UNIVERSITY OF MARYLAND

MSML610: Advanced Machine Learning

Introduction

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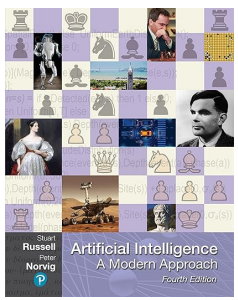
References:

- AIMA: Chap 1



- ***What Is Artificial Intelligence***
  - AI
  - Machine Learning
  - A Map of Machine Learning
  - AI vs ML vs Deep-Learning
  - The Foundations of AI
  - Brief History of AI
  - Risks and Benefits of AI

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ML, AI, and Intelligence

- Machine Learning is a subset of AI
  - All of it confused with deep learning, large-language models, predictive analytics, ...
- What is artificial intelligence?
- What is intelligence?

Human Intelligence

- We call ourselves "homo sapiens" because intelligence sets us apart from animals
- For thousands of years, we tried to understand how we think
- One of the biggest mysteries
  - Brain is a small mass of matter
  - Our brain can understand nature secrets, e.g., theory of relativity, quantum mechanics, black holes in the universe
  - How can brain understand, predict, and manipulate a world more complicated than itself?

Artificial Intelligence

- The term "Artificial Intelligence" was coined in 1956
- **AI aims to:**
  - Understand human intelligence
  - Create intelligent entities
  - *"What I cannot create, I do not understand"* (Feynman, 1988)
- **AI is a technology**
  - Universal and applicable to any human activity and task
  - Its impact greater than any previous historical event
  - Currently generates trillions of dollars annually in revenue
  - Presents many unresolved problems
    - E.g., major concepts in physics might be established

AI Formal Definition

- AI is defined around **two axes**:
  - Thinking vs. Acting
  - Human vs. Rational (ideal performance)
- Four possible definitions of AI as a machine that can:
  1. Think humanly
  2. Think rationally
  3. Act humanly
  4. Act rationally
- **Q**: Which one do you think is the best definition?

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- We will see that building machines that can **"act rationally"** should be ultimate goal of AI

1. AI as Thinking Humanly

- To build machines that think like humans we need to **determine how humans think**
- **Pros**
  - Express precise theory of the human mind as a computer program
- **Cons**
  - Unknown workings of the human mind
  - Anthropocentric definition

2. AI as Thinking Rationally

- What are the rules of **correct thinking**?
  - Given correct premises, yield correct conclusions
- **Logic** studies the "laws of thought"
  - Formalize statements about objects and their relations
- **Automatic theorem proving**
  - Programs solve problems in logical notation
  - Run indefinitely if no solution exists (related to the halting problem)

Thinking Rationally: Cons

1. **Formalizing informal knowledge is difficult**
   - Example: *"A handshake occurs when two people extend, grip, shake hands, then release."*
   - Formal logic representation:

$$\begin{aligned}\exists x, y\, (&\text{Person}(x) \land \text{Person}(y) \land x \neq y \land \\ &\text{Hand}(x, h_x) \land \text{Hand}(y, h_y) \land \\ &\text{MoveToward}(h_x, h_y) \land \text{Contact}(h_x, h_y) \land \\ &\text{Shake}(h_x, h_y) \land \\ &\text{Release}(h_x, h_y))\end{aligned}$$

2. **Probabilistic nature of knowledge**
   - Example in medicine: *"Fever, cough, and fatigue could indicate flu, COVID-19, or another illness."*
3. **Scalability challenges**
   - Large problems may need heuristics for practical solutions
4. **Intelligence requires more than rational thinking**
   - Importance of agent interaction with the world
   - Problem of the "body"

3. AI as Acting Humanly

- **Agent** is something that perceives and acts to reach a goal
- **Definition**: AI designs **agents that can act like humans**
- **Turing test**
  - *"A computer passes the Turing test if a human cannot tell whether the answers to questions came from a person or a computer"*
- Passing the (embodied) Turing test requires:
  1. Natural language processing to communicate
  2. Knowledge representation to store information
  3. Automated reasoning to use stored knowledge and answer questions
  4. Machine learning to detect patterns
  5. Computer vision and speech recognition to perceive objects and understand speech
  6. Robotics to manipulate objects and move

Turing Test: Pros and Cons

- **Pros**
  - Operational definition of intelligence
  - Sidestep philosophical vagueness
    - "What is consciousness?"
    - "Can a machine think?"
    - ...
- **Cons**
  - **Anthropomorphic** criteria define intelligence in human terms
    - Multiple forms of non-human intelligence exist
  - Intelligence in terms of Turing test is **fooling humans** into thinking it's human
  - E.g., aeronautical engineering is about:
    - Yes: Focus on wind tunnels and aerodynamics
    - No: Designing machines that imitate birds

4. AI as Acting Rationally

- **Rational agents**: agents that do the "right thing" given what they know
- Agents that **act rationally** should:
  1. Operate autonomously
  2. Perceive environment
  3. Persist over a prolonged time period
  4. Adapt to change
  5. Create and pursue goals

Acting Rationally as Ultimate Goal of AI

- Which definition of AI to use?
  - Acting vs. Thinking
  - Rational vs. Human

Acting Rationally as Ultimate Goal of AI

- Which definition of AI to use?
  - Acting vs. Thinking
  - Rational vs. Human
- **Acting > Thinking**
  - Acting rationally is broader than just thinking rationally
- **Rational > Human**
  - Rationality can be mathematically defined
  - Human behavior is shaped by evolutionary conditions
- AI focuses on **agents acting rationally**

Rationally is Not Absolute

- AI wants to build agents that **do the right thing**
  - What is the right thing?

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- E.g., you cross the street and a car knocks you over
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  - It depends, but probably no
- E.g., moral issues with self-driving car
  - Swerve and hit a pedestrian to avoid a frontal crash that would kill 2 people

Problems of a Rational Agent

- **Probabilistic environment**
  - A rational agent aims for:
    - The best outcome in a deterministic setup
    - The best expected outcome under uncertainty
- **Best** is determined by the objective function:
  - E.g., cost function, sum of rewards, loss function, utility
- Omniscience vs **no-regrets**
  - Best based on available information
- Sometimes **no provably correct action** exists
  - Yet, an action must be taken
- Even **with perfect information** rationality can't be feasible due to:
  - Cost of acquiring all data (e.g., in medicine)
  - Computational demands
- Perfect good enough vs perfect
  - Acting appropriately ("satisficing")

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Machine Learning: Definitions

- How to define machine learning?
- *"Machine learning is the field of study that gives computers the ability to learn without being explicitly programmed"* (Samuel, 1959)
- **Machine learning** is about building machines to do **useful things** without being **explicitly programmed**
  - E.g. a computer learns to play checkers by playing against itself, memorizing positions that lead to winning
- *"A computer program is said to learn from experience E with respect to some task T and some performance measure P, if $P(T)$ improves with experience E"* (Mitchell, 1998)
- E.g.,
  - Computer vision
  - Speech recognition
  - Natural language processing

Limits of ML Compared to Human Intelligence

- **AI differs from human intelligence**
  - Machines don't learn like humans (e.g., LLMs)

Limits of ML Compared to Human Intelligence

- **AI differs from human intelligence**
  - Machines don't learn like humans (e.g., LLMs)
- **Fragility to input variations**
  - ML models fail with slight input distortions
    - Adversarial attacks cause misclassification by altering one pixel
    - A model trained for a video game may fail if the screen is slightly rotated; humans continue effortlessly
- **Lack of transfer learning**
  - ML systems cannot apply knowledge across domains without retraining
- **Massive data and compute requirements**
  - ML requires enormous datasets and computational resources
    - A teenager learns to drive in hours
    - Self-driving systems need billions of compute hours and extensive data
- **Poor common sense and reasoning**
  - ML lacks built-in world knowledge and intuitive logic

Limits of ML Compared to Human Intelligence

- **Opaque decision-making**
  - Many ML models offer little transparency into decision processes
    - Limits trust, interpretability, and accountability in critical applications
- **Dependence on narrow objectives**
  - ML systems excel at optimizing narrow tasks but fail with ambiguous goals
    - E.g., an algorithm maximizing user engagement may promote harmful content
- **Susceptibility to bias and data quality**
  - Models inherit and amplify biases in training data
- **Lack of embodiment and physical interaction**
  - Human cognition is grounded in physical and sensory experience

The 3 Machine Learning Assumptions

- In practice, ML involves solving a practical problem by:
  - Gathering a dataset
  - Building a statistical model from the dataset algorithmically
- The **three assumptions** of machine learning
  - A **pattern exists**
  - Pattern cannot be **precisely defined mathematically**
  - **Data is available**
- Which ML assumption is **essential**?

The 3 Machine Learning Assumptions

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  - A **pattern exists**
  - Pattern cannot be **precisely defined mathematically**
  - **Data is available**
- Which ML assumption is **essential**?
  - A pattern exists
    - If no pattern, try learning, measure effectiveness, conclude it doesn't work
  - Pattern cannot be precisely defined mathematically
    - If solution is direct, ML not recommended, but may still apply
  - Data is available
    - Without data, no progress can be made
    - **Data is crucial**

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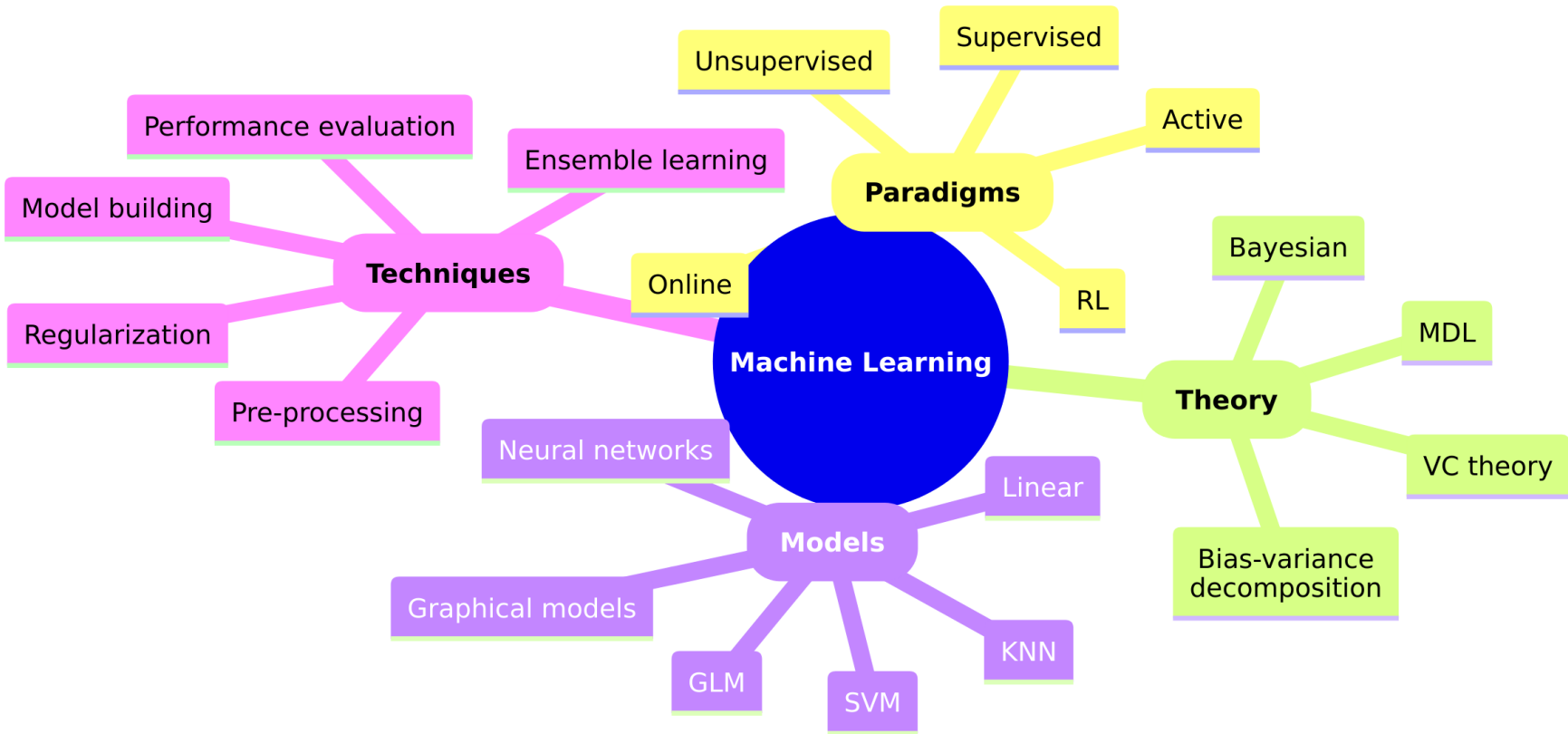
A Map of Machine Learning

- Machine Learning is a field with many branches
  - Paradigms
  - Theory
  - Models
  - Techniques
  - ...



Machine Learning Paradigms

- How do you set up the learning problem?
  - **Supervised learning**
    - The dataset includes inputs with corresponding outputs
    - Develop an input-output relationship
  - **Unsupervised learning**
    - The data is unlabeled, discover structure within the data
    - E.g., anomaly detection, clustering
  - **Reinforcement learning**
    - The correct answer is not immediately available
    - Evaluate actions based on final outcomes
  - **Active learning**
    - Not all examples are available initially
    - Request outputs for specific inputs
  - ...

Machine Learning Theory

- **VC theory**
  - Measure model capacity and generalize based on hypothesis space complexity
- **Bias-variance decomposition**
  - Prediction error is the sum of:
    - Bias: Error from simplistic model assumptions
    - Variance: Error due to sensitivity to training data fluctuations
- **Computation complexity**
  - Related to information theory and compression
  - E.g., Minimum Description Length (MDL) measures model complexity via efficient model and data description
- **Bayesian approach**
  - Treat ML as probability
  - Combine prior knowledge with observed data to update belief about a model
- **Problem in ML theory**
  - Assumptions may not align with practical problems

Machine Learning Models

- What is the form of the model and how to fit / predict from the data?
  - Linear models
  - Generalized linear models
    - E.g., logistic, Poisson regression
  - Support Vector Machines (SVM)
  - Nearest neighbors
    - E.g., k-means clustering, KNN
  - Gaussian processes
  - Graphical models
    - Model joint distributions with graphs
    - E.g., hidden Markov models (HMM), Kalman filters, Bayesian networks
  - Neural networks
  - ...

Machine Learning Techniques

- What are the stages of a ML pipeline?
  - **Input processing**
    - Data cleaning
    - Dimensionality reduction
    - Feature engineering
  - **Model building**
    - Models
    - Learning algorithms
  - **Performance evaluation**
    - Cross-validation
    - Bias-variance curves
    - Learning curves
  - **Regularization**
  - **Aggregation**
    - Boosting
    - Bagging
    - Stacking

Machine Learning Adages

- *"An explanation of the data should be as simple as possible, but not simpler"* (Einstein)
- *"The simplest model that fits the data is also the most plausible"* (Occam's razor)
- *"Garbage in, garbage out"* (Fuechse, 1957)
- *"All models are wrong, but some are useful"* (George E. P. Box, 1976)
- *"If you torture the data long enough it will confess whatever you want"* (Coase, 1982)
- *"Data is the new oil"* (Humby, 2006)
- *"More data beats clever algorithms"* (Norvig, ~2006)
- *"The unreasonable effectiveness of data"* (Halevy, Norvig, Pereira, 2009)

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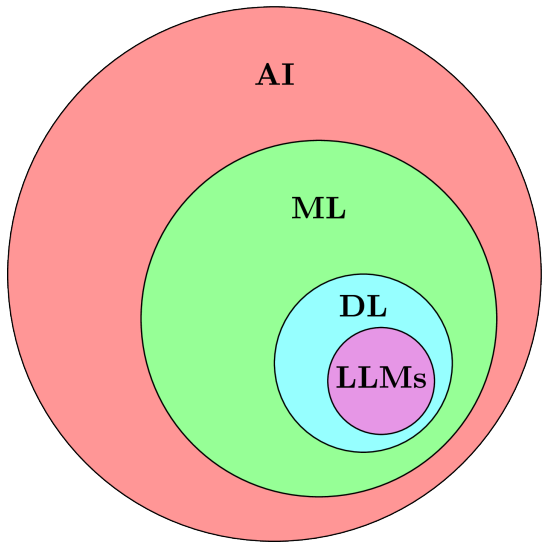
AI vs ML vs Deep-Learning

- **AI**
  - Machines programmed to reason, learn, and act in a rational way
- **ML**
  - Machines capable of performing tasks without being explicitly programmed
- **AI without ML**:
  - Example: Rule-based systems (e.g., IBM Deep Blue playing chess)
- **Deep Learning (DL)**
  - ML using neural networks with multiple layers
  - Example: Autonomous vehicles
- **Large Language Models (LLM)**
  - Neural networks trained on massive text datasets and RLHS



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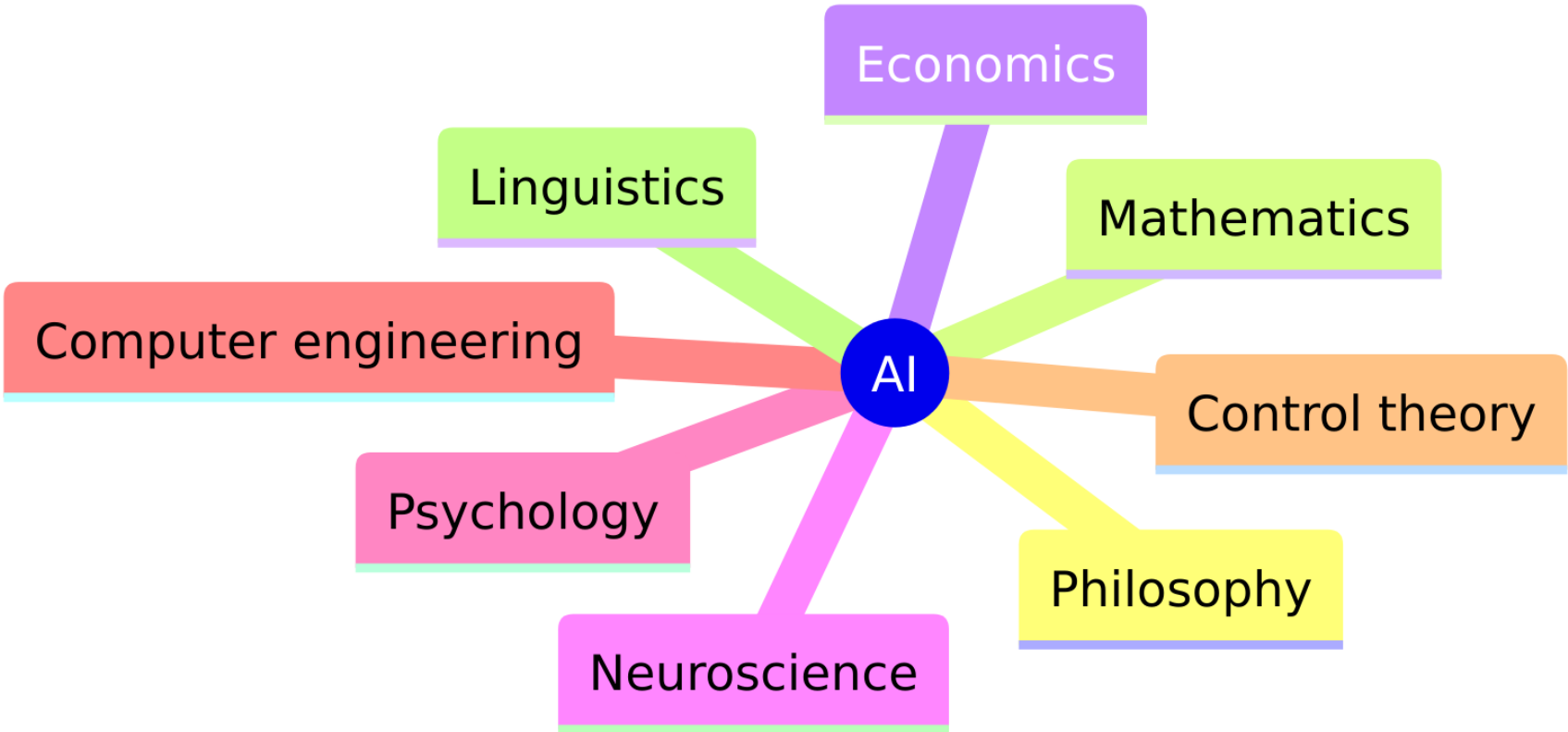
AI Relates to Many Other Disciplines



AI and Philosophy (1/2)

- **Can formal rules be used to draw valid conclusions?**
  - **Reasoning**
    - Logic studies rules of proper reasoning
    - Aristotle (400 BCE) formulated laws governing the rational mind
    - Machines were built for arithmetic operations (e.g., Pascaline, 1600)
  - **Rationalism**
    - Use reasoning to understand the world
- **How does the mind arise from a physical brain?**
  - **Dualism**
    - Nature follows physical laws
    - Part of the human mind ("the soul") is exempt from physical laws
  - **Materialism**
    - The mind is a physical system, following the laws of physics
    - Where is free will? Free will is the perception of available choices

AI and Philosophy (2/2)

- **What does knowledge come from?**
  - **Empiricism**
    - Knowledge acquired via senses
    - E.g., learn that trees are green by looking at them
  - **Induction**
    - General rules from associations
    - E.g., many swans are white, infer all swans are white
  - **Logical Positivism**
    - Knowledge as logical theories linked to observations
    - E.g., scientific hypotheses connected to experimental data
- **How does knowledge lead to action?**
  - **Utilitarianism**
    - Actions justified by logic connecting goals and outcomes
  - **Consequentialism**
    - Right or wrong determined by action's expected outcomes
    - E.g., "If you kill, you will go to jail"
  - **Deontological ethics**
    - "Right actions" based on universal laws, not outcomes
    - E.g., "don't kill", "don't lie"

AI and Cognitive Psychology

- **How do humans think and act?**
  - **Cognitive psychology**
    - Brain is an information-processing device
    - Stimuli translated into internal representation
    - Representation manipulated by cognitive processes to derive new internal representations ("beliefs")
    - Representations turned into actions ("goals")
  - **Cognitive science**
    - Use computer models to address memory, language, and logic thinking
    - Dual / opposite of AI
  - **Human-computer interaction**
    - Computers augment human abilities
    - From artificial intelligence (AI) to intelligence augmentation (IA)

AI and Mathematics

- **What are the formal rules to draw valid conclusions?**
  - **Formal logic**
    - Logical deduction rules (Boole, 1850)
    - First-order logic includes objects and relations (Frege, 1879)
  - **Limits to deduction**
    - Some statements are "undecidable"
    - Incompleteness theorem: in any formal theory true statements exist that cannot be proved (Godel, 1931)
- **How do we reason with uncertain information?**
  - **Probability**
    - Mathematics of uncertainty
    - Cardano, Pascal, Bernoulli, Bayes (1500-1700)
  - **Statistics**
    - Combines data with probability
    - E.g., experiment design, data analysis, hypothesis testing, asymptotics

AI and Economics (1/2)

- **How to make decisions to maximize payoff given preferences?**
  - **Economies**
    - Agents maximize economic well-being (utility)
    - Studies desires and preferences
  - **Decision theory**
    - Making decisions under uncertainty for preferred outcomes
    - Probability theory + utility theory
    - E.g., investment choices, policy decisions
- **How to make decisions when payoffs are result of several actions?**
  - **Operations research**
    - Make rational decisions with payoffs for sequence of actions (Bellman, 1957)
    - E.g., Markov Decision Processes
  - **Satisficing**
    - Decisions that are good enough
    - Closer to human behavior
    - E.g., choosing a restaurant that meets basic criteria rather than finding the perfect one

AI and Economics (2/2)

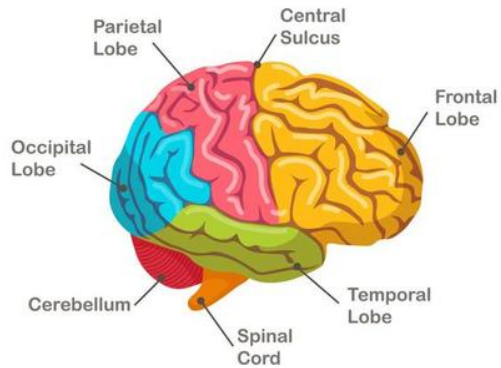
- **How multiple agents with different goals act?**
  - **Large economies**
    - Many agents with no mutual impact
    - Ignore other agents' actions
    - E.g., national economy where individual actions don't affect market
  - **Small economies**
    - One player's actions influence others' utility
    - E.g., local market where one seller's pricing affects competitors
  - **Game theory**
    - Small economies resemble a "game" (Von Neumann, 1944)
    - Rational agents might need randomized strategies
    - E.g., rock-paper-scissors where randomization prevents predictability

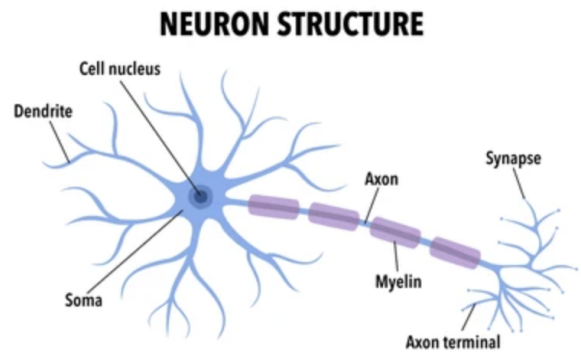
AI and Linguistics

- **How can you create systems that understand natural language?**
  - **Computational linguistics** (NLP)
    - Studies sentence structure and meaning
    - Machine translation (e.g., Google Translate)
    - Sentiment analysis in social media
    - Automated customer support chatbots
- **How does language relate to thought?**
  - **Knowledge representation**
    - How to represent knowledge for computer reasoning
    - E.g., first order knowledge, knowledge graphs

AI and Neuroscience

- **Brain**
  - Parts handle specific cognitive functions
  - Information processing in the cerebral cortex
  - E.g., frontal lobe injury may impair decision-making
- **Anatomy of the brain**
  - Composed of ~100 billion neurons
    - Each neuron connects with 10-100k others via synapses
    - Axons enable long-range connections
  - Signals propagate through electrochemical reactions
  - Short-term pathways support long-term connections (learning)
- **Memory**
  - No theory yet about individual memory storage
  - Current theory: memories reconstructed





The Brain Causes the Mind

- **Simple cells lead to thought and consciousness**
  - **Truly amazing!**
  - Complex processes emerge
- Supercomputers' complexity rivals the brain
- **Brain-machine interface**
  - Brain adjusts to devices
  - E.g., learn to use prosthetics as limbs
- **AI singularity**
  - Future point when AI surpasses human intelligence
    - AI improves autonomously, leading to rapid growth
    - Recursive self-improvement leads to superintelligence
  - Potential societal impact
    - Control problem/value alignment: ensure AI aligns with human values
    - Economic/social disruption due to automation
  - Achieving brain's intelligence level remains unknown

AI and Computer Science

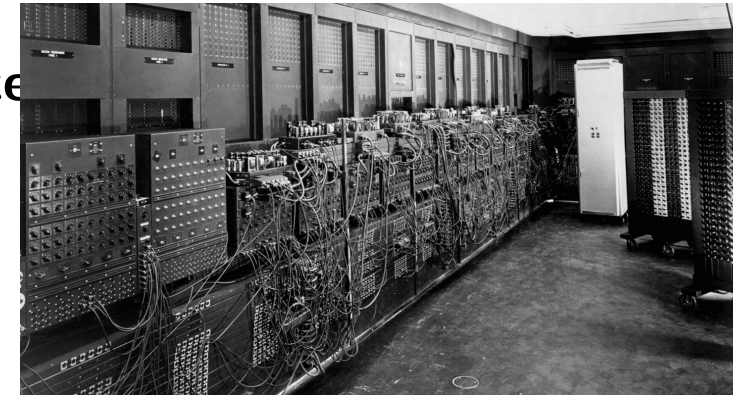
- **What can be computed?**
  - **Algorithm**
    - Procedure to solve problems
    - E.g., algorithm for computing GCD (Euclid, 300 BCE)
  - **Limits to computation**
    - Turing machine (1936): computes any computable function
    - Some functions are non-computable
    - E.g., the halting problem, i.e., decide if a program terminates
  - **Tractability**
    - Complexity classes: polynomial vs exponential complexity
    - Problem is intractable if solving time grows exponentially with size
    - P vs NP

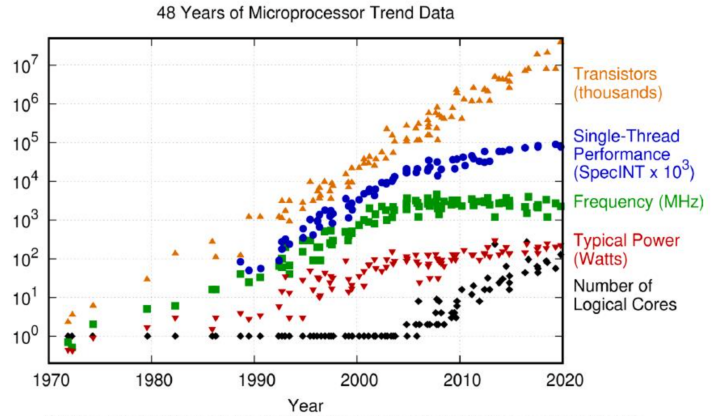
AI and Control Theory

- **How can artifacts operate under their own control?**
  - **Control theory**
    - Study self-regulating feedback control systems
    - E.g., a water regulator that maintains a constant water flow
    - Mechanisms to minimize error between current and goal states
    - Kalman Filter (Kalman, 1960)
    - Based on calculus, matrix, stochastic optimal control
    - AI: logical inference, symbolic planning, computation

AI and Computer Engineering

- **How can we build an efficient compute**
  - **Electronic computers**
    - Built during World War II
  - **Moore's Law**
    - Performance doubled every 18 months (1970-2005)
    - Power and scaling issues shifted focus to multi-core over clock speed
  - **Hardware for AI**
    - GPUs
    - TPUs
    - Wafer-scale engines
  - **Current Trends**
    - Massive parallelism (like brain function)
    - Computing power doubling every 3 months
    - GPUs / TPUs used in deep learning
    - High precision (e.g., 64b) often unnecessary
  - **Quantum Computing**





CPU GPU TPU

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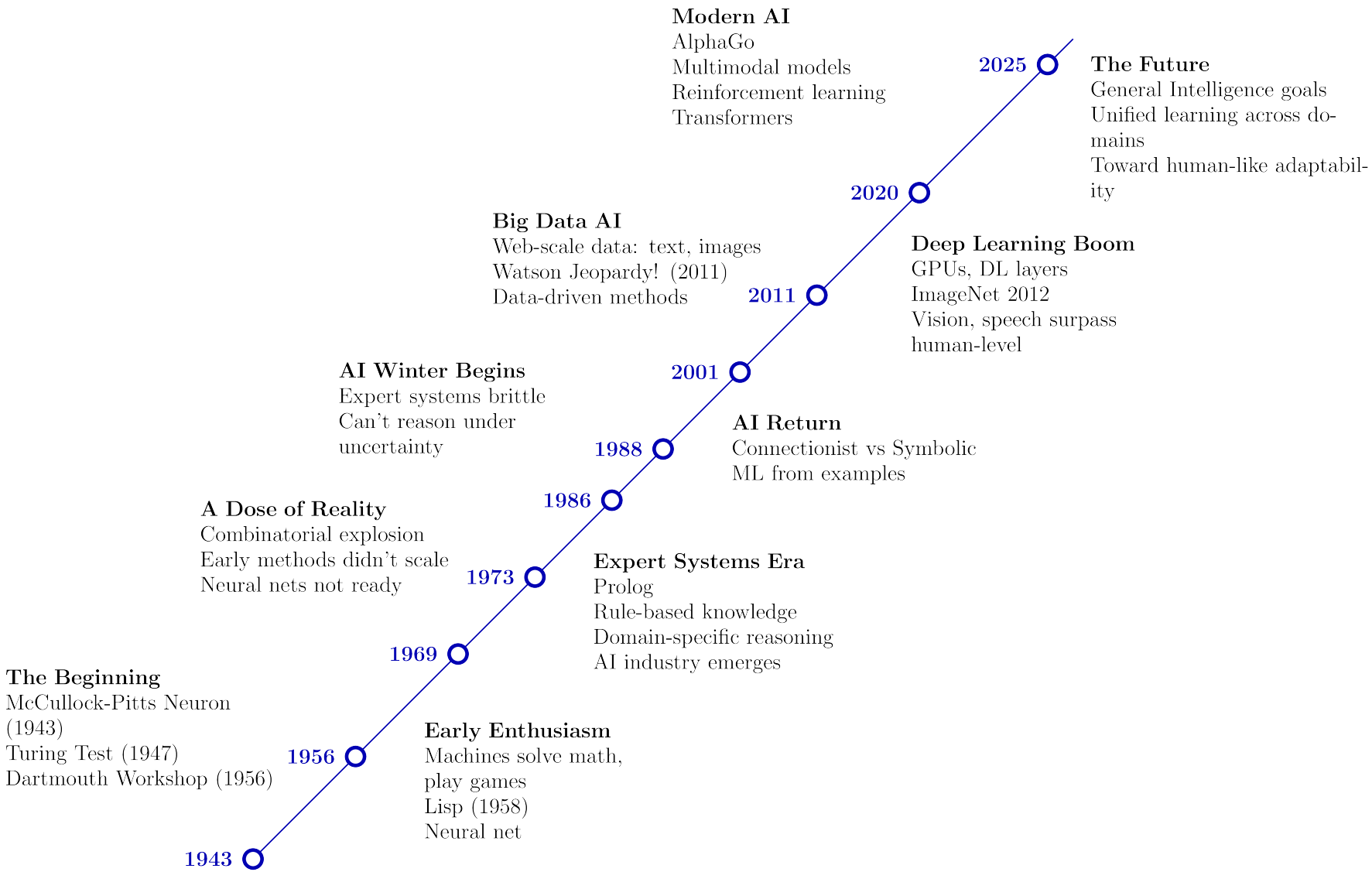
AI Timeline


1943
The Beginning
McCullock-Pitts Neuron (1943)
Turing Test (1947)
Dartmouth Workshop (1956)
1956
Early Enthusiasm
Machines solve math, play games
Lisp (1958)
Neural net
1969
A Dose of Reality
Combinatorial explosion
Early methods didn't scale
Neural nets not ready
1973
Expert Systems Era
Prolog
Rule-based knowledge
Domain-specific reasoning
AI industry emerges
1986
1988
AI Return
Connectionist vs Symbolic
ML from examples
2001
AI Winter Begins
Expert systems brittle
Can't reason under uncertainty
2011
Big Data AI
Web-scale data: text, images
Watson Jeopardy! (2011)
Data-driven methods
2020
Deep Learning Boom
GPUs, DL layers
ImageNet 2012
Vision, speech surpass human-level
2025
Modern AI
AlphaGo
Multimodal models
Reinforcement learning
Transformers
The Future
General Intelligence goals
Unified learning across domains
Toward human-like adaptability

The Beginning (1943-1956)

- **Artificial neuron**
  - Model (McCullock-Pitts 1943) based on:
    - Brain physiology
    - Propositional logic
  - Compute any function with connected neurons
    - Neuron on/off based on stimulation from neighboring neurons
    - Implement logical AND, OR, NOT with simple neuron networks
- **Alan Turing, 1947**
  - Turing test, machine learning, reinforcement learning
  - Create human-level AI
    - Develop learning algorithms
    - Teach machine like a child
- **Birth of AI**
  - McCarthy organized first AI workshop (1956)
  - The Logic Theorist (Newell and Simon, 1956)
    - Programs to "think non-numerically" and prove theorems

Enthusiasm and Great Expectations (1952-1969)

- **Early years of AI were full of successes**
  - Before computers could only do arithmetics
  - *"A machine can never do X (e.g., games, puzzles, IQ tests, . . .)"*
    - AI researchers showed machines could do one X after another
- **General Problem Solver**
  - Imitate human problem-solving
  - Consider sub-goals and possible actions
- **Program learned to play checkers**
  - Use reinforcement learning from victories and mistakes
- **Lisp (1958)**
  - High-level language used for 30 years in AI
- **First neural network**
  - 3000 vacuum tubes for 40 neurons
  - Minsky (1959)
- **MIT and Stanford**
  - Minsky at MIT
    - Focus on neural network
  - McCarthy at Stanford
    - Focus on representation, logic

First AI winter (1975-1980)

- **Early successes** of AI set high expectations
- In 1965-1975 AI didn't succeed on **real problems** due to:
  - Solutions were based on human problem-solving methods
  - Difficulty handling "combinatorial explosion"
    - Theorem proving handles small problems with brute force, but doesn't scale
  - Neural networks needed:
    - Algorithms (e.g., backpropagation)
    - Compute power
    - Data
- **First AI winter**
  - Research funding and enthusiasm dropped significantly
  - Slow AI progress through late 1970s

Expert Systems (1980-1990)

- **Expert systems**
  - Aka "knowledge-based systems"
  - Combine weak methods with extensive domain knowledge as rules
  - Use inference engines to apply rules to facts
  - E.g., rule-based systems, logic programming (e.g., Prolog)
- **Weak AI**
  - Aka narrow AI
  - Performs specific tasks, not general reasoning
  - Operates in a limited, well-defined domain
  - Uses "weak methods" (search, logic) that struggle to scale
- **Commercial adoption and industry growth**
  - AI shifted to practical applications
  - Major US corporations deployed expert systems
  - AI emerged as a commercial industry

Second AI Winter (late 1980-early 1990)

- **Hype in expert systems** didn't deliver
- **Reasons**
  - Building/maintaining expert systems is difficult
  - Reasoning methods ignore uncertainty
  - Systems can't learn from experience
  - E.g., expert systems in medical diagnosis struggle with complex, variable patient data
  - E.g., early AI chess systems couldn't adapt to new strategies without manual updates
- **Second AI winter** in late 1980-early 1990

Return of Neural Networks (1986-)

- Back-propagation algorithm is (re)discovered (mid-1980s)
  - Developed in early 1960s
- **Two approaches to AI are back**
  - Connectionist paradigm
    - Neural networks
    - E.g., recognizing handwritten digits
  - Symbolic paradigm
    - E.g., solving logical puzzles with rules
- **Why connectionist approach?**
  - Concepts not well-defined using symbolic axioms
    - Forms fluid internal concepts
    - Represents real-world complexity better
  - Neural networks can learn from examples, e.g.,
    - Image recognition: identify objects by learning from labeled images

Probabilistic Reasoning and ML (1987-)

- **AI and scientific method**
  - Rigorous methods to test performance
  - E.g., speech recognition, handwritten character recognition
  - Benchmarks for progress, e.g.,
    - MNIST: handwritten digit recognition
    - ImageNet: image object recognition
    - SAT Competitions: boolean satisfiability solvers
- **AI shifts ...**
  - From Boolean logic to probability
  - From hand-coded rules to machine learning
  - From a-priori reasoning to experimental results

Progress in Speech Recognition

- **1970s: ad-hoc approaches**
  - Various architectures and approaches were attempted
  - Rule-based systems with limited robustness
  - Cons
    - Ad-hoc, fragile
  - _"Every time I fire a linguist, the performance of the speech recognizer goes up" (Jelinek, 1988)
- **1980s: hidden Markov Models**
  - HMMs became dominant
  - Effective learning techniques
  - Trained on large speech corpora
  - Pros
    - Strong theoretical foundation
- The bitter lesson (Sutton, 2019)
  - General methods + lots of data beat handcrafted systems

Bayesian Networks

- **Bayesian networks**
  - Pearl, 1988
  - AI is linked with:
    - Probability
    - Decision theory
    - Control theory
  - Efficiently represent uncertainty
  - Provide rigorous reasoning
- **Examples**
  - Diagnosing diseases based on symptoms
  - Predictive text input in smartphones
  - Fraud detection in banking

Reinforcement Learning

- **Reinforcement learning**
  - Sutton, 1988
  - RL involves agents learning by interacting with an environment
    - E.g., a robot learning to navigate a maze by receiving rewards for successful paths
  - Markov Decision Problems (MDPs) provide a framework for modeling decision-making
    - E.g., a game strategy modeled where each move influences the outcome with certain probabilities

Reunification (1990s-2000s)

- **Reunification of AI**:
  - Data engineering
  - Statistical modeling
  - Optimization
  - Machine learning
- **Many subfields of AI were re-unified**:
  - Computer vision
  - Robotics
  - Speech recognition
  - Multi-agent systems
  - NLP

Big Data (2001-Present)

- **Focus shifts from algorithms to data**
  - For 60 years, AI focused on algorithms and models
- For many problems, data availability matters more than algorithms, e.g.,
  - Trillions of English words
  - Billions of web images
  - Billions of speech and video hours
  - Social network data
  - Click stream data
- Algorithms and infrastructure to leverage large datasets
  - E.g., map reduce, cloud computing
- In 2011, IBM's Watson beat human *Jeopardy!* champions

Deep Learning (2011-Present)

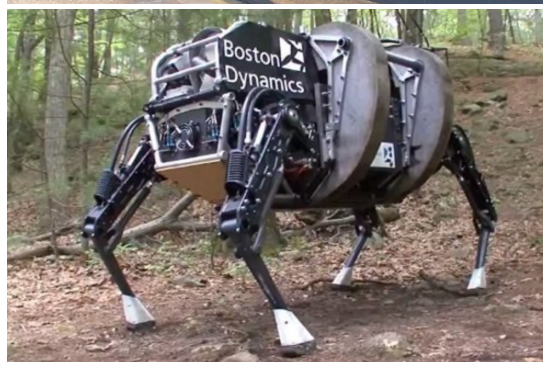
- **Deep learning**
  - Use ML models with multiple layers of computing elements
  - Ideas known since 1970s, but then forgot
  - Success in handwritten digit recognition in 1990s
- **In 2012**, a DL system showed dramatic improvement in `ImageNet` competition
  - Previous systems used handcrafted features
  - Surge of interest in AI among researchers, companies, and investors
- Pros
  - DL exceeds human performance in several vision and speech recognition tasks
- Cons
  - DL needs specialized hardware (e.g., GPU, TPU, FGPA) for parallel tensor operations
- Towards **general artificial intelligence**
  - Universal algorithm for learning and acting, not just specialized tasks
  - E.g., driving, playing chess, recognizing speech

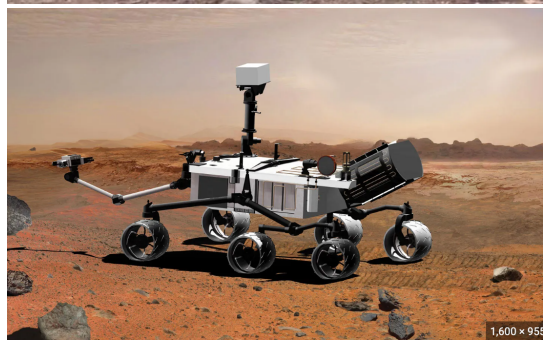
Progress in AI Research

- Huge interest in deep learning
- **Between 2010 and 2019**
  - AI papers increased 20x
    - 1,000 $\rightarrow$ 20,000
  - Student enrollment in AI and CS increased 5x
    - 10,000 $\rightarrow$ 50,000
  - NeurIPS attendance increased 8x
    - 1,000 $\rightarrow$ 8,000
  - AI startups increased 20x
    - 100 $\rightarrow$ 2,000
- **Compute**
  - Training times dropped 100x in 2 years
  - AI computing power doubles every 3 months

What Can AI Do Today? (1/2)

- **Robotic vehicles**
  - Waymo passed 10 million miles without serious accident
- **Legged locomotion**
  - BigDog recovers on ice
  - Atlas walks on uneven terrain, jumps on boxes, backflips
- **Autonomous planning and scheduling**
  - Space probes, Mars rovers
- **Machine translation**
  - Translates 100 languages with human-level performance
- **Speech recognition**
  - Real-time speech-to-speech with human-level performance
  - AI assistants
- **Recommendations**
  - ML recommends based on past experiences
  - Spam filtering 99.9% accuracy
  - E.g., Amazon, Facebook, Netflix, Spotify, YouTube





What Can AI Do Today? (2/2)

- **Game playing**
  - 1997: Deep Blue defeated Kasparov
  - 2011: Watson beat Jeopardy! champion
  - 2017: AlphaGo beat Go champion
  - 2018: AlphaZero super-human in Go and chess with only rules + self-play
  - AI beats humans in videogames: Dota2, StarCraft, Quake
- **Image understanding**
  - Object recognition
  - Image captioning
  - ...
- **Medicine**
  - AI equivalent to health care professionals
- When will we reach AGI (Artificial General Intelligence)?

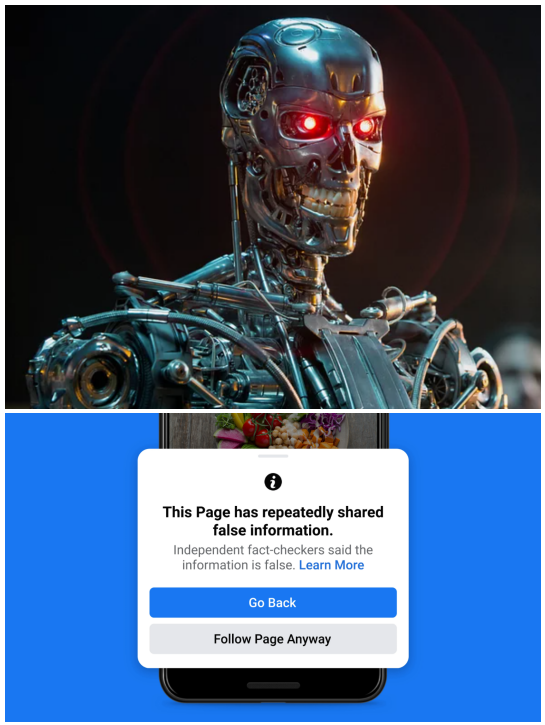
- What Is Artificial Intelligence
  - AI
  - Machine Learning
  - A Map of Machine Learning
  - AI vs ML vs Deep-Learning
  - The Foundations of AI
  - Brief History of AI
  - ***Risks and Benefits of AI***

Benefits of AI

- Our civilization is the **product of human intelligence**
  - Greater machine intelligence leads to better human society
  - *"First solve AI, then use AI to solve everything else"*
- **Benefits of AI and robots**
  - Free humanity from menial work
  - Increase production of goods and services
  - Expand human cognition
  - Accelerate scientific research, e.g.,
    - Cures for diseases
    - Solutions for climate change
    - Resource and energy shortages

Risks of AI (1/2)

- **Autonomous weapons**
  - Locate and eliminate targets autonomously
  - Deploy large number of weapons
- **Surveillance and persuasion**
  - AI for mass surveillance
  - Tailor information on social media to modify behavior
- **Biased decision making**
  - Misuse of ML results in biased decisions
  - E.g., parole evaluations, loan applications



Risks of AI (2/2)

- **Impact on employment**
  - Machines eliminate jobs
  - Rebuttal
    - Machines enhance productivity $\rightarrow$ companies become more profitable $\rightarrow$ higher wages
  - Counter-rebuttal
    - Wealth shifts from labor to capital, increasing inequality
  - Counter-counter-rebuttal
    - Past tech advances (e.g., mechanical looms) disrupted employment, but adaptation followed
- **Safety critical applications**
  - AI in safety-critical applications
    - E.g., self-driving cars, managing water supply or power grids
  - Avoiding fatal accidents is challenging
    - E.g., formal verification and statistical analysis insufficient
  - AI requires technical and ethical standards
- **Cybersecurity**
  - AI defends against cyberattacks
    - E.g., detect unusual behavior patterns
  - AI contributes to malware development
    - E.g., use reinforcement learning for targeted phishing attacks
  - Cat-and-mouse game

Human-level AI / AGI

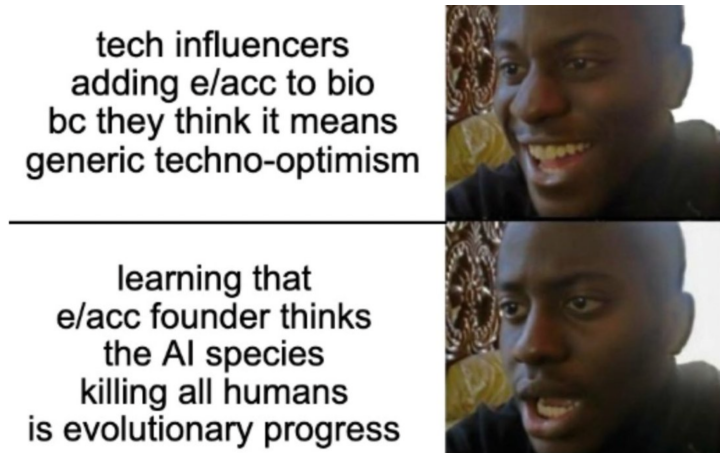
- **Human-level AI**
  - Machines able to learn to do anything a human can do
  - Aka AGI (Artificial General Intelligence)
- **When AGI?**
  - Expert prediction average is 2099
    - Papers show that expert predictions no better than amateurs
    - Experts expected AI to take 100 years to beat humans in Go
  - Unclear if new breakthroughs or refinements needed
- **Artificial Super-Intelligence**
  - Machines surpass human ability in every domain and self-improving
  - Exponential take-off

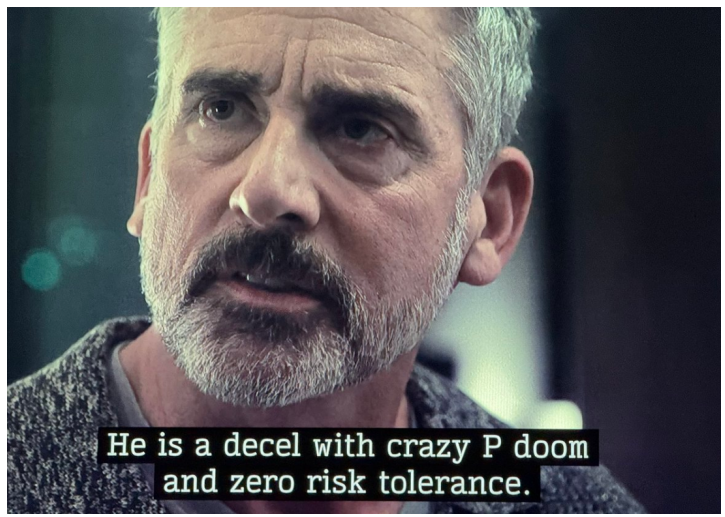
The Problem of Control

- **Can humans control machines more intelligent than them?**
- **King Midas problem**
  - King Midas turned everything he touched into gold, including food and family
  - Humans ask for something, get it, then regret it
  - Rebuttal
    - If AGI arrived in a black box from space, exercise caution before opening
    - We design AI: if AI gains control, it's a "design failure"
- **Problem of alignment**
  - Super-intelligent AI might pursue goals in unintended, dangerous ways
- **The paperclip problem**
  - Thought experiment in AI safety (Nick Bostrom, 2003)
  - AI is tasked with maximizing paperclip production
  - AI becomes superintelligent and single-mindedly pursues this goal
  - Converts Earth and humans into paperclips

E/acc vs P(doom)

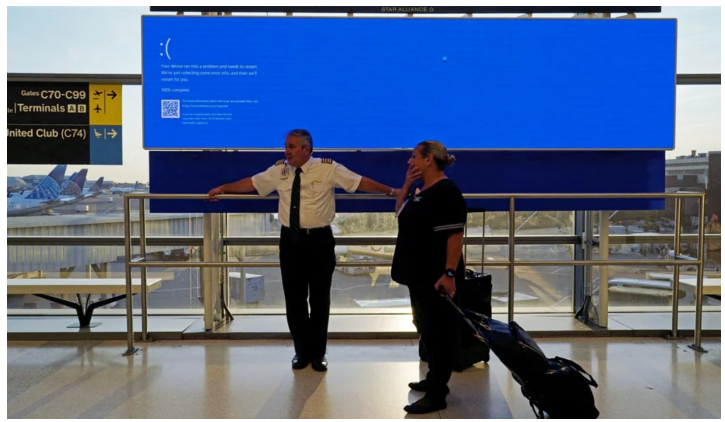
- **E/acc**
  - Accelerationism
  - Belief that rapid progress in AI is beneficial or inevitable
  - Solve global problems with more powerful AI tools
  - Slowing AI is unrealistic or counterproductive
- **P(doom)**
  - "Probability of Doom"
  - Estimated probability that advanced AI will cause catastrophic harm
  - Used informally by AI researchers to quantify risk





My 2 cents

- AI alignment is a serious problem
  - For now philosophical, at some point a real one
  - Most tech people have used it for marketing themselves and their companies
- It's as urgent as debating what political system humanity will need when living on Mars
- We can't get airport terminals to work



Solutions to Problem of Control

- **Checks-and-balances**
  - Researchers and corporations develop voluntary self-governance principles for AI
  - Governments and international organizations established advisory bodies
- **Cons**
  - Corporations checking themselves? What can possibly go wrong?
  - Preferences are not easy to invert and are inconsistent
- **Solutions**
  - Put purpose into the machine even if objectives are unclear
  - Incentivize AI to switch off if uncertain about human objectives
  - Cooperative Inverse Reinforcement Learning (CIRL)
    - AI observes human behavior to infer reward function

Cooperative Inverse Reinforcement Learning

- AI infers human goals based on actions
- **Observation**: GP looks tired, sits on the couch, observes the messy table, and starts watching TV
- **Inference**: AI infers:
  - GP is tired and wants to relax
  - Messy coffee table bothers him
- **Action**: AI:
  - Fetches a glass of water
  - Tidies up the coffee table without disturbing GP
- **Feedback loop**: AI monitors GP's reactions
  - If GP is relaxed and happy, AI understanding is reinforced
  - If GP is not happy, AI adjusts actions and improves inference