University of Idaho
Department of Computer Science

CS 404/504 Special Topics: Python Programming For Data Science

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Lecture 1

A Short History and Current State of Artificial Intelligence

Lecture Overview

- Artificial Intelligence vs. Machine Learning vs. Data Science
- How to develop intelligent machines?
- AI timeline
  - DL success in computer vision
  - DL success in natural language processing
  - Generative text-to-image models
  - Foundation models
- AI limitations and challenges
- Prospective trends in AI

Artificial Intelligence

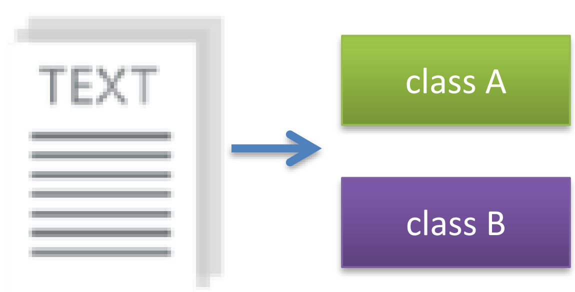
AI vs. Machine Learning vs. Data science

- ***Artificial Intelligence (AI)*** is a scientific field concerned with the development of algorithms that allow computers to reason or learn without being explicitly programmed
  - AI is opposite to natural intelligence displayed by humans and animals
- AI as an academic discipline was founded in 1956
- AI studies theories and technologies related to:
  - Planning and reasoning
  - Knowledge representation
  - Machine learning
  - Natural language processing
  - Perception
  - Motion and manipulation

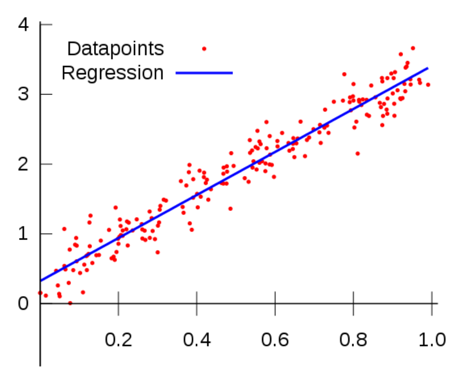
Machine Learning

AI vs. Machine Learning vs. Data science

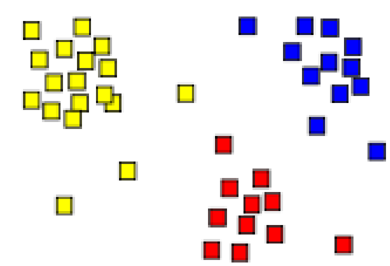
- ***Machine Learning*** is a subfield of Artificial Intelligence, that focuses on methods that learn from data and make predictions on unseen data
- Categories of ML approaches
  - Supervised learning: learning with labeled data
    - Example: image classification, email classification
    - Example: regression for predicting real-valued outputs
  - Unsupervised learning: discover patterns in unlabeled data
    - Example: cluster similar data points
  - Reinforcement learning: learn to act based on feedback/reward
    - Example: learn to play Go



Classification



Regression

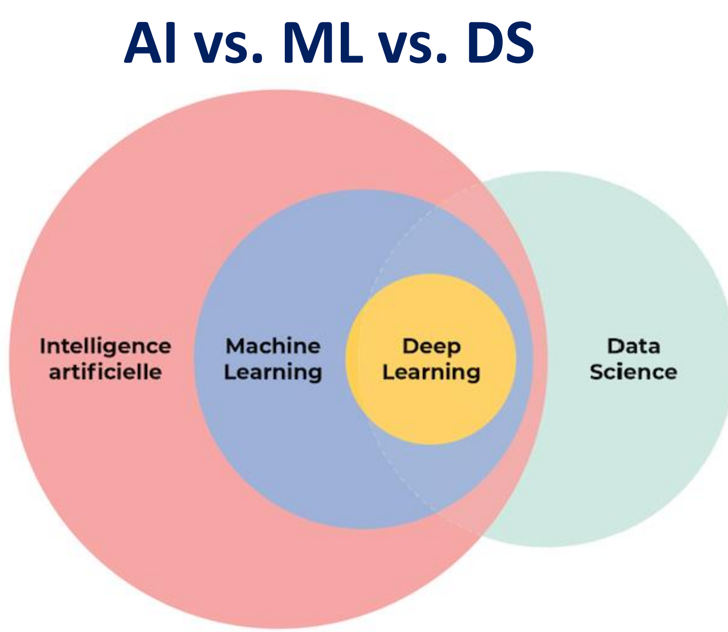


Clustering

Data Science

AI vs. Machine Learning vs. Data science

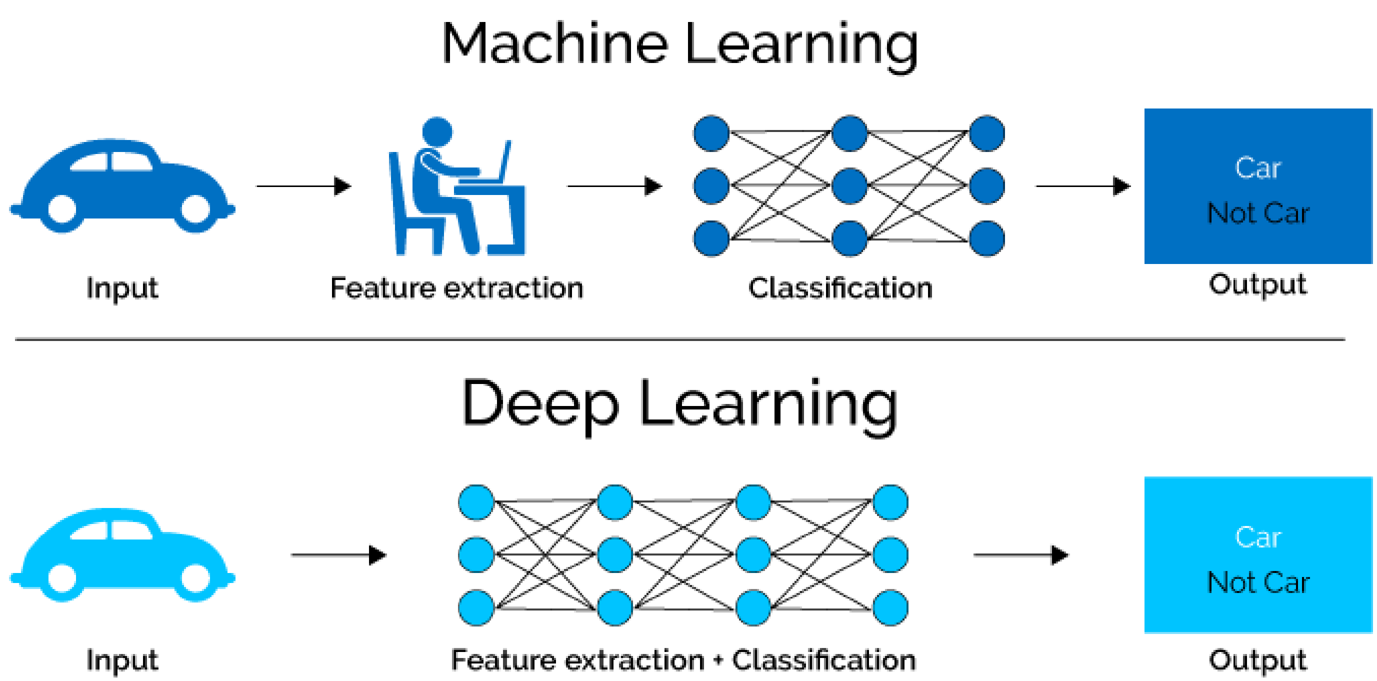
- *Data Science (DS)* is an interdisciplinary field that uses scientific methods and algorithms to extract knowledge from data, and applies the insights to application domains, such as to make business decisions
- Data Science versus Machine Learning
  - DS focuses on extracting knowledge and insights from data
  - DS can rely on ML approaches, but it can also obtain insights via statistical analysis, data cleaning, data visualization, exploratory data analysis, feature engineering



Deep Learning

AI vs. Machine Learning vs. Data science

- *Deep Learning* (DL) is a subarea in machine learning that uses artificial neural networks (ANNs) with multiple layers for learning data representations
  - A major advantage of DL is the ability to automatically extract features in data
  - The most common architectures in deep ANNs are: multi-layer perceptron NNs, convolutional NNs, recurrent NNs (LSTM, GRU), graph NNs, transformer NNs



What is Intelligence?

How to Develop Intelligent Machines?

- An intelligent agent is any system that perceives the environment and takes actions to maximize the chances of achieving its goals
  - Goals can vary, e.g., human goals can be to make a coffee, build a wall, solve a math problem, drive a car, cook a meal, etc.
- Definition: ***Intelligence*** is an agent's ability to achieve goals in a wide range of environments
- Intelligent agents should be able to acquire and retain knowledge, and use it to respond effectively to new tasks or act in new situations and environments
  - E.g., more intelligent humans should be able to solve many physics problems that they haven't seen before (e.g., think Einstein)
  - Intelligence encompasses many related abilities for:
    - Reasoning and rational thinking, comprehend ideas, apply planning, problem-solving
    - Learning and adaptation, deal with unexpected situations and uncertainties
    - Interacting with the real world to perceive, understand, and act

How to Develop Intelligent Machines?

How to Develop Intelligent Machines?

- AI scientists in 1950s believed that machines with human-level intelligence can be achieved within 10 to 20 years
- Initial AI approaches
  - Imitate step-by-step reasoning that humans use to solve a problem
  - Create a knowledge database based on human domain knowledge about a task, and develop an inference engine to process the states and make decisions
  - Challenges: handling uncertainties, combinatorial explosion (the space of solutions quickly becomes too large for most problems)
- These approaches failed to deliver, as the scientists underestimated the complexity of human intelligence
- Various misconceptions about intelligence has perpetuated in the AI field
  - E.g., computers can process information -> human thinking is similar to logic processing -> encoding human thinking into a program can lead to intelligent machines
  - E.g., chess is a game of intellect and chess players are very intelligent people -> developing computers that can reason and play chess at a human expert level can lead to machines with human-level intelligence

Weak vs. Strong AI

How to Develop Intelligent Machines?

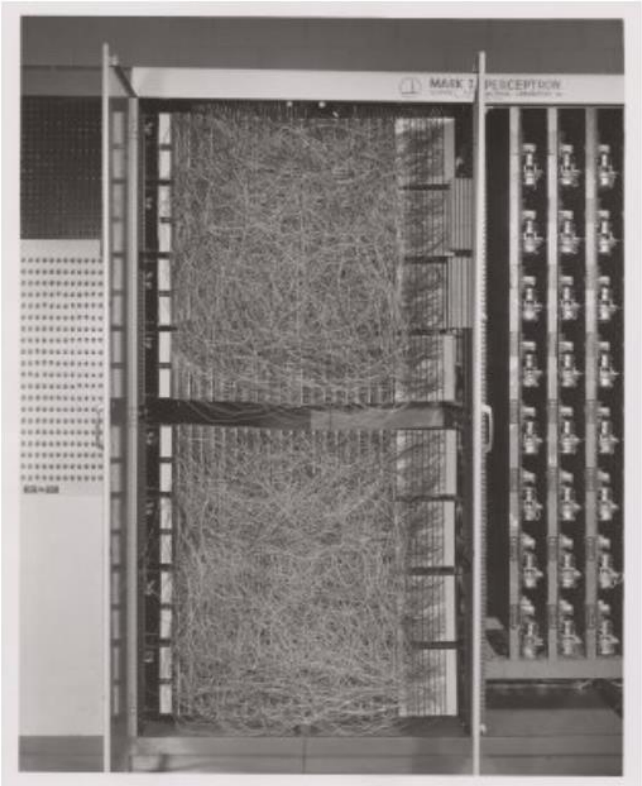
- AI systems can be classified into weak AI and strong AI systems
- ***Weak AI***, or ***narrow AI***: can solve one specific task
  - E.g., image classification ML models
  - E.g., Deep Blue computer that defeated the world chess champion
- ***Strong AI***, of ***artificial general intelligence (AGI)***: can solve a variety of tasks
  - AGI is the ability to understand or learn any intellectual task that a human being can
    - AGI performance would be indistinguishable from that of humans
  - At present, AGI systems do not exist

- How to evaluate AI?
  - ***Turing test***, proposed by Alan Turing in 1950
    - "A computer would deserve to be called intelligent if it could deceive a human into believing that it was human"
    - Test: a human interacts with other humans and an AI agent; the test is passed if the human cannot distinguish the AI agent from the humans
    - Turing called the test "Imitation Game"
    - The test has not been passed yet by an AI system

AI Timeline

AI Timeline

- 1943 – The first model of a simple artificial neuron proposed
- 1950 – Alan Turing introduced the Turing test
- 1955 – The term Artificial Intelligence used for the first time
- ***1956 – Workshop on AI held in Dartmouth College***, New Hampshire, organized by John McCarthy, Marvin Minsky, Nathaniel Rochester, Claude Shannon
  - “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."
  - Official beginning of AI as academic discipline



- 1958 – Perceptron algorithm proposed by Rosenblatt
  - Shown is the Mark I Perceptron computer, used for implementing the algorithm

AI Timeline

AI Timeline

- 1966 – Eliza, a chatbot that simulates conversations with a psychotherapist
- 1970-1980 – First AI winter, agencies reduced funding for AI projects due to unsatisfactory progress
- 1982 – An expert systems deployed for configuring computer orders
- 1987-1992 – Second AI winter, DARPA cut AI funding for expert systems
- 1995 – The advent of machine learning and statistical methods
- 1997 – IBM's supercomputer Deep Blue won against world chess champion Gary Kasparov

AI Timeline

AI Timeline

- 2011 – IBM's supercomputer Watson won against two human rivals in the quiz show Jeopardy

- 2012 – Deep NN model AlexNet won image classification contest - ***beginning of the era of deep learning***

- 2015 – GAN (Generative Adversarial Network) introduced

- 2016 – Google's DeepMind program AlphaGo defeated the Go grandmaster Lee Sedol
  - The game of Go is more difficult than chess, because the number of possible moves is much greater

AI Timeline

AI Timeline

- 2017 – Transformer network architecture was introduced in the paper by Vaswani et al. “Attention Is All You Need”
- 2020 – OpenAI’s GPT-3 is the first large language model with 175B parameters, performed well on many NLP tasks
- 2021 – DeepMind’s AlphaFold achieved high accuracy in predicting the 3-dimensional shape of proteins
- 2022 – OpenAI’s DALL·E 2 generated photorealistic images with remarkable quality
- 2022 – Facebook’s NLLB (No Language Left Behind) model for machine translation between 200 languages
- 2022 – Deep Minds’ Gato model was trained to perform over 450 tasks

DL Success in Computer Vision

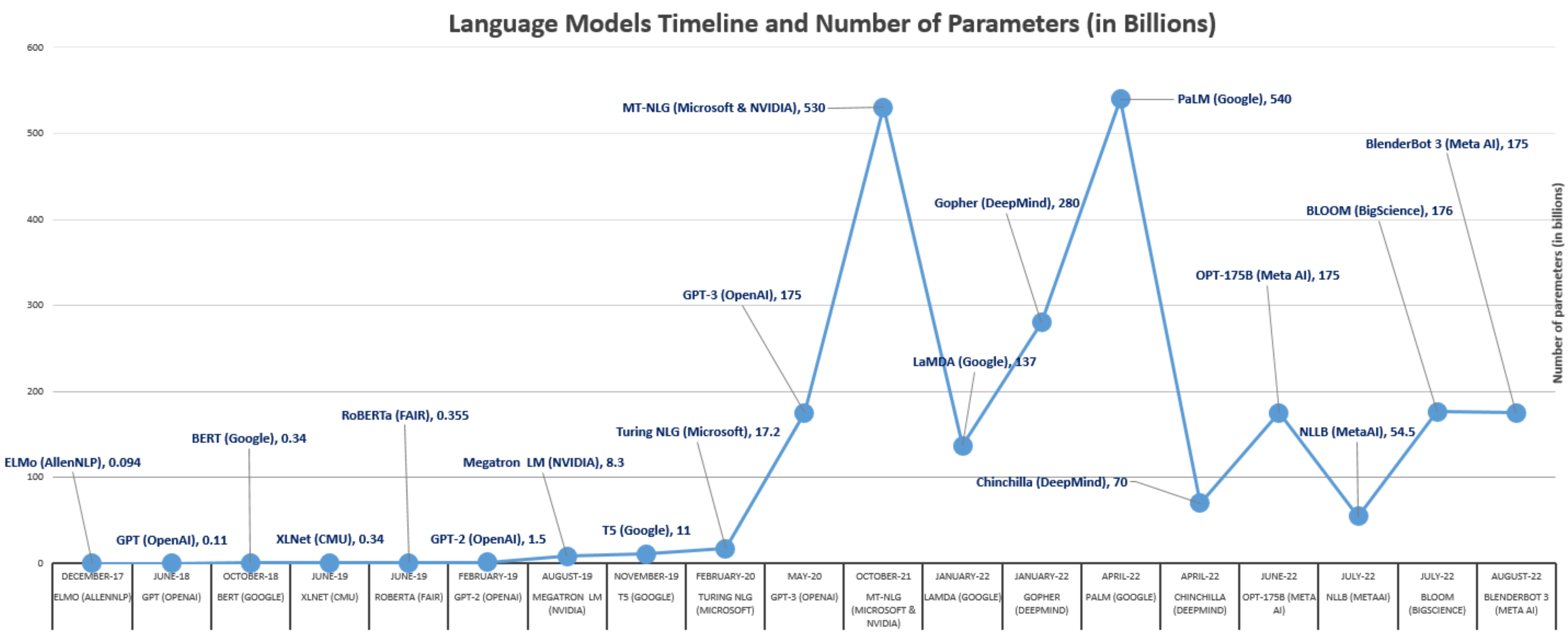
DL Success in Computer Vision

- *Computer vision* tasks
  - Image and video recognition/classification, segmentation, object detection, image synthesis
- Important architectures
  - AlexNet – 2012
    - Convolutional NNs for image recognition, 5 layers, GPU for parallel processing
    - ImageNet Large Scale Visual Recognition Challenge (ILSVRC): AlexNet reduced the error on ImageNet from 26% by traditional ML approaches to 15%
  - VGG – 2014
    - 16 layers CNN architecture
  - Inception – 2015
    - Stacked 1x1 convolutions, 22 convolutional layers
  - ResNet - 2015
    - Introduced residual connections, it is a family of networks with 18, 34, 50, 101, and 152 layers
    - Several related models were proposed afterwards, e.g., ResNeXt (2017), EfficientNet (2019)
  - Vision Transformers – 2020
    - Employ attention layers, inspired by the transformer models used in NLP

DL Success in Natural Language Processing

DL Success in Natural Language Processing

- *Natural Language Processing* (NLP) tasks
  - Text classification, text summarization, speech recognition, machine translation, dialog generation, part-of-speech tagging
- In the last 4 years, *Language models (LMs)* powered by deep NNs achieved unprecedented success in NLP tasks
  - A side note: compared to the human brain having between 100 and 500 trillion synaptic connections, these models are still fairly small



GPT-3

- *GPT-3* (Generative Pretrained Transformer 3)
  - Number of parameters: 175 billion
  - Training dataset: 45 TB of text (= a large portion of all text available on the web)
  - Training time and GPUs: 36 days with 1,024 NVIDIA A100 GPUs
  - Training cost: $US 12 million
- GPT-3 training
  - Self-supervised learning – it is a form of unsupervised learning (from unlabeled data)
  - Very simple approach: predict (assign probability to) the next word in a given sequence of words

Input: A quick brown	Output: fox
Input: Marry had a little	Output: lamb
Input: Nothing is	Output: impossible

  - Finite, discrete solution space: the next word must be from a finite dictionary
    - There are about 170,000 words in the English language
    - A person on average uses 20,000 to 30,000 words
    - About 3,000 words cover 95% of all written text

Large Language Models

DL Success in Natural Language Processing

- ***Large language models*** (LLMs)
  - The architecture of all LLMS is based on the transformer networks
  - Transformers employ the attention mechanism to identify the words in a sentence that impact the meaning of other words
  - I.e., important characteristics is the ability for modeling words based on the context
- LLMs work with projected words into an embeddings space, where each word is replaced with a numerical token
  - Given a sequence of tokens from a dictionary, the training objective is to estimate the probability of the next token
- The quality of generated text by recent large LMs is often undistinguishable from human-written text
- Concerns regarding LLMs:
  - Misuse and unethical use of AI, amplifying disinformation, environmental impact (high carbon emissions), increasing economic inequalities, centralization of power (e.g., affordable only by the largest corporations)

Generative Text-to-Image Models

Generative Text-to-Image Models

- ***Generative models*** learn to generate new data instances, given a training set
  - The family of GAN models (StyleGAN, CycleGAN, SRGAN) were the most important generative models in recent years
- Latest text-to-image models released this year include:
  - DALL·E 2 by OpenAI
  - Imagen by Google
  - Stable Diffusion by Stability.ai
- Remarks:
  - Significant progress has been made since 2014 when GAN was introduced
  - The above text-to-image models employ text embeddings from pretrained LLMs (e.g., GPT-3 used with DALL·E 2)
  - Produce images with remarkable photorealism, accurate fine details, compositionally, spatial relations of the objects in images, and even with creativity in image synthesis
  - They employ diffusion probabilistic models, which outperformed GANs
    - Diffusion models use NNs to learn the steps of adding and removing noise to images
  - Can create new images which are unlikely to have been seen in the training data

Images Generated by DALL·E 2

Generative Text-to-Image Models

- These are a few (cherry-picked) examples of images generated by DALL·E 2

A photo of a quaint flower shop storefront with a pastel green and clean white facade and open door and big window

Cat sipping tea and posting to twitter while sitting on a couch

A rabbit detective sitting on a park bench and reading a newspaper in a victorian setting

A lion in a hoodie hacking on a laptop

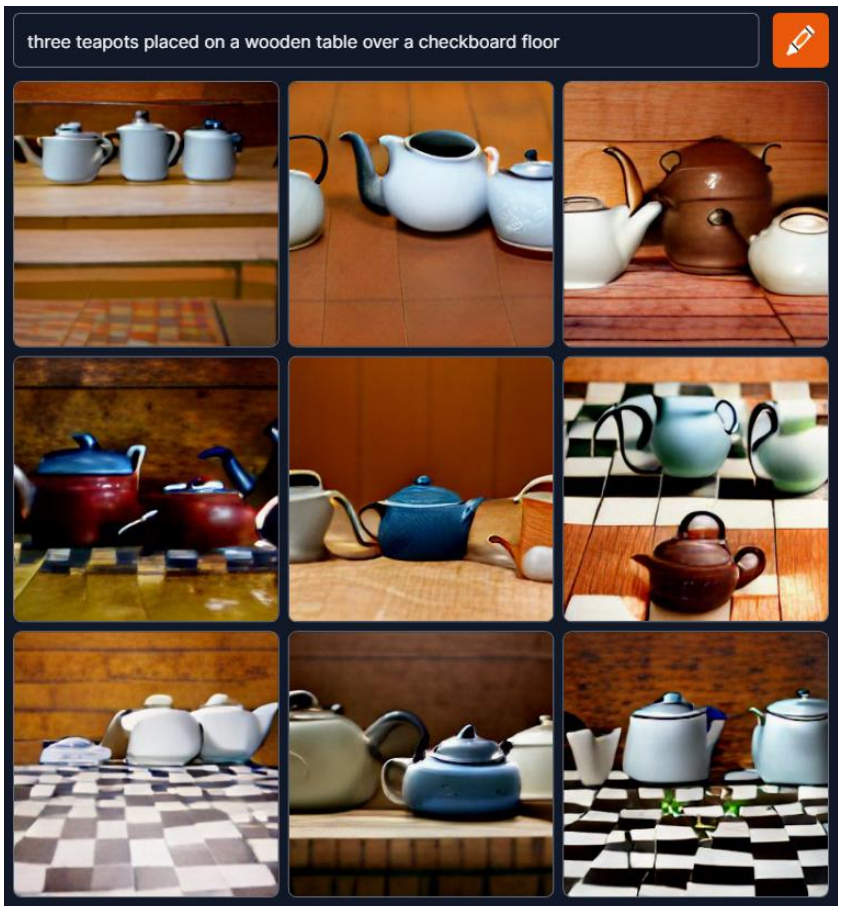
Teddy bears shopping for groceries in ancient Egypt

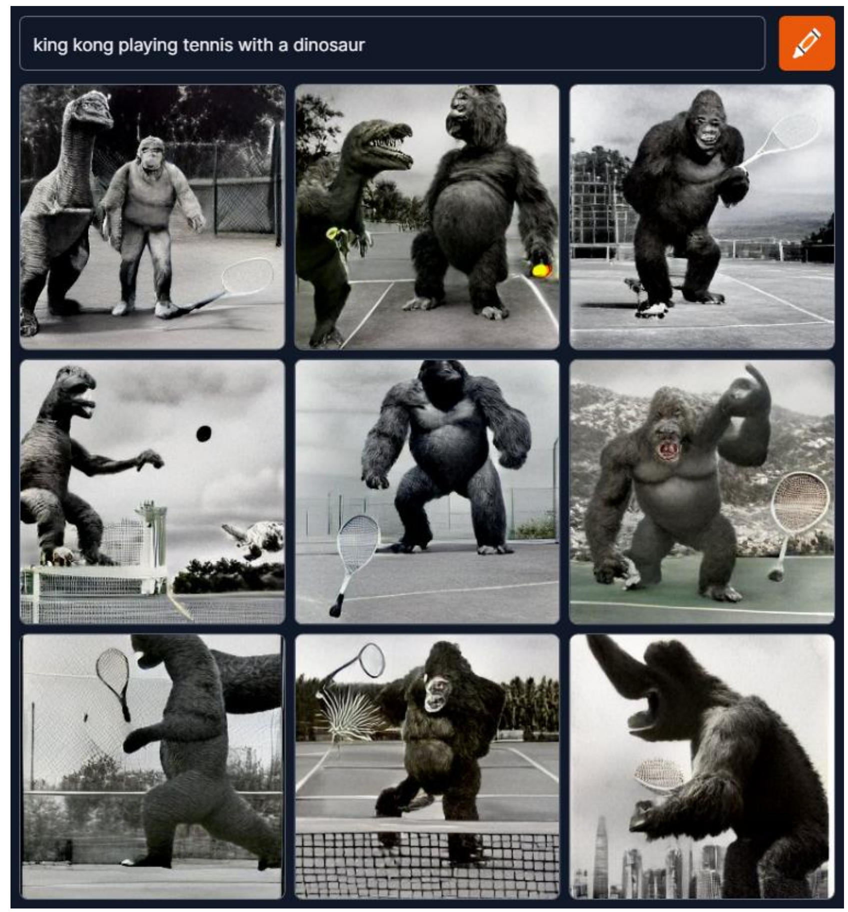
Teddy bears working on new AI research on the moon in the 1980s

Open-Source Text-to-Image Models

Generative Text-to-Image Models

- A smaller model called ***Crayon*** (a.k.a. ***DALL·E Mini***) is freely available here
  - It takes about 2 minutes to create 9 images to a text prompt
  - However, it is less powerful, and the results are less impressive
- ***Stable Diffusion*** was released recently, can be accessed here





Foundation Models

- ***Foundation models*** are large NN models trained at scale with high capabilities for transfer learning to many other applications
  - Early examples of foundation models are the LLMs, such as GPT-3 and PaLM
- The scale of these models results in new emergent capabilities – e.g., perform well on tasks on which they were not explicitly trained to do
  - "Emergence is when quantitative changes in a system result in qualitative changes in behavior"
  - This allow fine-tuning to new tasks with small number of training data instances
    - E.g., few-shot learning refers to fine-tuning with only a few instances
- Notable applications of pretrained LLMs include:
  - Programming code completion models: CoPilot, AlphaCode, Codex, Codegen
  - Text-to-image generative models: DALL·E 2, Imagen, Stable Diffusion
  - Protein sequence prediction, solving math problems, preparing legal documents

  (other task examples are listed on the next page)
- Transfer learning is what makes foundation models possible, but scale is what makes them powerful

Foundation Models

Foundation Models

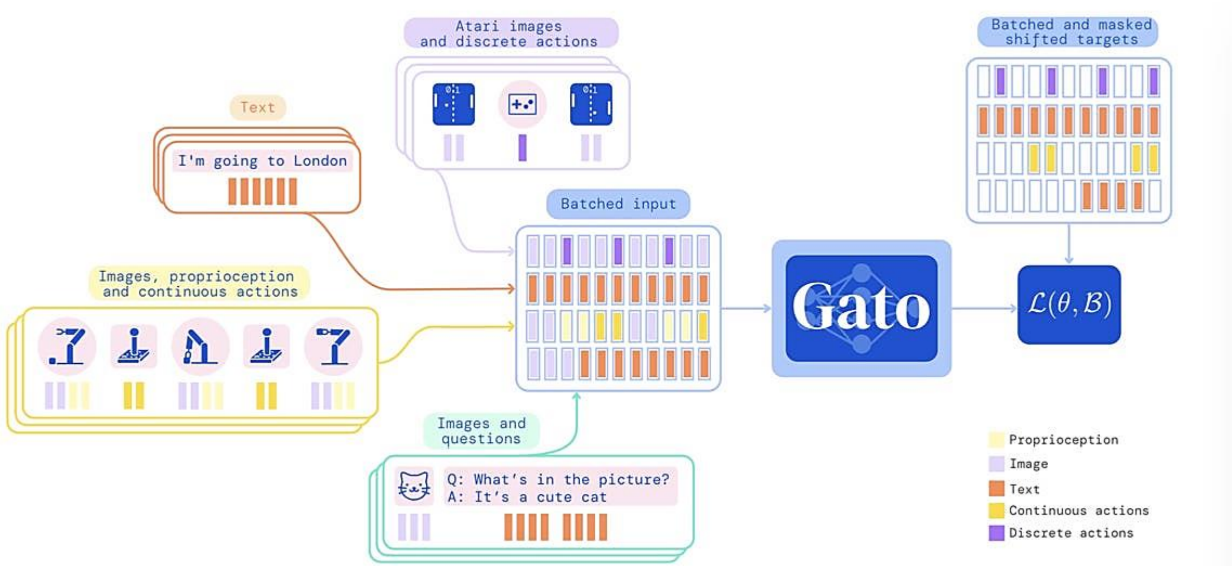
- Examples of applications and downstream tasks in which foundations models are being used

Program writing	**Image captioning**	**Generate images**	**Parse data**	**Classify text**
Use natural language to generate SQL/ Python/Java code	Describe and classify images	Create images based on natural language	Extract data from images	Identify entities, parts-of-speech, and other text categories
Q&A	**Writing assistant**	**Summarize**	**Solve homework**	**Translate**
Answer natural language questions based on knowledge base	Correct your writing	Summarize text to key concepts	Solve basic math and programming problems	Translate text from one language to another
Code explanation	**Copywriting**	**Sentiment rating**	**Recipe creation**	**Chat**
Writes the description of code functionality in natural language	Generate ad/product/job descriptions based on short prompts	Rates the sentiment, toxicity, warmth, etc. of text	Use at your own risk	Talks like a human

Gato – A Generalist Agent

Foundation Models

- *Gato* by Deep Mind is a multi-modal, multi-task, multi-environment network
- The same model with the same weights can: play games, manipulate a robot, caption images, generate dialog, navigate in 3D, and many other tasks
  - Inputs: text, images, robotic joint torques (proprioception), button presses (for games)
  - Outputs are based on context: text (dialog, translate, summarize), torque powers (for the actuators of a robotic arm), button presses (to play games), etc.
- Gato demonstrates versatility and adaptability to many tasks (over 450 tasks)
  - The model has “only” 1.2 billion parameters



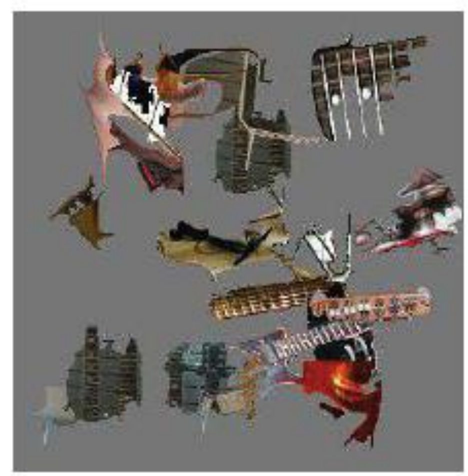
AI Limitations and Challenges

- Despite excellent pattern recognition abilities, current DL models are unable to reason about the objects in images or take context into consideration
- E.g., predictions by a DL model on images of randomly positioned parts
  - The model assigns weights to different features in images, and outputs a category based on the sum of weights for all features
  - It does not take into account the spatial relations between the features in making the prediction

Basketball

Zebra

Electric Guitar



Trustworthy AI

AI Limitations and Challenges

- *Trustworthy AI* – efforts to address the limitations to ensure that end-users can trust the predictions by AI models
- Topics in trustworthy AI include:
  - Robustness
    - Even unnoticeably small perturbations can impact the model predictions
  - Generalization
    - OOD (out-of-distribution) inputs; e.g., a model trained on medical images in one hospital performs poorly on images in another hospital (due to different equipment of settings used)
  - Explainability
    - The decision-making process of large models is non-transparent and difficult to understand
  - Fairness
    - Predictions can show bias against demographic groups, based on gender, age, culture
  - Privacy protection
    - Models can memorize and reveal input data; e.g., a model can reveal sensitive private information in medical records used for training
  - Ethics
    - The models should produce ethical decisions that are aligned with our human values (also referred to as AI Alignment)

Engineering vs Science Phase of Technology

AI Limitations and Challenges

- Theoretical guarantees about the AI performance are currently lacking
  - Currently, AI is in ***Engineering phase***: models are designed to solve tasks, are integrated into new products, add value to companies, have economic impact
  - ***Science phase*** of AI is to follow: develop theory to guarantee convergence, prove stability, interpret the decisions, explain successes and failures of models
- Various technologies historically began with an engineering phase (inventions made, products built) to be later followed by a science phase (theory developed)
  - Steam engines were used in paper mills and factories since 1776; the theory of Thermodynamics was developed between 1820s and 1850s
  - Airplanes were constructed and flown since 1904-1905; the modern theory of Aerodynamics was developed in 1930s
  - Electric circuits were discovered around 1800; the theory of Electromagnetism was founded between 1820s and 1830s

The Bitter Lesson

AI Limitations and Challenges

- ***The Bitter Lesson*** (2019) is a short paper by Rich Sutton
  - http://www.incompleteideas.net/IncIdeas/BitterLesson.html
- The Bitter Lesson is based on his observations regarding the historical development of AI methods, which can be characterized with three phases:
  - Phase 1 - AI researchers incorporate human domain knowledge into their AI methods, which helps in short term
  - Phase 2 - In the long term, the performance of such models plateaus without further progress
  - Phase 3 - Progress is eventually achieved by general methods that scale computation with search and learning
- In conclusion:
  - AI methods that leverage computation and search at scale are the most effective
  - Human-centric approaches complicate methods and make them less suited to leveraging computation and search at scale
  - The search for solutions should be done by our methods, not by us
  - We want AI methods that can discover like us, and not based on our discoveries

Prospective Trends in AI

Prospective Trends in AI

- *Unsupervised/self-supervised learning*
  - Increased use of raw data without annotations or labels
- *Homogenization*
  - Convergence of architectures and methodologies in building AI systems across different applications
  - E.g., transformers are replacing convolutional, recurrent networks, and are increasingly being used in computer vision, NLP, time-series, tabular data tasks
- *Training at scale*
  - We can expect to see further scaling along the three main factors: amount of computation, number of model parameters, and training dataset size
- *Multi-modal learning*
  - Capacity to learn from multiple simultaneous sources of information (like humans)
  - Task-specific models being replaced with general models that can solve multiple tasks
- *Causal learning*
  - Can new learning algorithms be developed that are capable of learning cause and effect, semantic relationships?