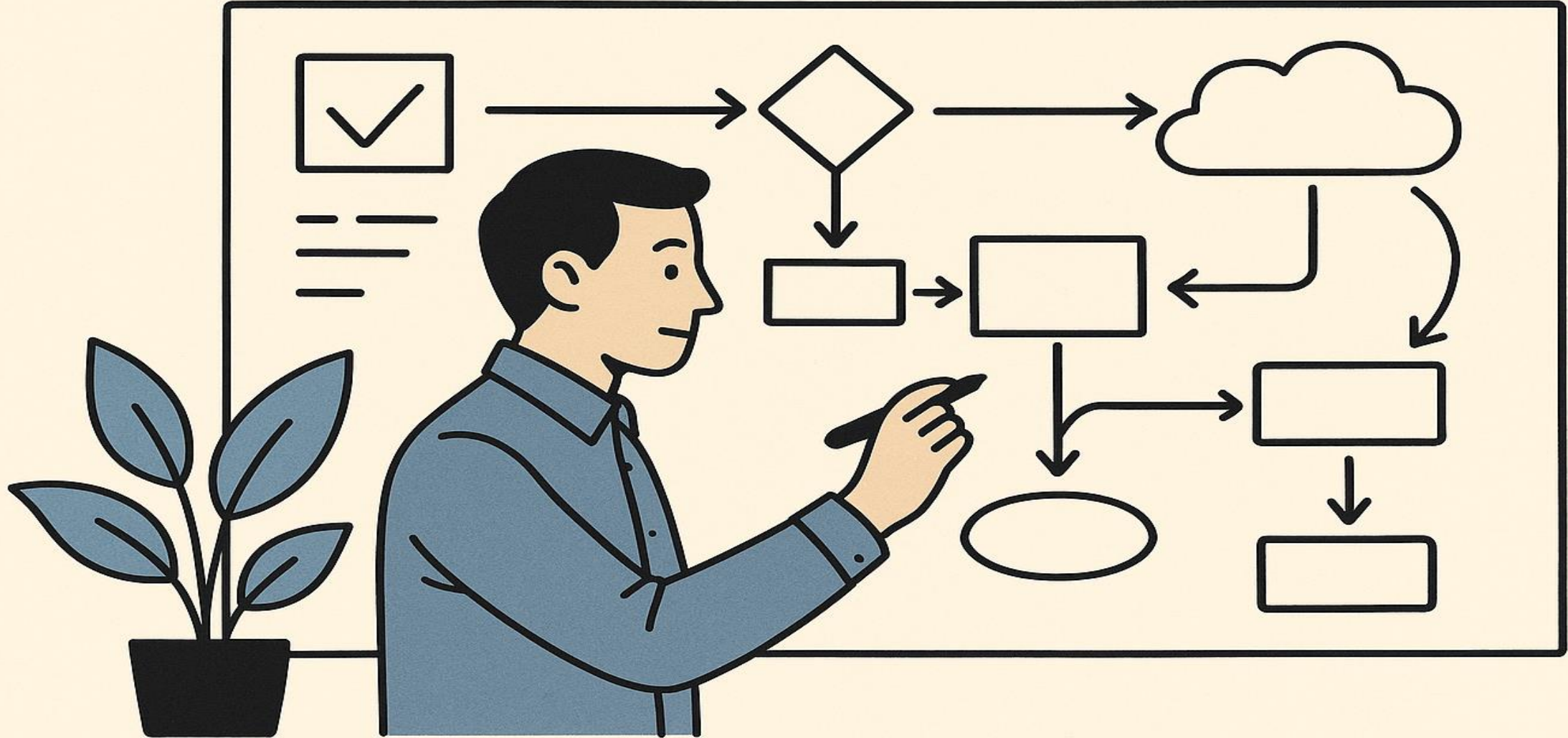


Session 2: Solving Planning Problems



PLANNING IN THE PRE-LLM ERA



Solving Classical PDDL Planning



STRIPS

Fikes & Nilsson, AIJ 1971

GraphPlan

Blum & Furst, IJCAI 1995

SATPlan

Kautz & Selman, AAAI 1996

POCL

Penberthy & Weld, KR 1992

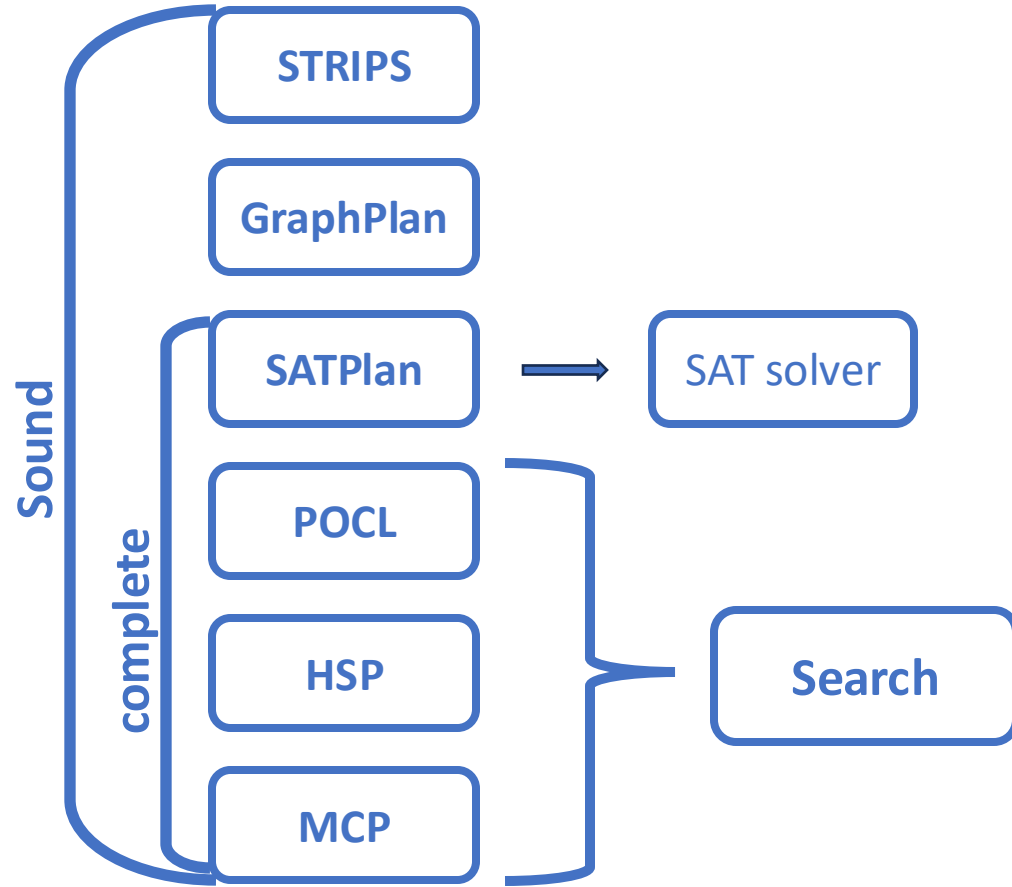
HSP

Bonet & Geffner, AIJ 2001

MCP

Cimatti et. al., ECP 1997

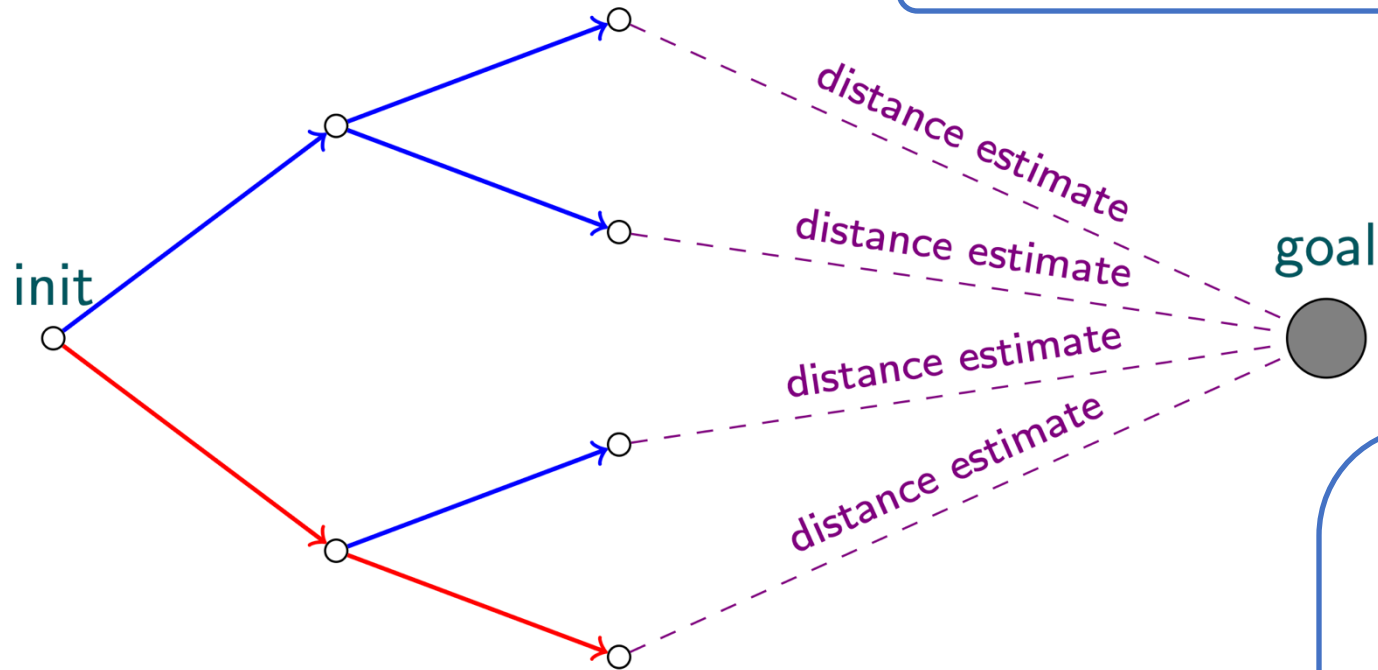
Solving Classical PDDL Planning



Solving Classical PDDL Planning



Heuristic Search



Best-First Search

- Distance estimate: **h**
- Distance from init: **g**
- Explores nodes in the order of $f = g + w \cdot h$
- $w=1$ — A^*
- $w>1$ — wA^*
- $w \rightarrow \infty$ — GBFS

Solving Classical PDDL Planning



Heuristic Search Planner

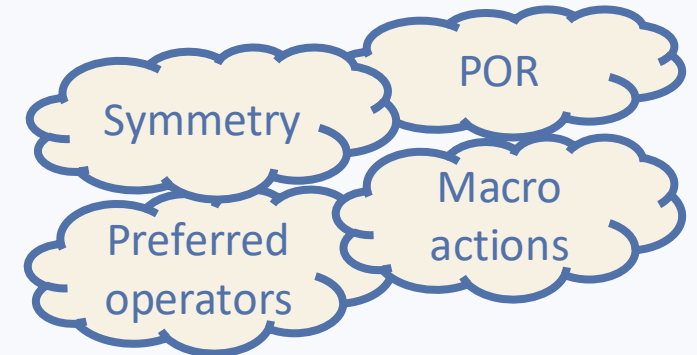
Search algorithms



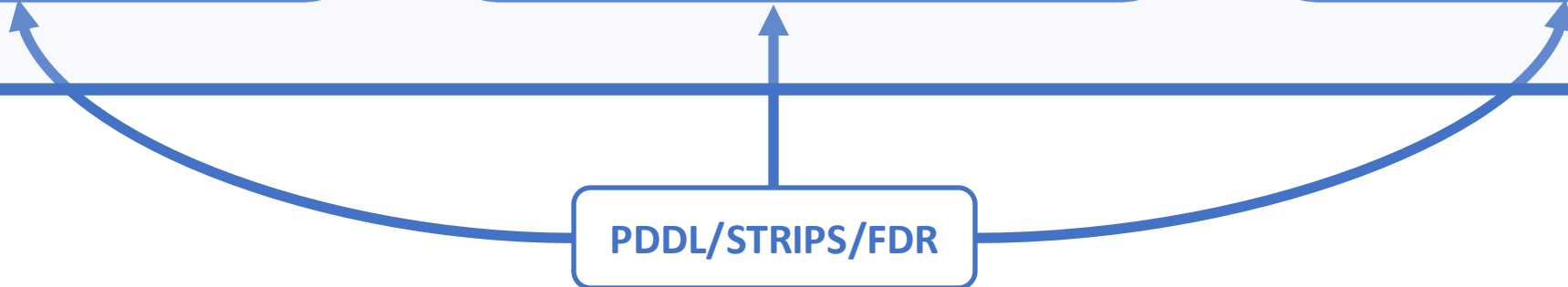
Distance estimates



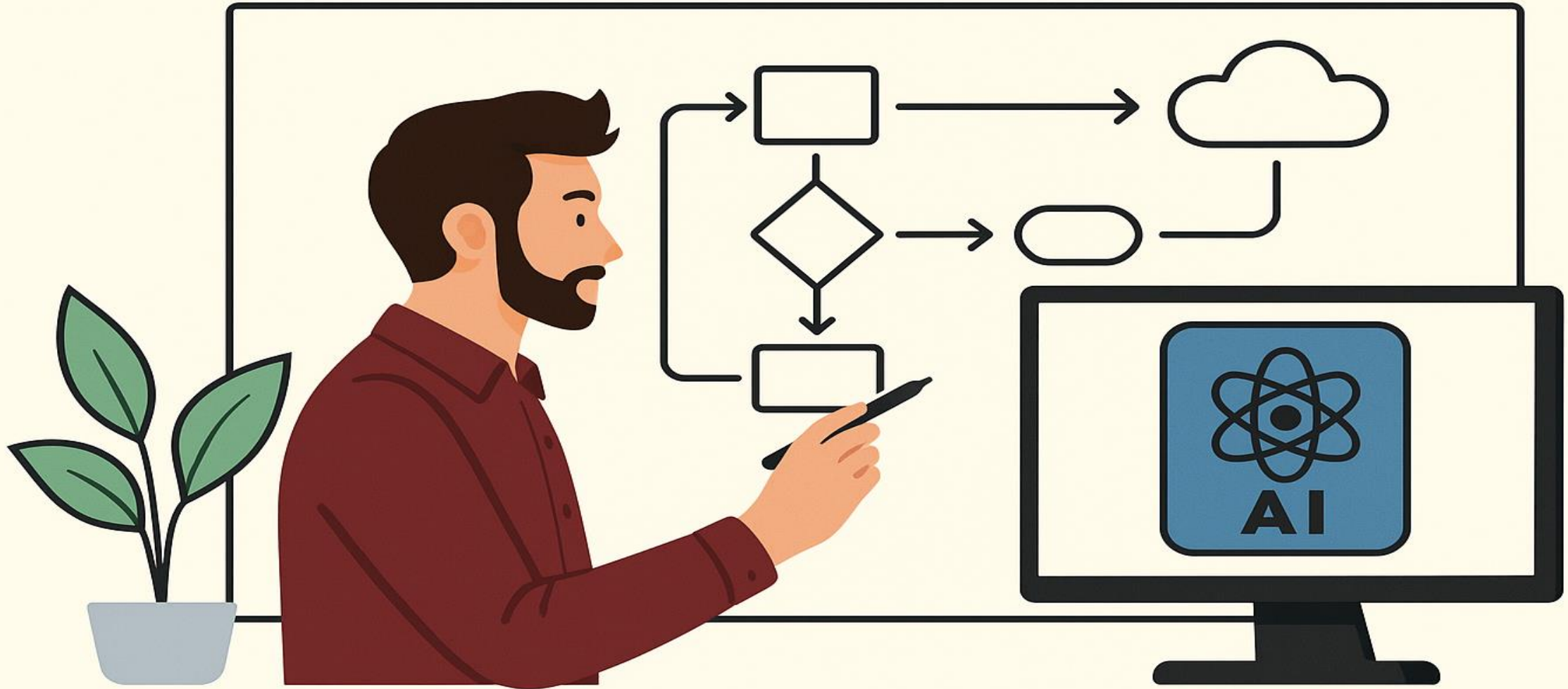
Search boosting/pruning



PDDL/STRIPS/FDR



PLANNING IN THE EARLY LLM ERA



Solving NL/PDDL Planning Problems

Silver et al. FMDM@NeurIPS 2022

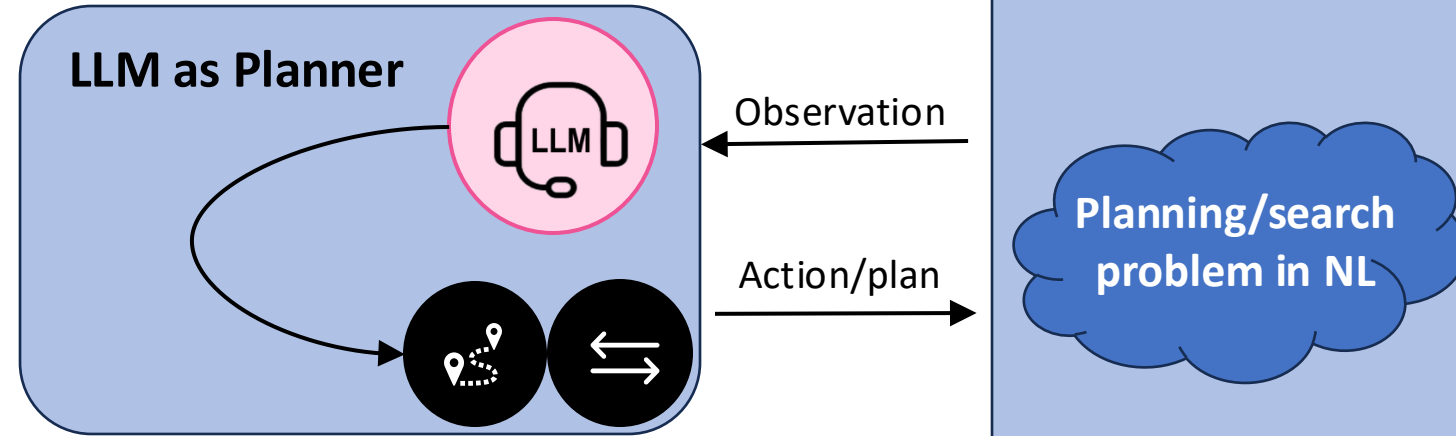
Valmeekam et al. NeurIPS 2023

Kambhampati et al. ICML 2024

Bohnet et al. Arxiv 2024

Zhao et al. ICLR 2025

Most of the focus since 2022



Yao et al. ICLR 2023

Xu et al. Arxiv 2023

Hao et al. EMNLP 2023

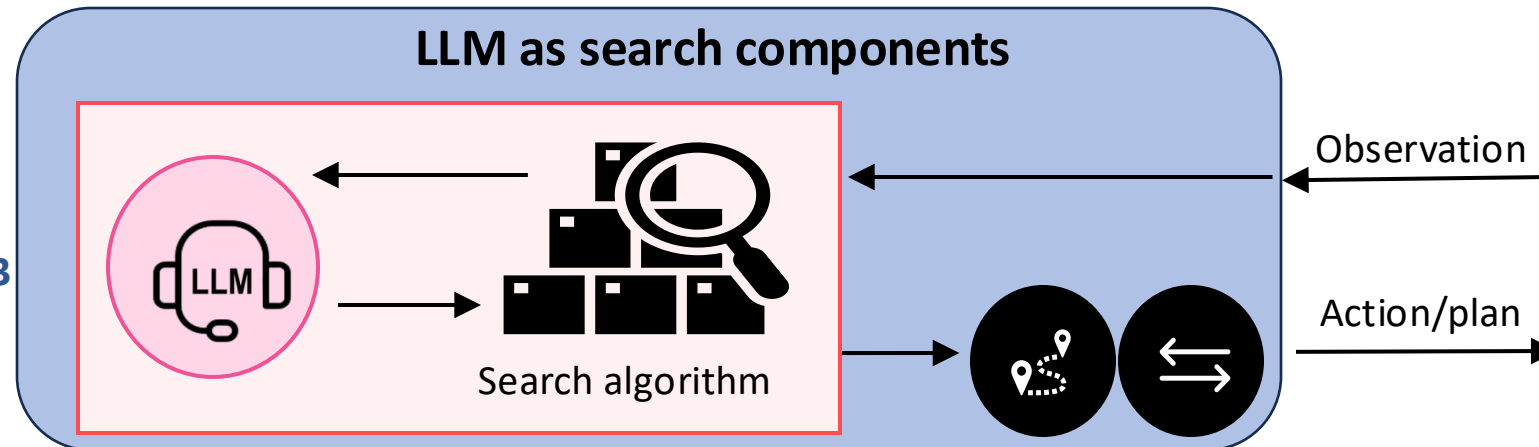
Yao et al. NeurIPS 2023

Shinn et al. NeurIPS 2023

Zhou et al. ICML 2024

Sel et al. ICML 2024

Besta et al. AAAI 2024



What are the properties of these algorithms?

Sound?

No!

If validator exists, we can make it sound

Complete?

No!

Optimal?

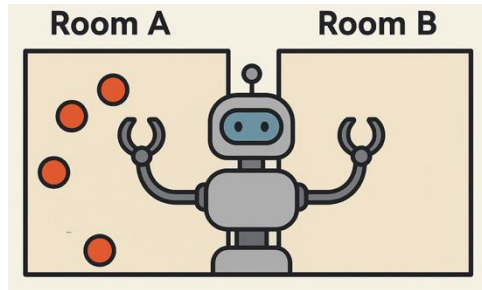
No!

Computational complexity?

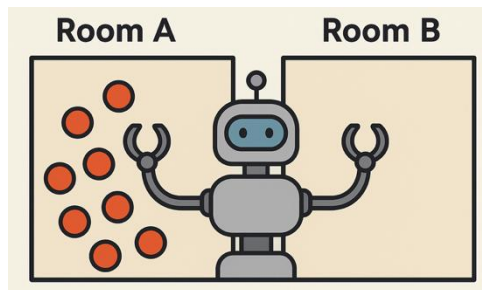
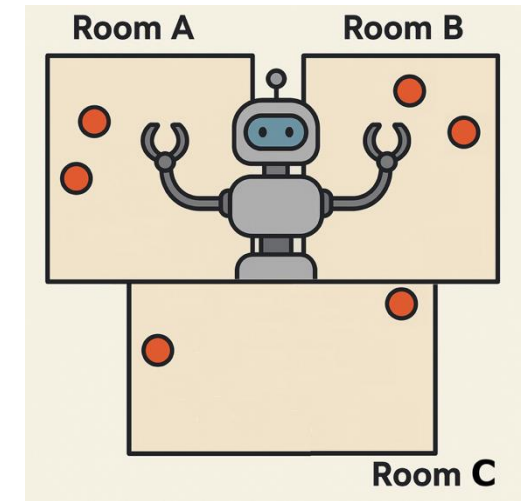
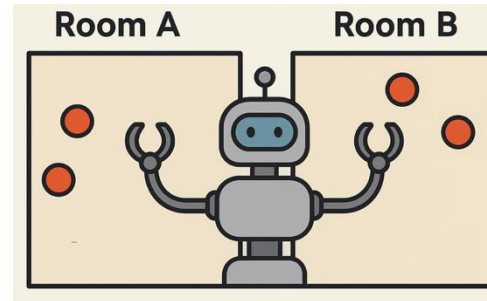
- Hard to measure. Most expensive operation is LLM call
- Computational effort vs. state space portion explored

Approach	Complexity	24Game		Crossword		BlocksWorld		PrOntoQA	
		States	Calls	States	Calls	States	Calls	States	Calls
IO	O(D)	0.02%	1362	4e-9%	20	0.5%	502	4%	4000
CoT	O(D)	0.02%	1362	4e-9%	20	0.5%	502	4%	4000
ReAct	O(LD)	0.07%	4086	4e-8%	200	7.8%	8032	24.6%	24K
ReWOO	O(LD)	0.07%	4086	4e-8%	200	7.8%	8032	24.6%	24K
RAP	O(TbLD)	3.3%	245K	2e-6%	12K	388%	482K	1229%	1.44M
ToT	O(bmLD)	1.6%	102K	1e-6%	5K	194%	201K	615%	600K
GoT	O(bLD)	0.3%	20K	2e-7%	1K	39%	40K	122%	120K
Reflection	O(LTD)	0.7%	68K	4e-7%	2.4K	77.6%	90K	245%	320K
LATS	O(TbLD)	3.3%	286K	2e-6%	14K	388%	562K	1229%	1.68M

Why did it work in the first place?



(pick o1 A L)
(pick o2 A R)
(move A B)
(drop o1 B L)
(drop o2 B R)
(move B A)
(pick o3 A L)
(pick o4 A R)
(move A B)
(drop o3 B L)
(drop o4 B R)

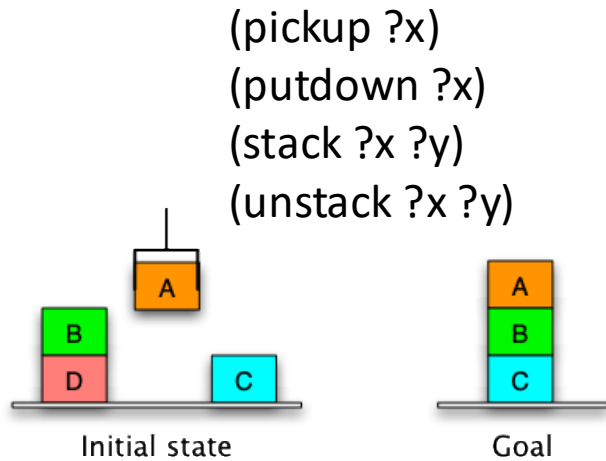


(pick o1 A L)
(pick o2 A R)
(move A B)
(drop o1 B L)
(drop o2 B R)
(move B A)
...
(drop o7 B L)
(drop o8 B R)

Conclusions (see [1]):

- Be aware of instance generator limitations
- Show generalization outside of training set
- Show performance on multiple domains

Why did it work in the first place?



What does it mean to restrict $|\pi| \leq 10$?

- At most 5 blocks are moved (even if the instance has 100s of blocks)
- Total of 1331 possible plan patterns
- When trained on a large collection of instances, most (all?) possible plan patterns appear in the training set

How do plans look like?

- pickup -> stack
- stack -> unstack | pickup
- unstack -> stack | putdown
- putdown -> unstack | pickup

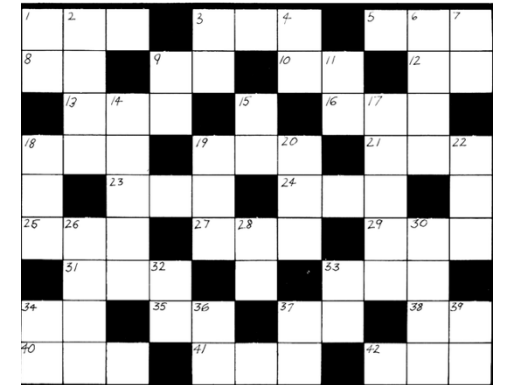
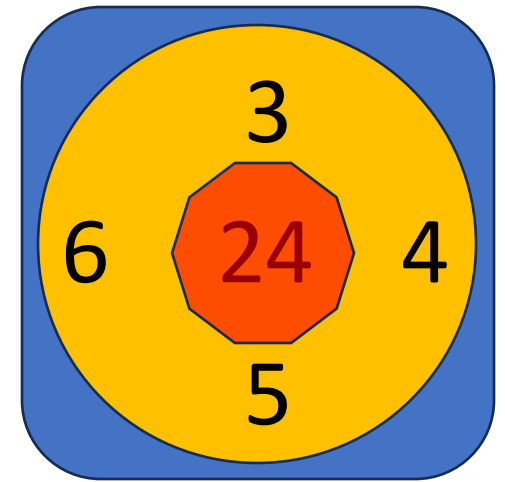
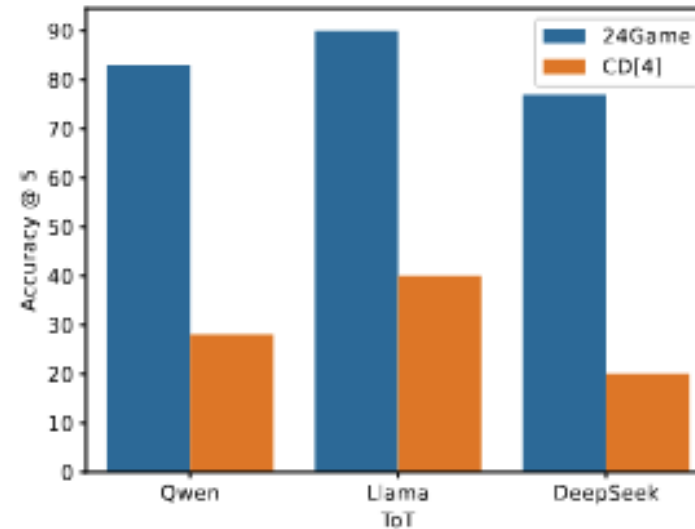
Conclusions (see [1]):

- There are many planning domains out there and BlocksWorld is among the simplest
- Show generalization outside of training set
- Show performance on multiple domains

Why did it work in the first place?

- Tested on data scraped from the internet
 - Data contamination concerns
- No external validator, lenient success criteria

	Model	IO		CoT		ToT	
		24Game	CD[4]	24Game	CD[4]	24Game	CD[4]
acc@5	Qwen	6	2	8	2	83	28
	Llama	7	2	32	7	90	40
	DeepSeek	38	5	48	13	77	20
mean	Qwen	2	1	2	0	47	9
	Llama	1	0	9	1	48	12
	DeepSeek	10	1	18	4	28	4



Katz et al, Arxiv 2025, **Seemingly Simple Planning Problems are Computationally Challenging: The Countdown Game**

Conclusions:

- Must have precise definition of solution and sound validators for candidate solutions
- Should have large instance space and dynamic generation procedure to avoid memorization concerns.

PLANNING IN THE MODERN LLM ERA



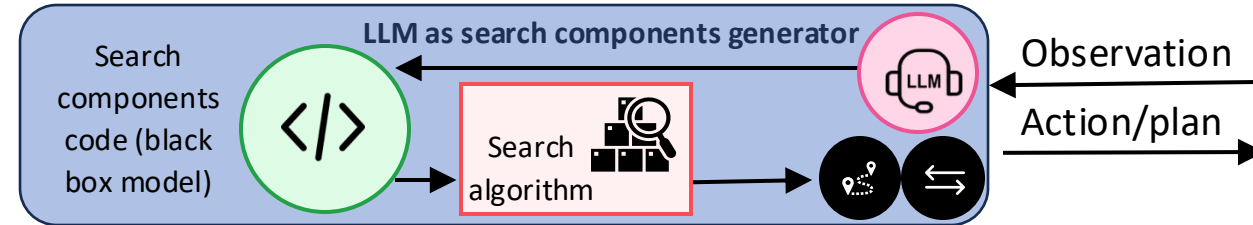
Solving NL/PDDL Planning Problems

Katz et al, NeurIPS 2024

Cao et al, OWA@NeurIPS 2024

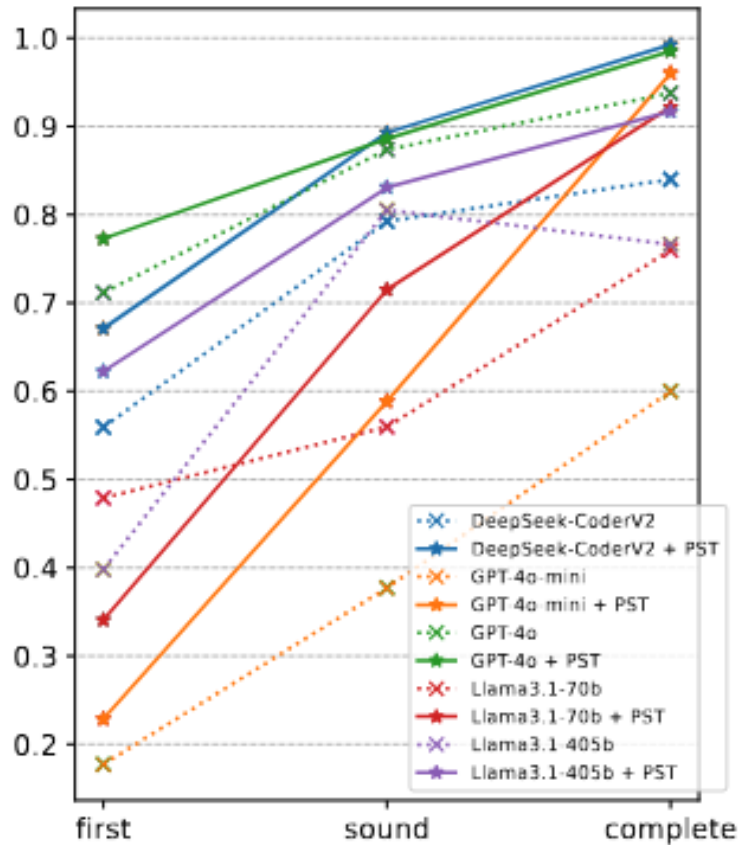
Tuisov et al, Arxiv 2024

Correa et al, NeurIPS 2025



Environment

Planning/search problem in NL



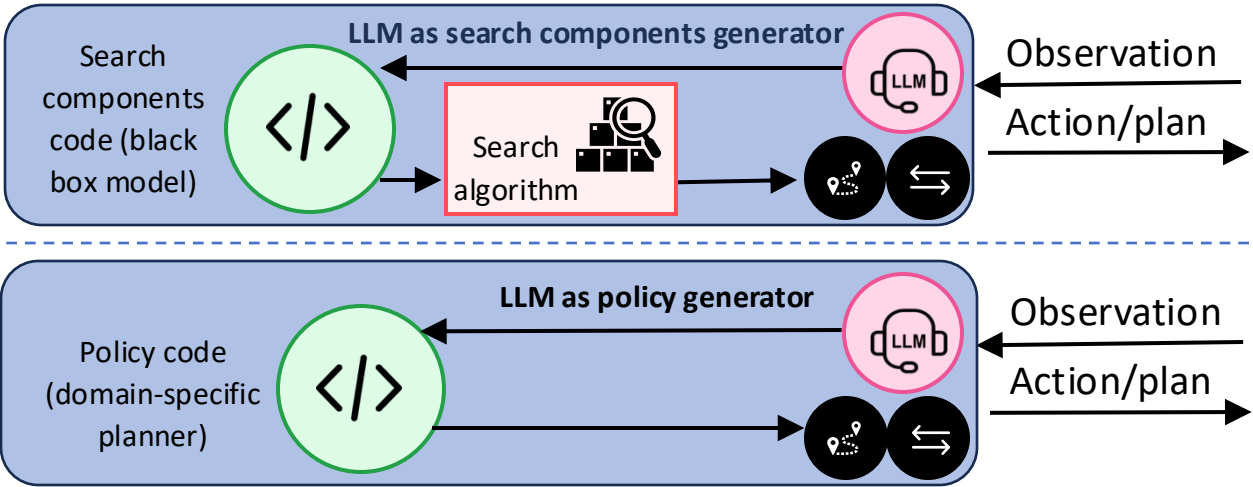
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LATS	O(TbLD)	3.3%	286K	2e-6%	14K	388%	562K	1229%	1.68M
ToS (ours)	O(1)	27.0%	2.2	3e-4%	3.8	125%	3.8	175%	2.6

		24 Game	PrOntoQA	Sokoban	Crossword	BlocksWorld
AutoToS	GPT-4o-mini	8.8	4.8	6.4	9.6	10.0
	GPT-4o	3.4	2.6	2.2	5.8	2.0
	Llama3.1-405b	3.4	2.0	2.6	4.0	3.2
	Llama3.1-70b	7.4	2.0	8.2	6.2	5.8
	DeepSeek-CoderV2	4.4	2.0	2.8	6.6	4.2
ToS GPT-4		2.2	2.6	NA	3.8	3.8

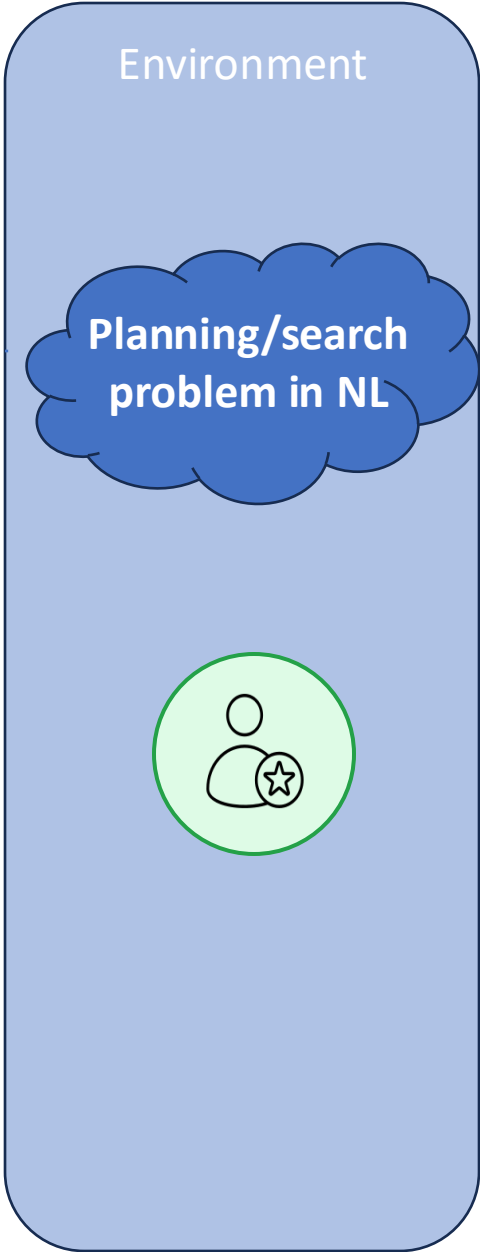
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Katz et al, NeurIPS 2024
Cao et al, OWA@NeurIPS 2024
Tuisov et al, Arxiv 2024
Correa et al, NeurIPS 2025

Silver et al, AAAI 2024
Hodel, BSc Thesis 2024
Stein et al, Arxiv 2025



Coverage best run							Cov. symbolic			
S11	Bas	F5-3	F3-6	-MC	-SD	-CR	1m=	ff=	1m	ff
100	100	100	100	100	100	100	0	100	0	100
100	100	100	100	100	100	100	31	100	43	100
100	100	100	100	100	100	100	15	100	40	100
100	100	100	100	100	100	100	100	100	100	100
100	0	100	100	0	0	100	100	100	100	100
32	12	100	100	0	3	12	56	100	62	100
0	15	100	100	100	100	100	15	15	41	59



Solving NL/PDDL Planning Problems

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Cao et al, OWA@NeurIPS 2024

Tuisov et al, Arxiv 2024

Correa et al, NeurIPS 2025

Silver et al, AAI 2024

Hodel, BSc Thesis 2024

Stein et al, Arxiv 2025

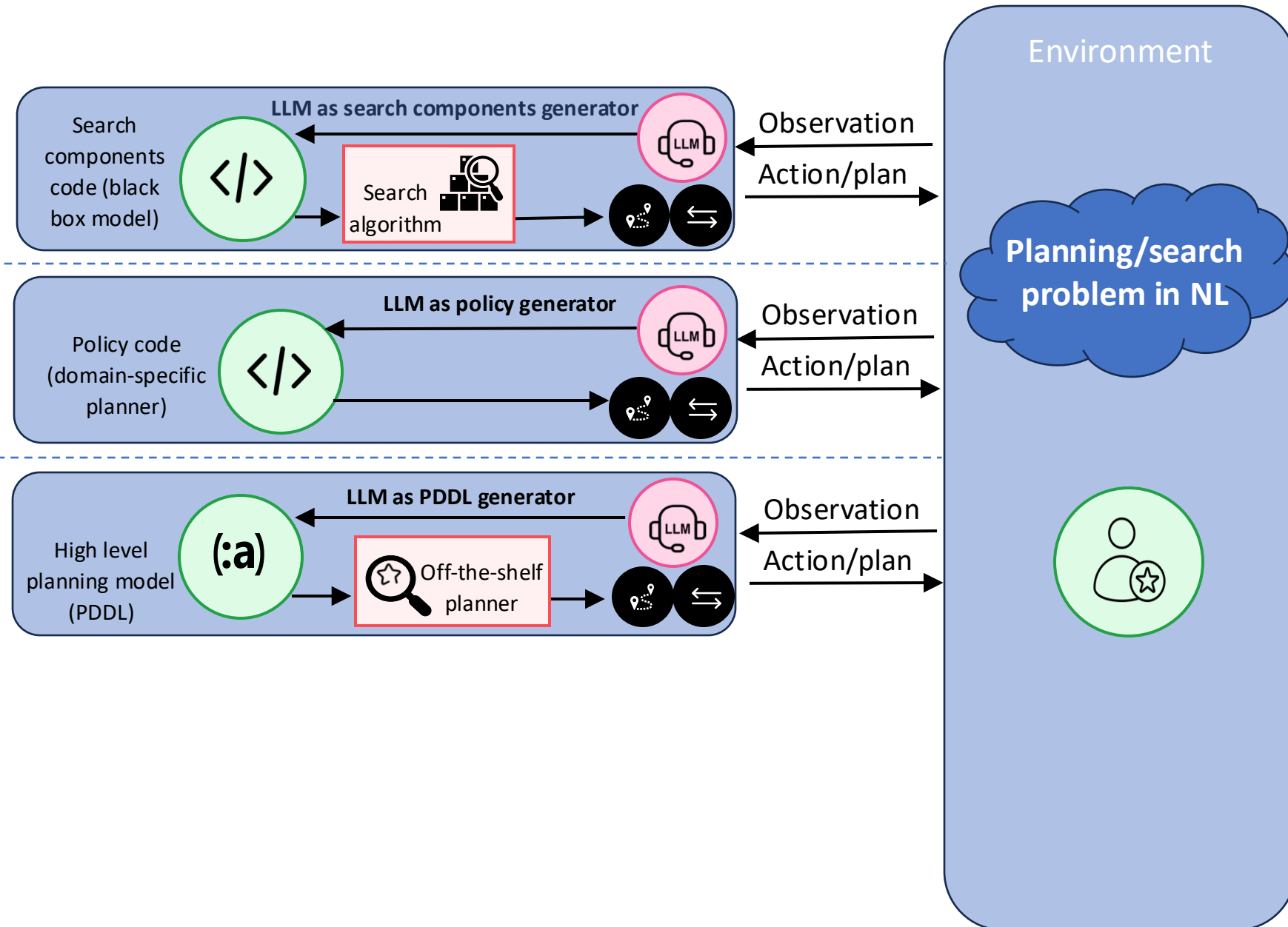
Guan et al, NeurIPS 2023

Gestrin et al, Arxiv 2024

Oswald et al, ICAPS 2024

Huang et al, AAI 2025

Tantakoun et al, ACL Findings 2025



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International Planning Competition 2026

IPC 2026



International Planning Competition 2026

Classical Tracks

Learning Tracks

Probabilistic Tracks

Numeric Tracks

HTN Tracks

International Planning Competition 2026

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