

Informed Search

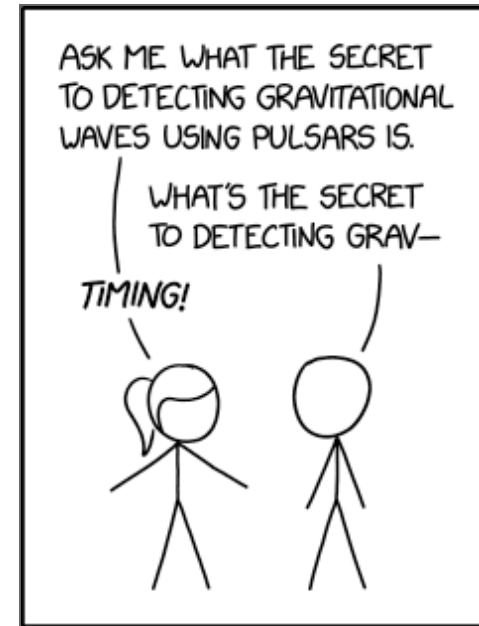
CS5491: Artificial Intelligence
ZHICHAO LU

Content Credits: **Prof. Wei**'s CS4486 Course
and **Prof. Boddeti**'s AI Course

TODAY (PART 2)

Informed Search Methods

- Heuristics
- Greedy Search
- A^* Search



XKCD

Reading

- Today's Lecture: RN Chapter 3.5-3.6, 4.1-4.2

SEARCH PROBLEMS

Uninformed Search

Methods we saw:

- DFS
- BFS
- UCS

Searching with your **EYES CLOSED**

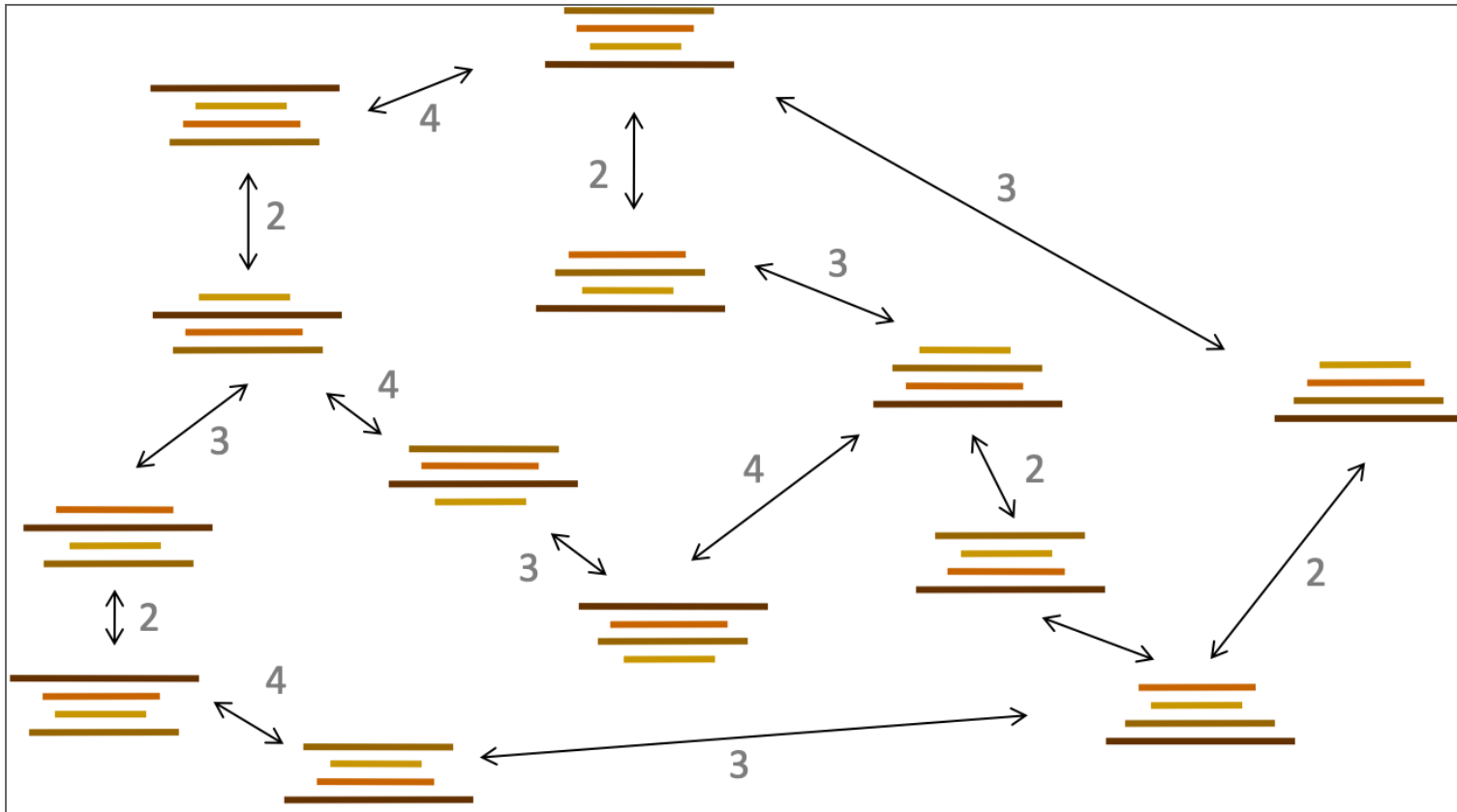
Informed Search

Methods we will see:

- Greedy
- A^*

Searching with your **EYES OPEN**

EXAMPLE: PANCAKE PROBLEM

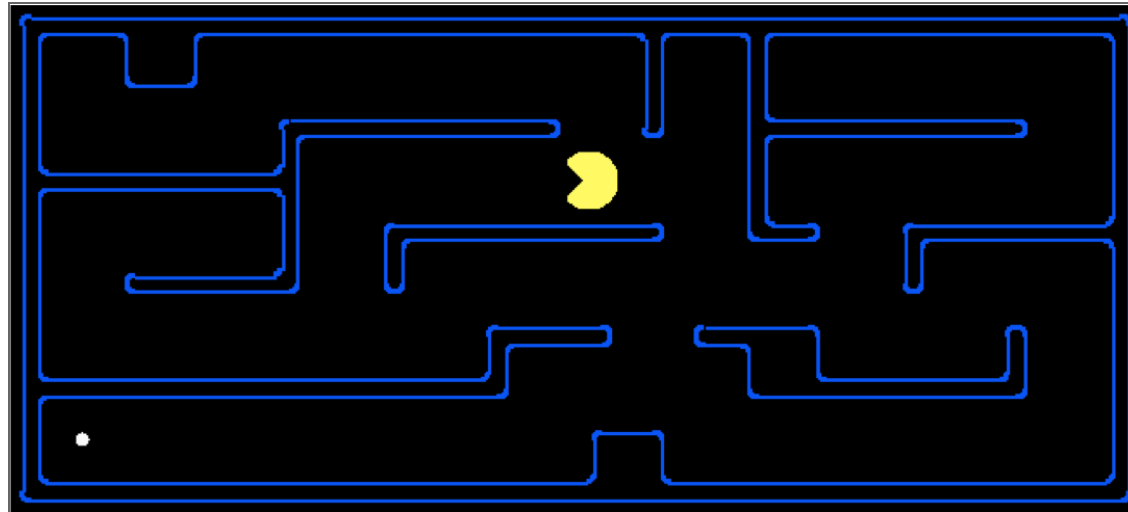


HEURISTICS

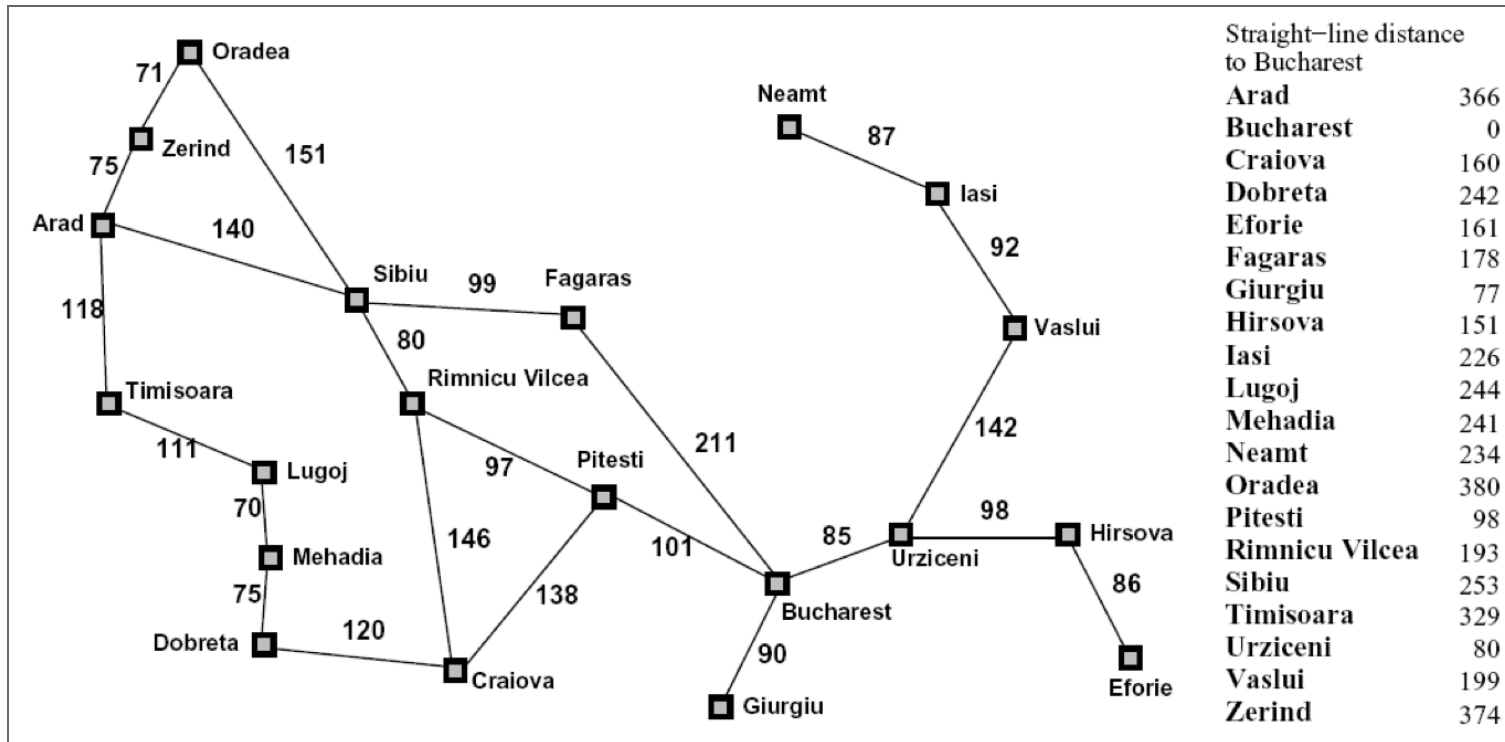
SEARCH HEURISTICS

A heuristic is:

- A function that estimates how close a state is to a goal
- Designed for a particular search problem
- Examples: Manhattan distance, Euclidean distance

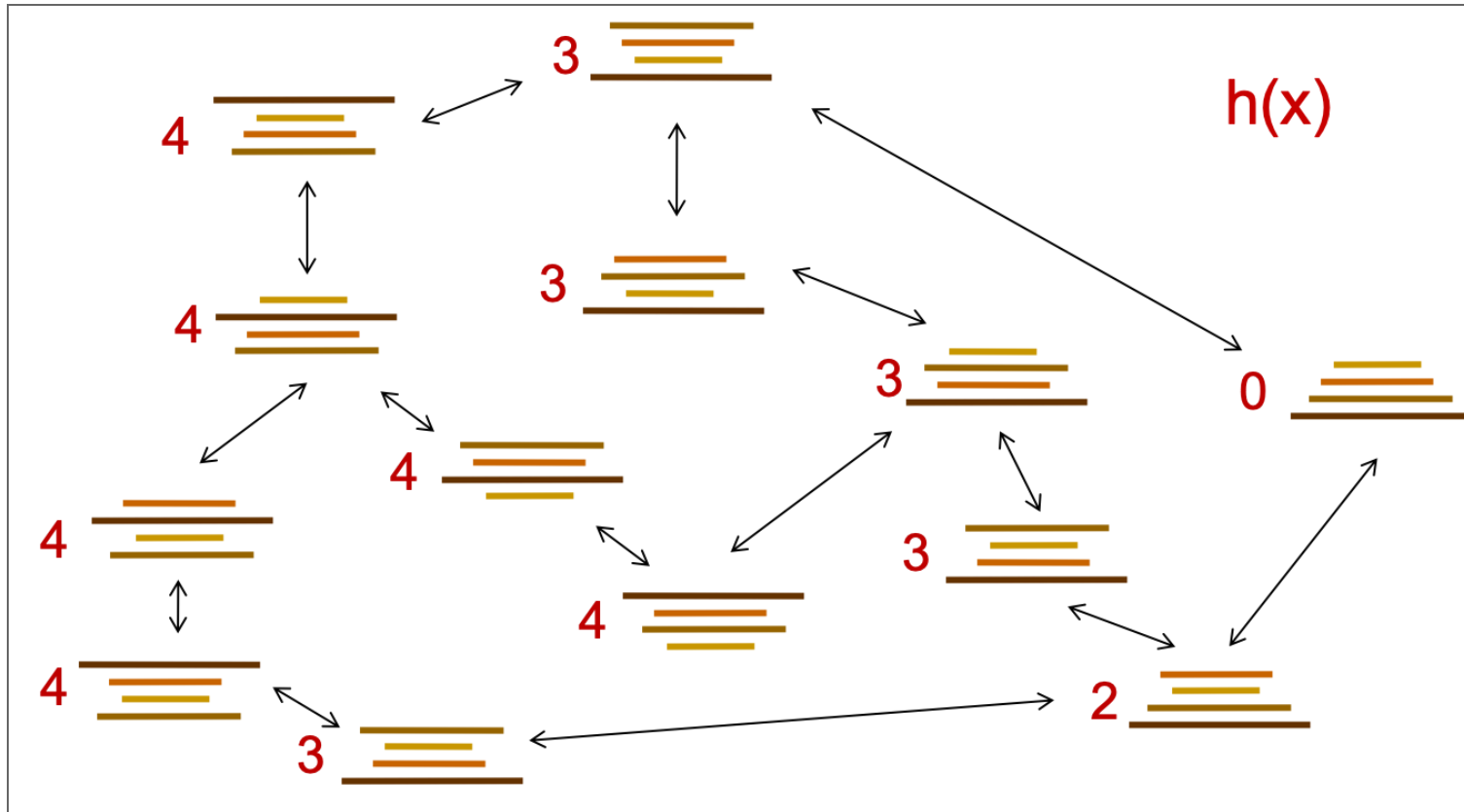


EXAMPLE: HEURISTIC FUNCTION



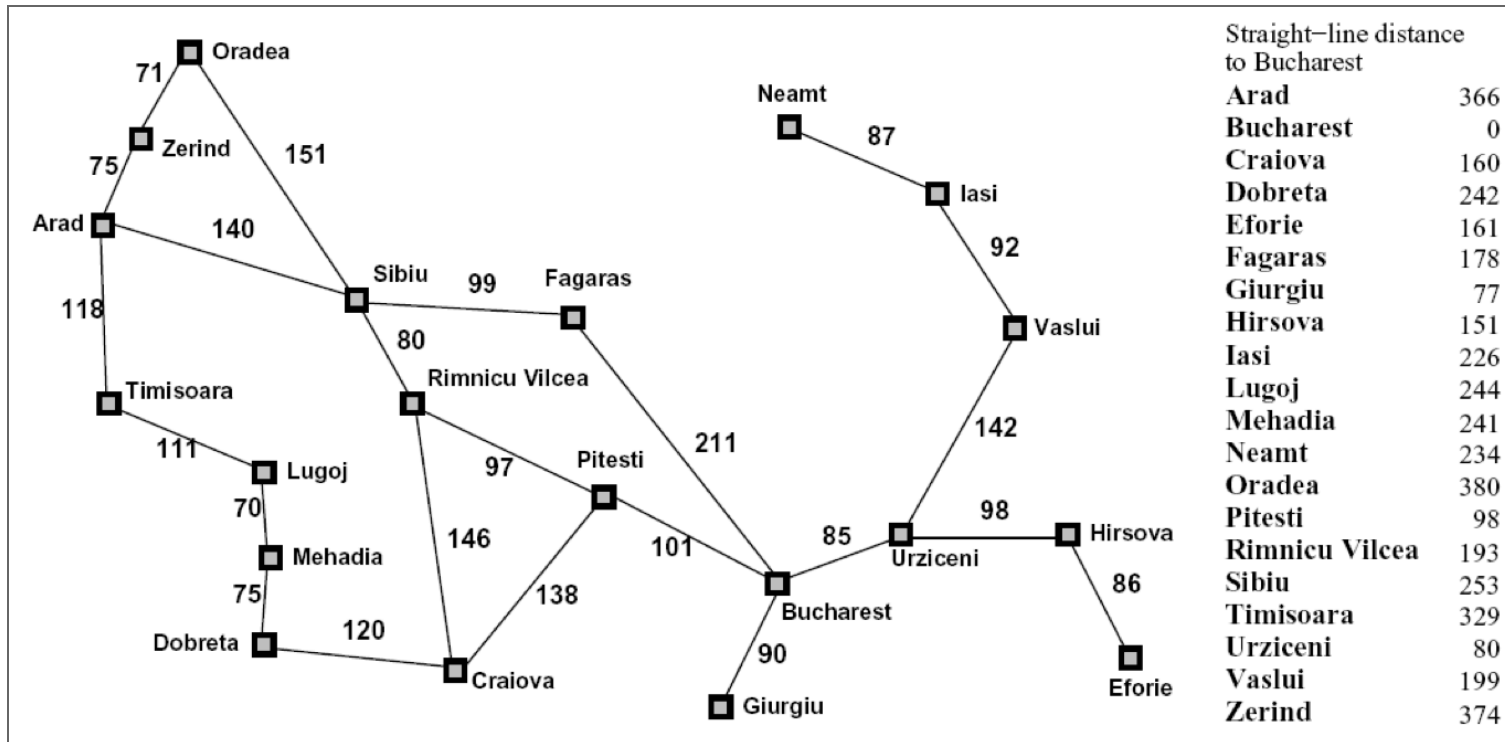
EXAMPLE: HEURISTIC FUNCTION

Eg: index of the largest pancake that is still out of place



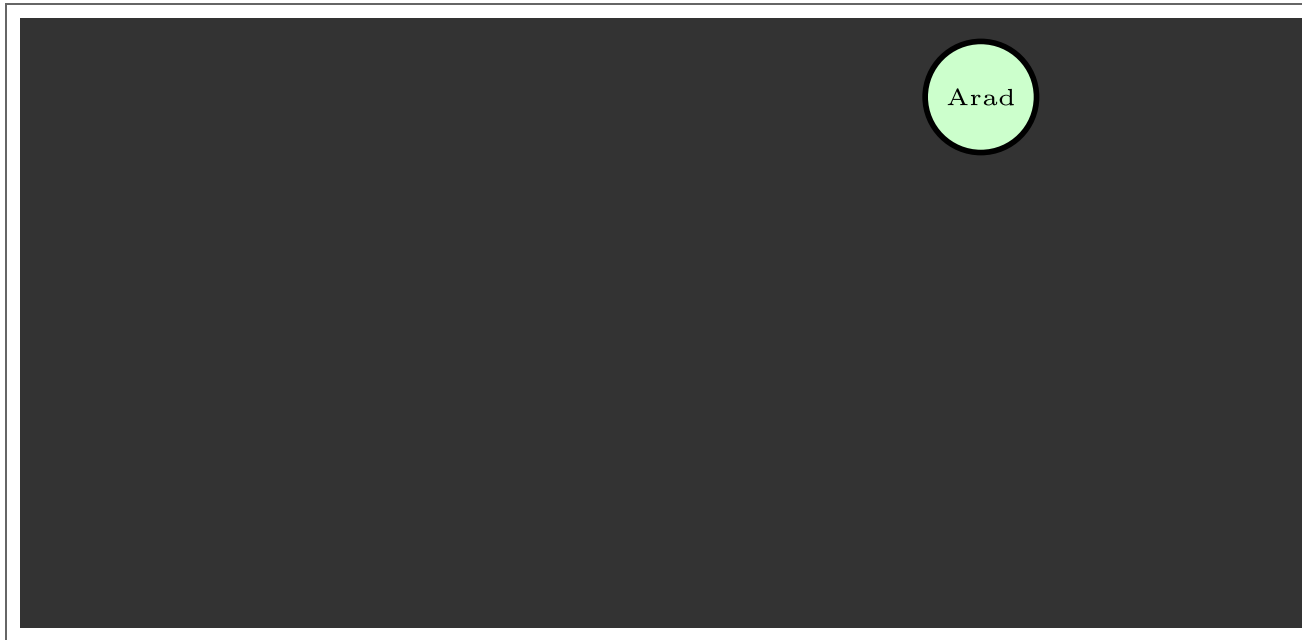
GREEDY SEARCH

EXAMPLE: HEURISTIC FUNCTION

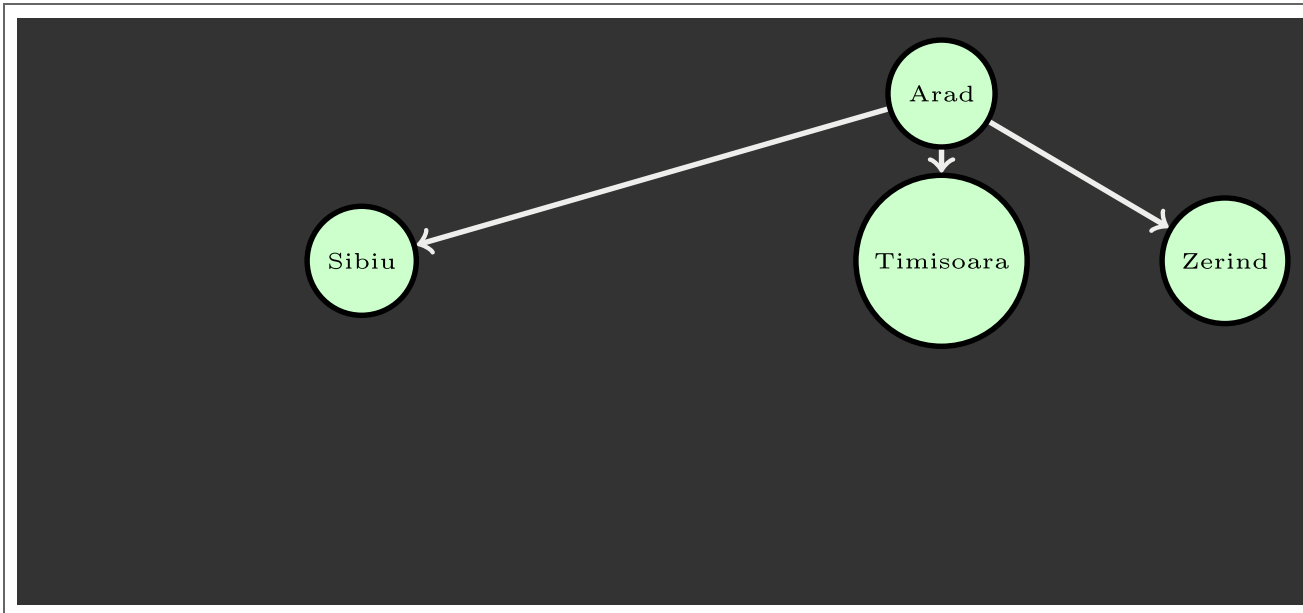


GREEDY SEARCH: ROMANIA

Expand the node that seems closest...



Straight-line distance to Bucharest	
Arad	366
Bucharest	0
Craiova	160
Dobreta	242
Eforie	161
Fagaras	178
Giurgiu	77
Hirsova	151
Iasi	226
Lugoj	244
Mehadia	241
Neamt	234
Oradea	380
Pitesti	98
Rimnicu Vilcea	193
Sibiu	253
Timisoara	329
Urziceni	80
Vaslui	199
Zerind	374



GREEDY SEARCH

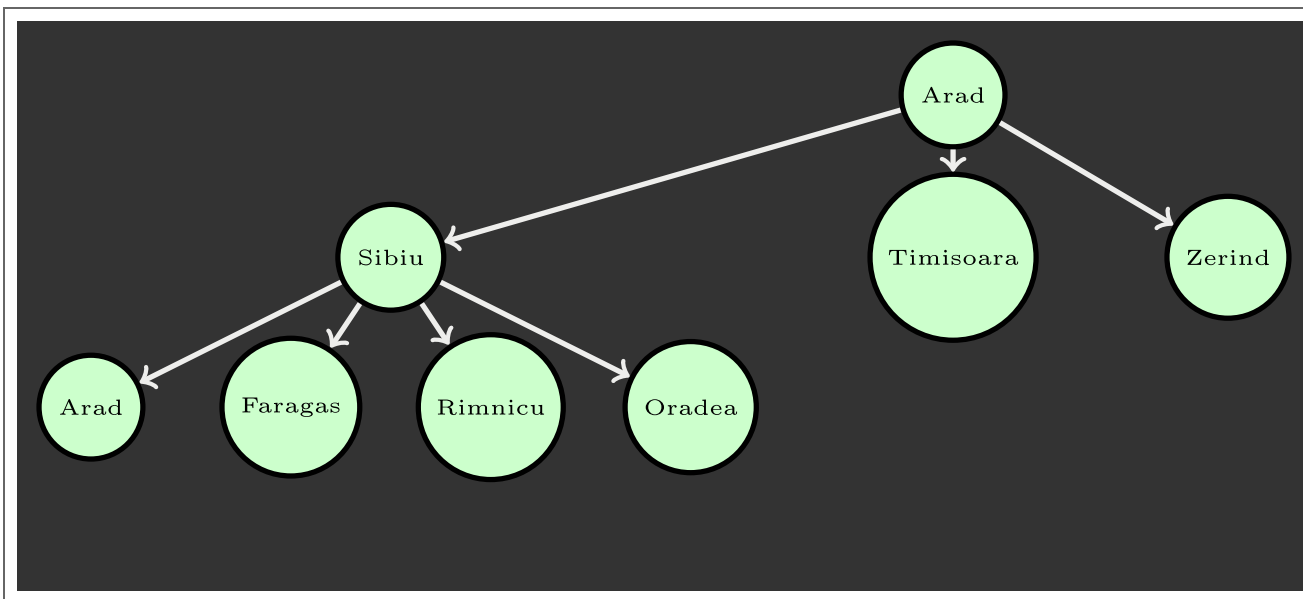
Strategy: expand a node that you think is closest to a goal state

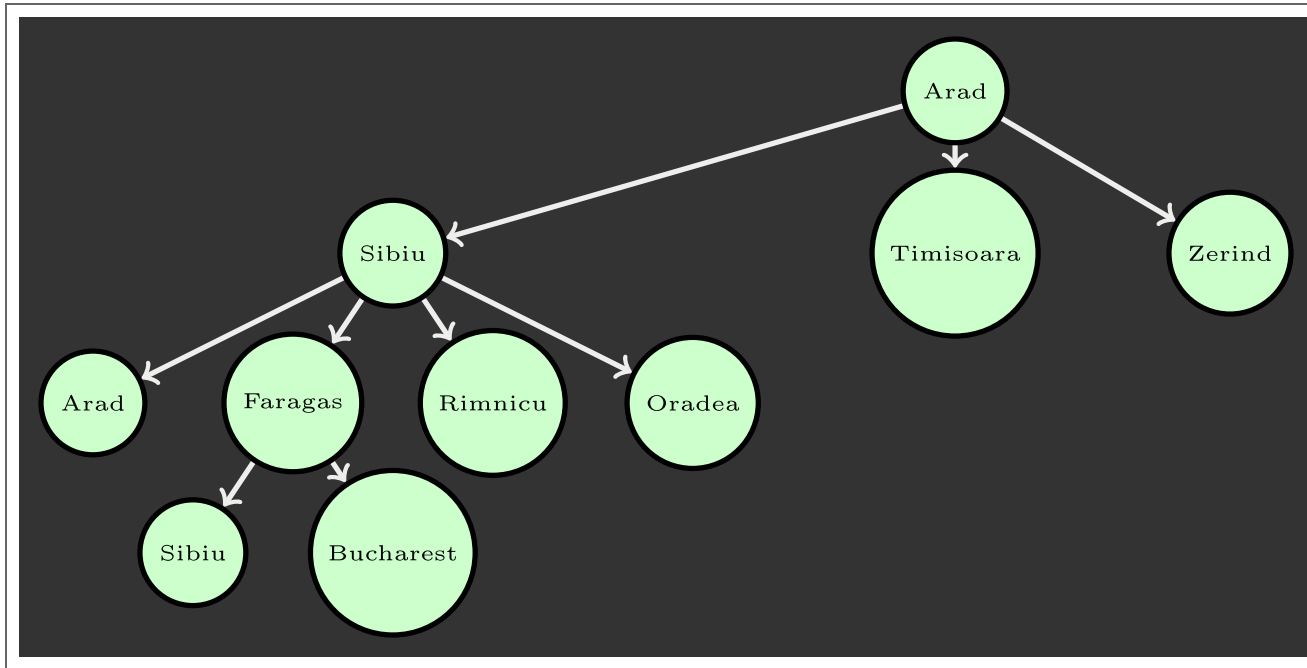
Heuristic: distance estimate to nearest goal for each state

A common case:

Best-first takes you straight to the (wrong) goal

Worst-case: like a badly-guided DFS





GREEDY DEMO

What can go wrong?



A* SEARCH

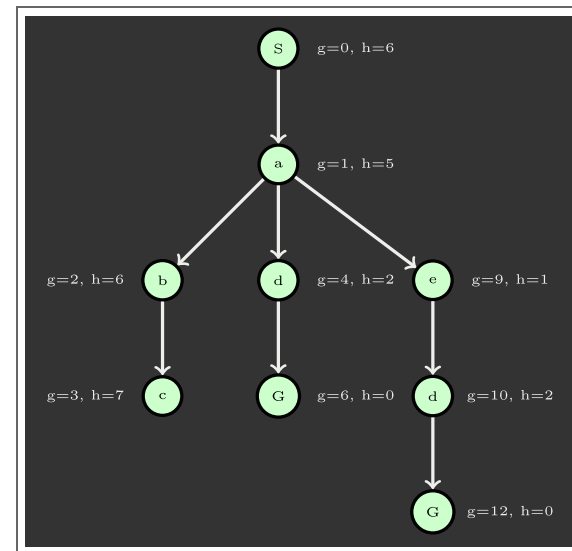
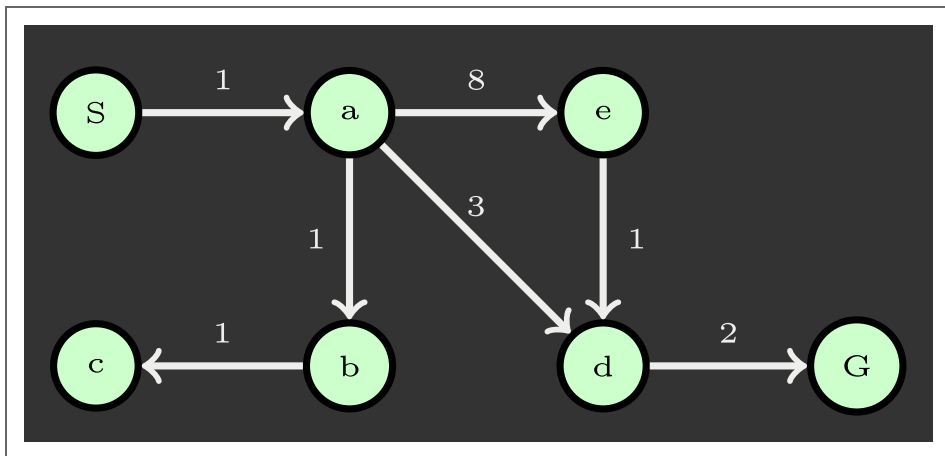
KEY IDEA: COMBINE UCS AND GREEDY

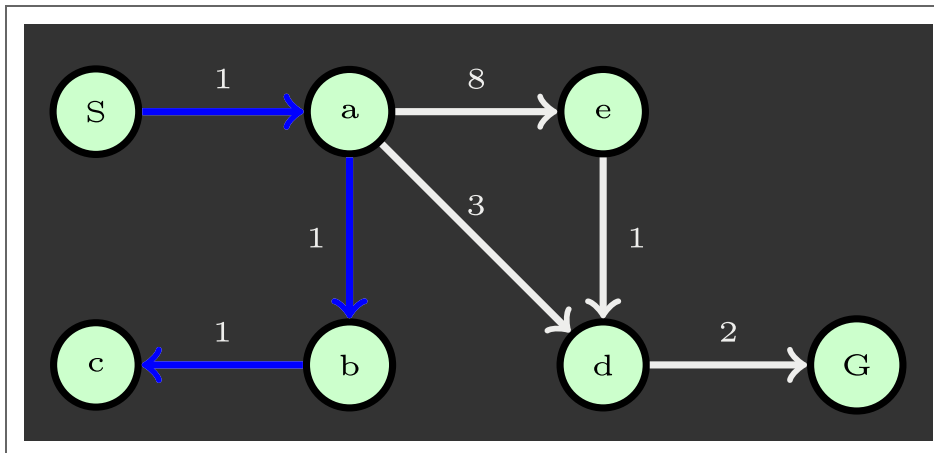
COMBINING UCS AND GREEDY

Uniform-cost orders by path cost, or backward cost $g(n)$.

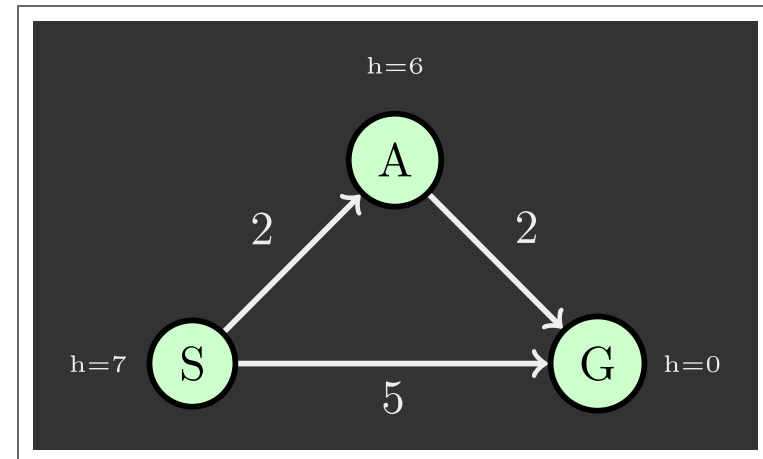
Greedy orders by goal proximity, or forward cost $h(n)$.

A* Search orders by the sum: $f(n) = g(n) + h(n)$





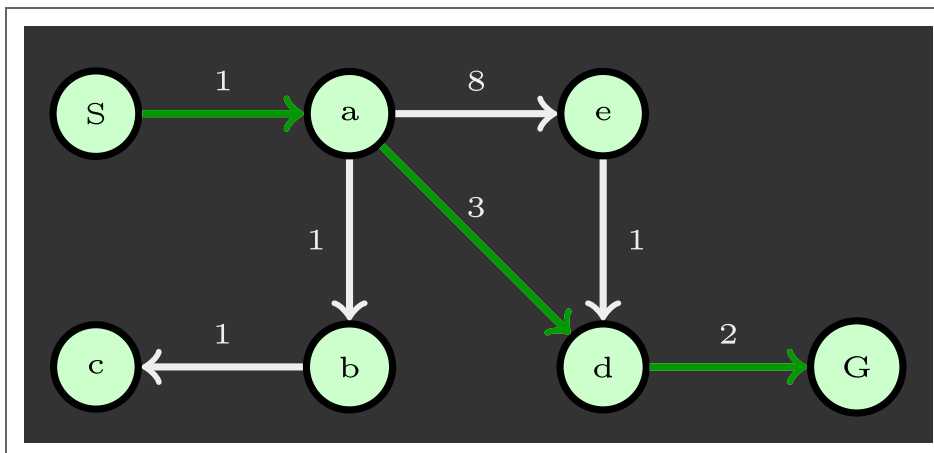
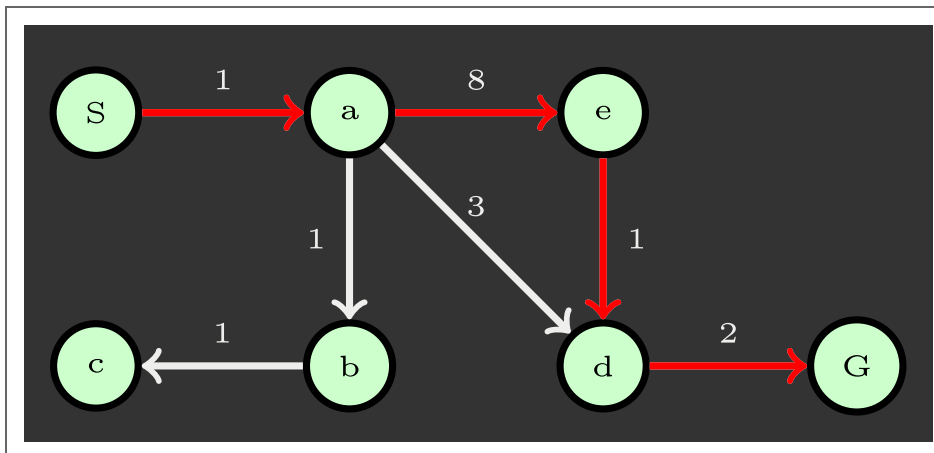
IS A^* OPTIMAL?



What went wrong?

Actual goal cost \leq estimated goal cost

We need estimates to be less than actual costs



ADMISSIBILITY

Inadmissible (pessimistic) heuristics break optimality by trapping good plans on the fringe.

Admissible (optimistic) heuristics slow down bad plans but never outweigh true costs

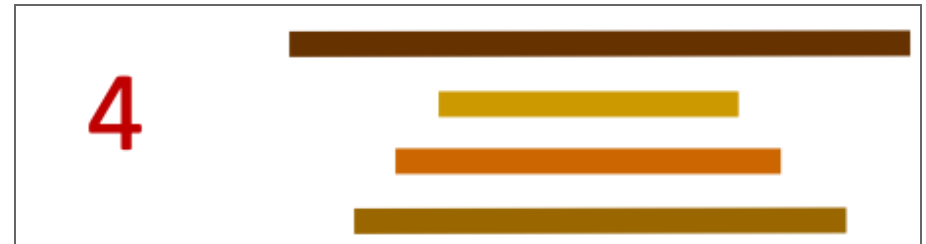
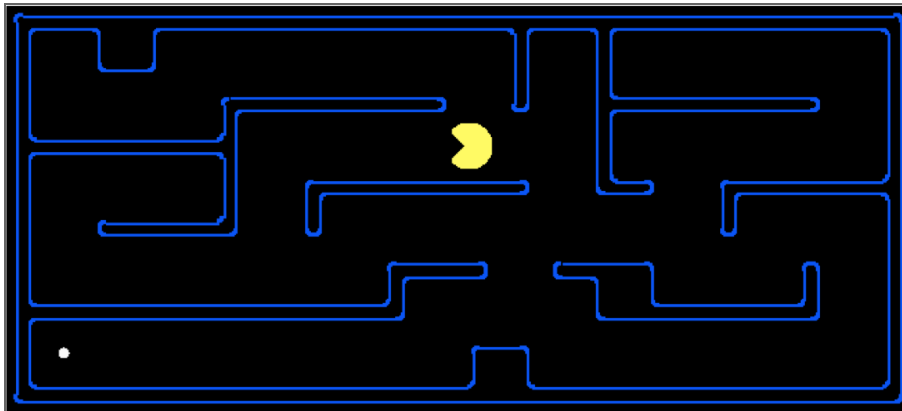
ADMISSIBLE HEURISTICS

A heuristic h is admissible (optimistic) if:

$$0 \leq h(n) \leq h^*(n)$$

where $h^*(n)$ is the true cost to a nearest goal

Example:



In practice, coming up with an admissible heuristic is most of what is involved in using A^* .

OPTIMALITY OF A^* TREE SEARCH

Assume:

- A is an optimal goal node
- B is a suboptimal goal node
- h is admissible

Claim:

- A will exit the fringe before B

OPTIMALITY OF A^* TREE SEARCH

Proof:

Imagine B is on the fringe

Some ancestor n of A is on the fringe too

Claim: n will be expanded before B

- $f(n)$ is less or equal to $f(A)$
- $f(A)$ is less than $f(B)$
- n expands before B

All ancestors of A expand before B

A expands before B

A^* search is optimal

$$f(n) = g(n) + h(n)$$

$$f(n) \leq g(A) \text{ admissibility of } g$$

$$g(A) = f(A) \quad h = 0 \text{ at goal}$$

$$g(A) \leq g(B) \quad B \text{ is suboptimal}$$

$$f(A) \leq f(B) \quad h = 0 \text{ at goal}$$

$$f(n) \leq f(A) < f(B)$$

UCS VS A^* CONTOURS

Uniform-cost expands equally in all “directions”

A^* expands mainly toward the goal, but does hedge its bets to ensure optimality

A* DEMO

A* APPLICATIONS

Video games

Pathing / routing problems

Resource planning problems

Robot motion planning

Language analysis

Machine translation

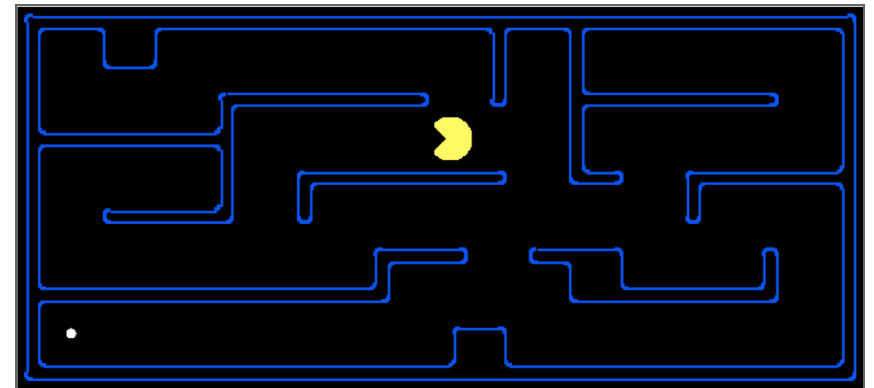
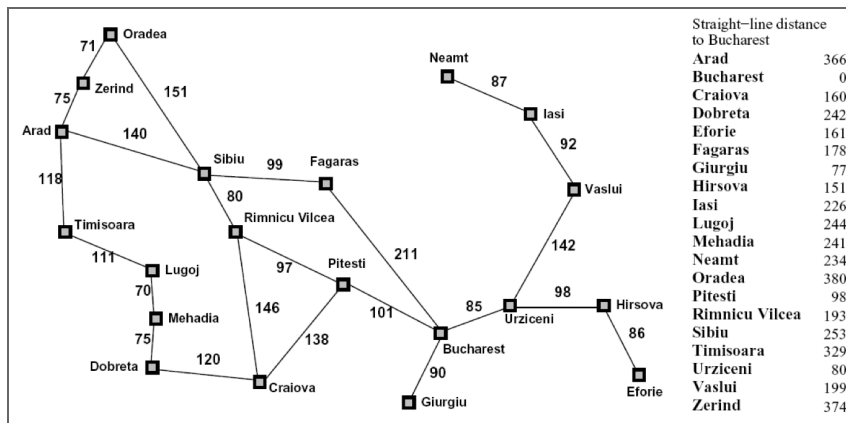
Speech recognition

...

CREATING ADMISSIBLE HEURISTICS

Most of the work in solving hard search problems optimally is in coming up with admissible heuristics

Often, admissible heuristics are solutions to relaxed problems, where new actions are available



Inadmissible heuristics can often be useful too.

A^* SUMMARY

A^* uses both backward costs and (estimates of) forward costs

A^* is optimal with admissible heuristics

Heuristic design is key: often use relaxed problems

DESIGNING HEURISTIC AS A SEARCH PROBLEM

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Mathematical discoveries from program search with large language models

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Abstract

Large language models (LLMs) have demonstrated tremendous capabilities in solving complex tasks, from quantitative reasoning to understanding natural language. However, LLMs sometimes suffer from confabulations (or hallucinations), which can result in them making plausible but incorrect statements^{1,2}. This hinders the use of current large models in scientific discovery. Here we introduce FunSearch (short for searching in the function space), an evolutionary procedure based on pairing a pretrained LLM with a systematic evaluator. We demonstrate the effectiveness of this approach to surpass the best-known results in important problems, pushing the boundary of existing LLM-based approaches³. Applying FunSearch to a central problem in extremal combinatorics—the cap set problem—we discover new constructions of large cap sets going beyond the best-known ones, both in finite dimensional and asymptotic cases. This shows that it is possible to make discoveries for established open problems using LLMs. We showcase the generality of FunSearch by applying

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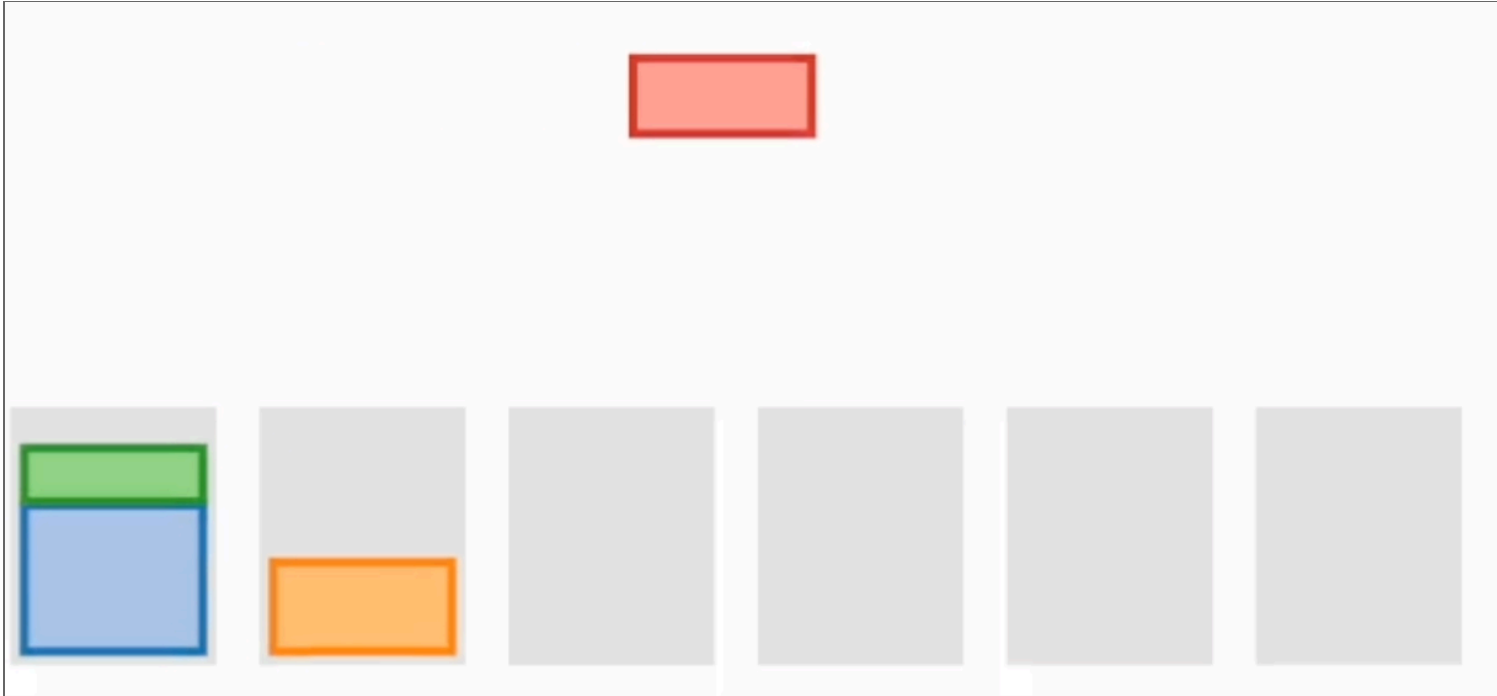
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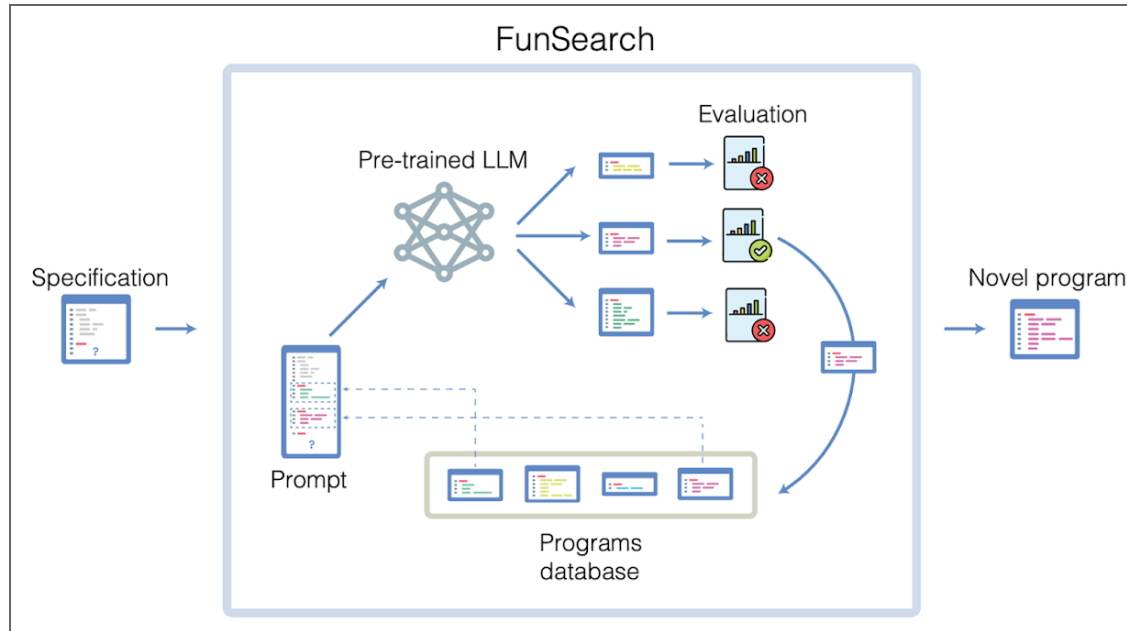
DESIGNING HEURISTIC AS A SEARCH PROBLEM

ONLINE BIN PACKING



DESIGNING HEURISTIC AS A SEARCH PROBLEM

ONLINE BIN PACKING



DESIGNING HEURISTIC AS A SEARCH PROBLEM

ONLINE BIN PACKING

```
def best_fit_heuristic(item: float, bins: np.ndarray) -> np.ndarray:
    """Returns priority with which we want to add item to each bin.

    Args:
        item: Size of item to be added to the bin.
        bins: Array of capacities for each bin.

    Return:
        Array of same size as bins with priority score of each bin.
    """
    return np.argmin(bins - item)
```

```
def FunSearch_heuristic(item: float, bins: np.ndarray) -> np.ndarray:
    """Heuristic discovered for the Weibull datasets."""
    max_bin_cap = max(bins)
    score = (bins - max_bin_cap)**2 / item + bins**2 / (item**2)
    score += bins**2 / item**3
    score[bins > item] = -score[bins > item]
    score[1:] -= score[:-1]
    return np.argmax(score)
```

DESIGNING HEURISTIC AS A SEARCH PROBLEM

ONLINE BIN PACKING

Q & A



XKCD

Speaker notes

