI Decision Making Framework

- How does ML connect to business strategy?

- What types of problems are suitable for ML? Are there problems that are *not* suitable?

- ML is about predictions. How can predictions be transformative?

- How does ML connect to business strategy?

- What types of problems are suitable for ML?
  Are there problems that are *not* suitable?

- ML is about predictions. How can predictions
  be transformative?

- Converting a problem to a prediction question

Module B: AI Decision Making Framework

- How does ML connect to business strategy?

- What types of problems are suitable for ML? Are there problems that are *not* suitable?

- ML is about predictions. How can predictions be transformative?

- Converting a problem to a prediction question

- Have machines disrupted humans in prediction? Where do humans fit in?

Module B: AI Decision Making Framework

- How does ML connect to business strategy?

- What types of problems are suitable for ML? Are there problems that are *not* suitable?

- ML is about predictions. How can predictions be transformative?

- Converting a problem to a prediction question

- Have machines disrupted humans in prediction? Where do humans fit in?

- Predictions $\implies$ Decisions

Module B: AI and Society

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

Module B: AI and Society

- How do human stakeholders view AI and decisions made by AI?
- Are AI decisions biased or unfair? Relative to humans? Why?

Module B: AI and Society

- How do human stakeholders view AI and decisions made by AI?
- Are AI decisions biased or unfair? Relative to humans? Why?
  - If yes, (how) can we fix it?
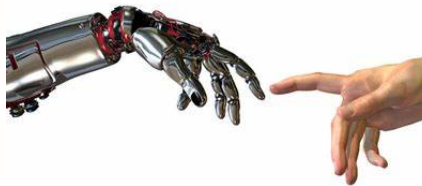
Module B: AI and Society

- How do human stakeholders view AI and decisions made by AI?
- Are AI decisions biased or unfair? Relative to humans? Why?
  - If yes, (how) can we fix it?

- How can managers build trust and avoid fragility in AI systems?
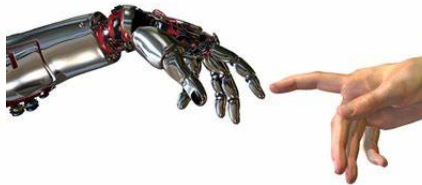
Module B: AI and Society

- How do human stakeholders view AI and decisions made by AI?
- Are AI decisions biased or unfair? Relative to humans? Why?
  - If yes, (how) can we fix it?
- How can managers build trust and avoid fragility in AI systems?
- What is the role of industry bodies and regulators?
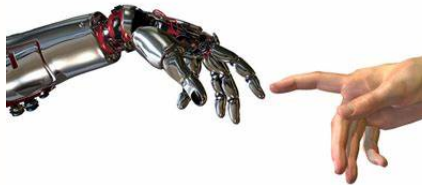
- How is AI used in practice?

Case Studies:
Uber
Zebra
Miroglio Fashion
Guest Speaker?

Module C: AI in Business + Society

- How is AI used in practice?
- What are the skills and resources required to implement?

Case Studies:
Uber
Zebra
Miroglio Fashion
Guest Speaker?

Module C: AI in Business + Society

- How is AI used in practice?
- What are the skills and resources required to implement?
- What strategic and operational decisions do firms face in making AI choices?

Case Studies:
Uber
Zebra
Miroglio Fashion
Guest Speaker?

Module C: AI in Business + Society

- How is AI used in practice?

- What are the skills and resources required to implement?

- What strategic and operational decisions do firms face in making AI choices?

- How do AI projects integrate within the organization?

Case Studies:
Uber
Zebra
Miroglio Fashion
Guest Speaker?

Module C: AI in Business + Society

- How is AI used in practice?

- What are the skills and resources required to implement?

- What strategic and operational decisions do firms face in making AI choices?

- How do AI projects integrate within the organization?

- What are the biggest challenges and risks firms face in deploying AI?
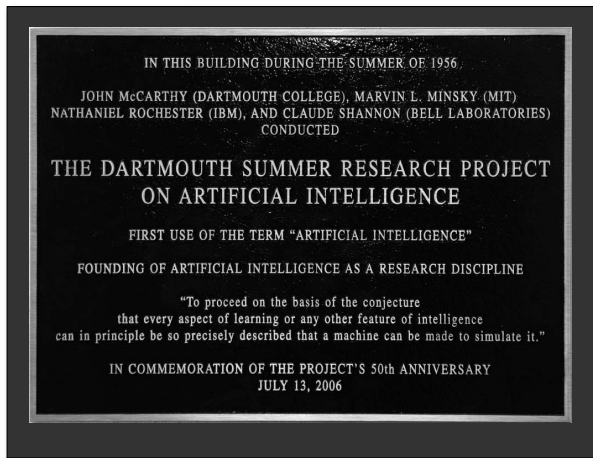
Case Studies:
Uber
Zebra
Miroglio Fashion
Guest Speaker?

Historical Overview

IN THIS BUILDING DURING THE SUMMER OF 1956

JOHN McCARTHY (DARTMOUTH COLLEGE), MARVIN L. MINSKY (MIT)
NATHANIEL ROCHESTER (IBM), AND CLAUDE SHANNON (BELL LABORATORIES)
CONDUCTED

THE DARTMOUTH SUMMER RESEARCH PROJECT
ON ARTIFICIAL INTELLIGENCE

FIRST USE OF THE TERM "ARTIFICIAL INTELLIGENCE"

FOUNDING OF ARTIFICIAL INTELLIGENCE AS A RESEARCH DISCIPLINE

"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."

IN COMMEMORATION OF THE PROJECT'S 50th ANNIVERSARY
JULY 13, 2006

Photographer: Joe Mehling

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

History of AI

Source: https://pixelspark.nl/2019/
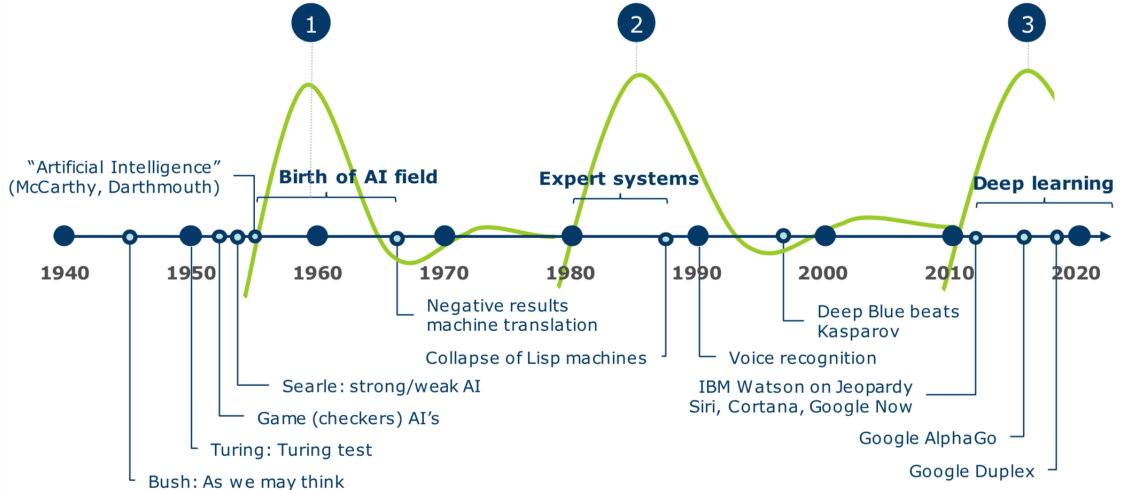
Humans and Machines
Context for Turing

- 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

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.
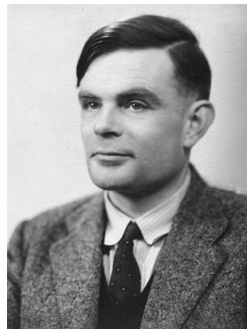
Turing's Test

In Turing's time, a parlor game:

- Consider 3 people: a man (M) and woman (W) and an interrogator / questioner (Q) in different rooms

Turing's Test

In Turing's time, a parlor game:

- Consider 3 people: a man (M) and woman (W) and an interrogator / questioner (Q) in different rooms
- (Q) wants to identify who is (M) and who is (W)

Turing's Test

In Turing's time, a parlor game:

- Consider 3 people: a man (M) and woman (W) and an interrogator / questioner (Q) in different rooms
- (Q) wants to identify who is (M) and who is (W)
- Only written communications can be passed from one person to another (nothing else)

Turing's Test

In Turing's time, a parlor game:

- Consider 3 people: a man (M) and woman (W) and an interrogator / questioner (Q) in different rooms
- (Q) wants to identify who is (M) and who is (W)
- Only written communications can be passed from one person to another (nothing else)
- (M) aims to fool (Q) while (W) tries to help (Q)

Turing's Test

In Turing's time, a parlor game:

- Consider 3 people: a man (M) and woman (W) and an interrogator / questioner (Q) in different rooms
- (Q) wants to identify who is (M) and who is (W)
- Only written communications can be passed from one person to another (nothing else)
- (M) aims to fool (Q) while (W) tries to help (Q)

Turing's Test

In Turing's time, a parlor game:

- Consider 3 people: a man (M) and woman (W) and an interrogator / questioner (Q) in different rooms
- (Q) wants to identify who is (M) and who is (W)
- Only written communications can be passed from one person to another (nothing else)
- (M) aims to fool (Q) while (W) tries to help (Q)

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:

If the computer (C) can fool the interrogator (Q) into thinking it is human, then it is said to possess **"Artificial Intelligence"**

(Simplified) Turing's Test

Turing suggests:

If the computer (C) can fool the interrogator (Q) into thinking it is human, then it is said to possess **"Artificial Intelligence"**

General idea for AI is to achieve human-level intelligence

Types of AI
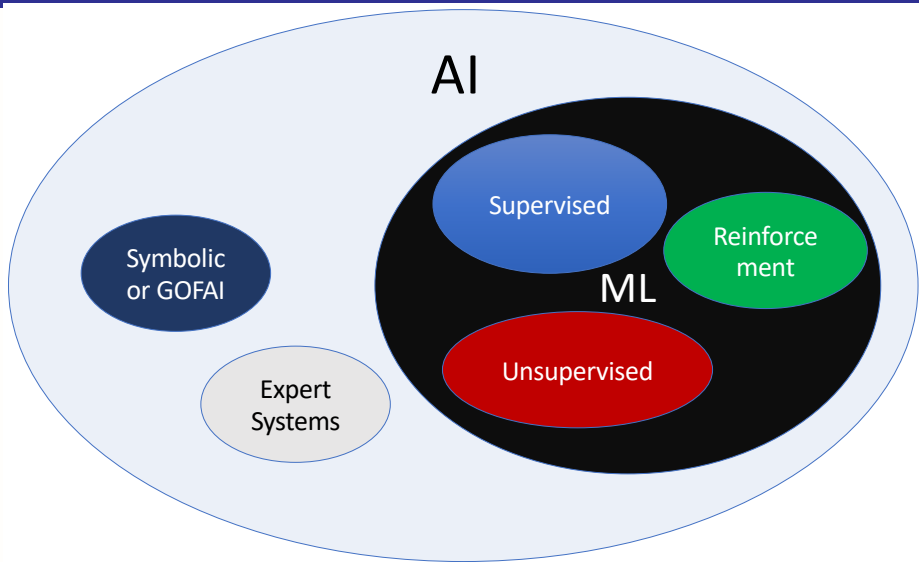
GOFAI
Good Old Fashioned AI

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

GOFAI
Good Old Fashioned AI

- Classical / Symbolic AI (Newell & Simon, 1970s)
- Intelligence is encoded using symbols

GOFAI
Good Old Fashioned AI

- Classical / Symbolic AI (Newell & Simon, 1970s)
- Intelligence is encoded using symbols
- Idea: Thoughts might be similar to language (which can be encoded)

GOFAI

Good Old Fashioned AI

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

GOFAI
Good Old Fashioned AI

- Classical / Symbolic AI (Newell & Simon, 1970s)
- 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
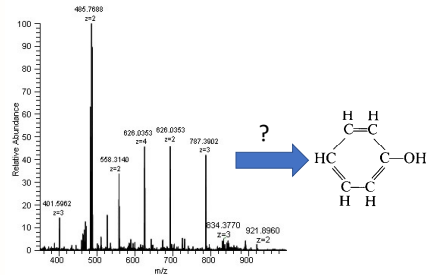- (-) Typically suitable for small or toy problems

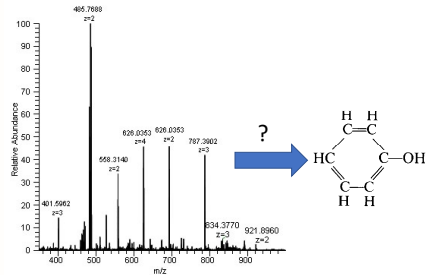- "Solve problems within a specialized domain that ordinarily requires human expertise"
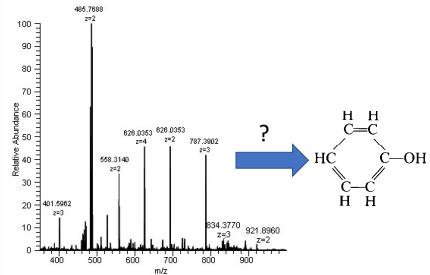
Expert Systems

- "Solve problems within a specialized domain that ordinarily requires human expertise"
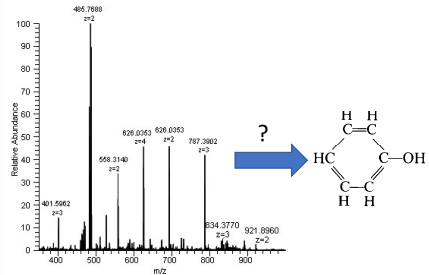- Human expert trains the expert system, gives it a task-specific knowledge base

Expert Systems

- "Solve problems within a specialized domain that ordinarily requires human expertise"
- Human expert trains the expert system, gives it a task-specific knowledge base
- Key distinction is it is rule based (can be probabilistic)

Expert Systems

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

- Human expert trains the expert system, gives it a task-specific knowledge base

- Key distinction is it is rule based (can be probabilistic)

- First application: Use mass spectrometry for *structure elucidation in chemistry*

Expert Systems

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

- Human expert trains the expert system, gives it a task-specific knowledge base

- Key distinction is it is rule based (can be probabilistic)

- First application: Use mass spectrometry for *structure elucidation in chemistry*

- Other applications in disease diagnosis (e.g. glaucoma), fraud detection etc.
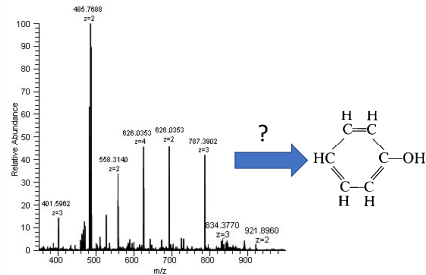
Definitions: AI and ML

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?

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)
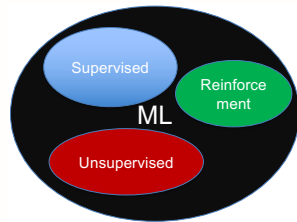
Machine Learning

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

- "Improve over Task T with resect to some performance measure P based on experience E" (Tom Mitchell)
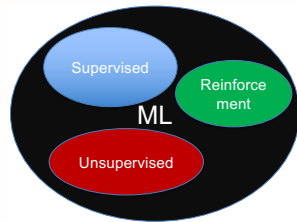
What's the difference?

Differences between ML and other AI approaches

- ML primarily is "learning from data"
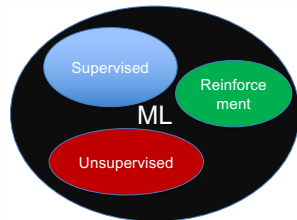
Differences between ML and other AI approaches

- ML primarily is "learning from data"
- Human domain knowledge is *not* required or even expected

Differences between ML and other AI approaches

- ML primarily is "learning from data"
- Human domain knowledge is *not* required or even expected
- Same algorithm can be used for very different applications (e.g. cancer detection or astronomy or cats /dogs)

Differences between ML and other AI approaches

- ML primarily is "learning from data"
- Human domain knowledge is *not* required or even expected
- Same algorithm can be used for very different applications (e.g. cancer detection or astronomy or cats /dogs)
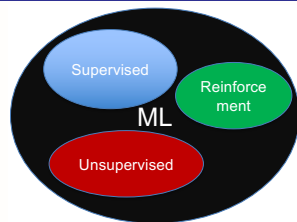- Since 2010+ ML, especially Deep Learning, has dominated other approaches when measured by accuracy

Differences between ML and other AI approaches

- ML primarily is "learning from data"
- Human domain knowledge is *not* required or even expected
- Same algorithm can be used for very different applications (e.g. cancer detection or astronomy or cats /dogs)
- Since 2010+ ML, especially Deep Learning, has dominated other approaches when measured by accuracy

Differences between ML and other AI approaches

- ML primarily is "learning from data"
- Human domain knowledge is *not* required or even expected
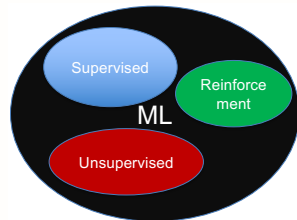- Same algorithm can be used for very different applications (e.g. cancer detection or astronomy or cats /dogs)
- Since 2010+ ML, especially Deep Learning, has dominated other approaches when measured by accuracy
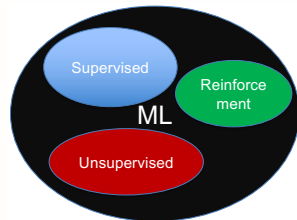

Rest of the course will focus on ML (use interchangeably with AI)

Supervised Learning

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

Supervised Learning

- Trying to predict some variable y based on other data X
- y: label / target / output / dependent variable

Supervised Learning

- Trying to predict some variable y based on other data X
- y: label / target / output / dependent variable
- X: predictor, covariate, explanatory variable

Supervised Learning

- Trying to predict some variable y based on other data X
- y: label / target / output / dependent variable
- X: predictor, covariate, explanatory variable
- Represent this as $\boxed{y = f(X)}$

Supervised Learning

- Trying to predict some variable y based on other data X
- y: label / target / output / dependent variable
- X: predictor, covariate, explanatory variable
- Represent this as $\boxed{y = f(X)}$
- Do Humans learn like this?

Supervised Learning

- Trying to predict some variable y based on other data X
- y: label / target / output / dependent variable
- X: predictor, covariate, explanatory variable
- Represent this as $\boxed{y = f(X)}$
- Do Humans learn like this?

Supervised Learning

- Trying to predict some variable y based on other data X
- y: label / target / output / dependent variable
- X: predictor, covariate, explanatory variable
- Represent this as $\boxed{y = f(X)}$
- Do Humans learn like this?

Most commonly used form of ML in practice

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

Unsupervised Learning

- Trying to identify patterns in the data

Unsupervised Learning

- Trying to identify patterns in the data
- We do not have a output label y only X variables

Unsupervised Learning

- Trying to identify patterns in the data
- We do not have a output label y only X variables
- Cannot represent this as with structured learning

Unsupervised Learning

- Trying to identify patterns in the data
- We do not have a output label y only X variables
- Cannot represent this as with structured learning
- Not trying to make any prediction here

Unsupervised Learning

- Trying to identify patterns in the data
- We do not have a output label y only X variables
- Cannot represent this as with structured learning
- Not trying to make any prediction here

Unsupervised Learning

- Trying to identify patterns in the data
- We do not have a output label y only X variables
- Cannot represent this as with structured learning
- Not trying to make any prediction here

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

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

Reinforcement Learning

- Learn how to make good "sequence of decisions" under uncertainty
- Formalizes the model of how humans do "trial and error" or "exploration / exploitation"

Reinforcement Learning

- Learn how to make good "sequence of decisions" under uncertainty
- Formalizes the model of how humans do "trial and error" or "exploration / exploitation"
  - But do it optimally

Reinforcement Learning

- Learn how to make good "sequence of decisions" under uncertainty
- Formalizes the model of how humans do "trial and error" or "exploration / exploitation"
  - But do it optimally
- Acquires knowledge through experience

Reinforcement Learning

- Learn how to make good "sequence of decisions" under uncertainty
- Formalizes the model of how humans do "trial and error" or "exploration / exploitation"
  - But do it optimally
- Acquires knowledge through experience
- Don't need any initial data, but need rules and rewards

Reinforcement Learning

- Learn how to make good "sequence of decisions" under uncertainty
- Formalizes the model of how humans do "trial and error" or "exploration / exploitation"
  - But do it optimally
- Acquires knowledge through experience
- Don't need any initial data, but need rules and rewards
- Can generate its own data by exploration

Reinforcement Learning

- Learn how to make good "sequence of decisions" under uncertainty
- Formalizes the model of how humans do "trial and error" or "exploration / exploitation"
  - But do it optimally
- Acquires knowledge through experience
- Don't need any initial data, but need rules and rewards
- Can generate its own data by exploration

Reinforcement Learning

- Learn how to make good "sequence of decisions" under uncertainty
- Formalizes the model of how humans do "trial and error" or "exploration / exploitation"
  - But do it optimally
- Acquires knowledge through experience
- Don't need any initial data, but need rules and rewards
- Can generate its own data by exploration

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.
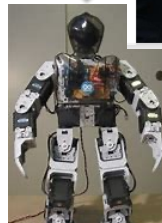
Why AI Now?

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

- ⇑ Systems with Available Data (Internet, Mobile devices, IoT)

Why AI Now?

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

- ⇑ Systems with Available Data (Internet, Mobile devices, IoT)

- Big Data: Volume, Velocity, Variety, Variation

Why AI Now?

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

- ⇑ Systems with Available Data (Internet, Mobile devices, IoT)

- Big Data: Volume, Velocity, Variety, Variation

- Unstructured Data is especially new-ish

Why AI Now?

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

- ⇑ Systems with Available Data (Internet, Mobile devices, IoT)

- Big Data: Volume, Velocity, Variety, Variation

- Unstructured Data is especially new-ish

- Algorithm Development (especially Deep Learning)

Why AI Now?

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

- ⇑ Systems with Available Data (Internet, Mobile devices, IoT)

- Big Data: Volume, Velocity, Variety, Variation

- Unstructured Data is especially new-ish

- Algorithm Development (especially Deep Learning)

- Computational Advances (from GPUs)

Why AI Now?

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

- ⇑ Systems with Available Data (Internet, Mobile devices, IoT)

- Big Data: Volume, Velocity, Variety, Variation

- Unstructured Data is especially new-ish

- Algorithm Development (especially Deep Learning)

- Computational Advances (from GPUs)
  - 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*

THE BUSINESS BENEFITS OF AI

We surveyed 250 executives who were familiar with their companies'
use of cognitive technologies to learn about their goals for AI
initiatives. More than half said their primary goal was to make existing
products better. Reducing head count was mentioned by only 22%.

PERCENTAGE OF EXECUTIVES WHO CITE
THE FOLLOWING AS BENEFITS OF AI

ENHANCE THE FEATURES, FUNCTIONS, AND PERFORMANCE OF OUR PRODUCTS	51%
MAKE BETTER DECISIONS	35%
CREATE NEW PRODUCTS	32%
OPTIMIZE INTERNAL BUSINESS OPERATIONS	36%
FREE UP WORKERS TO BE MORE CREATIVE BY AUTOMATING TASKS	36%
PURSUE NEW MARKETS	25%
CAPTURE AND APPLY SCARCE KNOWLEDGE WHERE NEEDED	25%
OPTIMIZE EXTERNAL PROCESSES LIKE MARKETING AND SALES	30%
REDUCE HEAD COUNT THROUGH AUTOMATION	22%

SOURCE DELOITTE 2017

Summary & Takeaways

- AI not a new technology, has been around for some time

Summary & Takeaways

- AI not a new technology, has been around for some time
- Recent trends in algorithms, data and computing have converged to make AI more valuable

Summary & Takeaways

- AI not a new technology, has been around for some time
- Recent trends in algorithms, data and computing have converged to make AI more valuable
- Currently AI ≈ ML, since classical AI not as common

Summary & Takeaways

- AI not a new technology, has been around for some time
- Recent trends in algorithms, data and computing have converged to make AI more valuable
- Currently AI ≈ ML, since classical AI not as common
- ML is focused on prediction and "learning from data" using many different methods

Summary & Takeaways

- AI not a new technology, has been around for some time
- Recent trends in algorithms, data and computing have converged to make AI more valuable
- Currently AI $\approx$ ML, since classical AI not as common
- ML is focused on prediction and "learning from data" using many different methods
- ML: Supervised, Unsupervised and Reinforcement (Next 2 classes)

Summary & Takeaways

- AI not a new technology, has been around for some time
- Recent trends in algorithms, data and computing have converged to make AI more valuable
- Currently AI $\approx$ ML, since classical AI not as common
- ML is focused on prediction and "learning from data" using many different methods
- ML: Supervised, Unsupervised and Reinforcement (Next 2 classes)
  - Designed to answer different types of questions, data different

Summary & Takeaways

- AI not a new technology, has been around for some time
- Recent trends in algorithms, data and computing have converged to make AI more valuable
- Currently AI $\approx$ ML, since classical AI not as common
- ML is focused on prediction and "learning from data" using many different methods
- ML: Supervised, Unsupervised and Reinforcement (Next 2 classes)
  - Designed to answer different types of questions, data different
- Integrating Prediction with decision making can be challenging (Module 2)

Summary & Takeaways

- AI not a new technology, has been around for some time
- Recent trends in algorithms, data and computing have converged to make AI more valuable
- Currently AI $\approx$ ML, since classical AI not as common
- ML is focused on prediction and "learning from data" using many different methods
- ML: Supervised, Unsupervised and Reinforcement (Next 2 classes)
  - Designed to answer different types of questions, data different
- 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
- Link to Code: `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.*