

Artificial Intelligence and Intelligent Agents; Problem Solving

1141AI02 MBA, IM, NTPU (M5276) (Fall 2025) Tue 2, 3, 4 (9:10-12:00) (B3F17)







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Institute of Information Management, National Taipei University

https://web.ntpu.edu.tw/~myday



Syllabus



Week Date Subject/Topics

- 1 2025/09/09 Introduction to Artificial Intelligence
- 2 2025/09/16 Artificial Intelligence and Intelligent Agents; Problem Solving
- 3 2025/09/23 Knowledge, Reasoning and Knowledge Representation; Uncertain Knowledge and Reasoning
- 4 2025/09/30 Case Study on Artificial Intelligence I
- 5 2025/10/07 Machine Learning: Supervised and Unsupervised Learning; The Theory of Learning and Ensemble Learning

Syllabus



Week Date Subject/Topics

6 2025/10/14 NVIDIA Fundamentals of Deep Learning I: Deep Learning; Neural Networks

7 2025/10/21 NVIDIA Fundamentals of Deep Learning II:
Convolutional Neural Networks;
Data Augmentation and Deployment

8 2025/10/28 Self-Learning

9 2025/11/04 Midterm Project Report

10 2025/11/11 NVIDIA Fundamentals of Deep Learning III:

Pre-trained Models; Natural Language Processing

Syllabus



Week Date Subject/Topics

- 11 2025/11/18 Case Study on Artificial Intelligence II
- 12 2025/11/25 Computer Vision and Robotics
- 13 2025/12/02 Generative AI, Agentic AI, and Physical AI
- 14 2025/12/09 Philosophy and Ethics of AI and the Future of AI
- 15 2025/12/16 Final Project Report I
- 16 2025/12/23 Final Project Report II

Artificial Intelligence Intelligent Agents Problem Solving

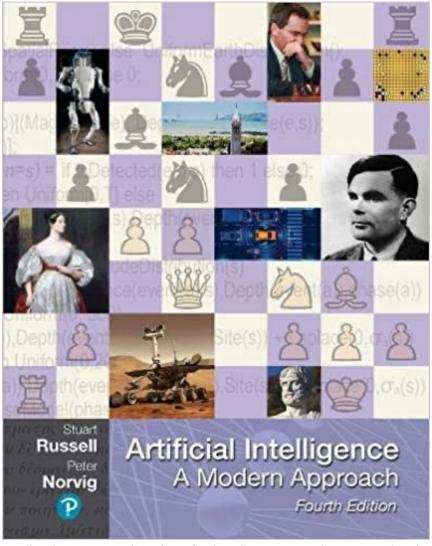
Outline

- Artificial Intelligence
- Intelligent Agents
- Problem Solving

Stuart Russell and Peter Norvig (2020),

Artificial Intelligence: A Modern Approach,

4th Edition, Pearson



Source: Stuart Russell and Peter Norvig (2020), Artificial Intelligence: A Modern Approach, 4th Edition, Pearson

Artificial Intelligence: A Modern Approach

- 1. Artificial Intelligence
- 2. Problem Solving
- 3. Knowledge and Reasoning
- 4. Uncertain Knowledge and Reasoning
- 5. Machine Learning
- 6. Communicating, Perceiving, and Acting
- 7. Philosophy and Ethics of Al

Artificial Intelligence: Intelligent Agents

Artificial Intelligence: 2. Problem Solving

- Solving Problems by Searching
- Search in Complex Environments
- Adversarial Search and Games
- Constraint Satisfaction Problems

Artificial Intelligence: 3. Knowledge and Reasoning

- Logical Agents
- First-Order Logic
- Inference in First-Order Logic
- Knowledge Representation
- Automated Planning

4. Uncertain Knowledge and Reasoning

- Quantifying Uncertainty
- Probabilistic Reasoning
- Probabilistic Reasoning over Time
- Probabilistic Programming
- Making Simple Decisions
- Making Complex Decisions
- Multiagent Decision Making

Artificial Intelligence: 5. Machine Learning

- Learning from Examples
- Learning Probabilistic Models
- Deep Learning
- Reinforcement Learning

6. Communicating, Perceiving, and Acting

- Natural Language Processing
- Deep Learning for Natural Language
 Processing
- Computer Vision
- Robotics

Artificial Intelligence: Philosophy and Ethics of Al The Future of Al





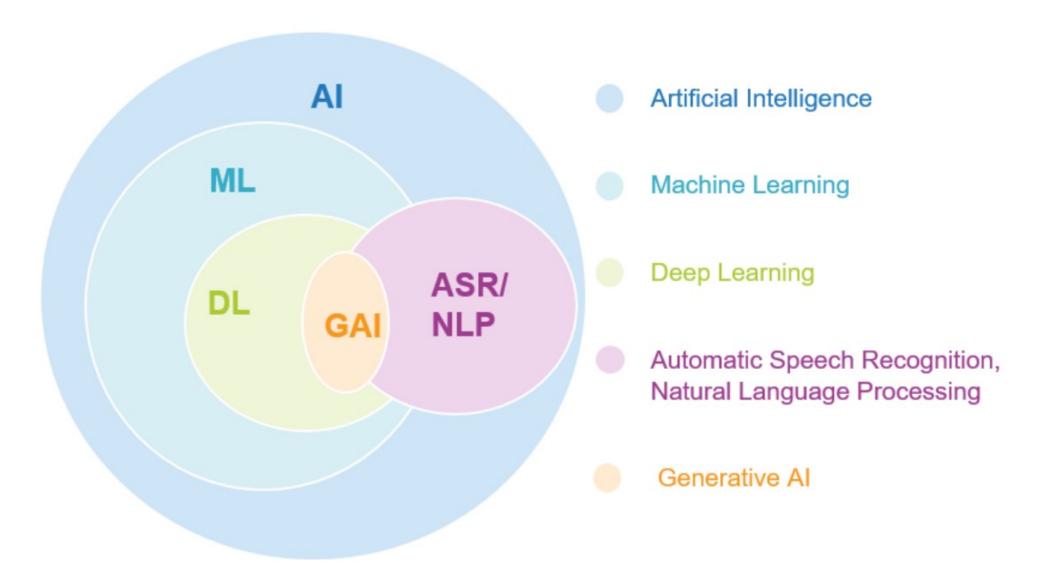
NVIDIA Developer Program

https://developer.nvidia.com/join-nvidia-developer-program

NVIDIA Deep Learning Institute (DLI)

https://learn.nvidia.com/

Al, ML, DL, Generative Al



Generative AI, Agentic AI, Physical AI

Physical AI

Self-driving cars
General robotics

Agentic Al

Coding assistants
Customer service
Patient care

Generative Al

Digital marketing Content creation

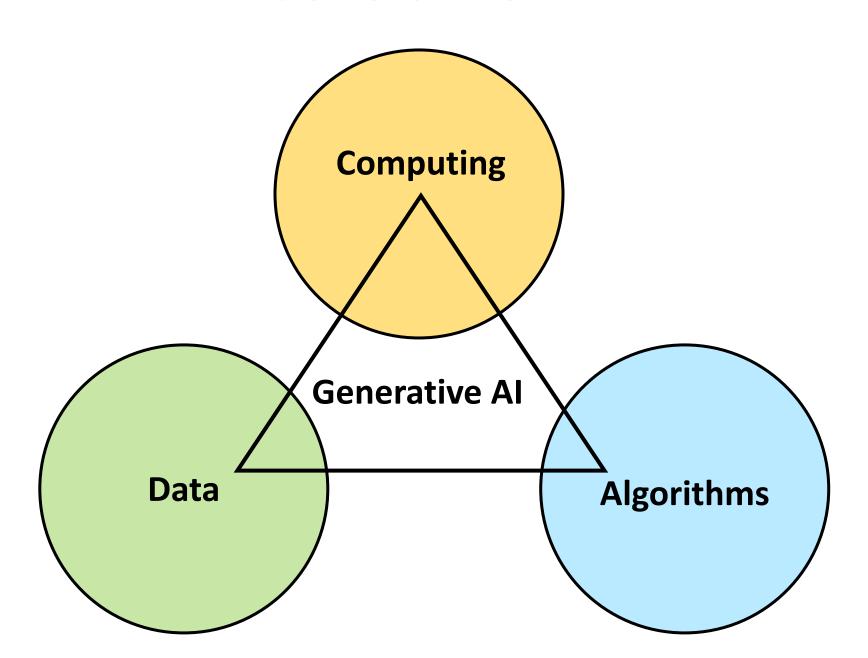
Perception Al

Speech recognition
Deep recommender systems
Medical imaging

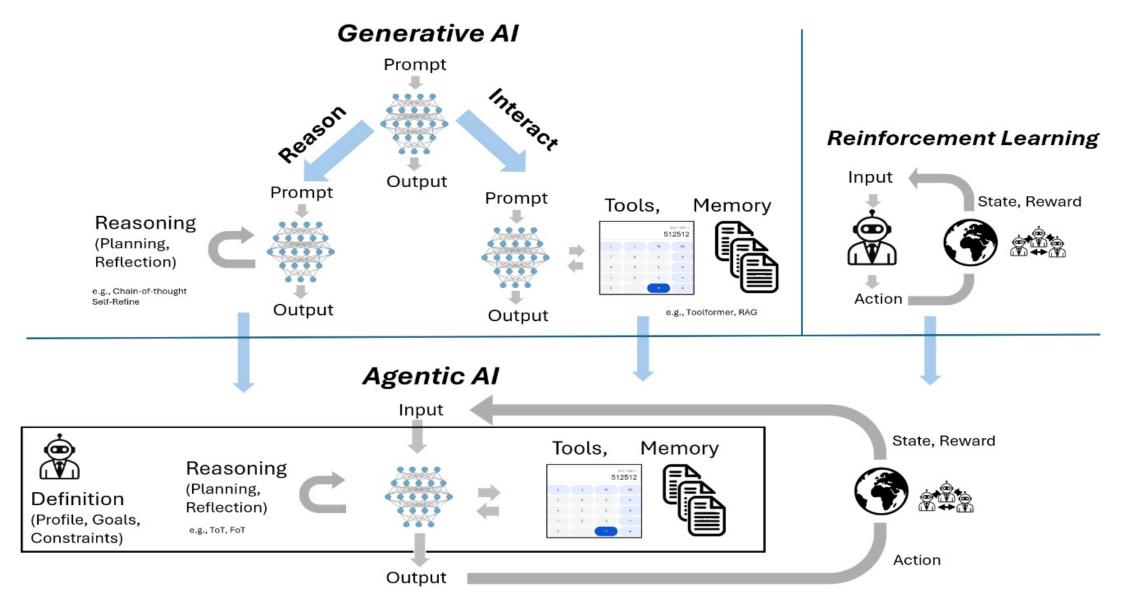
2012 AlexNet

Deep learning breakthrough

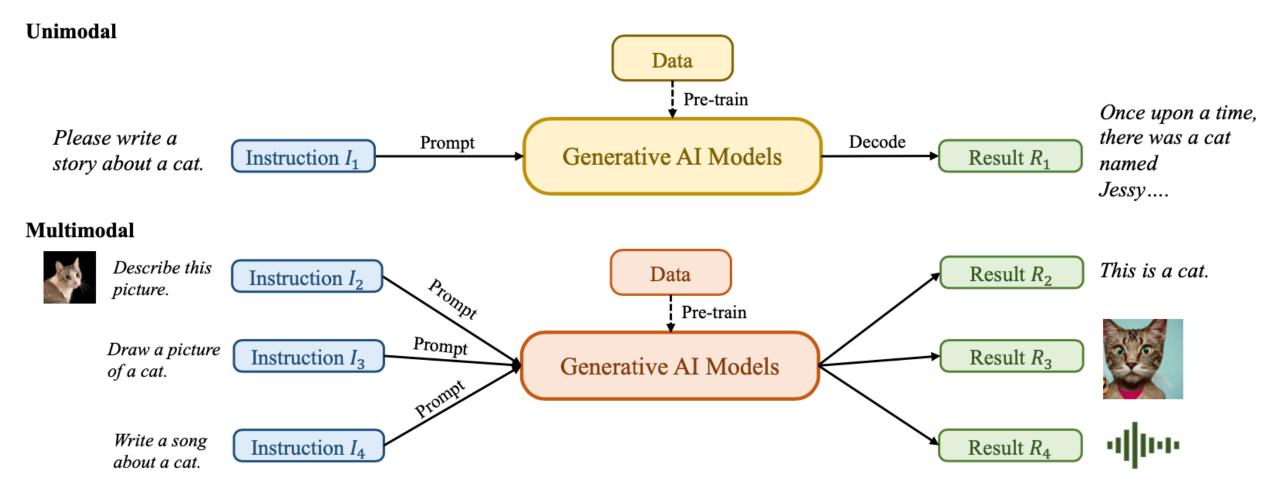
Generative Al



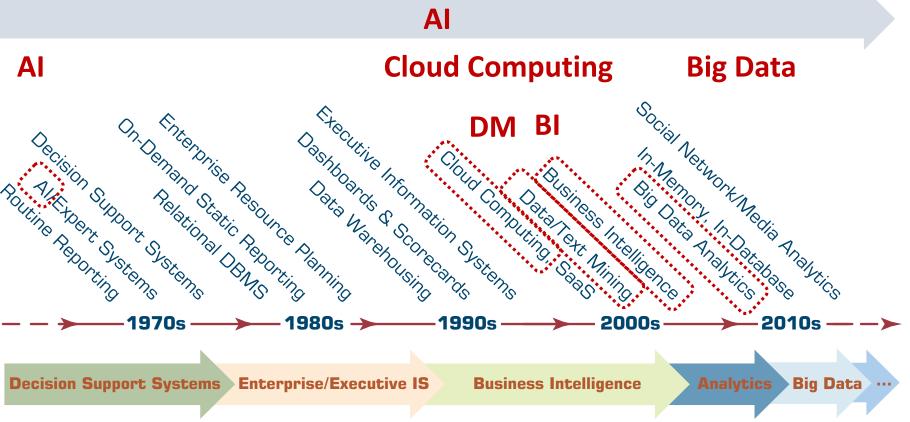
From Generative AI to Agentic AI



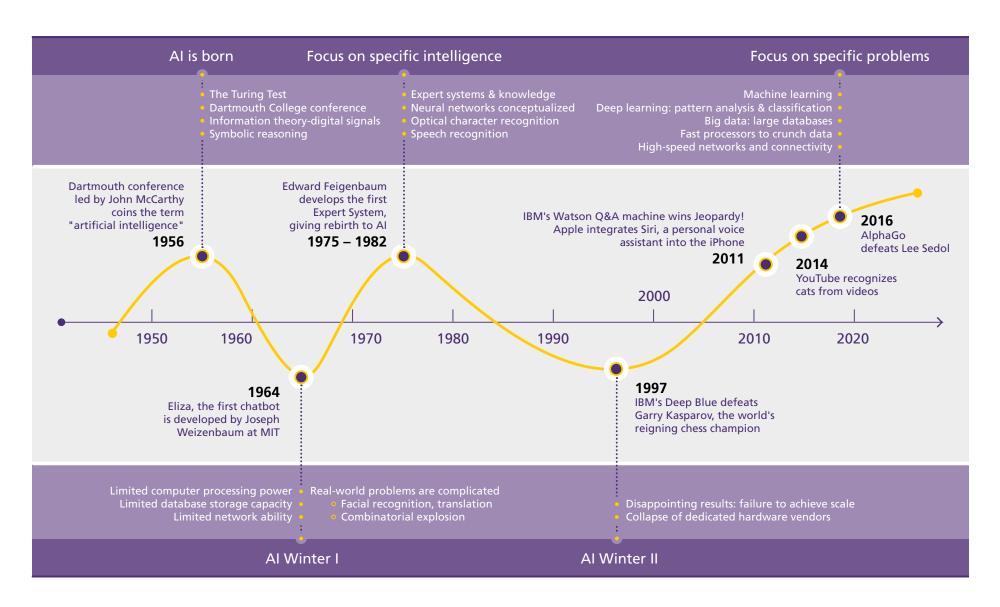
Generative AI (Gen AI) AI Generated Content (AIGC)



AI, Big Data, Cloud Computing Evolution of Decision Support, Business Intelligence, and Analytics



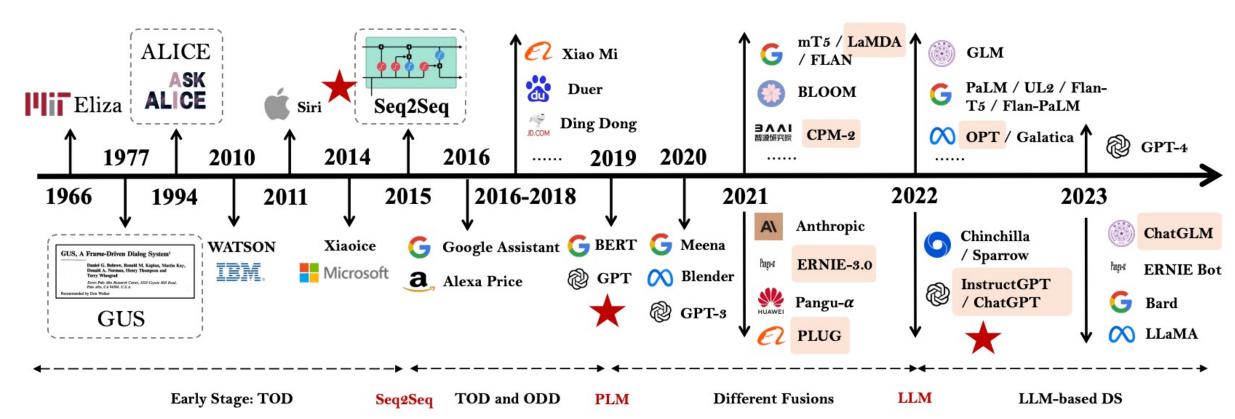
The Rise of Al



The Development of LM-based Dialogue Systems

1) Early Stage (1966 - 2015)

- 2) The Independent Development of TOD and ODD (2015 2019)
 - 3) Fusions of Dialogue Systems (2019 2022)
 - 4) LLM-based DS (2022 Now)



Task-oriented DS (TOD), Open-domain DS (ODD)

Definition of **Artificial Intelligence** (A.I.)

"... the Science and engineering making intelligent machines" (John McCarthy, 1955)

"... technology that thinks and acts like humans"

"... intelligence exhibited by machines or software"

4 Approaches of Al

Thinking Rationally Thinking Humanly Acting Rationally Acting Humanly

4 Approaches of Al

2.

Thinking Humanly:
The Cognitive
Modeling Approach

3.

Thinking Rationally:
The "Laws of Thought"
Approach

1.

Acting Humanly:
The Turing Test
Approach (1950)

4.

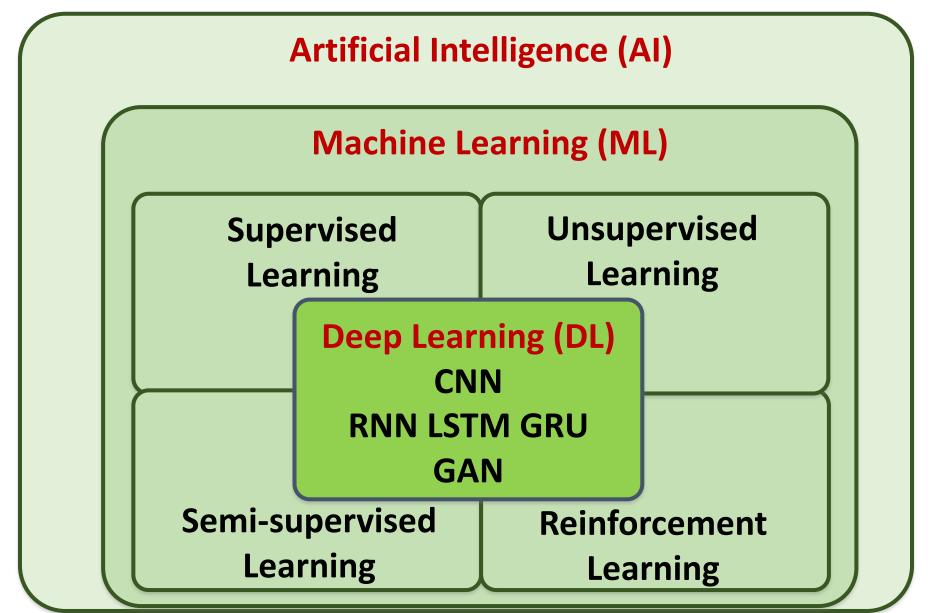
Acting Rationally:
The Rational Agent
Approach

Al Acting Humanly: The Turing Test Approach

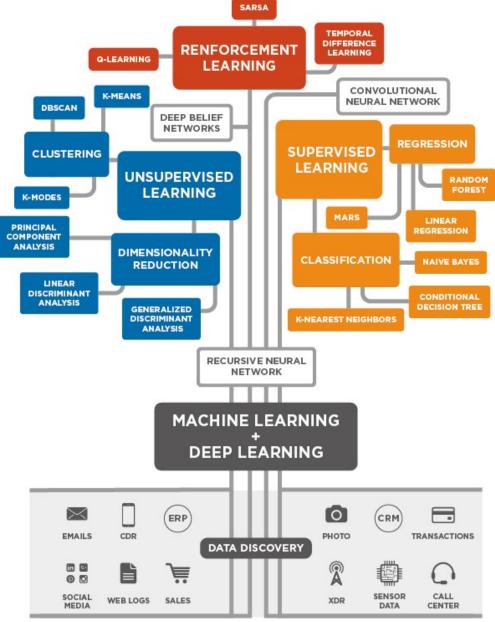
(Alan Turing, 1950)

- Knowledge Representation
- Automated Reasoning
- Machine Learning (ML)
 - Deep Learning (DL)
- Computer Vision (Image, Video)
- Natural Language Processing (NLP)
- Robotics

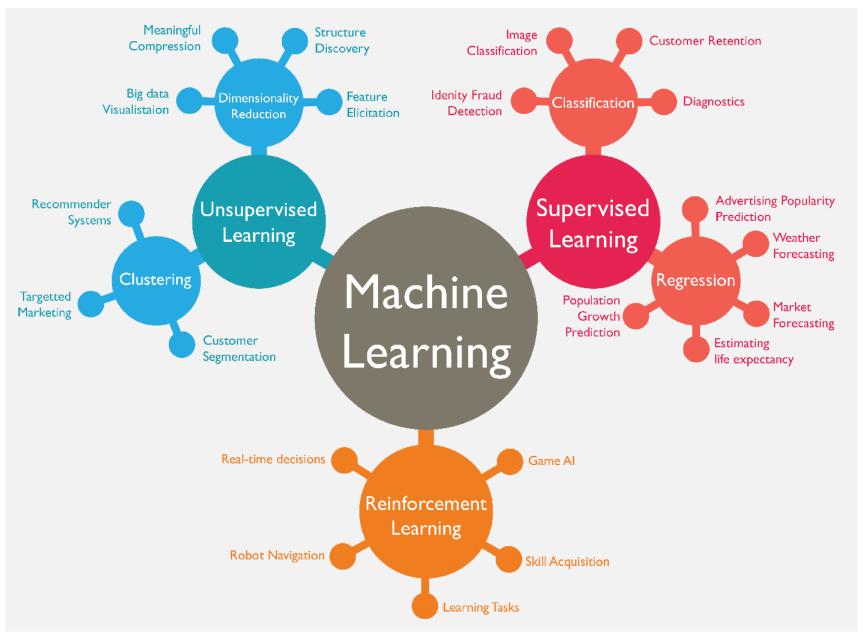
AI, ML, DL



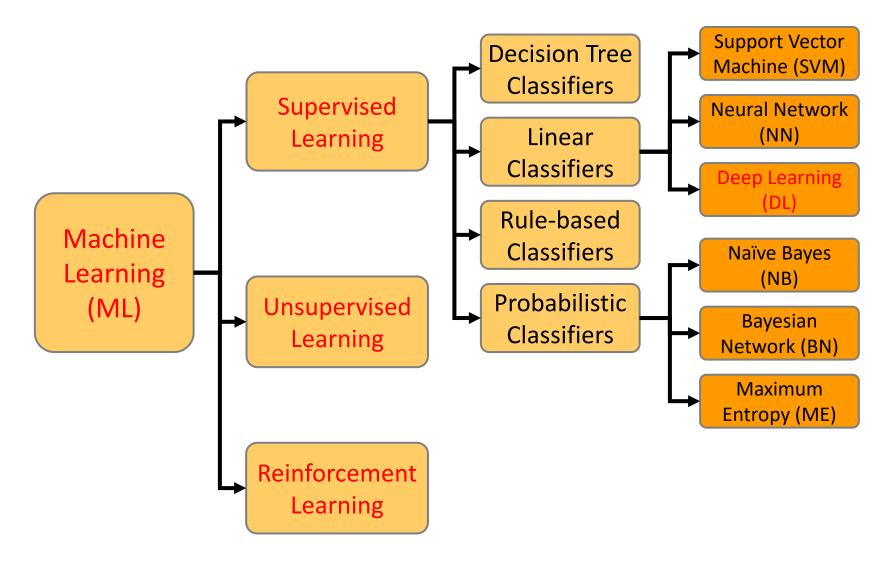
3 Machine Learning Algorithms



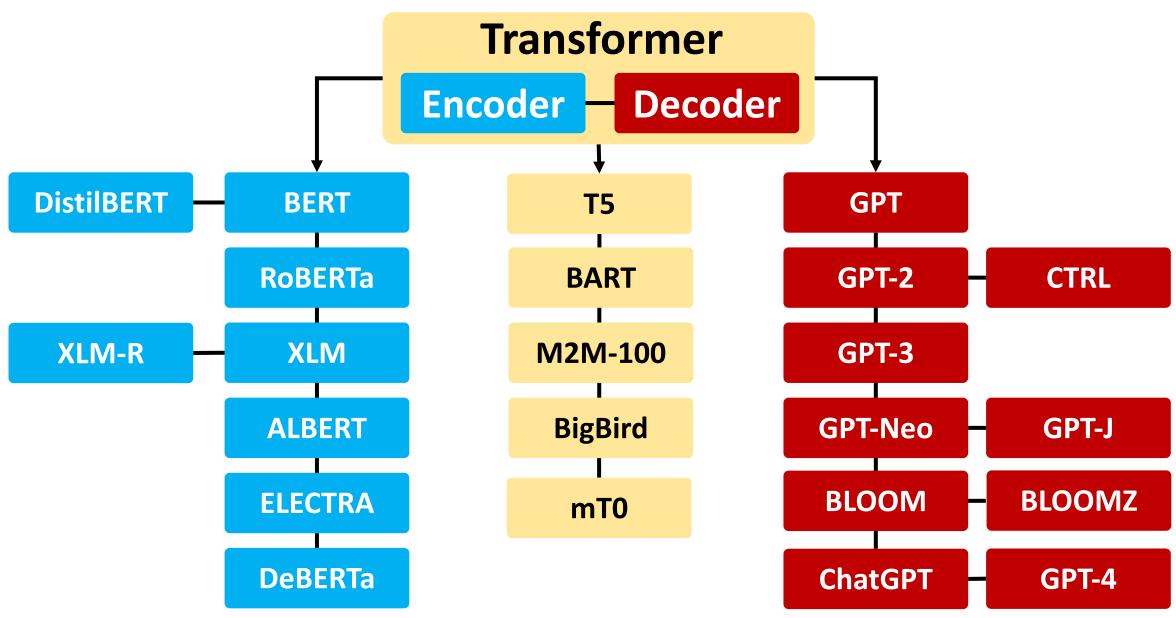
Machine Learning (ML)



Machine Learning (ML) / Deep Learning (DL)



Transformer Models



Four Paradigms in NLP (LM)

Paradigm	Engineering	Task Relation
a. Fully Supervised Learning (Non-Neural Network)	Feature (e.g. word identity, part-of-speech, sentence length)	CLS TAG LM GEN
b. Fully Supervised Learning (Neural Network)	Architecture (e.g. convolutional, recurrent, self-attentional)	CLS TAG LM GEN
Transfer Learning: Pre-t	CLS	
c. Pre-train, Fine-tune	Objective (e.g. masked language modeling, next sentence prediction)	LM
GAI: Pre-train, Prompt,	and Predict (Prompting)	CLS
d. Pre-train, Prompt, Predict	Prompt (e.g. cloze, prefix)	LM

Generative Al Text, Image, Video, Audio **Applications**

Comparison of Generative AI and Traditional AI

Feature Generative Al Traditional Al

Output type New content

Classification/Prediction

Creativity

High

Low

Interactivity Usually more natural Limited

Generative Al

- Generative AI: The Art of Creation
- Definition: Al systems capable of creating new content
- Characteristics: Creativity, interactivity

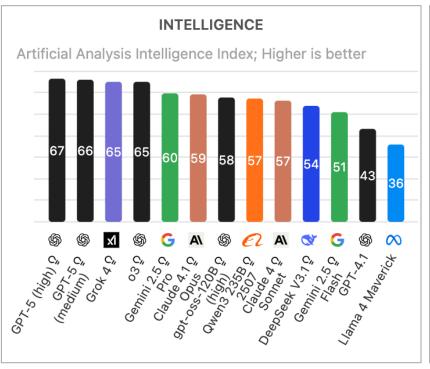
LMArena Leaderboard

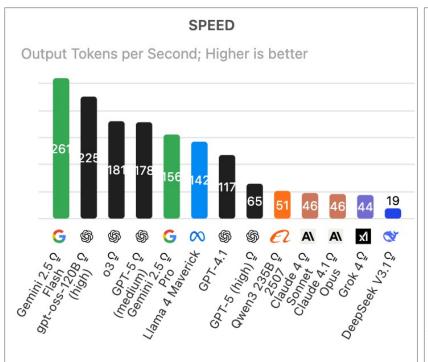
Rank (UB) ↑	Model ↑↓	Score ↑↓	95% CI (±) ↑↓	Votes ↑↓	Organization ↑↓	License ↑↓
1	G gemini-2.5-pro	1455	±5	41,731	Google	Proprietary
1	A\ claude-opus-4-1-20250805-thinking-16k	1451	±6	11,750	Anthropic	Proprietary
2	\$\oldsymbol{6}\oldsymbol{0} \oldsymbol{0}3-2025-04-16	1444	±4	43,898	OpenAl	Proprietary
2		1442	±6	15,076	OpenAl	Proprietary
2	\$\text{\$\text{\$\text{\$chatgpt-40-latest-20250326}}\$	1441	±4	36,426	OpenAl	Proprietary
3	\$\text{gpt-4.5-preview-2025-02-27}	1439	±6	15,271	OpenAl	Proprietary
3	A\ claude-opus-4-1-20250805	1438	±6	18,341	Anthropic	Proprietary
5		1430	±6	11,808	OpenAl	Proprietary
6	<pre> qwen3-max-preview</pre>	1428	±7	8,781	Alibaba	Proprietary
8	x grok-4-0709	1422	±5	21,446	xAI	Proprietary

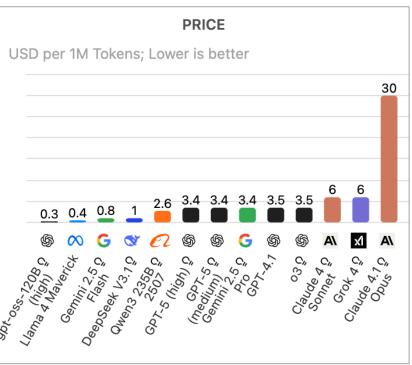
LMArena Leaderboard

Q Model > 239 / 239	Overall ↑↓	Hard Prompts ↑↓	Coding ↑↓	Math ↑↓	Creative Writing ↑↓	Instruction Following	Longer Query ↑↓	Multi-Turn ↑↓
A\ claude-opus-4-1	1	1	1	1	1	1	1	1
G gemini-2.5-pro	1	2	3	1	1	1	1	1
	2	4	3	13	2	5	4	1
	2	2	3	1	7	5	11	6
	2	4	3	1	8	6	13	7
A\ claude-opus-4-1	3	2	1	1	1	1	1	1
₲ gpt-4.5-preview	3	5	4	8	1	4	3	1
₲ gpt-5-chat	5	3	3	8	3	5	3	1
	6	4	2	1	7	4	4	3
A\ claude-opus-4-20	8	4	3	6	2	2	2	7
❤ deepseek-r1-0528	8	8	4	10	8	15	13	14
♥ deepseek-v3.1	8	6	4	1	7	6	5	9
❤ deepseek-v3.1-th	8	4	3	1	2	4	1	7
x grok-4-0709	8	10	12	1	4	6	8	7
kimi-k2-0711-pre	8	10	7	13	16	24	22	7
kimi-k2-0905-pre	8	5	3	-	6	16	12	7
🦻 qwen3-235b-a22b	8	4	3	2	9	6	4	7
Z glm-4.5	10	7	4	7	14	7	8	10

Artificial Analysis Intelligence Index Intelligence, Speed, Price





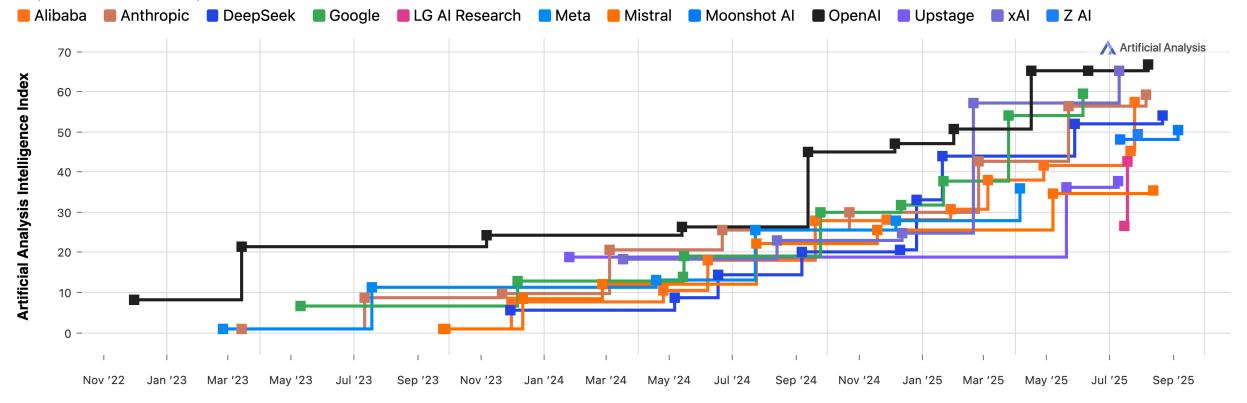


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Artificial Analysis Intelligence Index 2022-2025

Frontier Language Model Intelligence, Over Time

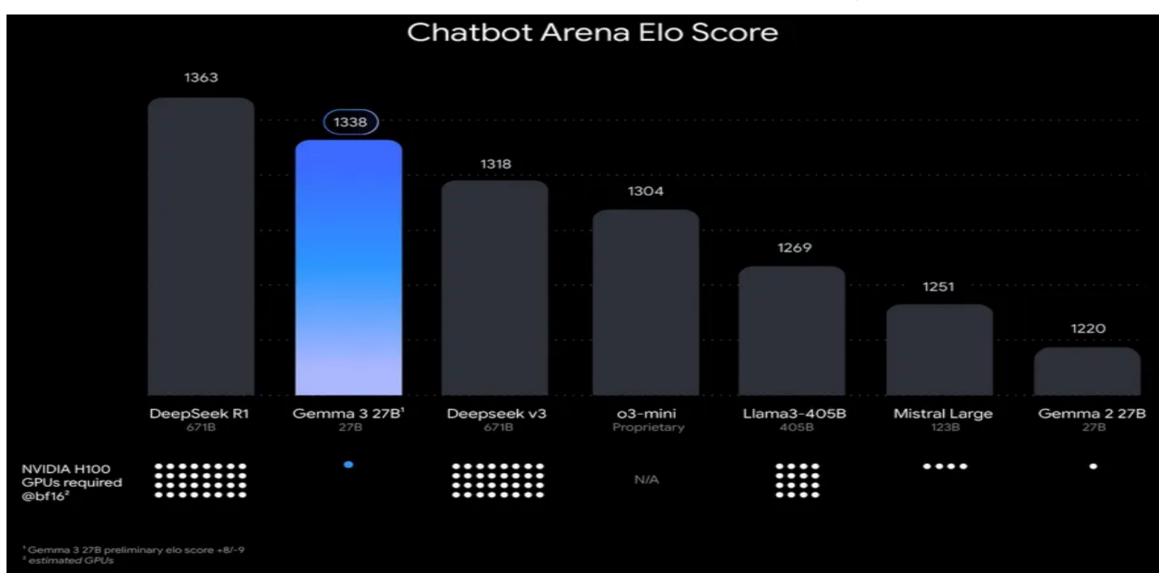
Artificial Analysis Intelligence Index v3.0 incorporates 10 evaluations: MMLU-Pro, GPQA Diamond, Humanity's Last Exam, LiveCodeBench, SciCode, AIME 2025, IFBench, AA-LCR, Terminal-Bench Hard, τ^2 -Bench Telecom



Release Date

Google Gemma 3 27B

The most capable model you can run on a single GPU or TPU

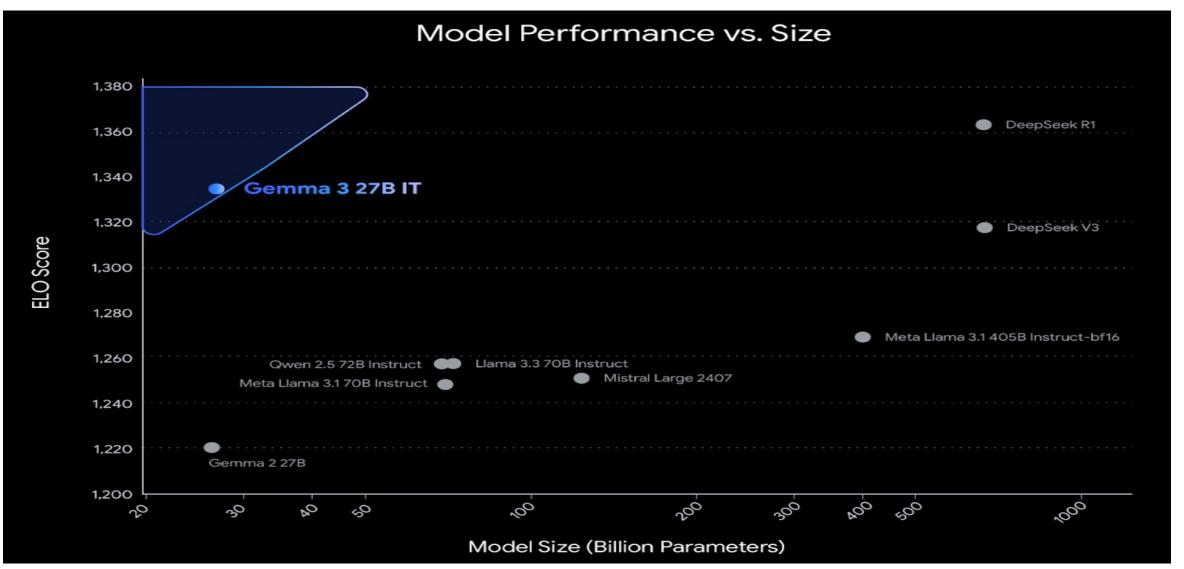


Google Gemma 3 Multimodality (vision-language input and text outputs)

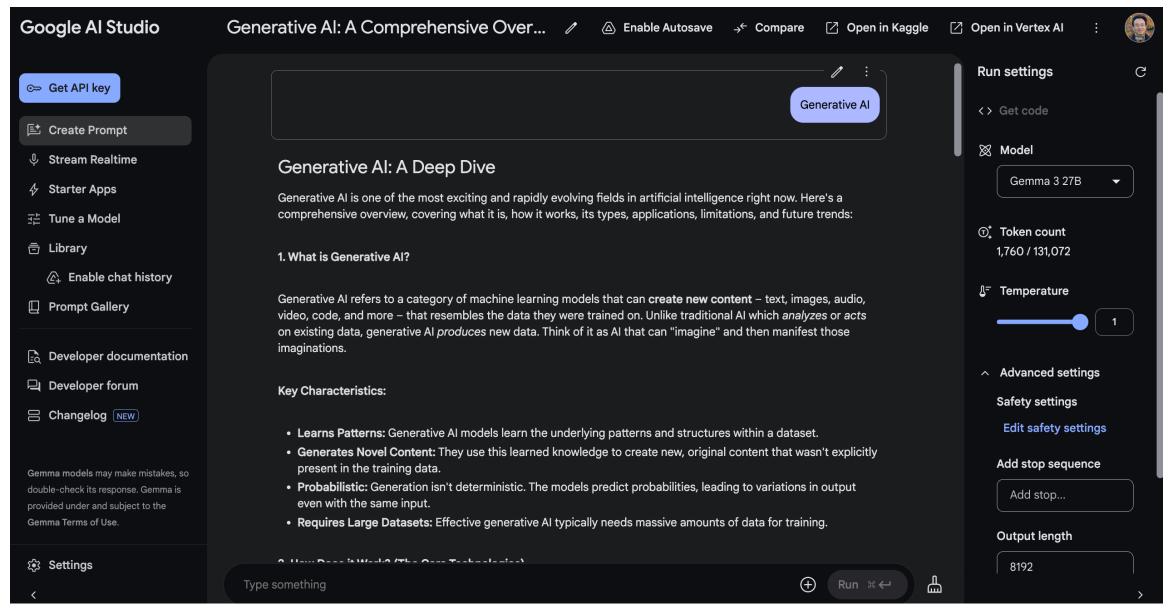
MODEL	SIZE (in billion parameter)	CONTEXT LENGTH	LANGUAGES	INPUT MODALITIES
Gemma 3 1B (IT)	1B	32k	English	Input: Text Output: Text
Gemma 3 4B (IT)	4B	128k	+140 Languages	Input: Text, Image Output: Text
Gemma 3 12B (IT)	12B	128k	+140 Languages	Input: Text, Image Output: Text
Gemma 3 27B (IT)	27B	128k	+140 Languages	Input: Text, Image Output: Text
Shield Gemma 2	4B	8k	+140 Languages	Input: Text, Image Output: Text

Google Gemma 3: Pre-training and Post-training

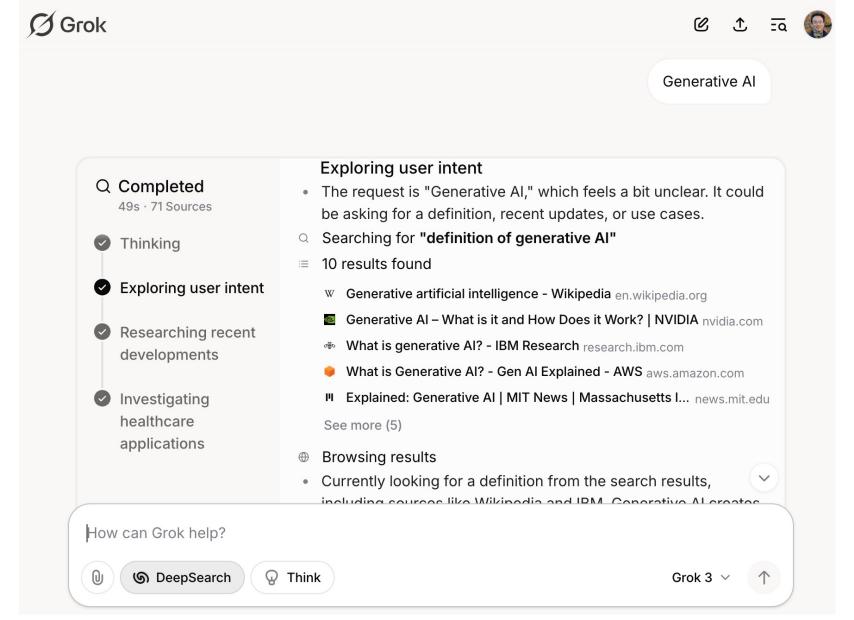
(distillation, reinforcement learning, and model merging)



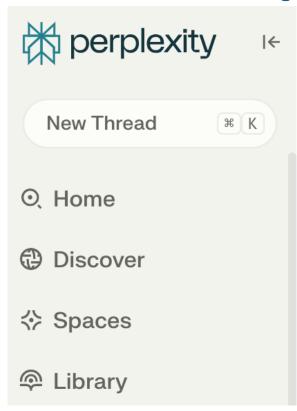
Google Al Studio (Gemma 3 27B)

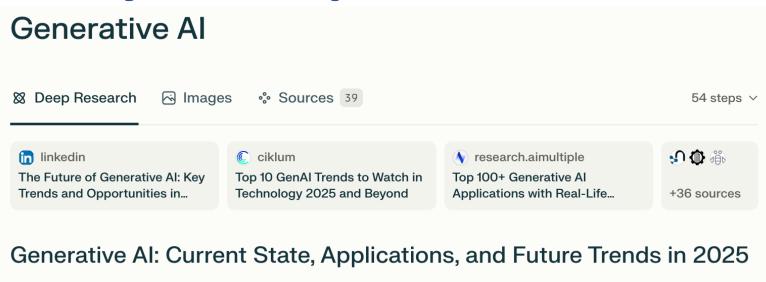


Grok 3 Deep Search



Perplexity.ai Deep Research





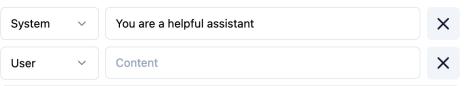
Generative AI has rapidly evolved into a transformative technology, revolutionizing content creation, business operations, and digital interactions across industries. As of early 2025, this technology has moved beyond experimental phases into mainstream adoption, with McKinsey reporting that 65% of organizations now regularly use generative AI, demonstrating its growing significance in the business landscape 4.



Networks), which have enabled increasingly sophisticated applications 1.

Token

Tiktokenizer



Add message

<|im_start|>system<|im_sep|>You are a helpful
assistant<|im_end|><|im_start|>user<|im_sep|><|im_end|>
<|im_start|>assistant<|im_sep|>

```
gpt-4o ≎
```

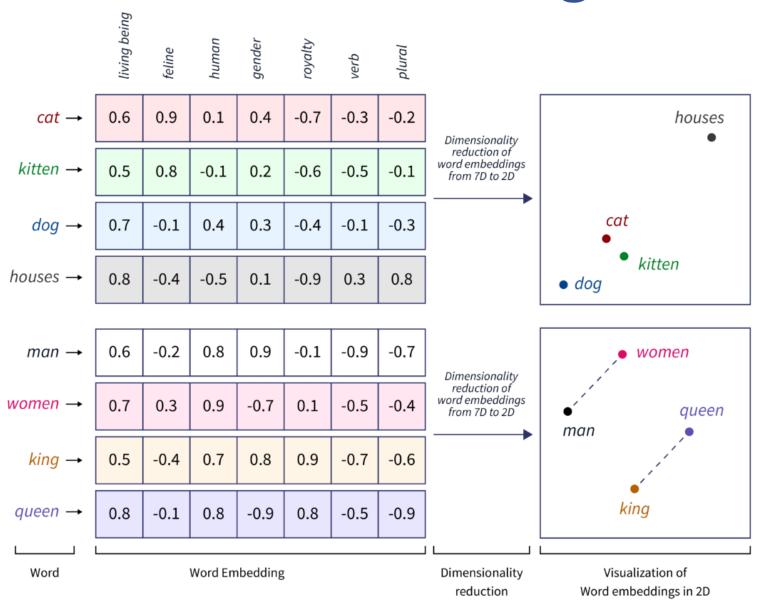
Token count 16

<|im_start|>system<|im_sep|>You are a helpful assistan
t<|im_end|><|im_start|>user<|im_sep|><|im_end|><|im_st
art|>assistant<|im_sep|>

200264, 17360, 200266, 3575, 553, 261, 10297, 29186, 2 00265, 200264, 1428, 200266, 200265, 200264, 173781, 2 00266

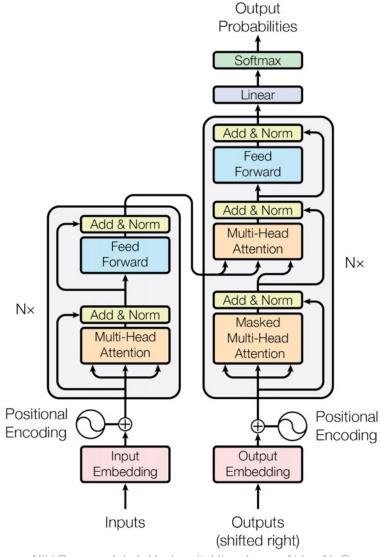
Show whitespace

Word Embeddings



Transformer (Attention is All You Need)

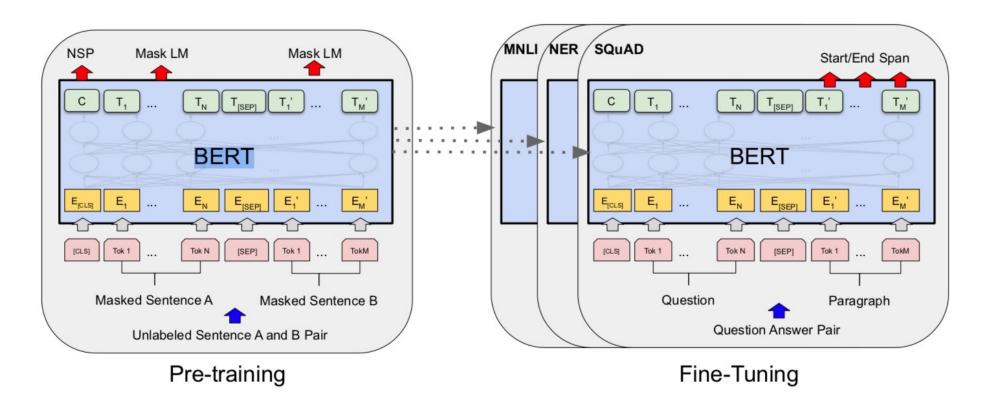
(Vaswani et al., 2017)



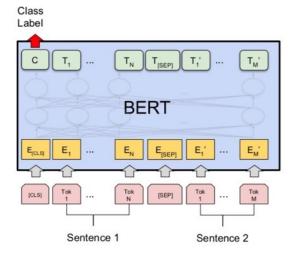
BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding

BERT (Bidirectional Encoder Representations from Transformers)

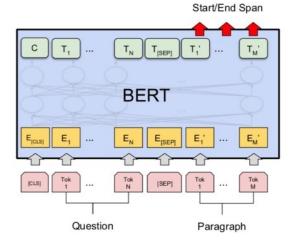
Overall pre-training and fine-tuning procedures for BERT



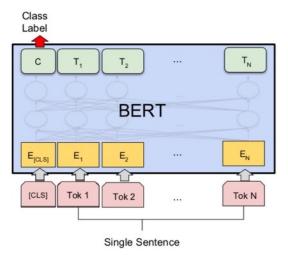
Fine-tuning BERT on Different Tasks



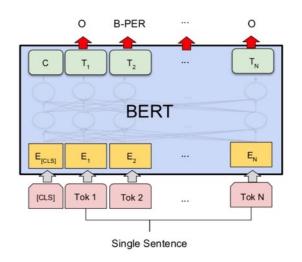
(a) Sentence Pair Classification Tasks: MNLI, QQP, QNLI, STS-B, MRPC, RTE, SWAG



(c) Question Answering Tasks: SQuAD v1.1

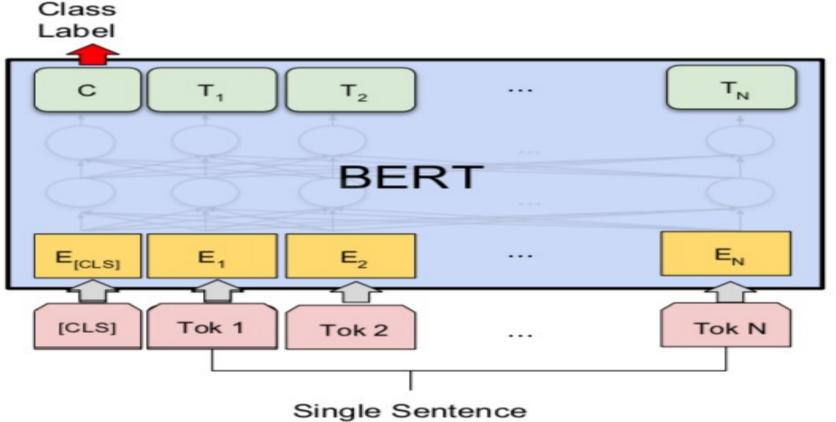


(b) Single Sentence Classification Tasks: SST-2, CoLA



(d) Single Sentence Tagging Tasks: CoNLL-2003 NER

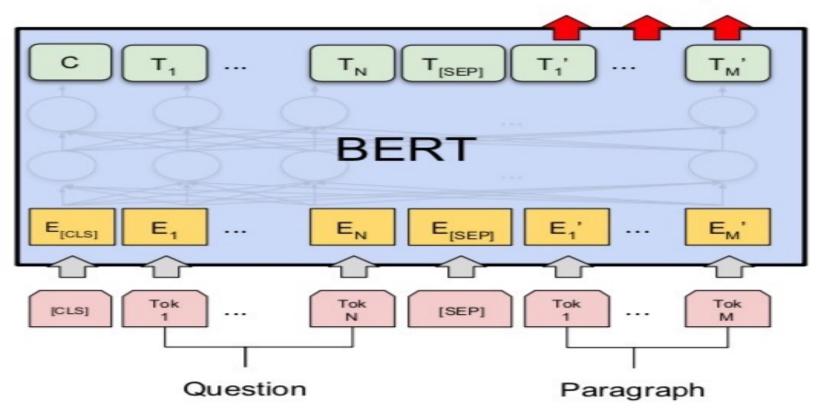
Sentiment Analysis: Single Sentence Classification



(b) Single Sentence Classification Tasks: SST-2, CoLA

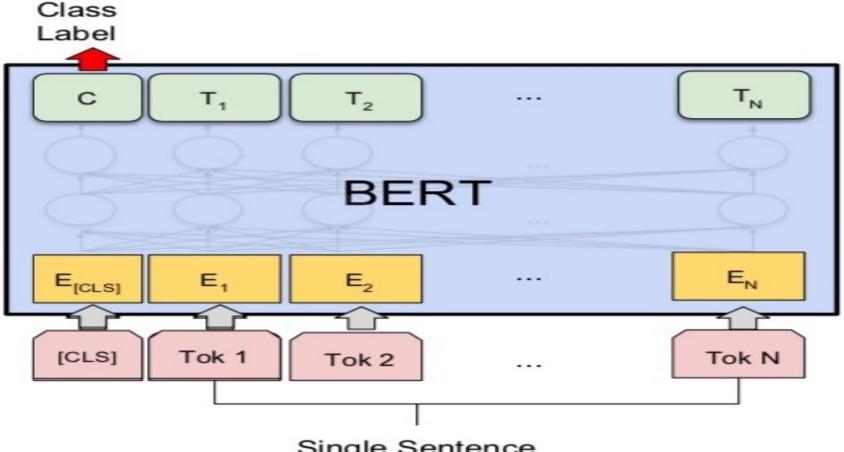
Fine-tuning BERT on Question Answering (QA)

Start/End Span



(c) Question Answering Tasks: SQuAD v1.1

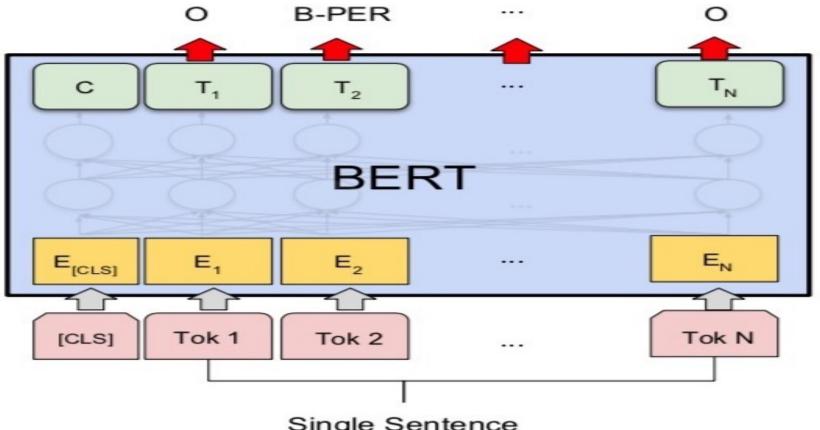
Fine-tuning BERT on Dialogue Intent Detection (ID; Classification)



Single Sentence

(b) Single Sentence Classification Tasks: SST-2, CoLA

Fine-tuning BERT on Dialogue Slot Filling (SF)

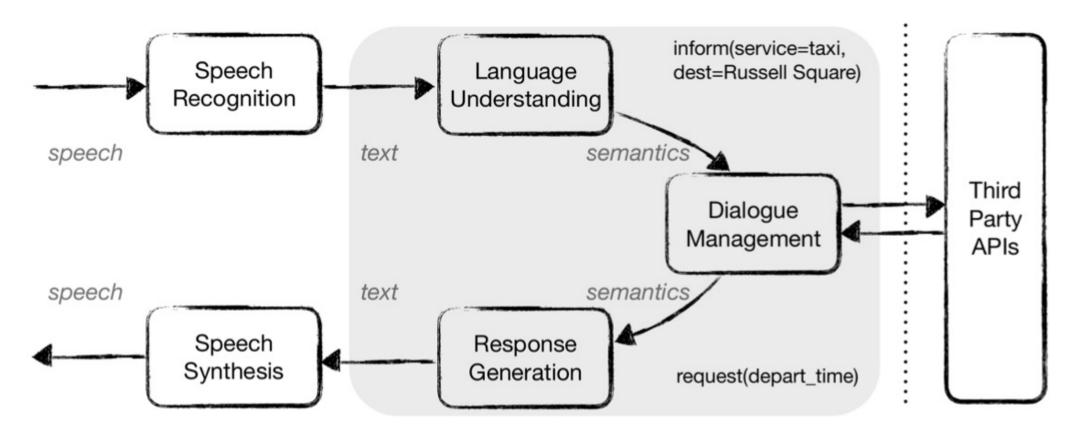


Single Sentence

(d) Single Sentence Tagging Tasks: CoNLL-2003 NER

Task-Oriented Dialogue (ToD) System Speech, Text, NLP

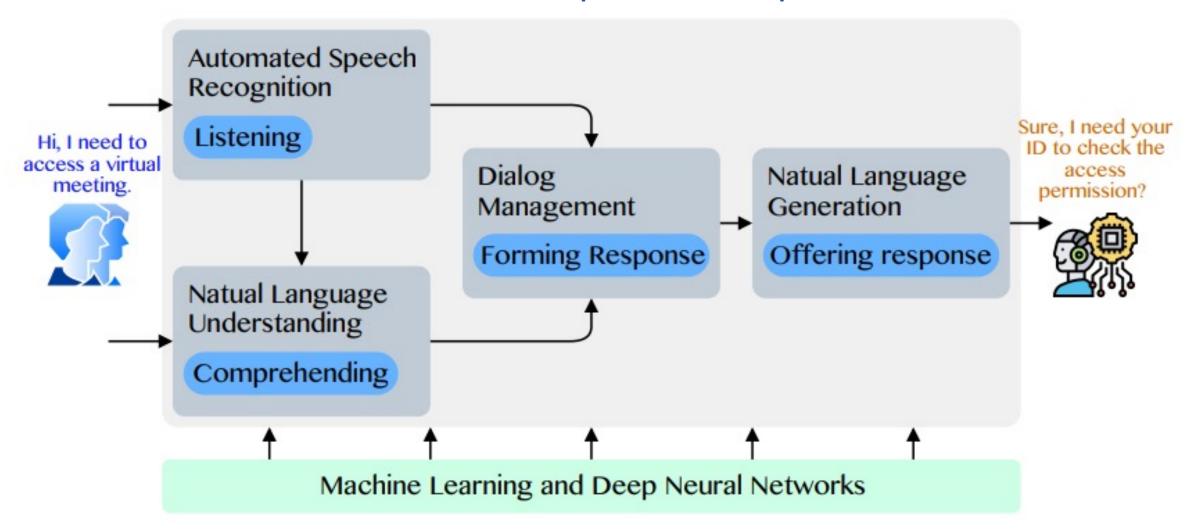
"Book me a cab to Russell Square"



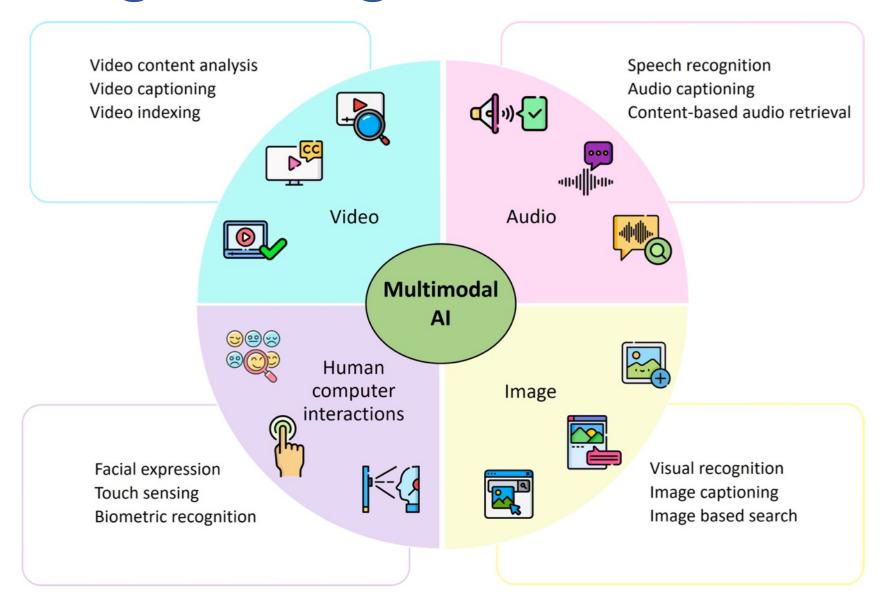
"When do you want to leave?"

Conversational Al

to deliver contextual and personal experience to users



Technological Integration for Multimodal AI



4 Approaches of Al

2.

Thinking Humanly:
The Cognitive
Modeling Approach

3.

Thinking Rationally:
The "Laws of Thought"
Approach

1.

Acting Humanly:
The Turing Test
Approach (1950)

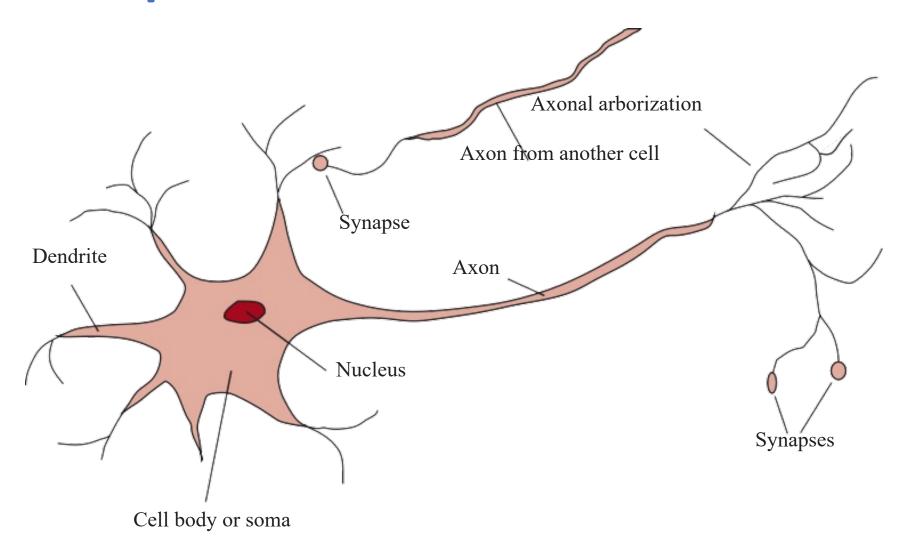
4.

Acting Rationally:
The Rational Agent
Approach

Acting Rationally: The Rational Agent Approach

- Al has focused on the study and construction of agents that do the right thing.
- Standard model

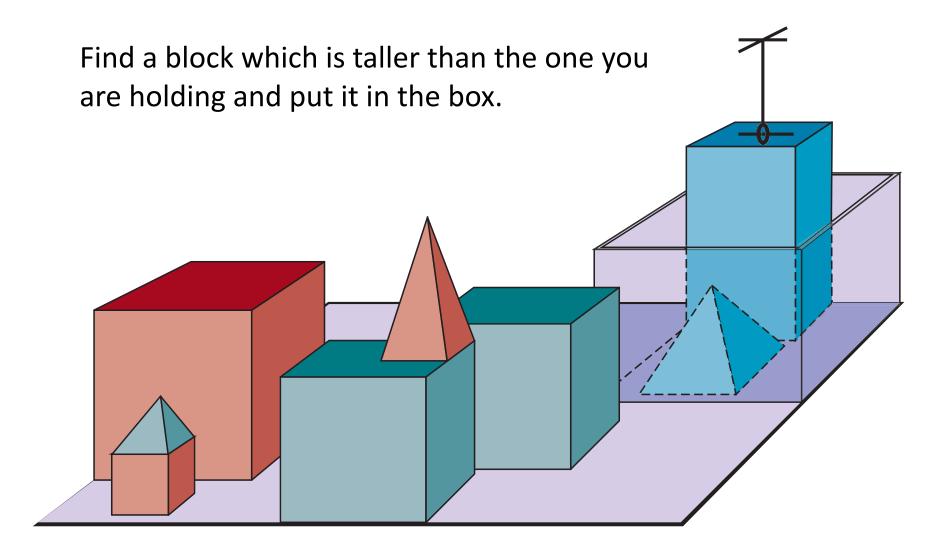
Neuroscience The parts of a nerve cell or neuron



Comparison of Computer and Human Brain

	Supercomputer	Personal Computer	Human Brain
Computational units	10 ⁶ GPUs + CPUs	8 CPU cores	10 ⁶ columns
	10 ¹⁵ transistors	10 ¹⁰ transistors	10 ¹¹ neurons
Storage units	10 ¹⁶ bytes RAM	10 ¹⁰ bytes RAM	10 ¹¹ neurons
	10 ¹⁷ bytes disk	10 ¹² bytes disk	10 ¹⁴ synapses
Cycle time	10 ⁻⁹ sec	10 ⁻⁹ sec	10 ⁻³ sec
Operations/sec	10 ¹⁸	10 ¹⁰	10 ¹⁷

A scene from the blocks world



Intelligent Agents

4 Approaches of Al

2.

Thinking Humanly:
The Cognitive
Modeling Approach

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The "Laws of Thought"
Approach

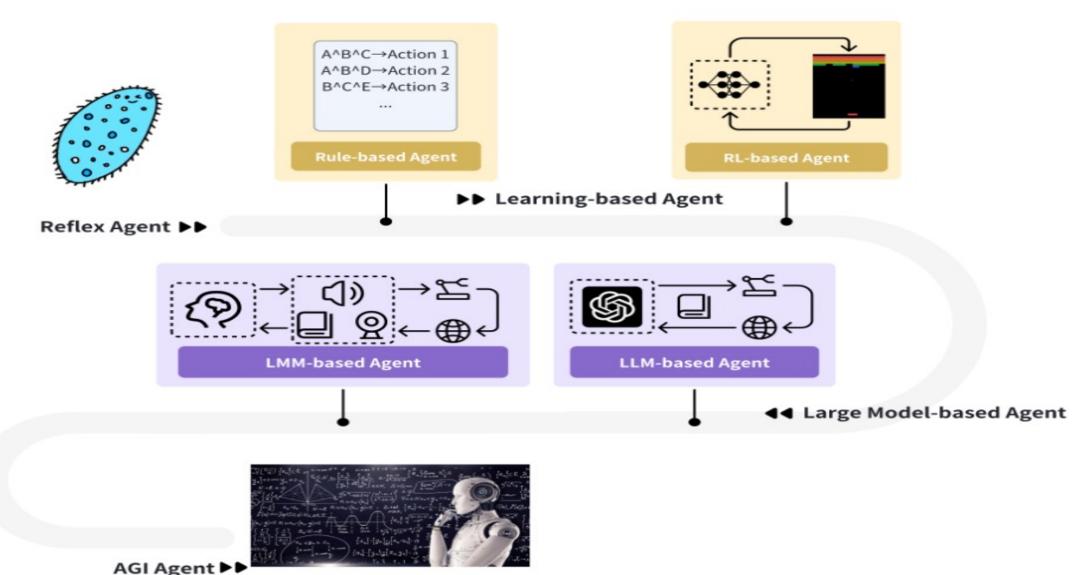
1.

Acting Humanly:
The Turing Test
Approach (1950)

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Acting Rationally:
The Rational Agent
Approach

Intelligent Agents Roadmap

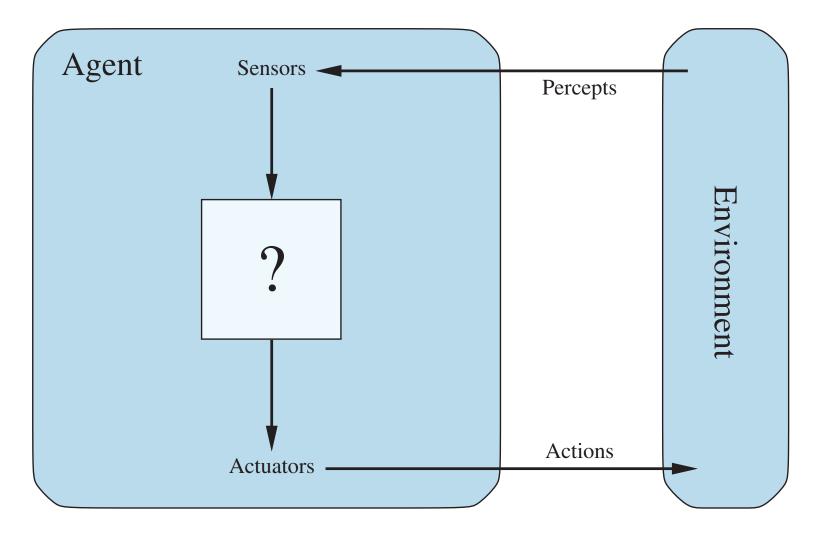


Al Agents

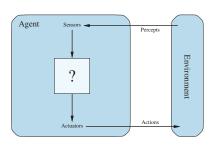
- Traditional AI Agents
 - Simple reflex agents
 - Model-based reflex agents
 - Goal-based agents
 - Utility-based agents
 - Learning agents

- Evolution of Al Agents
 - LLM-based Agents
 - Multi-modal agents
 - Embodied AI agents in virtual environments
 - Collaborative Al agents

Agents interact with environments through sensors and actuators



Al Agents



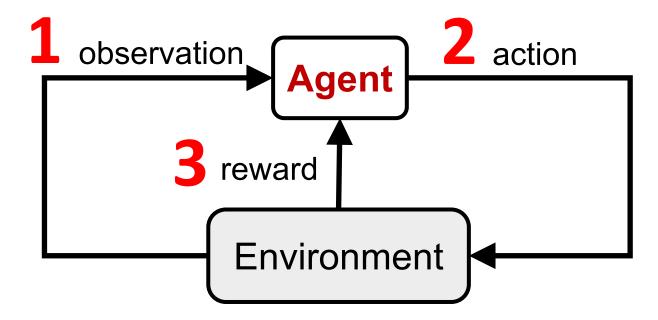
- Definition: An Al agent is an entity that perceives its environment and takes actions to achieve goals
- Components:
 - 1. Sensors: Perceive the environment
 - 2. Actuators: Act upon the environment
 - 3. Decision-making mechanism: Process inputs and decide on actions

Reinforcement Learning (DL)

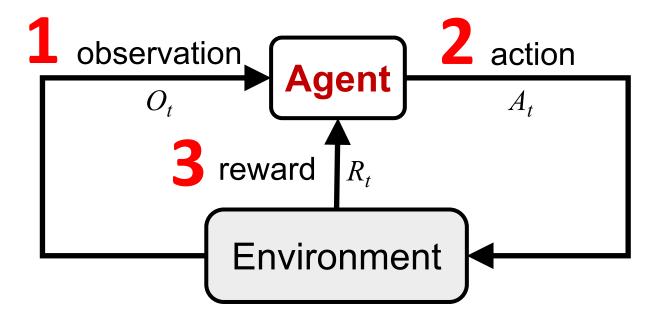
Agent

Environment

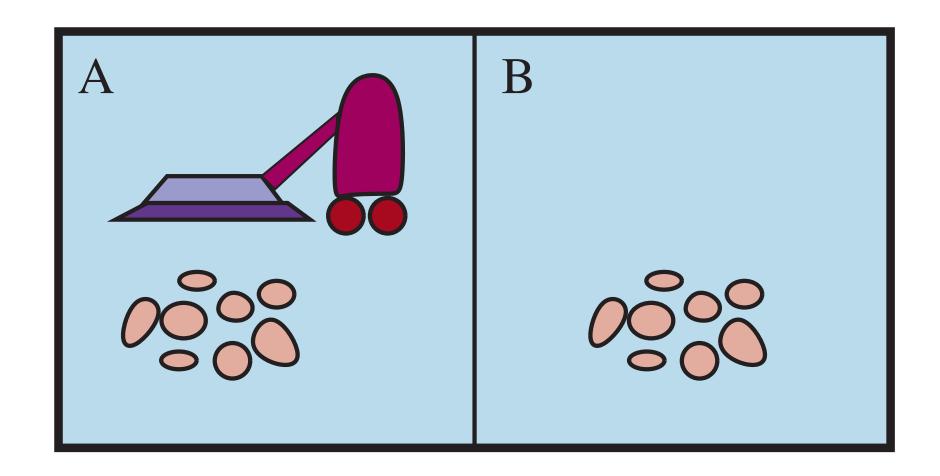
Reinforcement Learning (DL)



Reinforcement Learning (DL)



A vacuum-cleaner world with just two locations



Partial tabulation of a simple agent function for the vacuum-cleaner world

Percept sequence	Action
[A, Clean]	Right
[A, Dirty]	Suck
[B, Clean]	Left
[B, Dirty]	Suck
[A, Clean], [A, Clean]	Right
[A, Clean], [A, Dirty]	Suck
<u>:</u>	:
[A, Clean], [A, Clean], [A, Clean]	Right
[A, Clean], [A, Clean], [A, Dirty]	Suck
: :	: :

PEAS description of the task environment for an automated taxi driver

Agent Type	Performance Measure	Environment	Actuators	Sensors
Taxi driver	Safe, fast, legal, comfortable trip, maximize profits, minimize impact on other road users	Roads, other traffic, police, pedestrians, customers, weather	Steering, accelerator, brake, signal, horn, display, speech	Cameras, radar, speedometer, GPS, engine sensors, accelerometer, microphones, touchscreen

Examples of Agent Types and their PEAS descriptions

Agent Type	Performance Measure	Environment	Actuators	Sensors	
Medical diagnosis system	Healthy patient, reduced costs	Patient, hospital, staff	Display of questions, tests, diagnoses, treatments	Touchscreen/voice entry of symptoms and findings	
Satellite image analysis system	Correct categorization of objects, terrain	Orbiting satellite, downlink, weather	Display of scene categorization	High-resolution digital camera	
Part-picking robot	Percentage of parts in correct bins	Conveyor belt with parts; bins	Jointed arm and hand	Camera, tactile and joint angle sensors	
Refinery controller	Purity, yield, safety	Refinery, raw materials, operators	Valves, pumps, heaters, stirrers, displays	Temperature, pressure, flow, chemical sensors	
Interactive English tutor	Student's score on test	Set of students, testing agency	Display of exercises, feedback, speech	Keyboard entry, voice	

Examples of Task Environments and their Characteristics

Task Environment	Observable	Agents	Deterministic	Episodic	Static	Discrete
Crossword puzzle Chess with a clock	Fully	Single	Deterministic	Sequential	Static	Discrete
	Fully	Multi	Deterministic	Sequential	Semi	Discrete
Poker	Partially	Multi	Stochastic	Sequential	Static	Discrete
Backgammon	Fully	Multi	Stochastic	Sequential	Static	Discrete
Taxi driving	Partially	Multi	Stochastic	Sequential	Dynamic	Continuous
Medical diagnosis	Partially	Single	Stochastic	Sequential	Dynamic	Continuous
Image analysis Part-picking robot	Fully	Single	Deterministic	Episodic	Semi	Continuous
	Partially	Single	Stochastic	Episodic	Dynamic	Continuous
Refinery controller	Partially	Single	Stochastic	Sequential	Dynamic	Continuous
English tutor	Partially	Multi	Stochastic	Sequential	Dynamic	Discrete

The TABLE-DRIVEN-AGENT program is invoked for each new percept and returns an action each time.

It retains the complete percept sequence in memory.

```
function TABLE-DRIVEN-AGENT(percept) returns an action
```

persistent: percepts, a sequence, initially empty

table, a table of actions, indexed by percept sequences, initially fully specified

append percept to the end of percepts

 $action \leftarrow Lookup(percepts, table)$

return action

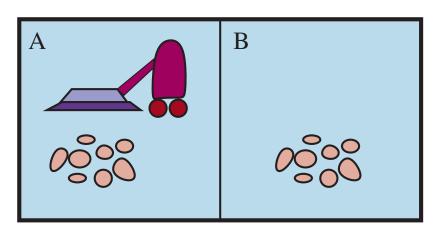
The agent program for a simple reflex agent in the two-location vacuum environment.

function Reflex-Vacuum-Agent([location, status]) returns an action

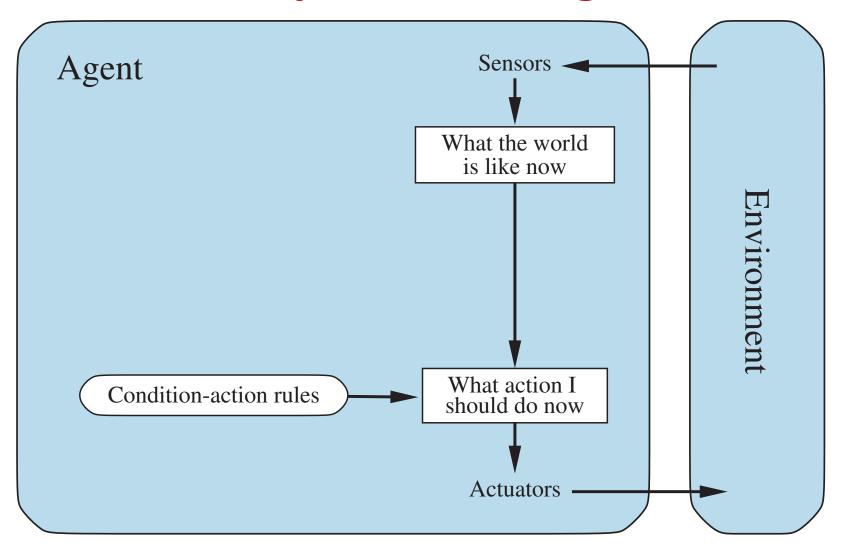
```
if status = Dirty then return Suck
```

else if location = A then return Right

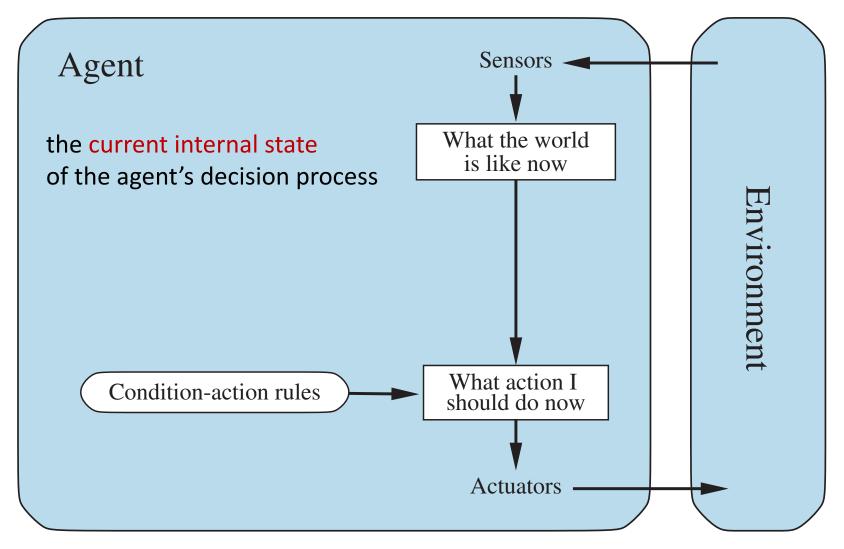
else if location = B then return Left



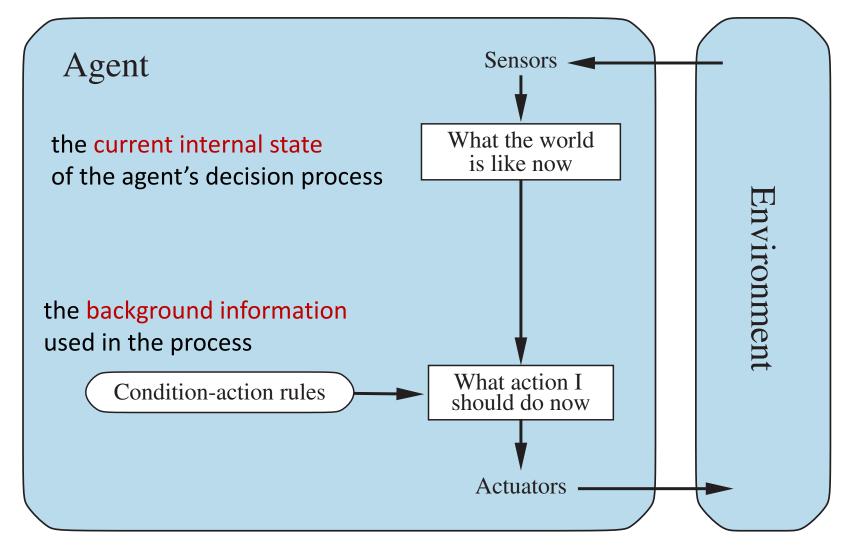
Schematic Diagram of a Simple Reflex Agent



Schematic diagram of a simple reflex agent



Schematic diagram of a simple reflex agent

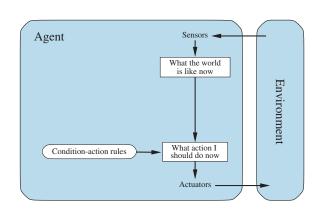


A Simple Reflex Agent

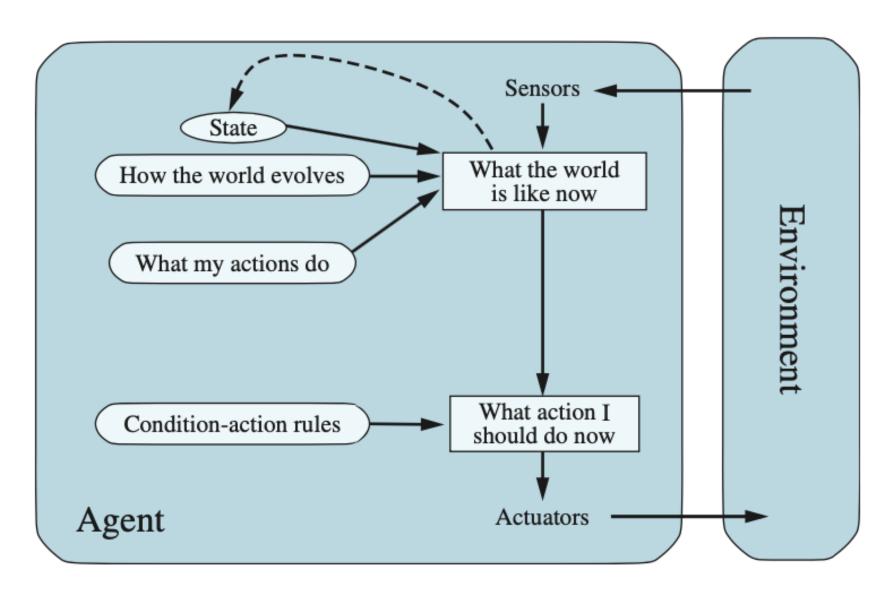
It acts according to a rule whose condition matches the current state, as defined by the percept.

function SIMPLE-REFLEX-AGENT(percept) **returns** an action **persistent**: rules, a set of condition—action rules

 $state \leftarrow \text{Interpret-Input}(percept)$ $rule \leftarrow \text{Rule-Match}(state, rules)$ $action \leftarrow rule. \text{Action}$ $return \ action$



A Model-based Reflex Agent



A model-based reflex agent

It keeps track of the current state of the world, using an internal model.

It then chooses an action in the same way as the reflex agent.

function Model-Based-Reflex-Agent(percept) returns an action

persistent: state, the agent's current conception of the world state

transition_model, a description of how the next state depends on

the current state and action

sensor_model, a description of how the current world state is reflected

in the agent's percepts

rules, a set of condition—action rules

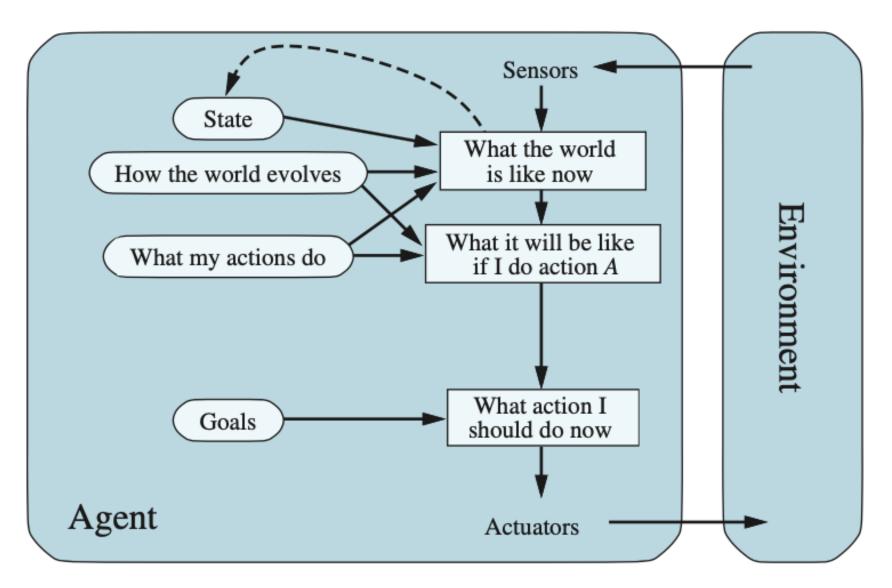
action, the most recent action, initially none

 $state \leftarrow \text{UPDATE-STATE}(state, action, percept, transition_model, sensor_model)$

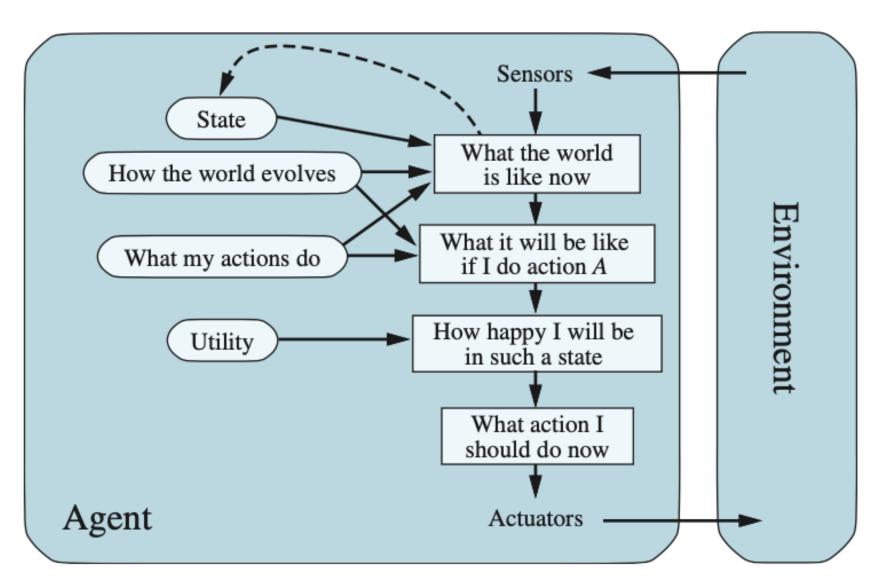
 $rule \leftarrow \texttt{RULE-MATCH}(state, rules) \\ action \leftarrow rule. \texttt{ACTION}$

return action

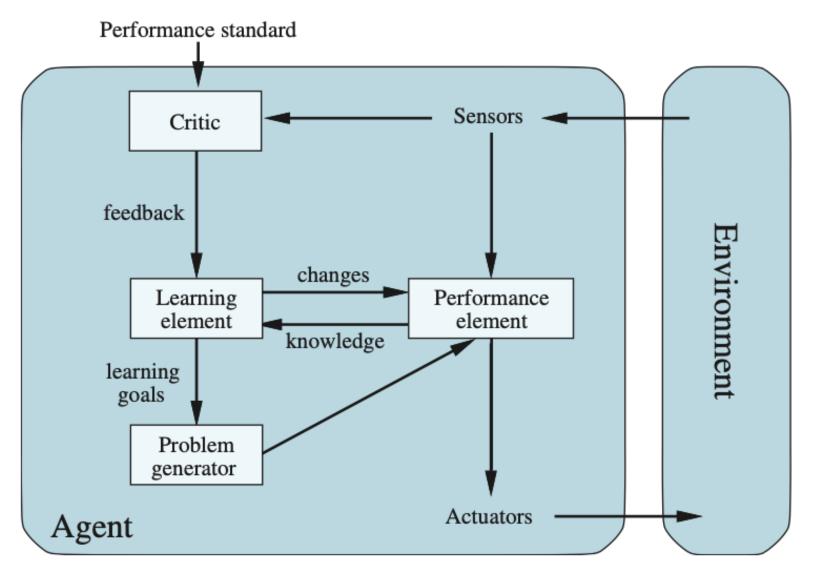
A model-based, goal-based agent



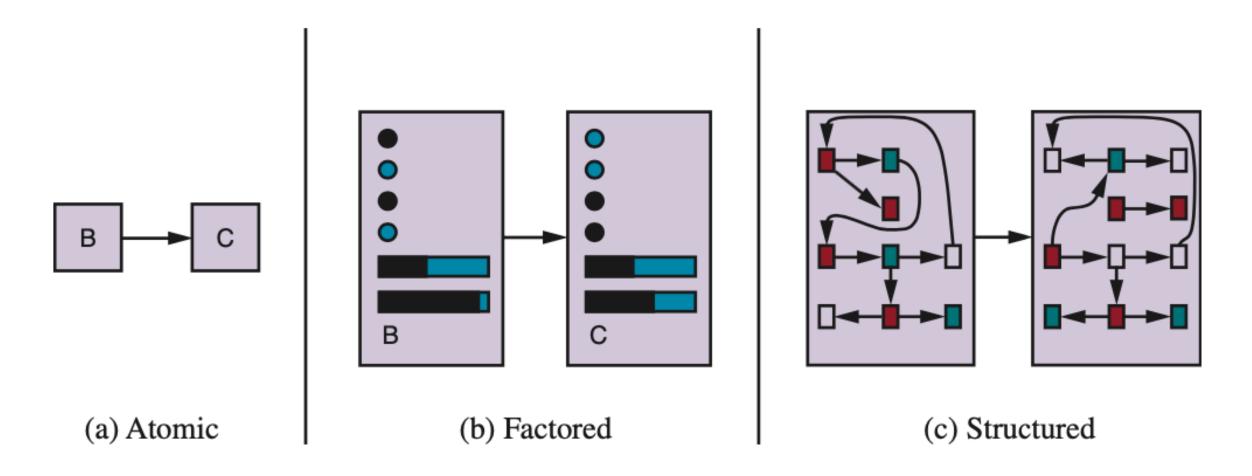
A model-based, utility-based agent



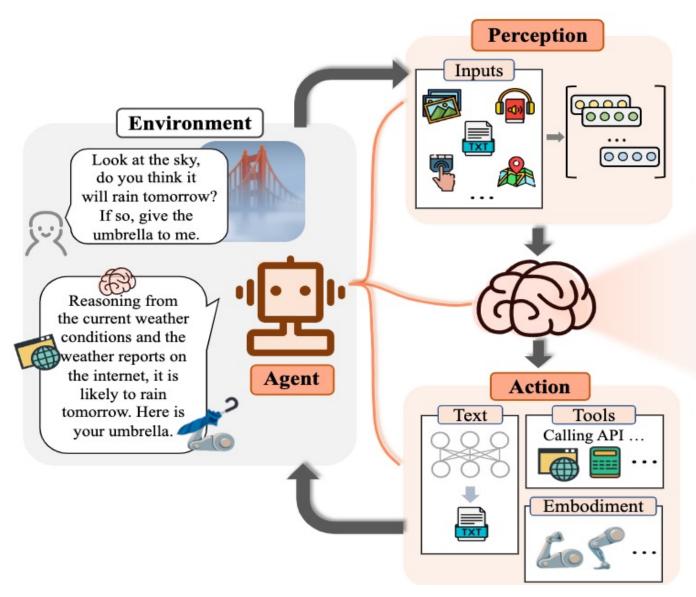
A general learning agent

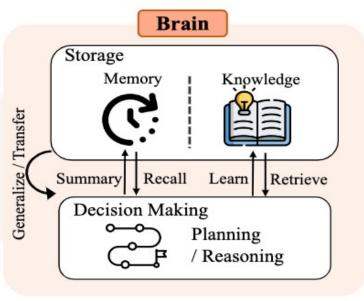


Three ways to represent states and the transitions between them



Large Language Model (LLM) based Agents

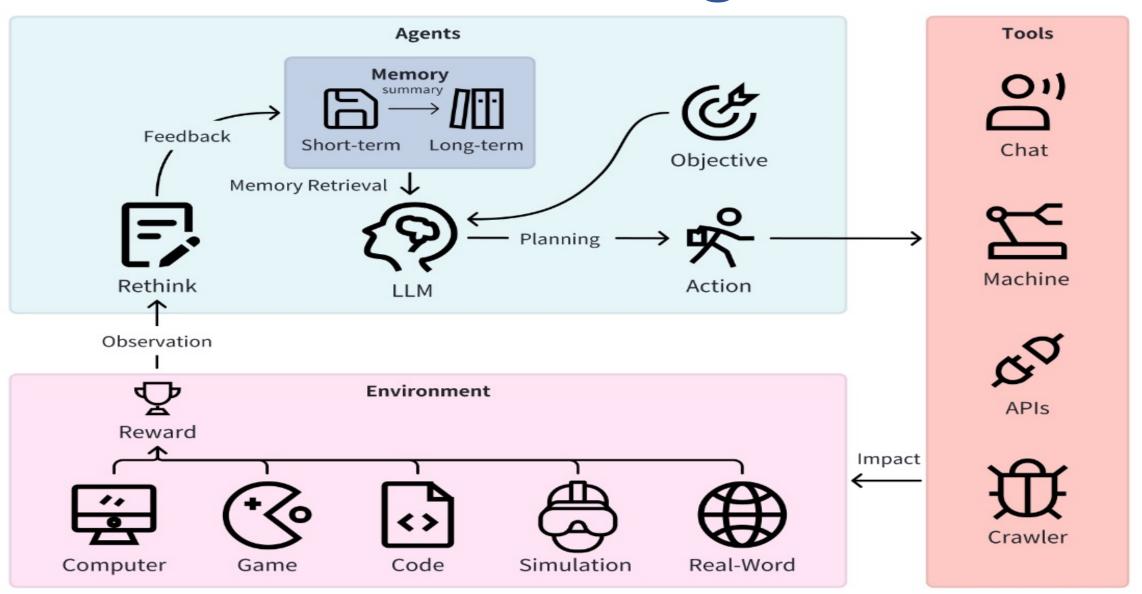




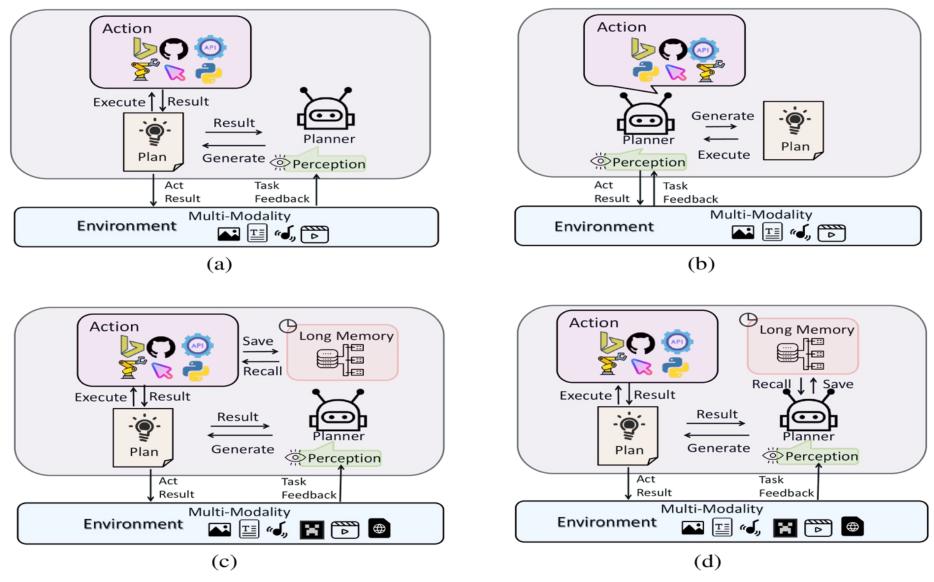
LLM-based Agents

- Definition: Al agents that use Large Language Models as their core decision-making mechanism
- Key Features:
 - Natural language interface
 - Vast knowledge base
 - Ability to understand context and nuance
 - Generalize to new tasks with minimal additional training

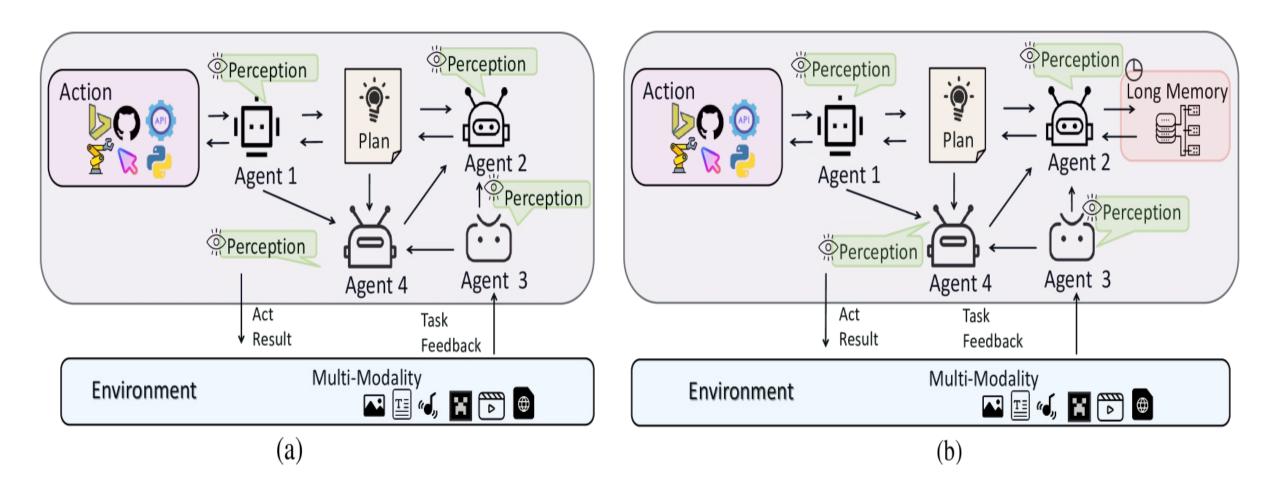
LLM-based Agents



Large Multimodal Agents (LMA)



Large Multimodal Agents (LMA)



A2A

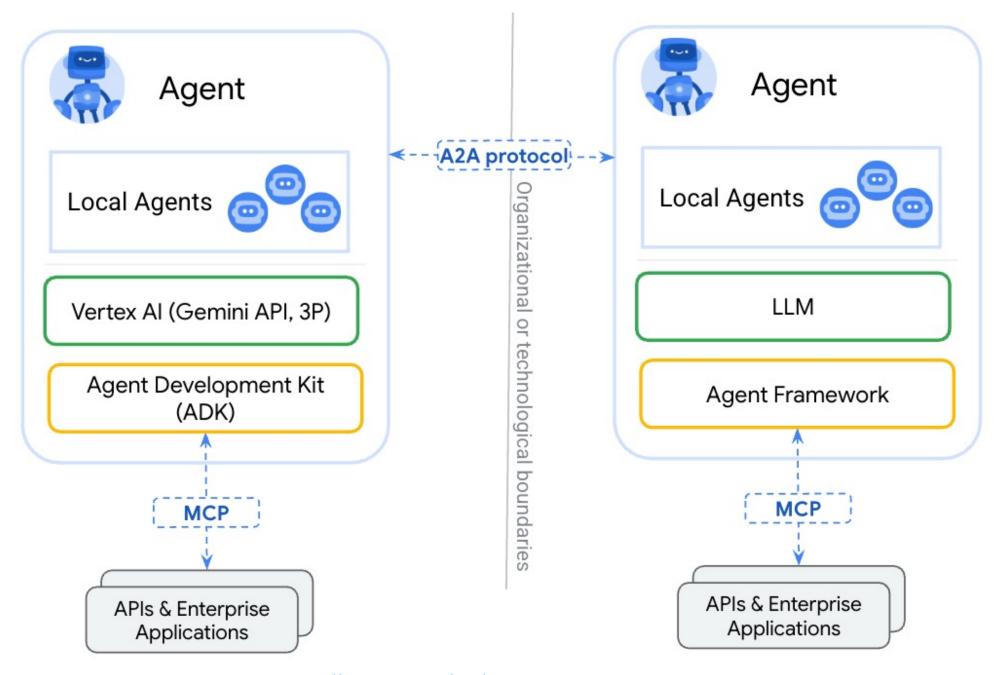
(Agent2Agent Protocol)

for agent-agent collaboration

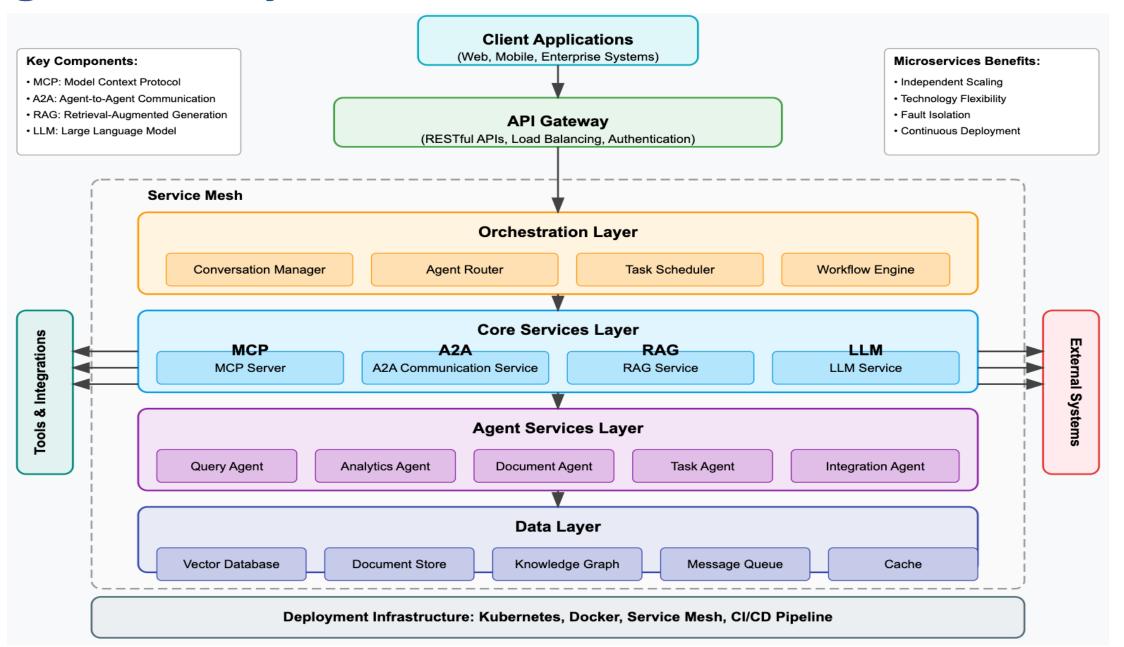
MCP

(Model Context Protocol)

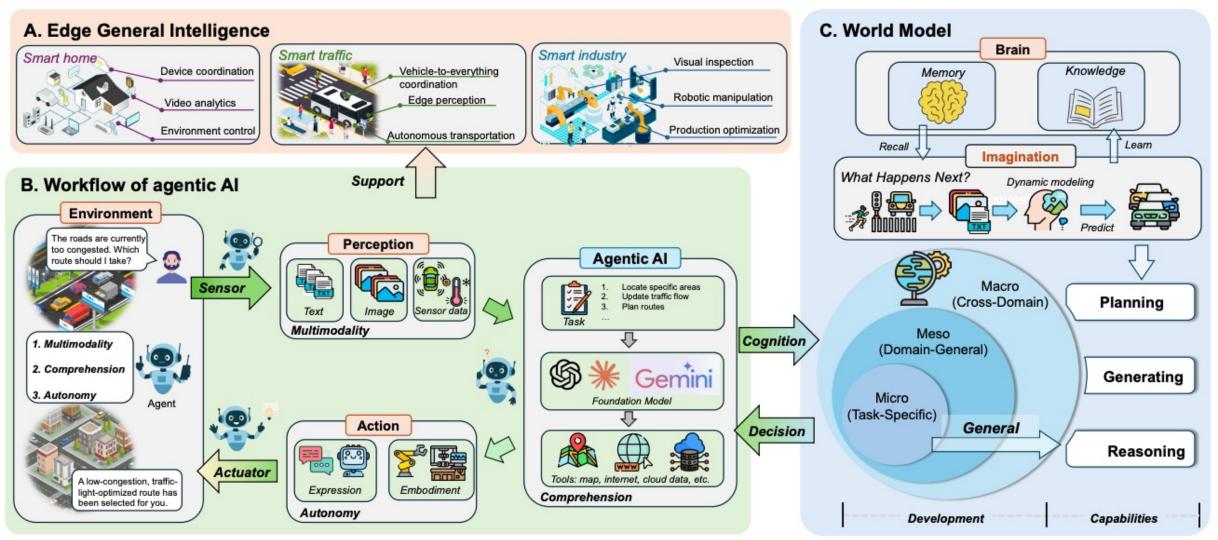
for tools and resources



Agentic AI System with Microservices Architecture



Agentic AI and World Model for Edge General Intelligence



Artificial Intelligence Problem Solving

Artificial Intelligence: A Modern Approach

- 1. Artificial Intelligence
- 2. Problem Solving
- 3. Knowledge and Reasoning
- 4. Uncertain Knowledge and Reasoning
- 5. Machine Learning
- 6. Communicating, Perceiving, and Acting
- 7. Philosophy and Ethics of Al

Artificial Intelligence: 2. Problem Solving

- Solving Problems by Searching
- Search in Complex Environments
- Adversarial Search and Games
- Constraint Satisfaction Problems

LLM-enhanced Problem Solving

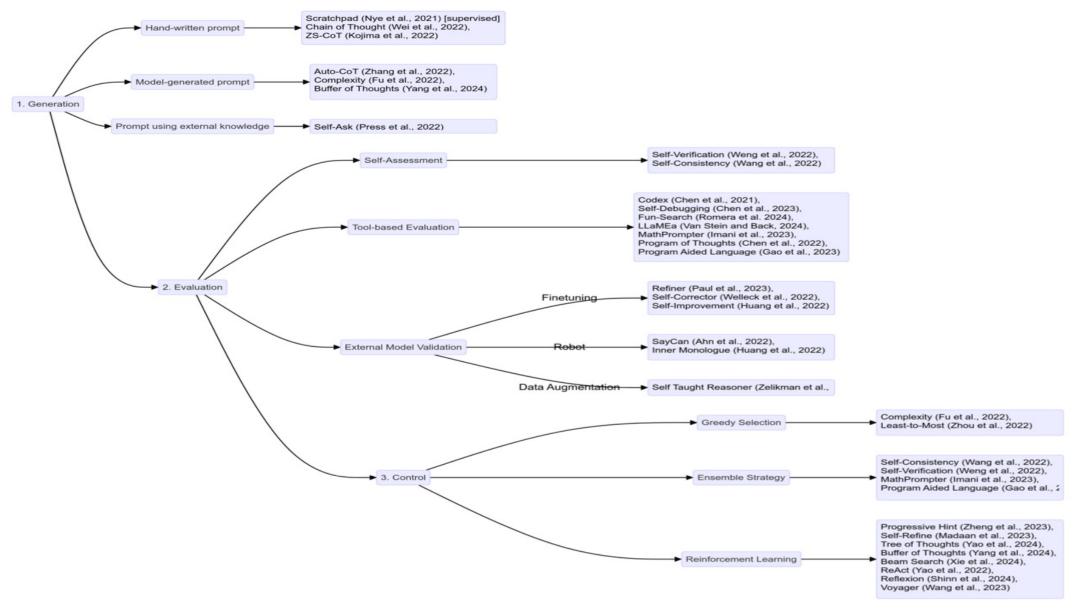
Problem Solving and LLM-enhanced Techniques

- Traditional Search Algorithms
 - Breadth-first Search (BFS)
 - Depth-first Search (DFS)
 - A* Search
- LLM-enhanced Problem Solving
 - Chain-of-thought (CoT) prompting
 - Few-shot learning for problem decomposition
 - Integration with external tools and APIs

LLM-based Agents for Complex Problem Solving

- ReAct: Reasoning and Acting in Language Models
- MRKL (Modular Reasoning, Knowledge and Language) systems
- LLM-powered planning and decision making
- Chain-of-thought Prompting
 - Solving a complex problem using chain-of-thought prompting

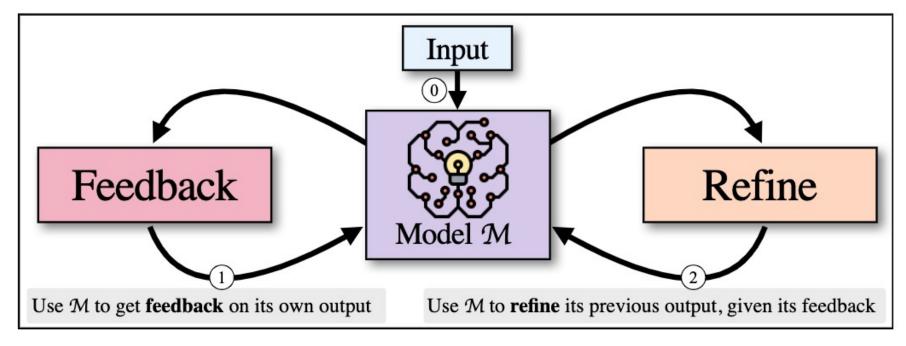
LLM-Reasoning Approaches: Prompt Generation, Evaluation, and Control



LLM-Reasoning Approaches: Prompt Generation, Evaluation, and Control

Approach	Domain	Step generation	Step evaluation	Step control
Scratchpad [Nye et al., 2021]	math word	hand-wr/supervised	-	greedy/1prompt
Chain-of-thought [Wei et al., 2022b]	math word	hand-written	-	greedy/1prompt
ZS-CoT [Kojima et al., 2022]	math word	hand-written	-	greedy/1prompt
Auto-CoT [Zhang et al., 2022]	math word	model-generated	-	clustering
Complexity [Fu et al., 2022]	math word	hand-written	self-consistency	greedy/1prompt
Self-ask [Press et al., 2022]	math word	external knowledge	LLM	multi-hop questions
Self-verification [Weng et al., 2022]	math word	hand-written	back-verify	ensemble
Self-consistency [Wang et al., 2022b]	math word	hand-written	majority	ensemble
Codex [Chen et al., 2021]	code	-	tool-based	-
Self-debugging [Chen et al., 2023]	code	hand-written	tool-based	greedy
Fun-search [Romera-Paredes et al., 2024]	code	hand-written	tool-based	evolutionary algorithm
LLaMEa [van Stein and Bäck, 2024]	code	hand-written	tool-based	evolutionary algorithm
MathPrompter [Imani et al., 2023]	math	hand-written	tool-based	ensemble
Program-of-thoughts [Chen et al., 2022]	math word	hand-written, Codex	Python+Consist.	decouple reason/compute
Program-aided-language [Gao et al., 2023]	math word	hand-written, Codex	NLP/Python	ensemble
Refiner [Paul et al., 2023]	math word	finetune	critic model	gen/crit feedback
Self-corrector [Welleck et al., 2022]	math word	finetune	corrector model	gen/corr feedback
Self-improvement [Huang et al., 2022a]	math word	finetune	self-assessment	CoT/consistency
Say-can [Ahn et al., 2022]	robot	model-generated	external model	greedy
Inner-monologue [Huang et al., 2022b]	robot	hand-written	various	greedy
Self-taught-reasoner [Zelikman et al., 2022]	math word	finetune	augmentation	greedy/feedback
Least-to-most [Zhou et al., 2022]	math word	hand-written	self-assessment	curriculum
Progressive-hint [Zheng et al., 2023]	math word	model-generated	self-assessment	stable prompt
Self-refine [Madaan et al., 2023]	math word	model-generated	self-assessment	greedy/feedback
Tree-of-thoughts [Yao et al., 2024]	puzzles	model-generated	self-assessment	BFS/DFS
Buffer-of-thoughts [Yang et al., 2024]	math word	thought template	self-assessment	buffer manager
Beam-search [Xie et al., 2024]	math word	model-generated	self-assessment	Beam Search
ReAct [Yao et al., 2022]	action	external knowledge	self-assessment	reinforcement learning
Reflexion [Shinn et al., 2024]	decision	model-generated	ext model	reinforcement learning
Voyager [Wang et al., 2023]	Minecraft	model-generated	Minecraft	reinforcement learning

Self-Refine: Iterative refinement with self-feedback



(a) **Dialogue:** x, y_t

(b) FEEDBACK fb

(c) REFINE y_{t+1}

User: I am interested in playing Table tennis.

Response: I'm sure it's a great way to socialize, stay active

Engaging: Provides no information about table tennis or how to play it.

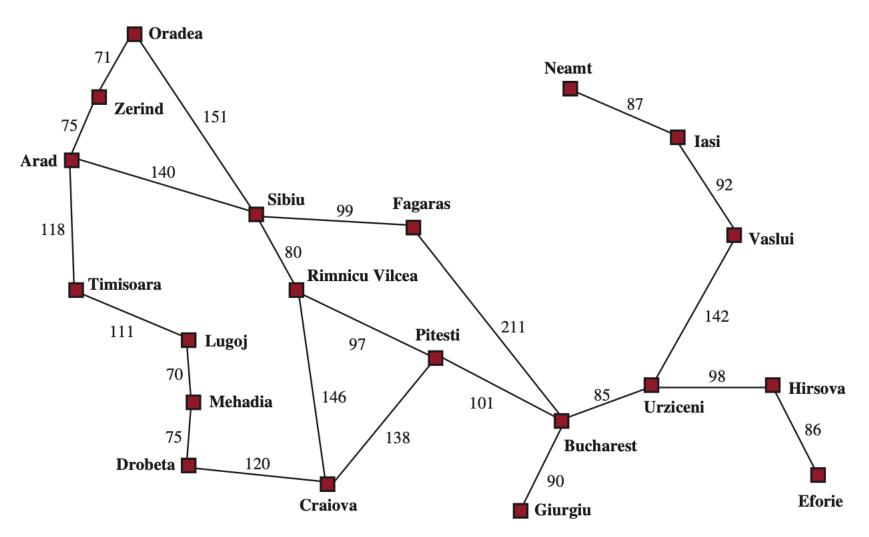
User understanding: Lacks understanding of user's needs and state of mind.

Response (refined): That's great to hear (...) ! It's a fun sport requiring quick reflexes and good hand-eye coordination.
Have you played before, or are you looking to learn?

Solving Problems by Searching

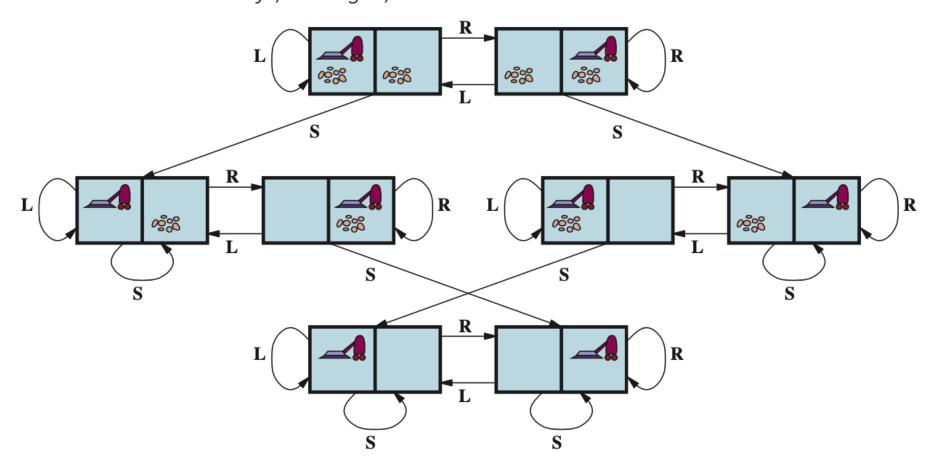
AI: Solving Problems by Searching

A simplified road map of part of Romania, with road distances in miles.

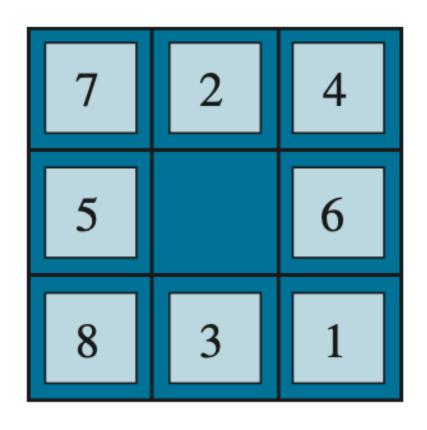


The state-space graph for the two-cell vacuum world

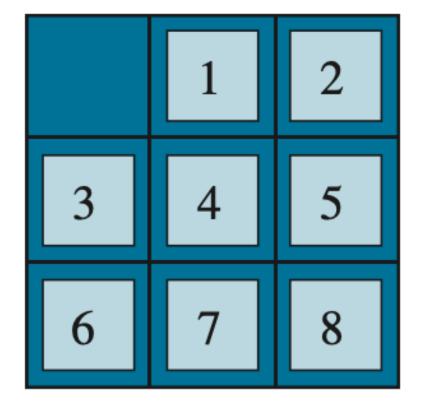
There are 8 states and three actions for each state: L = Left, R = Right, S = Suck.



A typical instance of the 8-puzzle

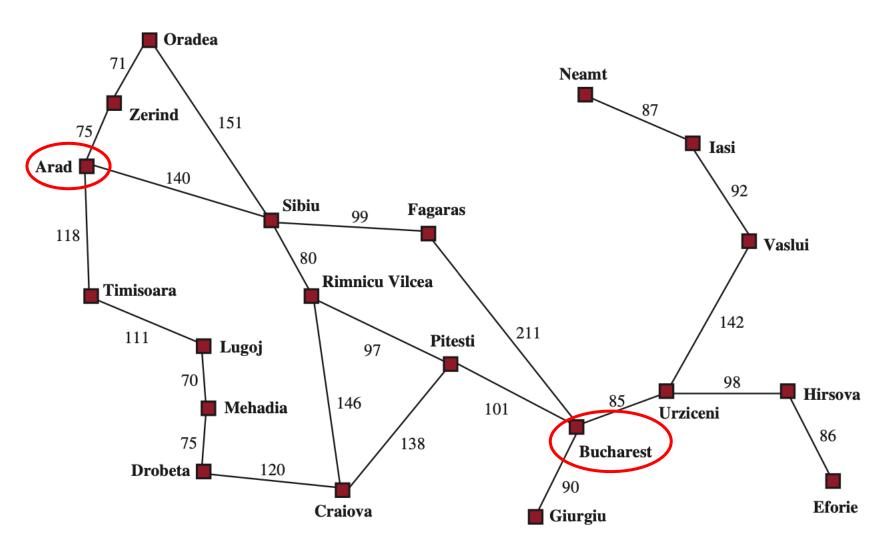


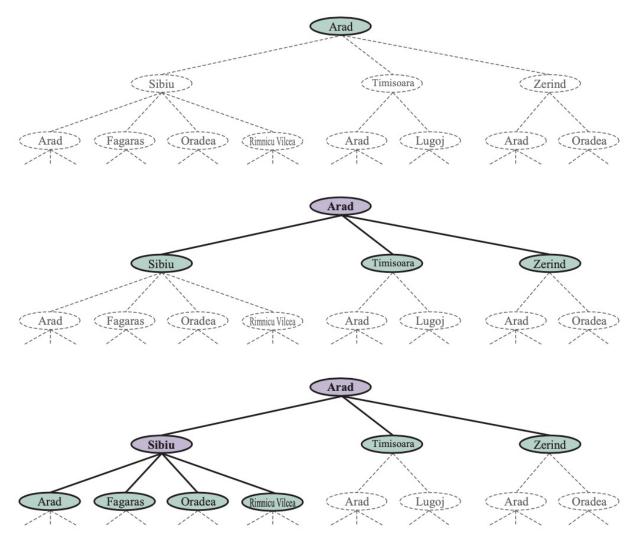
Start State

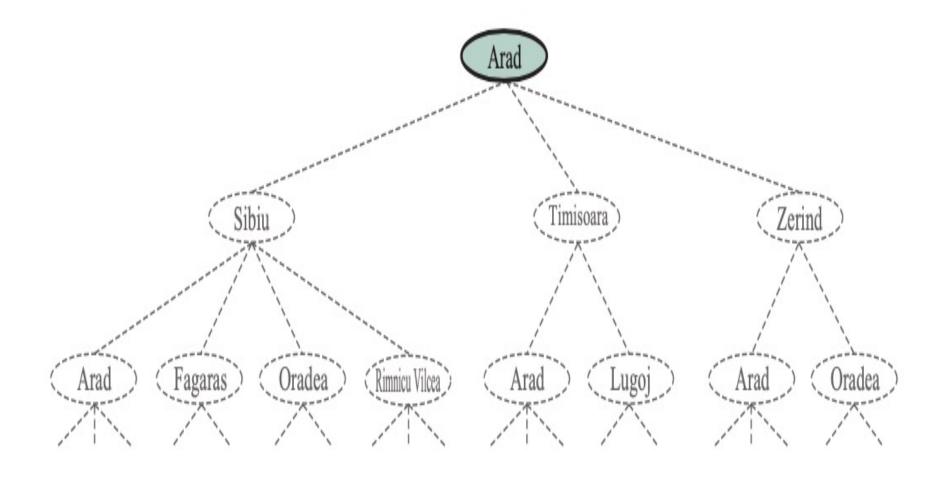


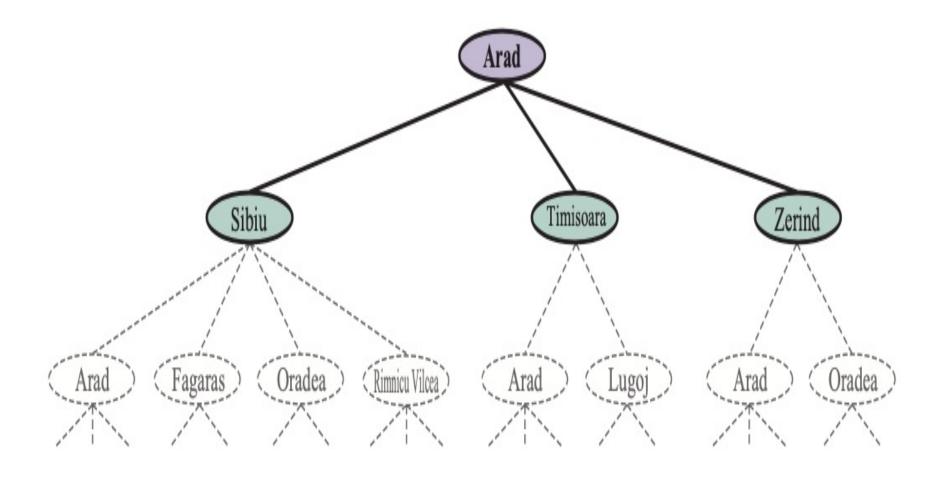
Goal State

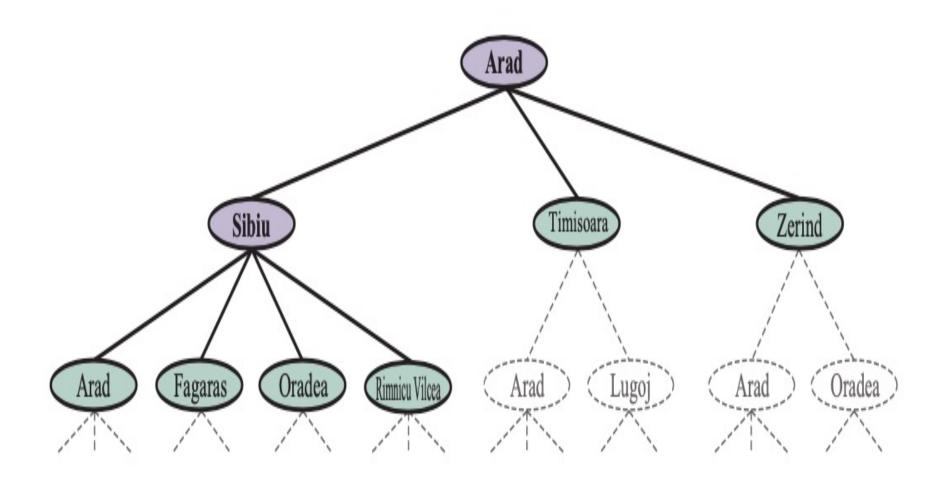
Arad to Bucharest



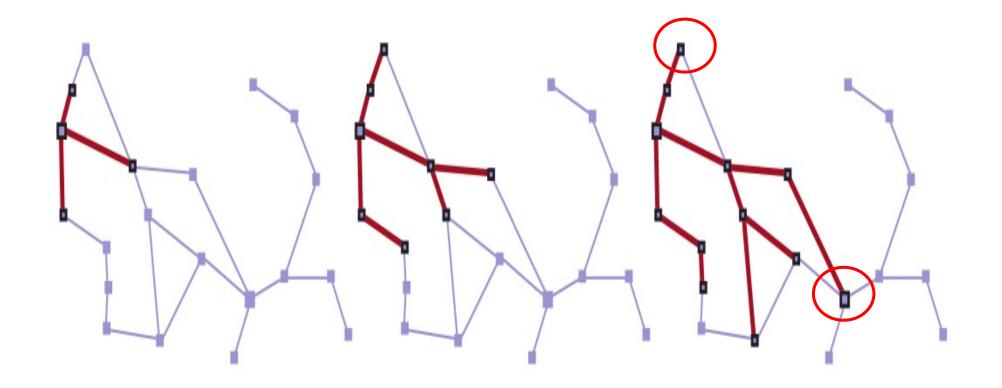








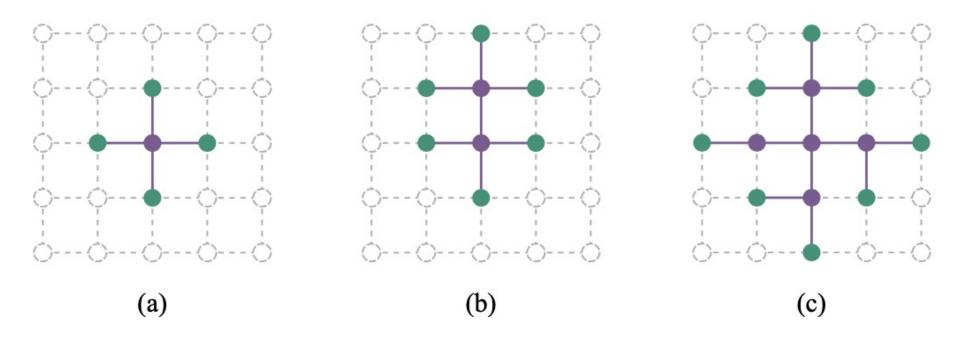
A sequence of search trees generated by a graph search on the Romania problem



The Separation Property of Graph Search

illustrated on a rectangular-grid problem

The frontier (green) separates the interior (lavender) from the exterior (faint dashed)

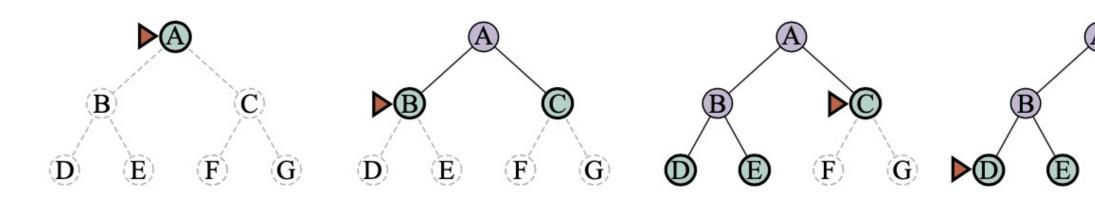


The Best-First Search (BFS) Algorithm

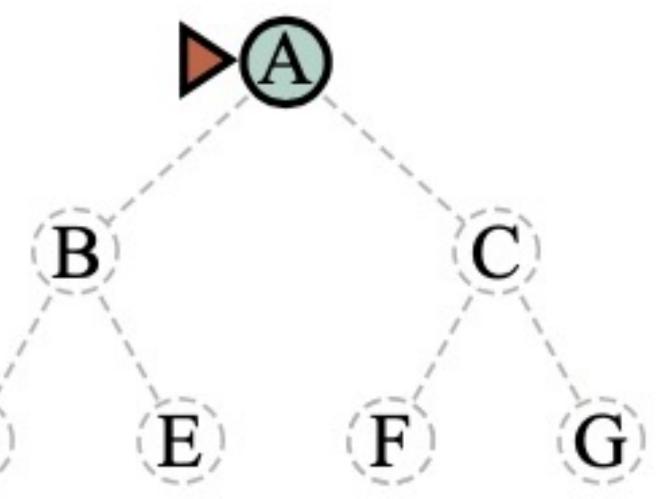
```
function BEST-FIRST-SEARCH(problem, f) returns a solution node or failure
  node \leftarrow Node(State=problem.initial)
  frontier \leftarrow a priority queue ordered by f, with node as an element
  reached \leftarrow a lookup table, with one entry with key problem. INITIAL and value node
  while not IS-EMPTY(frontier) do
     node \leftarrow Pop(frontier)
    if problem.IS-GOAL(node.STATE) then return node
    for each child in EXPAND(problem, node) do
       s \leftarrow child.STATE
       if s is not in reached or child.PATH-COST < reached[s].PATH-COST then
         reached[s] \leftarrow child
         add child to frontier
  return failure
function EXPAND(problem, node) yields nodes
  s \leftarrow node.STATE
  for each action in problem. ACTIONS(s) do
     s' \leftarrow problem.RESULT(s, action)
     cost \leftarrow node.PATH-COST + problem.ACTION-COST(s, action, s')
     yield Node(State=s', Parent=node, Action=action, Path-Cost=cost)
```

Breadth-First Search on a Simple Binary Tree

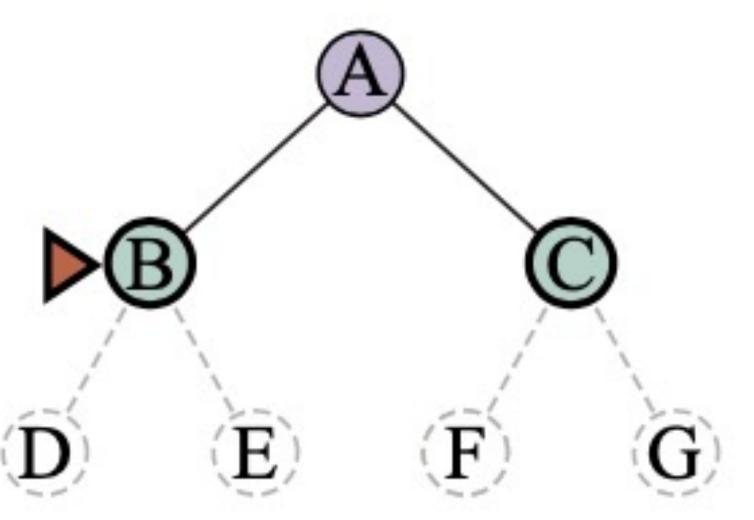
Bread-First Search (BFS)



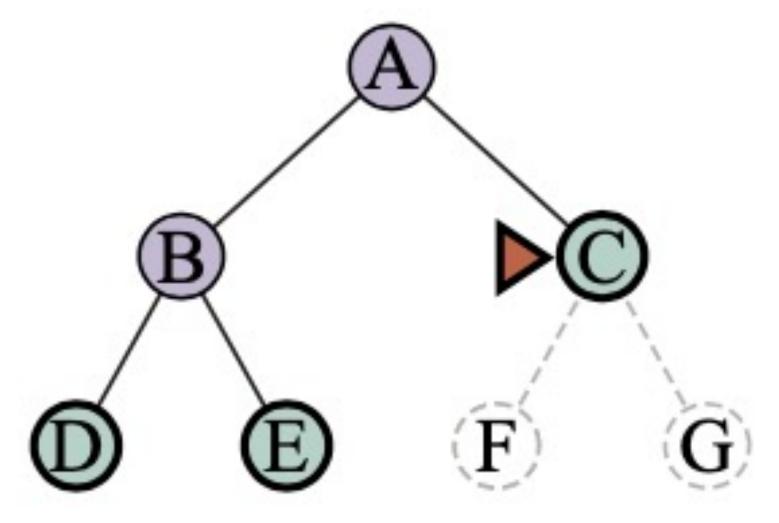




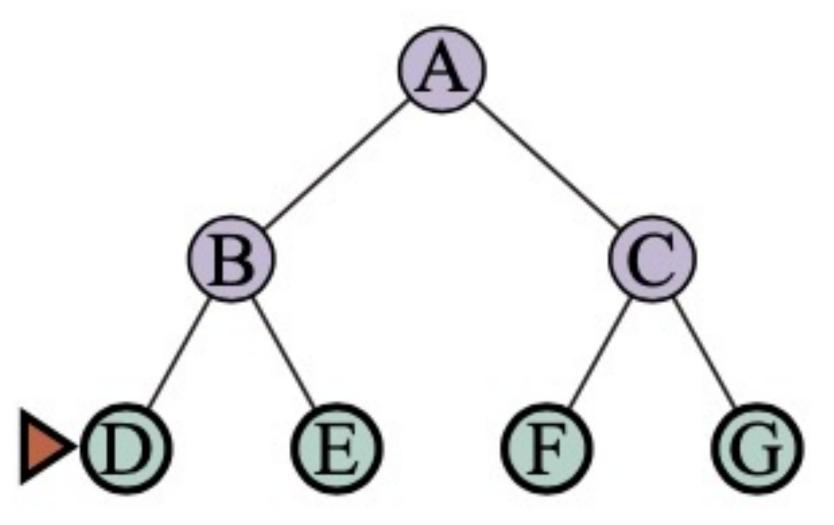
Breadth-First Search on a Simple Binary Tree



Breadth-First Search on a Simple Binary Tree



Breadth-First Search on a Simple Binary Tree

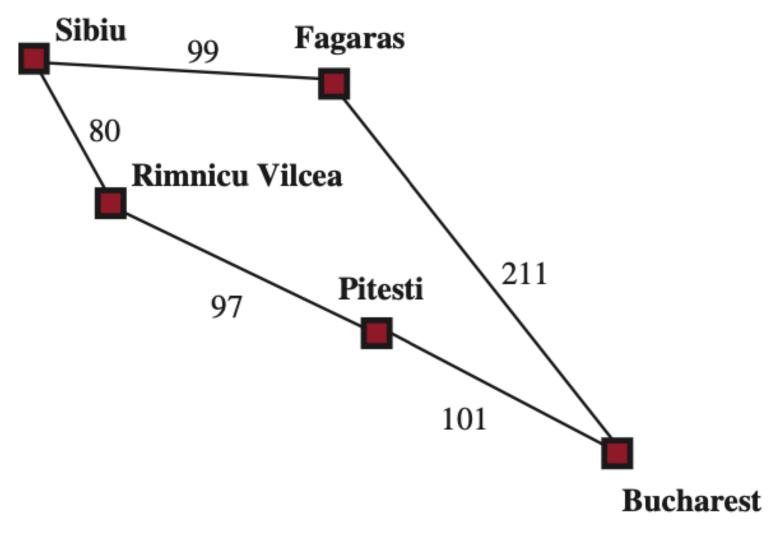


Breadth-First Search and Uniform-Cost Search Algorithms

```
function Breadth-First-Search(problem) returns a solution node or failure
  node \leftarrow \text{NODE}(problem.\text{INITIAL})
  if problem.Is-Goal(node.State) then return node
  frontier \leftarrow a FIFO queue, with node as an element
  reached \leftarrow \{problem.INITIAL\}
   while not IS-EMPTY(frontier) do
     node \leftarrow Pop(frontier)
     for each child in EXPAND(problem, node) do
        s \leftarrow child.STATE
       if problem.Is-GOAL(s) then return child
       if s is not in reached then
          add s to reached
          add child to frontier
  return failure
```

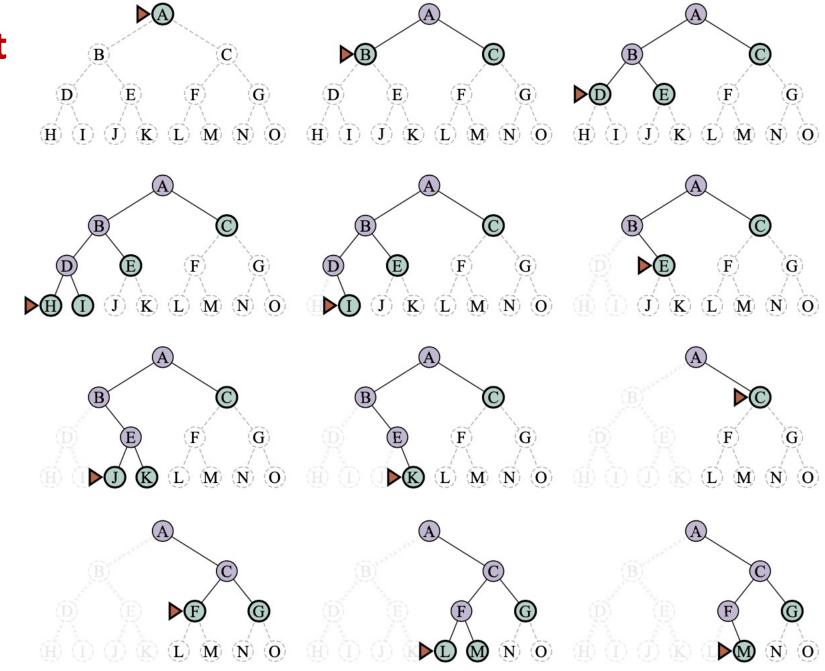
function UNIFORM-COST-SEARCH(problem) **returns** a solution node, or failure **return** BEST-FIRST-SEARCH(problem, PATH-COST)

Part of the Romania State Space Uniform-Cost Search



Depth-First Search (DFS)

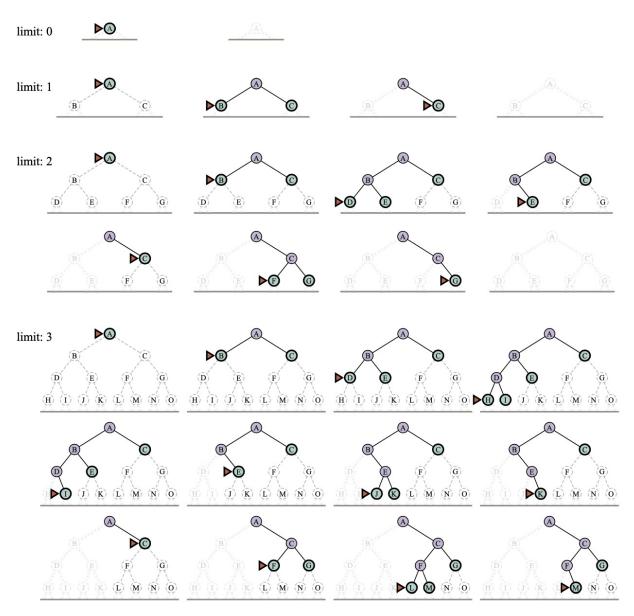
Depth-First Search (DFS)



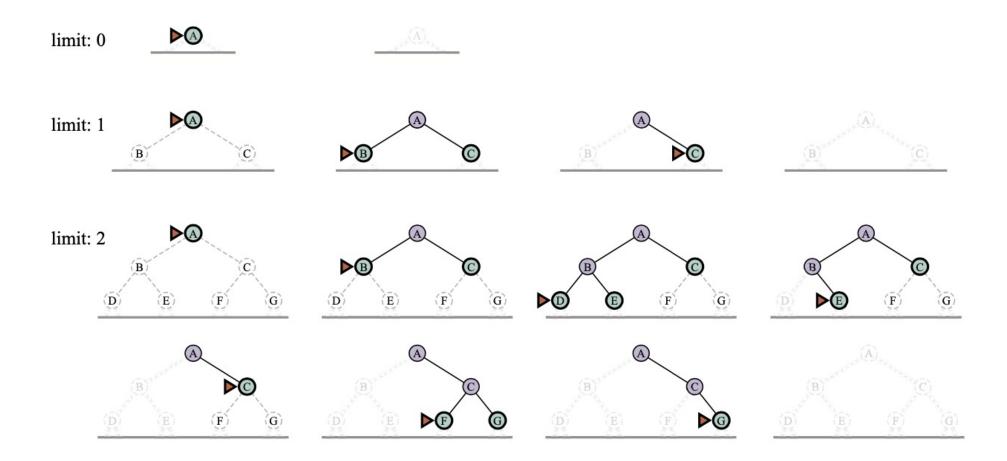
Iterative deepening and depth-limited tree-like search

```
function ITERATIVE-DEEPENING-SEARCH(problem) returns a solution node or failure
  for depth = 0 to \infty do
     result \leftarrow DEPTH-LIMITED-SEARCH(problem, depth)
    if result \neq cutoff then return result
function DEPTH-LIMITED-SEARCH(problem, \ell) returns a node or failure or cutoff
  frontier \leftarrow a LIFO queue (stack) with NODE(problem.INITIAL) as an element
  result \leftarrow failure
  while not IS-EMPTY(frontier) do
     node \leftarrow Pop(frontier)
    if problem.Is-GOAL(node.STATE) then return node
    if DEPTH(node) > \ell then
       result \leftarrow cutoff
     else if not IS-CYCLE(node) do
       for each child in EXPAND(problem, node) do
         add child to frontier
  return result
```

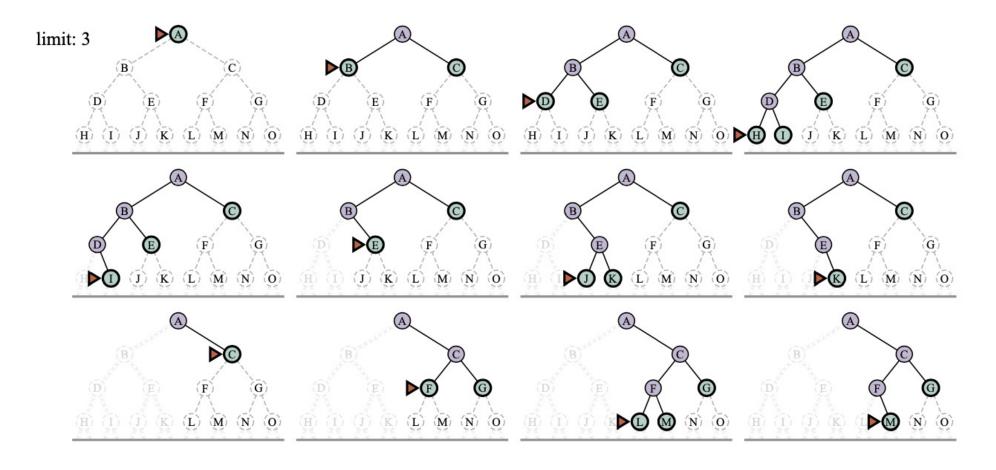
Four iterations of iterative deepening search



Four iterations of iterative deepening search



Four iterations of iterative deepening search



Bidirectional Best-First Search

keeps two frontiers and two tables of reached states

```
function BIBF-SEARCH(problem_F, f_F, problem_B, f_B) returns a solution node, or failure
  node_F \leftarrow Node(problem_F.INITIAL) // Node for a start state
  node_B \leftarrow Node(problem_B.INITIAL) // Node for a goal state
  frontier_F \leftarrow a priority queue ordered by f_F, with node_F as an element
  frontier_B \leftarrow a priority queue ordered by f_B, with node_B as an element
  reached_F \leftarrow a lookup table, with one key node_F. STATE and value node_F
  reached_B \leftarrow a lookup table, with one key node_B. STATE and value node_B
  solution \leftarrow failure
  while not TERMINATED(solution, frontier<sub>F</sub>, frontier<sub>B</sub>) do
    if f_F(\text{TOP}(frontier_F)) < f_B(\text{TOP}(frontier_B)) then
       solution \leftarrow PROCEED(F, problem_F, frontier_F, reached_F, reached_B, solution)
     else solution \leftarrow PROCEED(B, problem_B, frontier_B, reached_B, reached_F, solution)
  return solution
```

Bidirectional Best-First Search

keeps two frontiers and two tables of reached states

```
function Proceed (dir, problem, frontier, reached, reached<sub>2</sub>, solution) returns a solution
          // Expand node on frontier; check against the other frontier in reached<sub>2</sub>.
          // The variable "dir" is the direction: either F for forward or B for backward.
  node \leftarrow Pop(frontier)
  for each child in EXPAND(problem, node) do
     s \leftarrow child.STATE
     if s not in reached or PATH-COST(child) < PATH-COST(reached[s]) then
       reached[s] \leftarrow child
       add child to frontier
       if s is in reached_2 then
          solution_2 \leftarrow \text{JOIN-NODES}(dir, child, reached_2[s]))
          if PATH-COST(solution_2) < PATH-COST(solution) then
             solution \leftarrow solution_2
  return solution
```

Evaluation of search algorithms

Criterion	Breadth- First	Uniform- Cost	Depth- First	Depth- Limited	Iterative Deepening	Bidirectional (if applicable)
Complete? Optimal cost? Time Space	$egin{array}{l} ext{Yes}^1 \ ext{Yes}^3 \ O(b^d) \ O(b^d) \end{array}$	$ ext{Yes}^{1,2} \ ext{Yes} \ O(b^{1+\lfloor C^*/\epsilon floor}) \ O(b^{1+\lfloor C^*/\epsilon floor})$	No No $O(b^m)$ $O(bm)$	No No $O(b^\ell)$ $O(b\ell)$	$egin{array}{l} ext{Yes}^1 \ ext{Yes}^3 \ O(b^d) \ O(bd) \end{array}$	$egin{array}{l} ext{Yes}^{1,4} \ ext{Yes}^{3,4} \ O(b^{d/2}) \ O(b^{d/2}) \end{array}$

b is the branching factor; m is the maximum depth of the search tree;

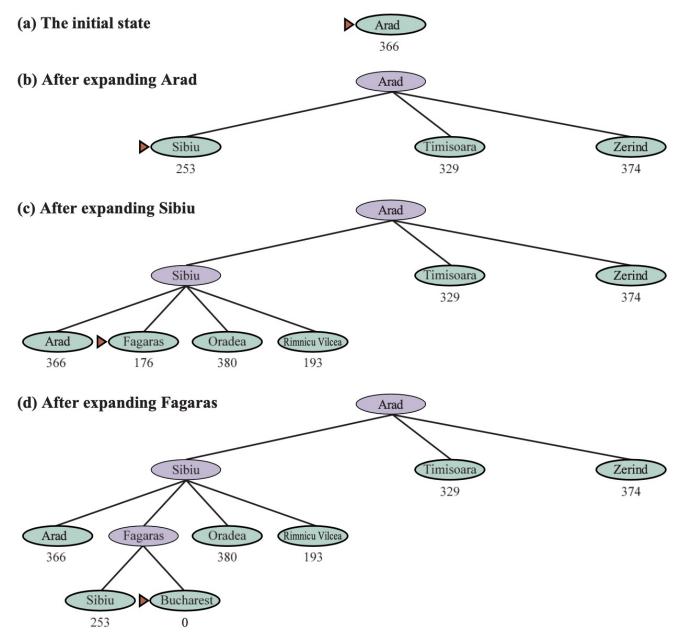
d is the depth of the shallowest solution, or is m when there is no solution;

 ℓ is the depth limit

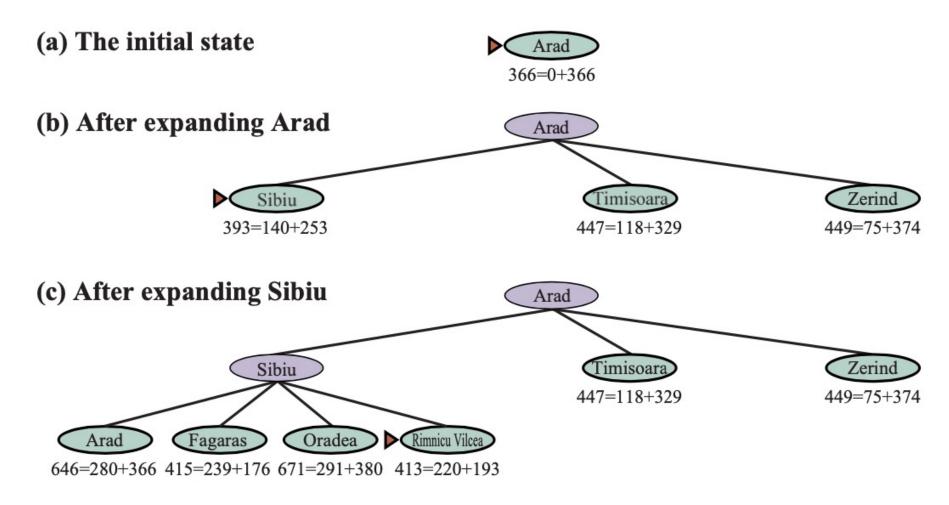
Values of *hSLD*

-straight-line distances to Bucharest.

Arad	366	Mehadia	241
Bucharest	0	Neamt	234
Craiova	160	Oradea	380
Drobeta	242	Pitesti	100
Eforie	161	Rimnicu Vilcea	193
Fagaras	176	Sibiu	253
Giurgiu	77	Timisoara	329
Hirsova	151	Urziceni	80
Iasi	226	Vaslui	199
Lugoj	244	Zerind	374

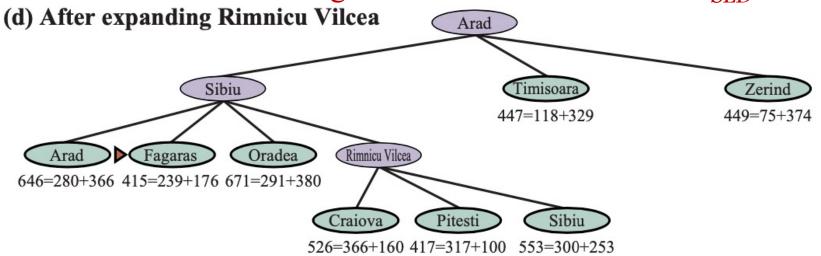


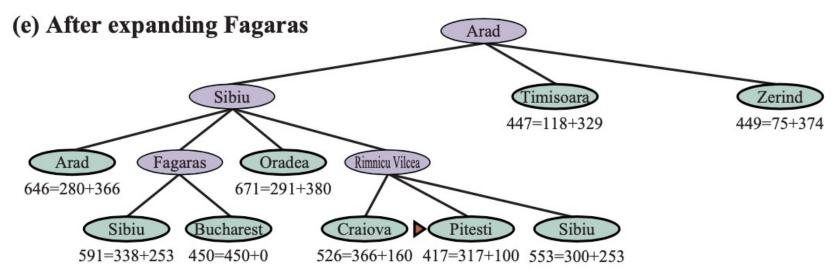
Nodes are labeled with f = g + h. The h values are the Straight-Line Distances heuristic h_{SLD}



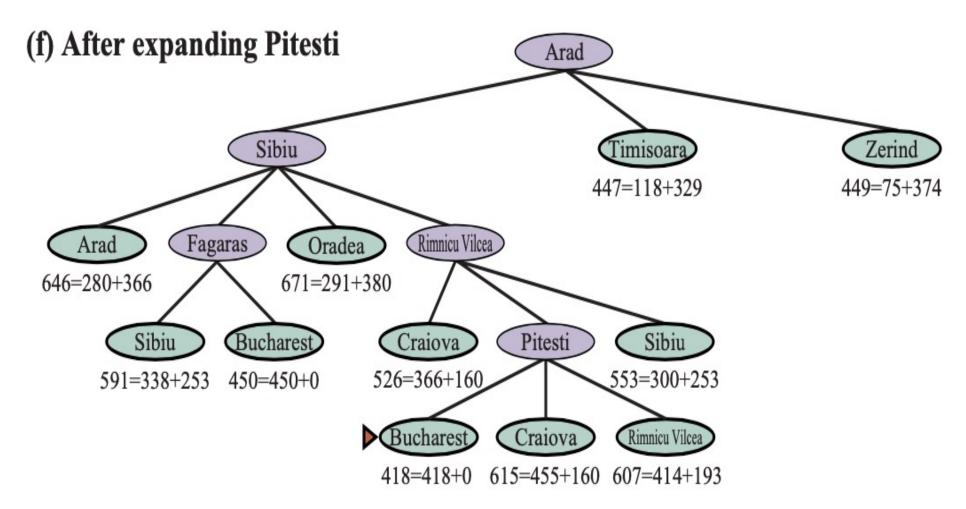
Nodes are labeled with f = g + h.

The h values are the Straight-Line Distances heuristic h_{SLD}

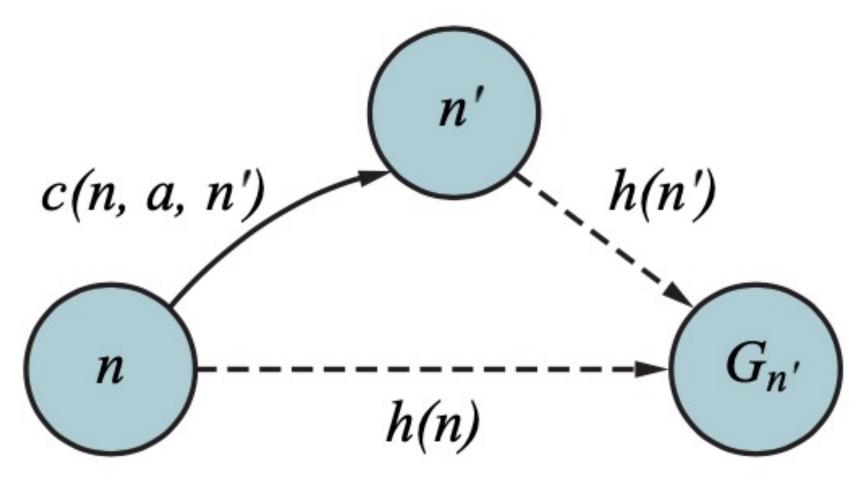




Nodes are labeled with f = g + h. The h values are the Straight-Line Distances heuristic h_{SLD}

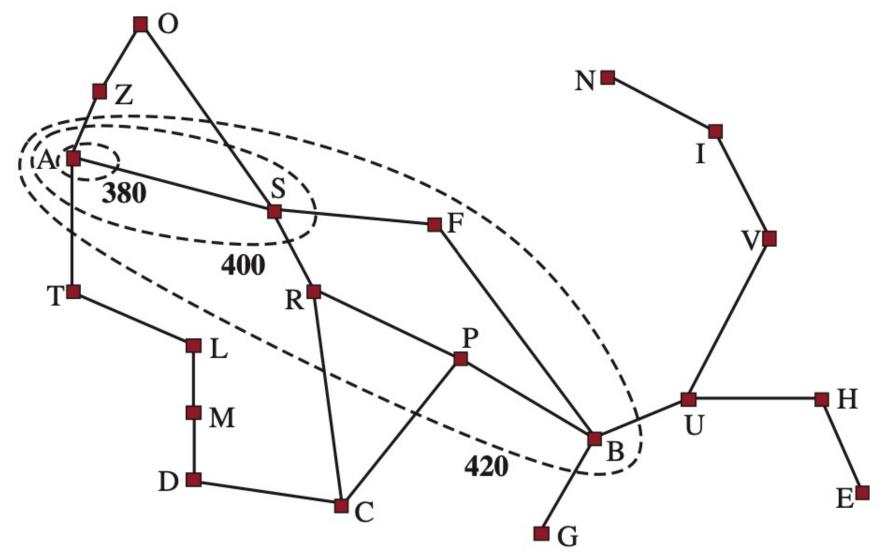


Triangle Inequality

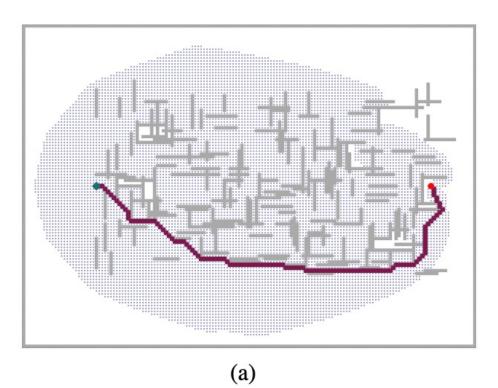


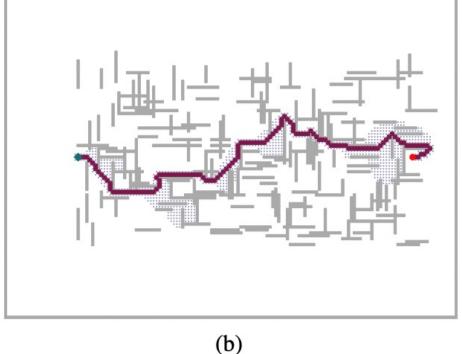
If the heuristic h is consistent, then the single number h(n) will be less than the sum of the cost c(n, a, a') of the action from n to n' plus the heuristic estimate h(n').

Map of Romania showing contours at f = 380, f = 400, and f = 420, with Arad as the start state



(a) A* Search(b) Weighted A* Search





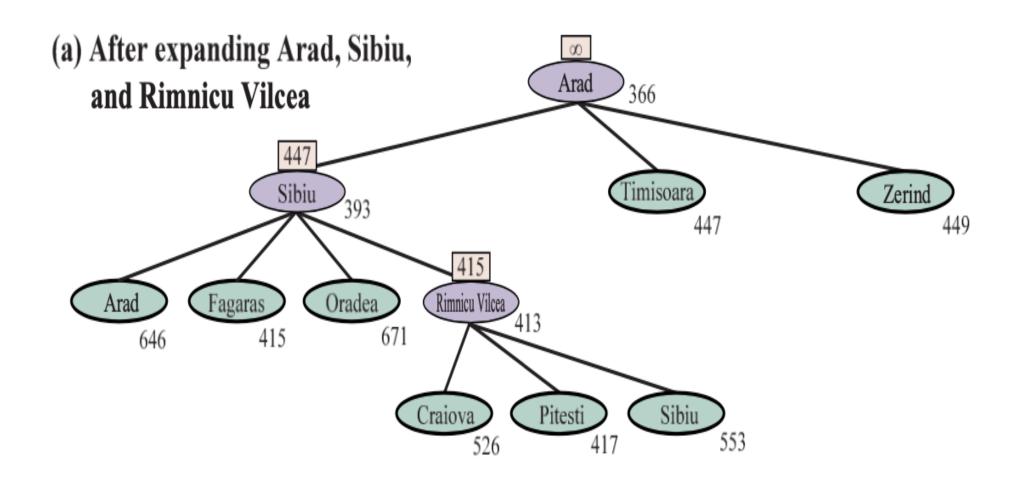
The gray bars are obstacles, the purple line is the path from the green start to red goal, and the small dots are states that were reached by each search.

On this particular problem, weighted A^* explores 7 times fewer states and finds a path that is 5% more costly.

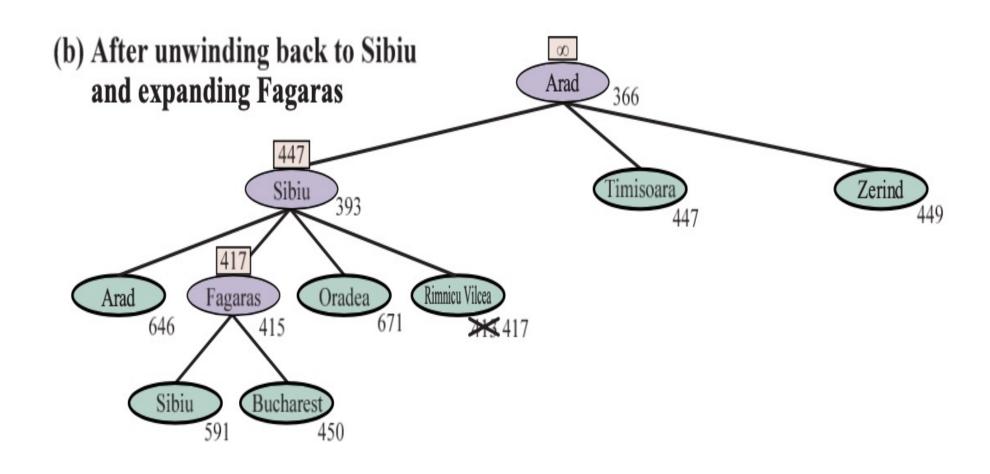
Recursive Best-First Search (RBFS) Algorithm

```
function RECURSIVE-BEST-FIRST-SEARCH(problem) returns a solution or failure
    solution, fvalue \leftarrow RBFS(problem, NODE(problem.INITIAL), \infty)
 return solution
function RBFS(problem, node, f\_limit) returns a solution or failure, and a new f-cost limit
  if problem.Is-GOAL(node.STATE) then return node
  successors \leftarrow LIST(EXPAND(node))
  if successors is empty then return failure, \infty
  for each s in successors do // update f with value from previous search
      s.f \leftarrow \max(s.\text{PATH-COST} + h(s), node.f))
  while true do
      best \leftarrow the node in successors with lowest f-value
      if best.f > f_{-}limit then return failure, best.f
      alternative \leftarrow the second-lowest f-value among successors
      result, best.f \leftarrow RBFS(problem, best, min(f_limit, alternative))
      if result \neq failure then return result, best.f
```

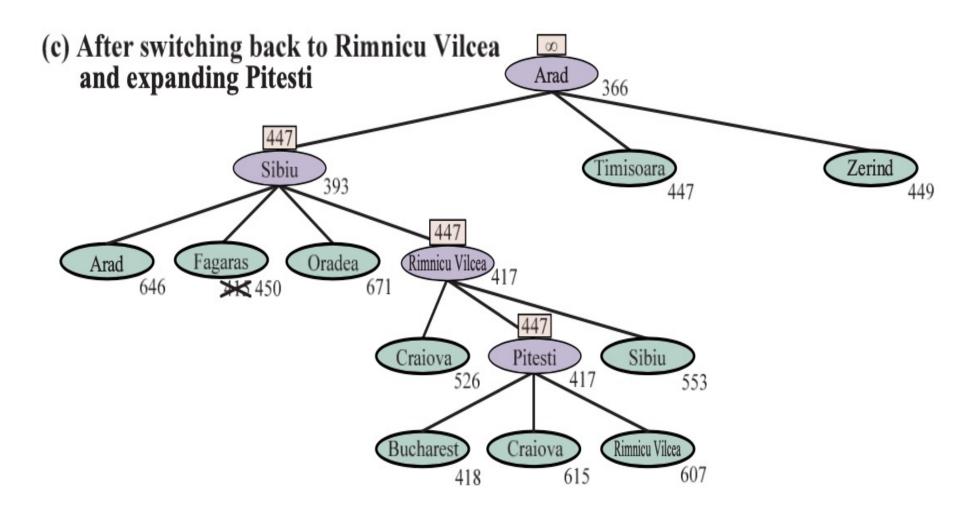
Recursive Best-First Search (RBFS)



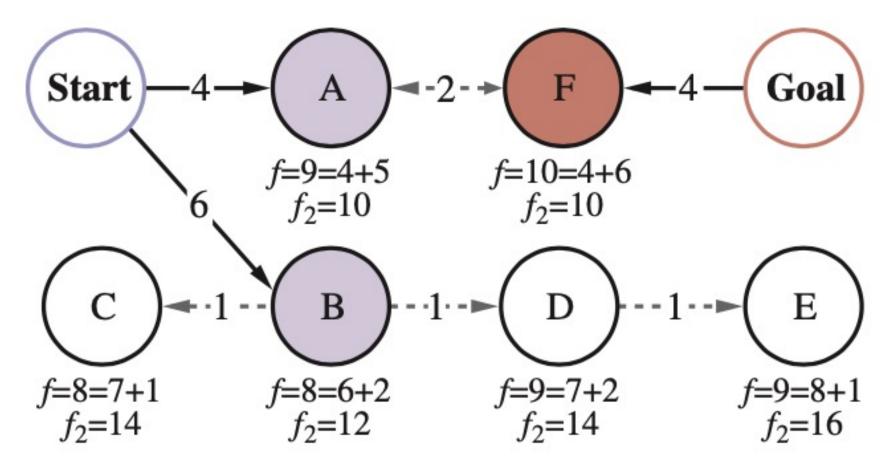
Recursive Best-First Search (RBFS)



Recursive Best-First Search (RBFS)



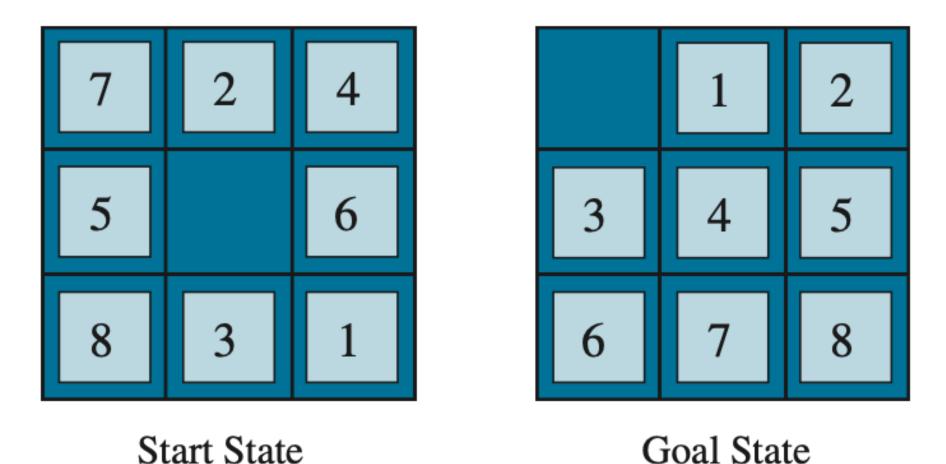
Bidirectional Search maintains two frontiers



On the left, nodes A and B are successors of Start; on the right, node F is an inverse successor of Goal

A typical instance of the 8-puzzle

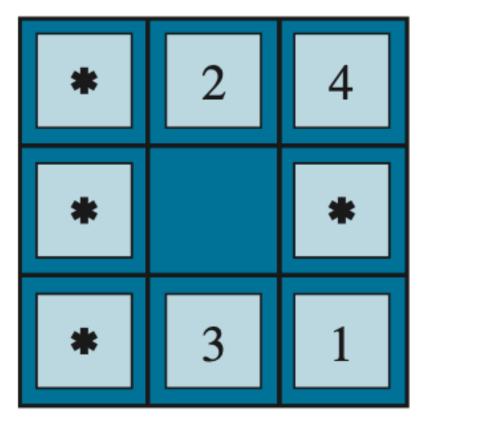
The shortest solution is 26 actions long

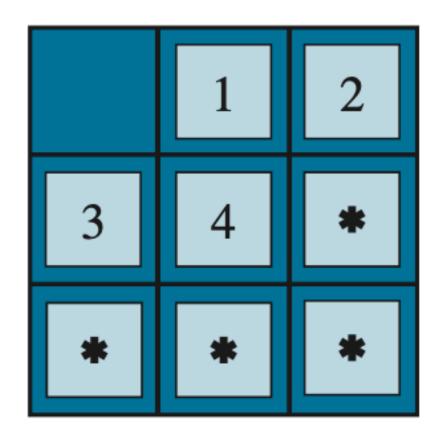


Comparison of the search costs and effective branching factors for 8-puzzle problems

	Search Cost (nodes generated)			Effective Branching Factor		
d	BFS	$A^*(h_1)$	$A^*(h_2)$	BFS	$A^*(h_1)$	$A^*(h_2)$
6	128	24	19	2.01	1.42	1.34
8	368	48	31	1.91	1.40	1.30
10	1033	116	48	1.85	1.43	1.27
12	2672	279	84	1.80	1.45	1.28
14	6783	678	174	1.77	1.47	1.31
16	17270	1683	364	1.74	1.48	1.32
18	41558	4102	751	1.72	1.49	1.34
20	91493	9905	1318	1.69	1.50	1.34
22	175921	22955	2548	1.66	1.50	1.34
24	290082	53039	5733	1.62	1.50	1.36
26	395355	110372	10080	1.58	1.50	1.35
28	463234	202565	22055	1.53	1.49	1.36

A subproblem of the 8-puzzle



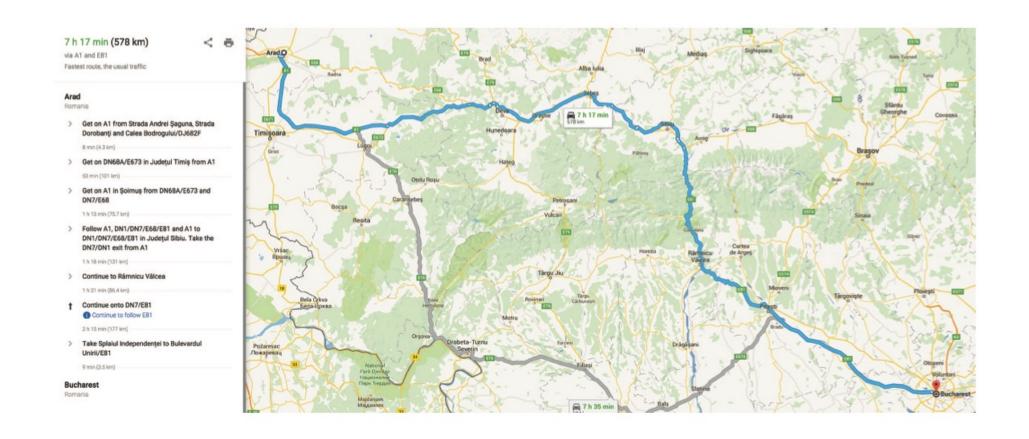


Start State

Goal State

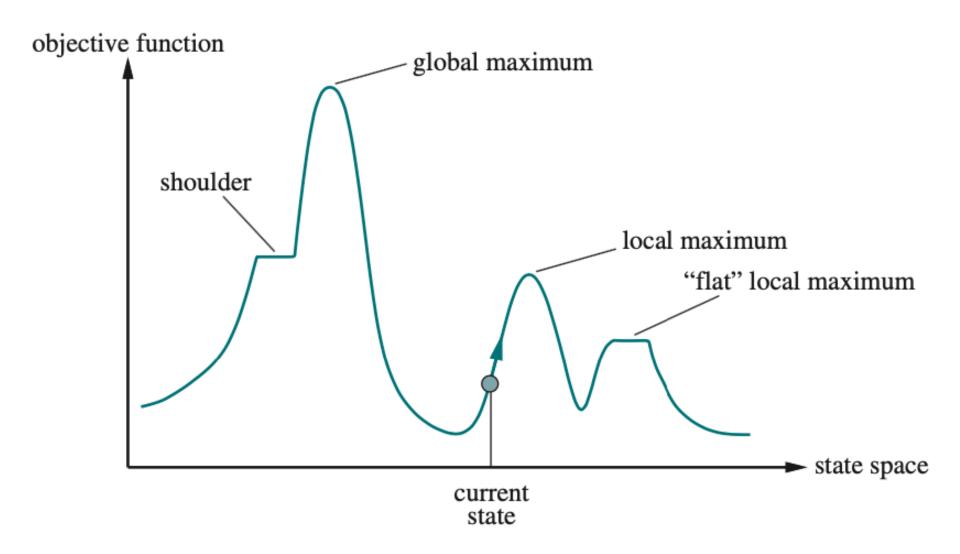
The task is to get tiles 1, 2, 3, 4, and the blank into their correct positions, without worrying about what happens to the other tiles

A Web service providing driving directions, computed by a search algorithm.



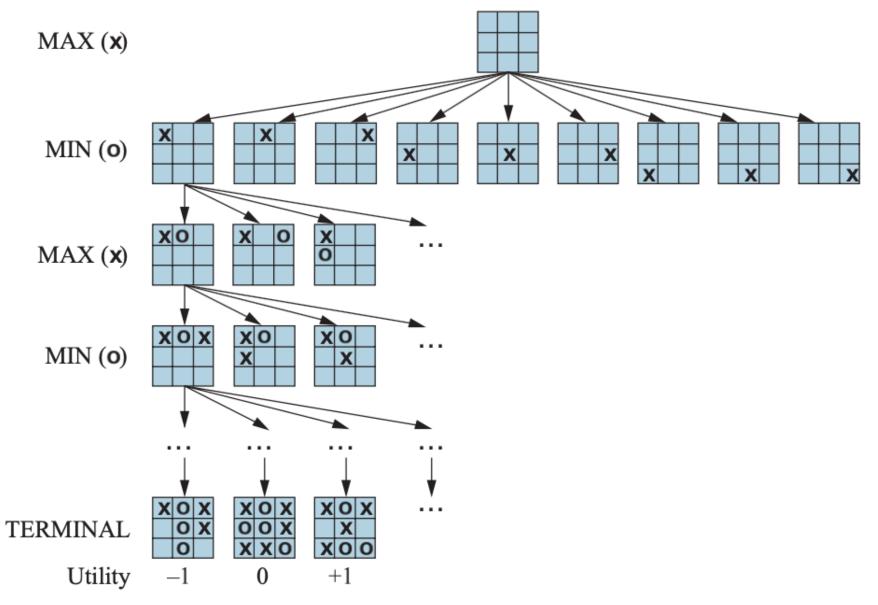
Search in Complex Environments

A one-dimensional state-space landscape



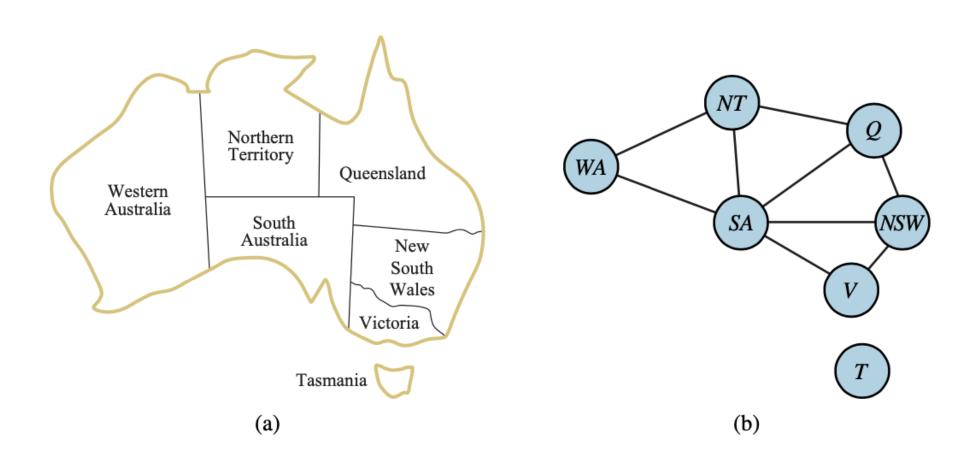
Adversarial Search and Games

Game Tree for the Game of Tic-tac-toe

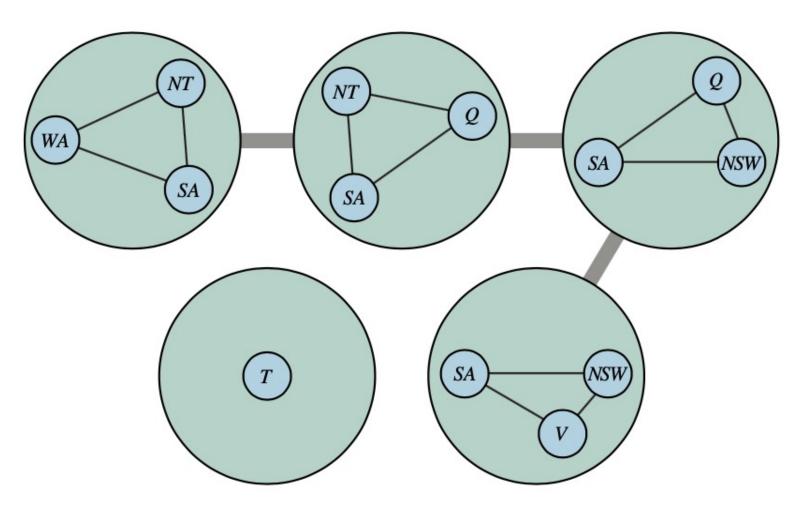


Constraint Satisfaction Problems

The Map-Coloring Problem Represented as a Constraint Graph



A Tree Decomposition of the Constraint Graph



Artificial Intelligence: A Modern Approach (AIMA)

- Artificial Intelligence: A Modern Approach (AIMA)
 - http://aima.cs.berkeley.edu/
- AIMA Python
 - http://aima.cs.berkeley.edu/python/readme.html
 - https://github.com/aimacode/aima-python
- Search
 - http://aima.cs.berkeley.edu/python/search.html
- Games: Adversarial Search
 - http://aima.cs.berkeley.edu/python/games.html
- CSP (Constraint Satisfaction Problems)
 - http://aima.cs.berkeley.edu/python/csp.html

Artificial Intelligence: A Modern Approach (AIMA)

P

△ US Edition

△ Global Edition

Acknowledgements

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Courses

Editions

Errata

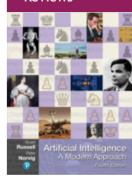
Exercises

Figures

Instructors Page

Pseudocode

Reviews



Artificial Intelligence: A Modern Approach, 4th US ed.

by **Stuart Russell** and **Peter Norvig**

The <u>authoritative</u>, <u>most-used</u> AI textbook, adopted by over <u>1500</u> schools.

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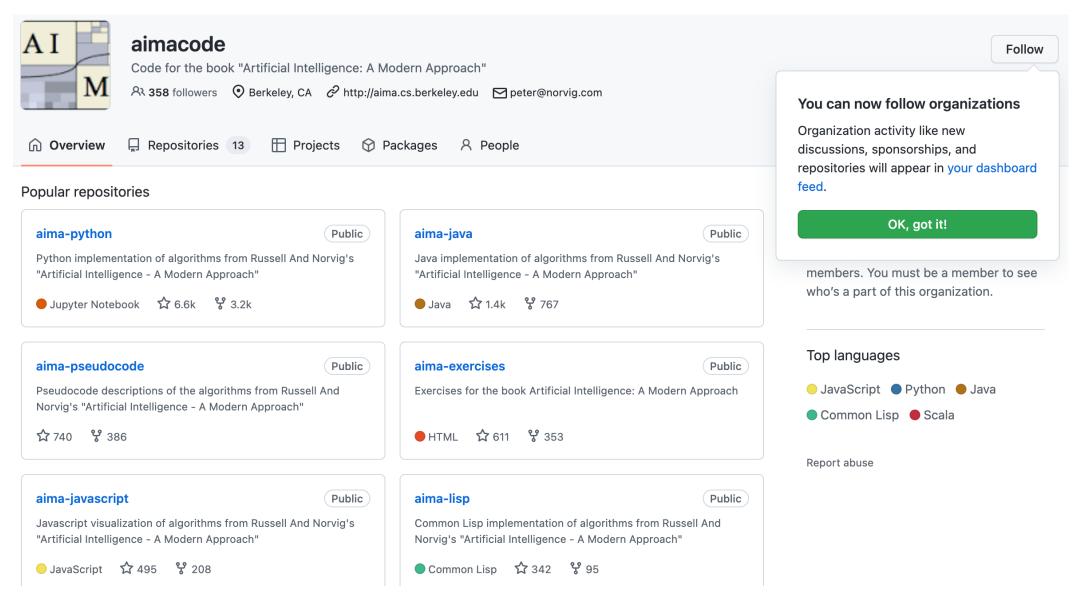
Exercises (website)

Figures (pdf)

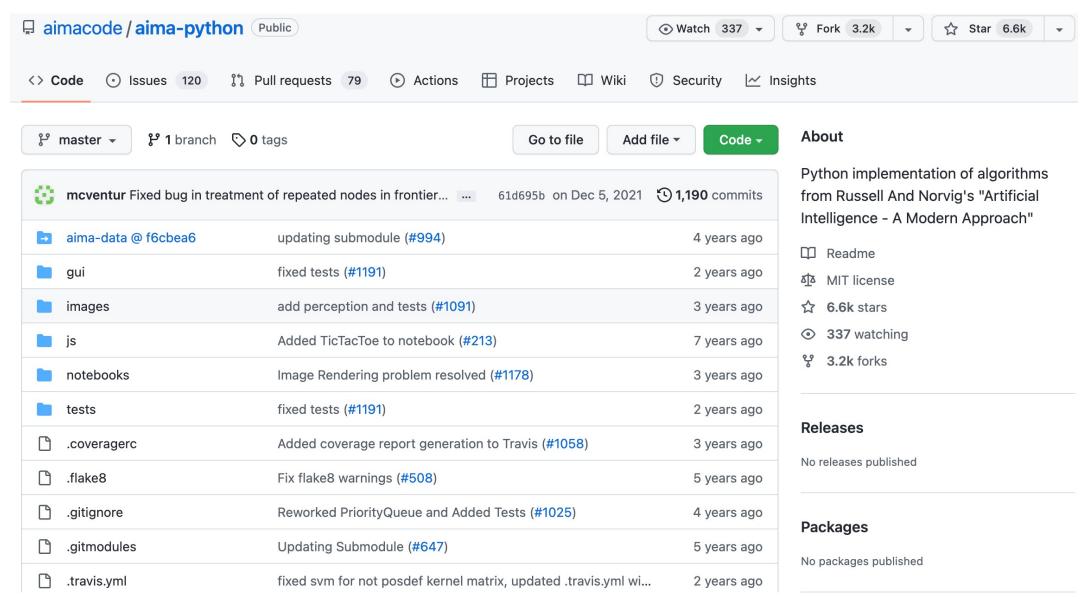
Code (website); Pseudocode (pdf)

Covers: US, Global

AIMA Code



AIMA Python



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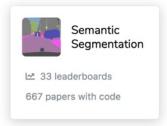
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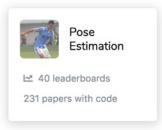
Computer Vision











▶ See all 707 tasks

Natural Language Processing





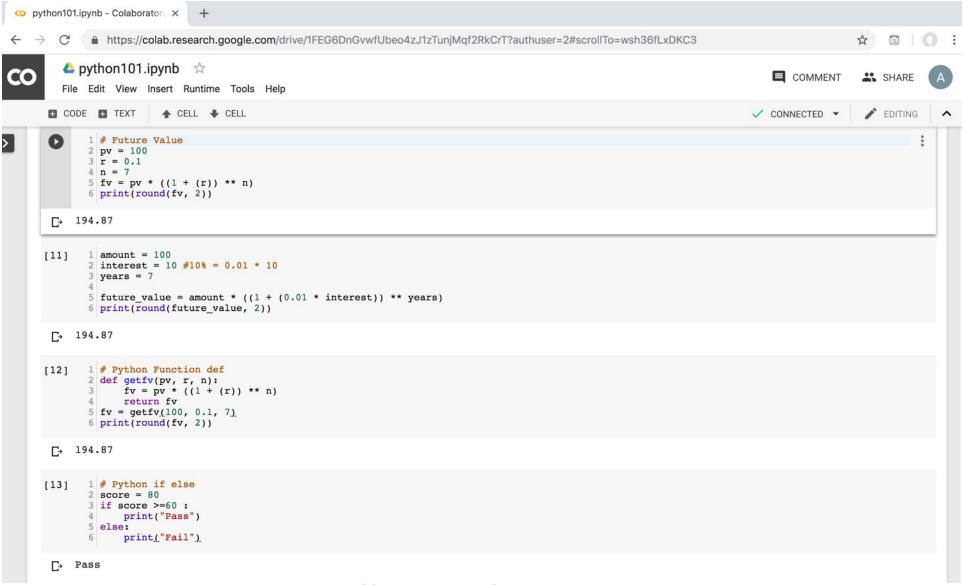






Python in Google Colab (Python101)

https://colab.research.google.com/drive/1FEG6DnGvwfUbeo4zJ1zTunjMqf2RkCrT



Summary

- Artificial Intelligence
- Intelligent Agents
- Problem Solving

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