

Introduction to MAPF

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Multi-Agent Pathfinding

- Goal: Assign collision-free paths on graphs to each agent.
- The fundamental building block of multi-robot coordination
- Real-world Applications
 - Fleet operations in automated warehouses
 - Requires solving instances with thousands of agents in real-time
 - Examples
 - [Brightpick](#) - real world execution
 - [Not perfect](#) - failure case: collision/livelock

MAPF Formulation

- MAPF instance

- Graph $G = (V, E)$
- Agents $A = \{1, \dots, n\}$
- Starts $S_{\text{start}} = (s_1, \dots, s_n)$
- Goals $S_{\text{goal}} = (g_1, \dots, g_n)$
- $s_i \neq s_j$ and $g_i \neq g_j$ for all $i \neq j$; $s_i, g_i \in V$

- Configuration

- A tuple of locations for all agents at a given timestep.

- Given MAPF instance

- Location of an agent i at discrete time t : $\pi_i[t] \in V$
- Path: Sequence of locations of an agent

- Valid moves

- At each discrete timestep t , an agent moves to an adjacent vertex or stays
 $\pi_i[t+1] \in \text{neigh}(\pi_i[t]) \cup \{\pi_i[t]\}$

- Collisions to avoid (for all $i \neq j$)

- Vertex conflict: $\pi_i[t] = \pi_j[t]$

- Swap conflict: $\pi_i[t] = \pi_j[t+1] \wedge \pi_i[t+1] = \pi_j[t]$

- Objective

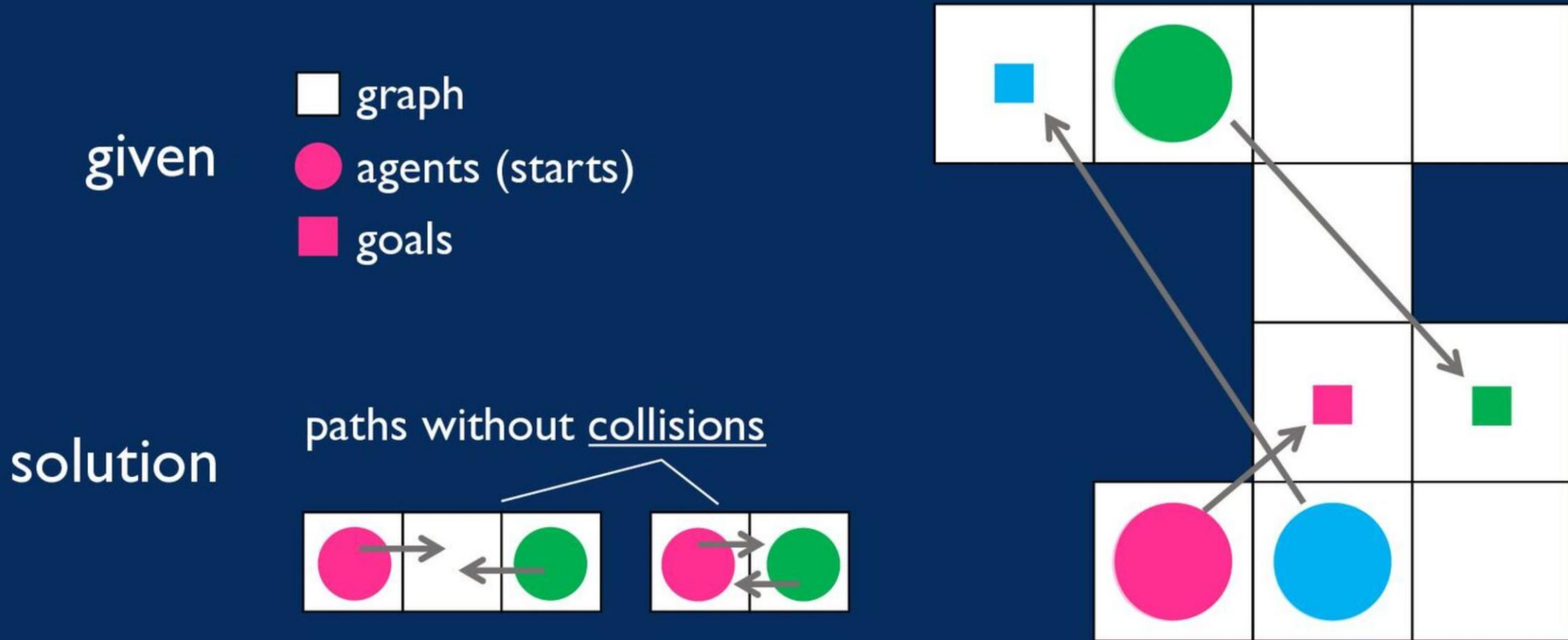
- T_i is the earliest timestep when agent i reaches its goal g_i and stays there

$$\pi_i[T_i] = \pi_i[T_i+1] = \dots = g_i$$

- Find a collision-free solution minimizing the Sum-of-Costs (SOC):

$$\sum_{i \in A} T_i$$

MAPF: Multi-Agent Path Finding



optimization is intractable in various criteria

[Yu+ AAI-13, Ma+ AAI-16, Banfi+ RA-L-17, Geft+ AAMAS-22]

The Complexity Bottleneck

- State Space Explosion
 - The total number of possible configurations is $O(|V|^{|A|})$.
- Massive Branching Factor
 - A standard search algorithm (e.g., A^*) generates $O(\Delta^{|A|})$ configurations from a single node, where Δ is the maximum degree of the graph.
- Intractability
 - Solving MAPF optimally is NP-hard in various criteria (Yu and LaValle 2013)
- Finding optimal paths for hundreds of agents in real-time is computationally intractable. We have no choice but to rely on sub-optimal algorithms for large instances.

complete
optimal

quick
scalable

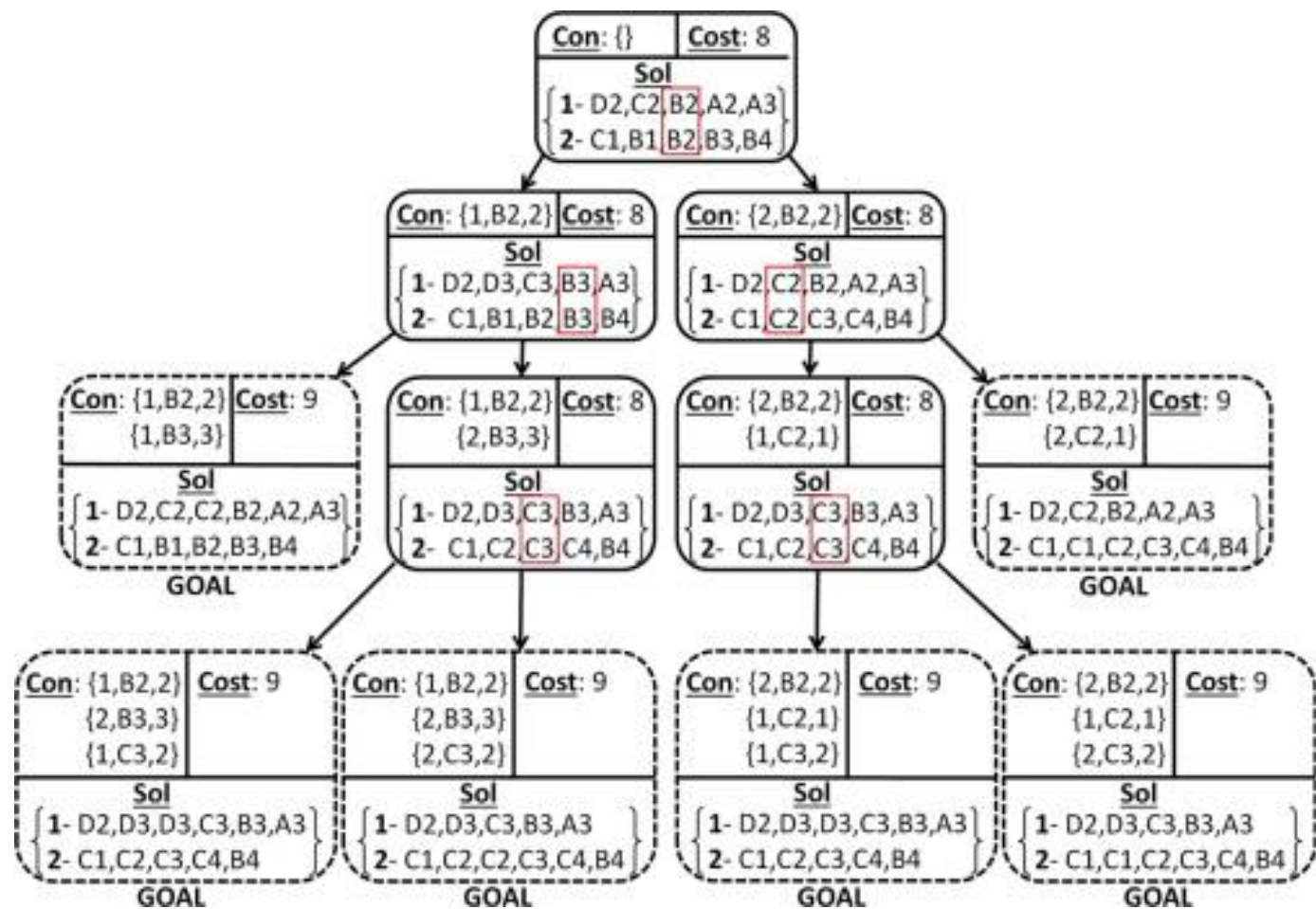
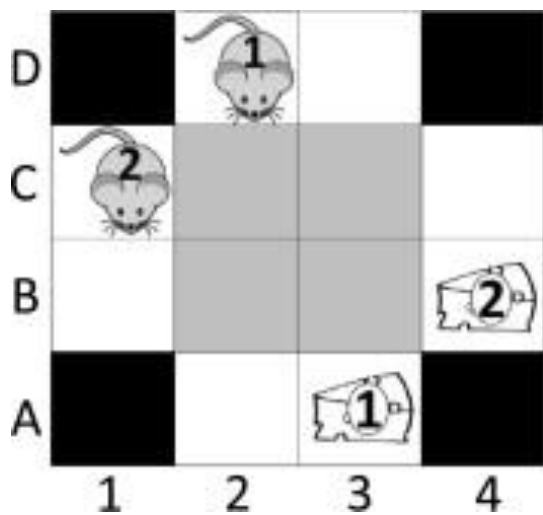


Trade-off in MAPF Algorithms

Search-Based Solvers: Conflict-Based Search (CBS)

- Two-level search architecture
- Low-level search
 - Single-agent pathfinding
 - Finds paths consistent with a given set of constraints.
- High-level search
 - Builds a Conflict Tree (CT) to resolve collisions
 - Core mechanism: Uses *negative constraints*
 - > Agent i cannot be at vertex v at time t : (a_i, v, t)
- Properties: Complete and optimal, but the constraint tree branches exponentially in dense scenarios

- Optimal Path Routes**
- 1: D2>D3>C3>B3>A3
 - D2>C2>C3>B3>A3
 - D2>C2>B2>B3>A3
 - D2>C2>B2>A2>A3
 - 2: C1>B1>B2>B3>B4
 - C1>C2>B2>B3>B4
 - C1>C2>C3>B3>B4
 - C1>C2>C3>C4>B4



CBS vs. A* Performance Factors

- Narrow Corridors / Bottlenecks
 - CBS wins - few conflicts, constraints are powerful
- Open Grids / High Density
 - A* can win – high conflict count leads to CT explosion
- CMS - $O(\textit{branching_factor}^{\textit{number of conflicts}})$
- A* - $O(\textit{branching_factor}^{\textit{number of agents}})$

Algorithm 1: high-level of CBS

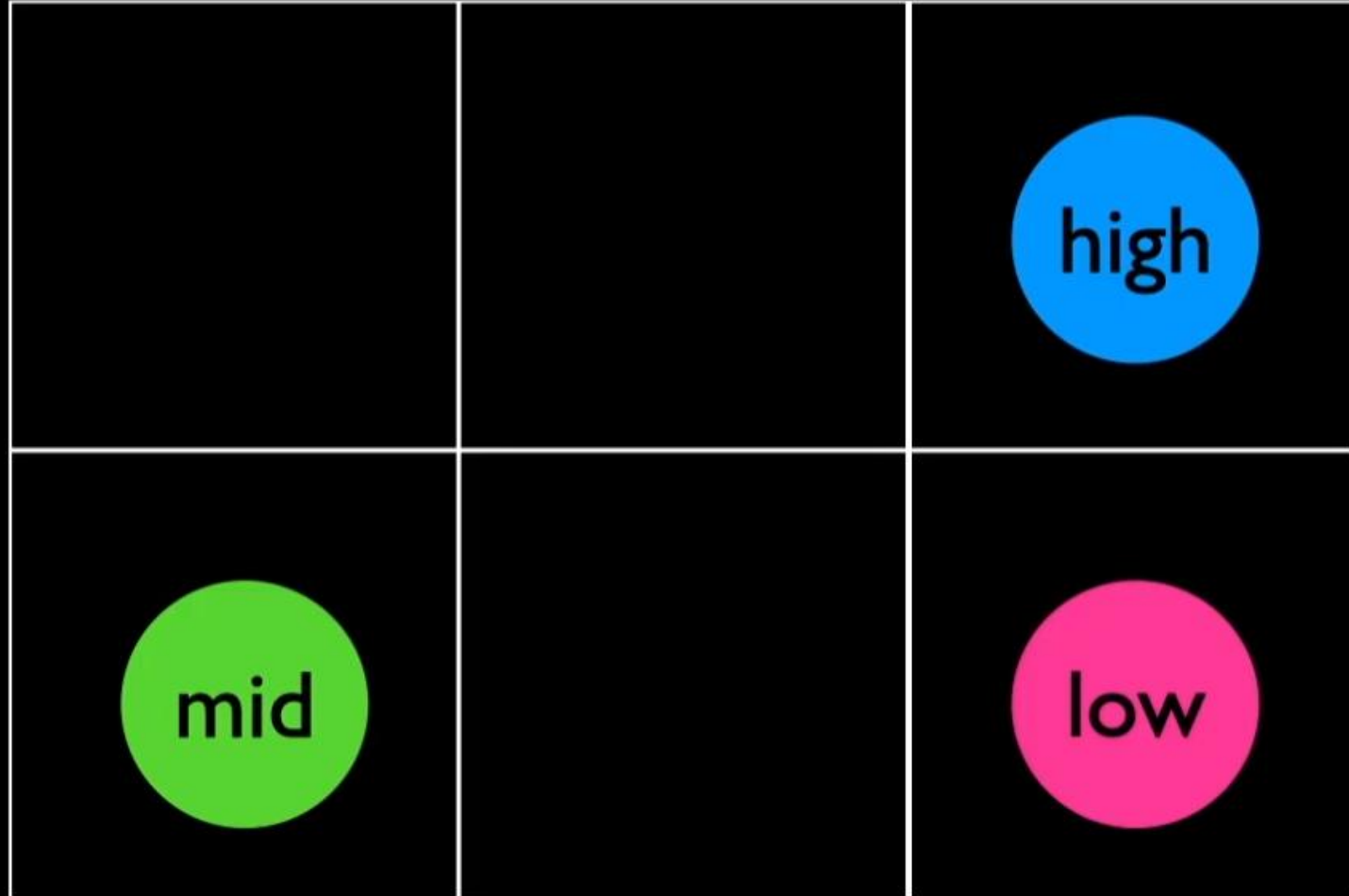
Input: MAPF instance

- 1 $R.constraints = \emptyset$
 - 2 $R.solution =$ find individual paths using the low-level()
 - 3 $R.cost = SIC(R.solution)$
 - 4 insert R to OPEN
 - 5 **while** OPEN *not empty* **do**
 - 6 P \leftarrow best node from OPEN // *lowest solution cost*
 - 7 Validate the paths in P until a conflict occurs.
 - 8 **if** P *has no conflict* **then**
 - 9 | **return** P.solution // *P is goal*
 - 10 C \leftarrow first conflict (a_i, a_j, v, t) in P
 - 11 **foreach** agent a_i in C **do**
 - 12 | A \leftarrow new node
 - 13 | A.constraints \leftarrow P.constraints + (a_i, s, t)
 - 14 | A.solution \leftarrow P.solution.
 - 15 | Update A.solution by invoking low-level(a_i)
 - 16 | $A.cost = SIC(A.solution)$
 - 17 | Insert A to OPEN
-

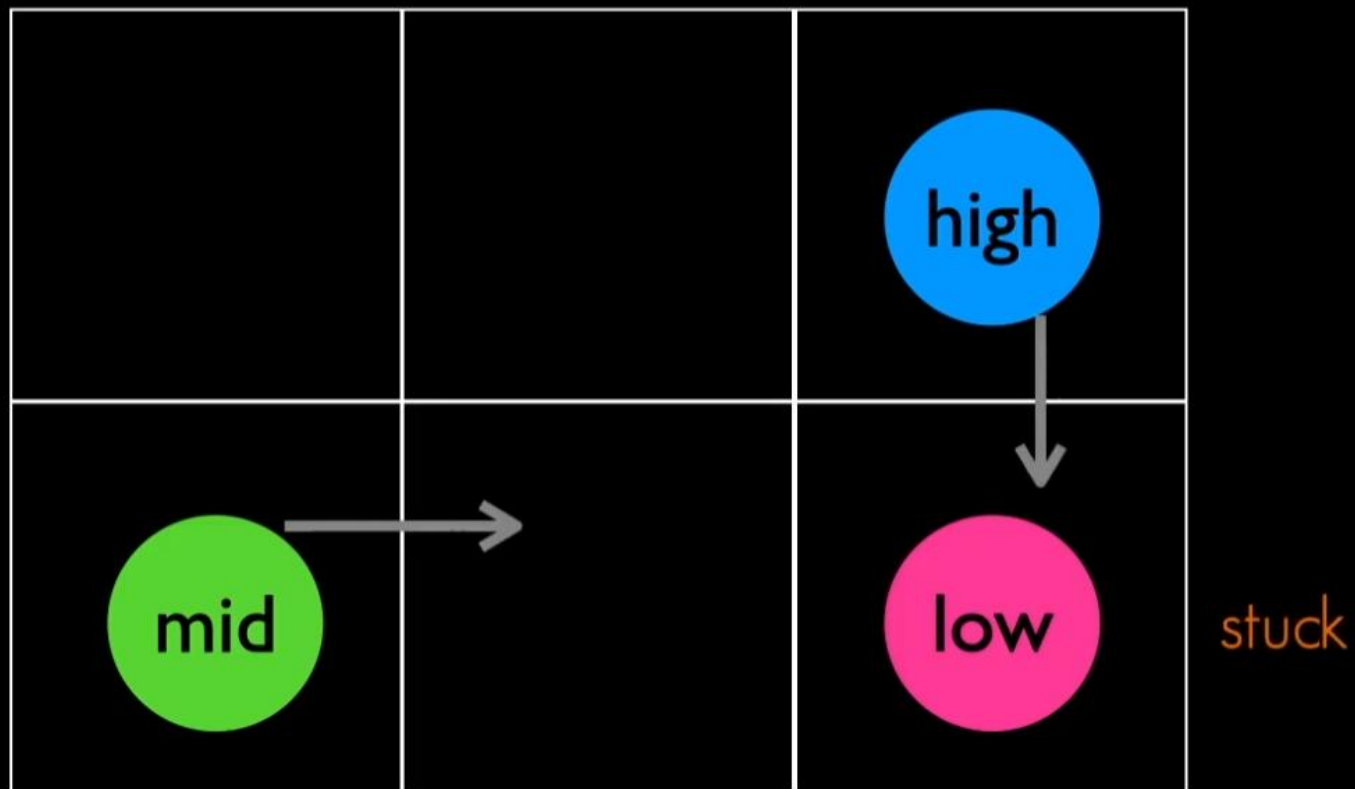
PIBT

- Priority Inheritance with Backtracking
- A rule-based, prioritized algorithm designed for massive scale
- How it works
 - Assigns a priority to each agent (often based on distance to goal)
 - In each timestep, agents pick their best move in order of priority
 - If a higher-priority agent is blocked, it "inherits" its priority to the blocking agent to push them out of the way
- Pros: Extremely fast: $O(|A| * \Delta)$, can handle 10000+ agents
- Cons: Incomplete (can get stuck in livelocks) and sub-optimal

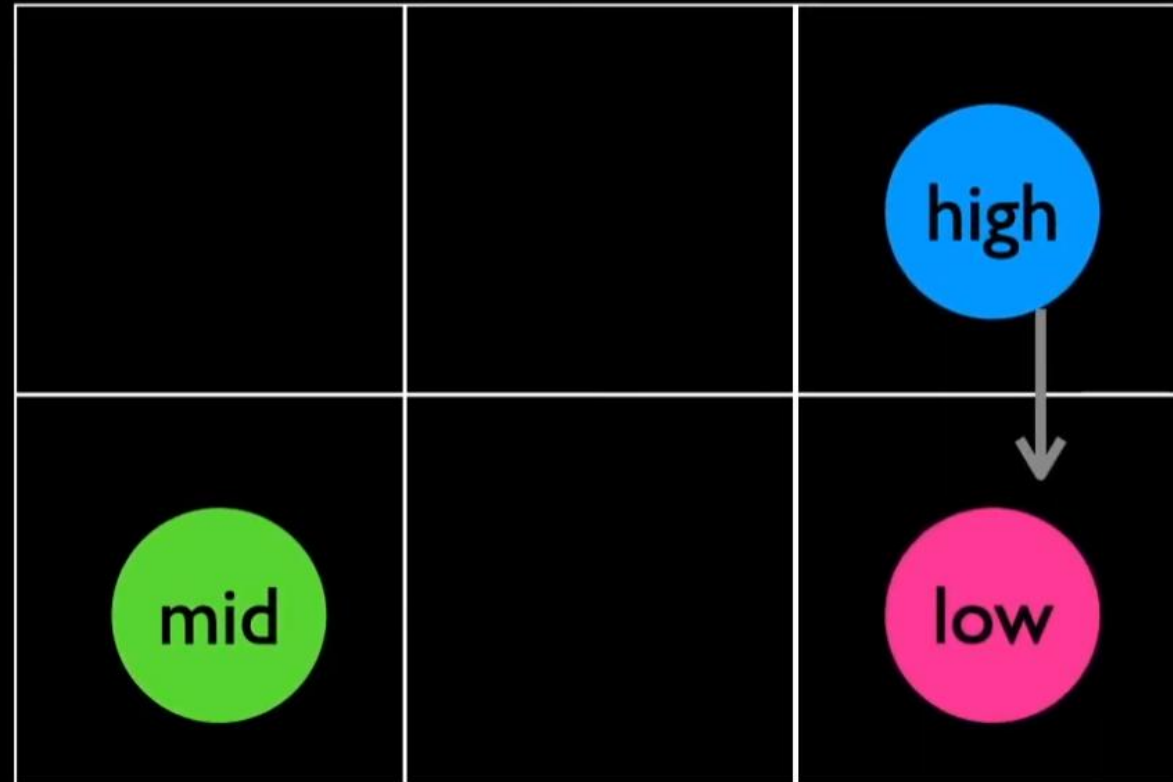
simple one-timestep prioritized planning is efficient but **incomplete**



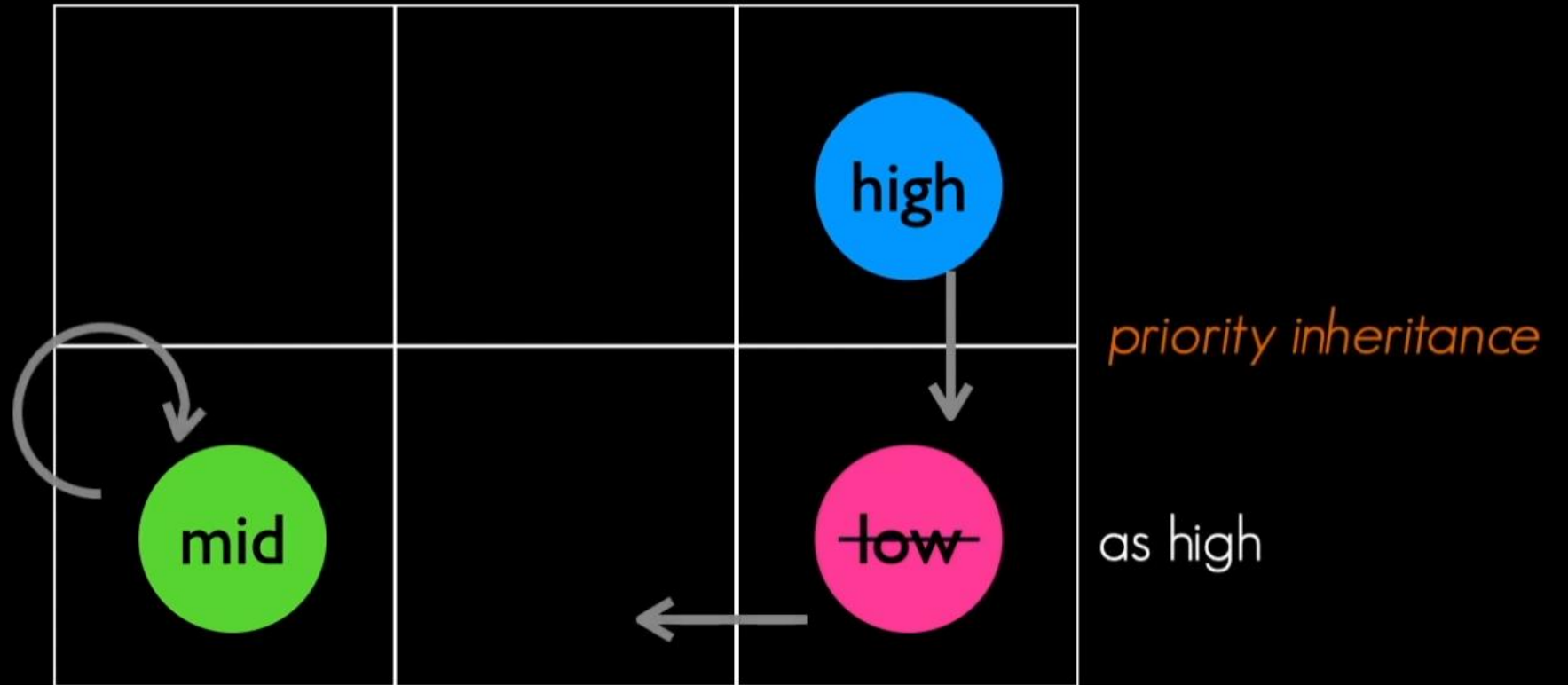
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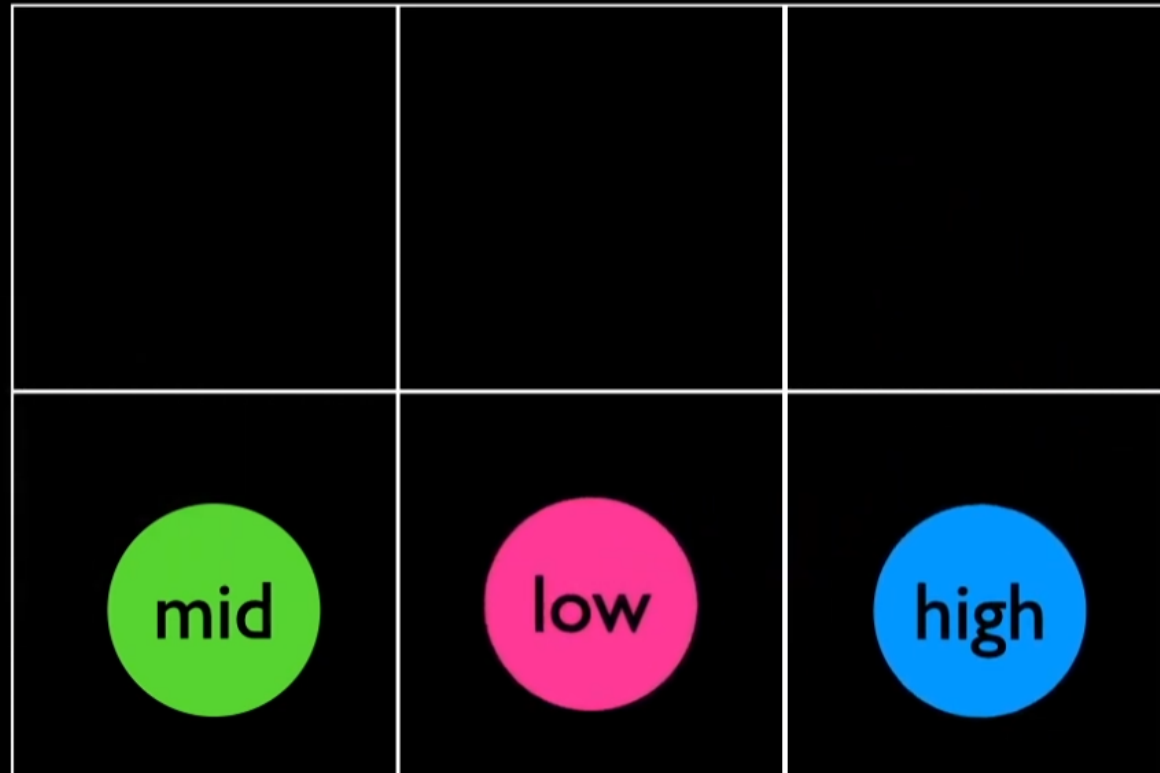
priority inheritance can deal with this situation



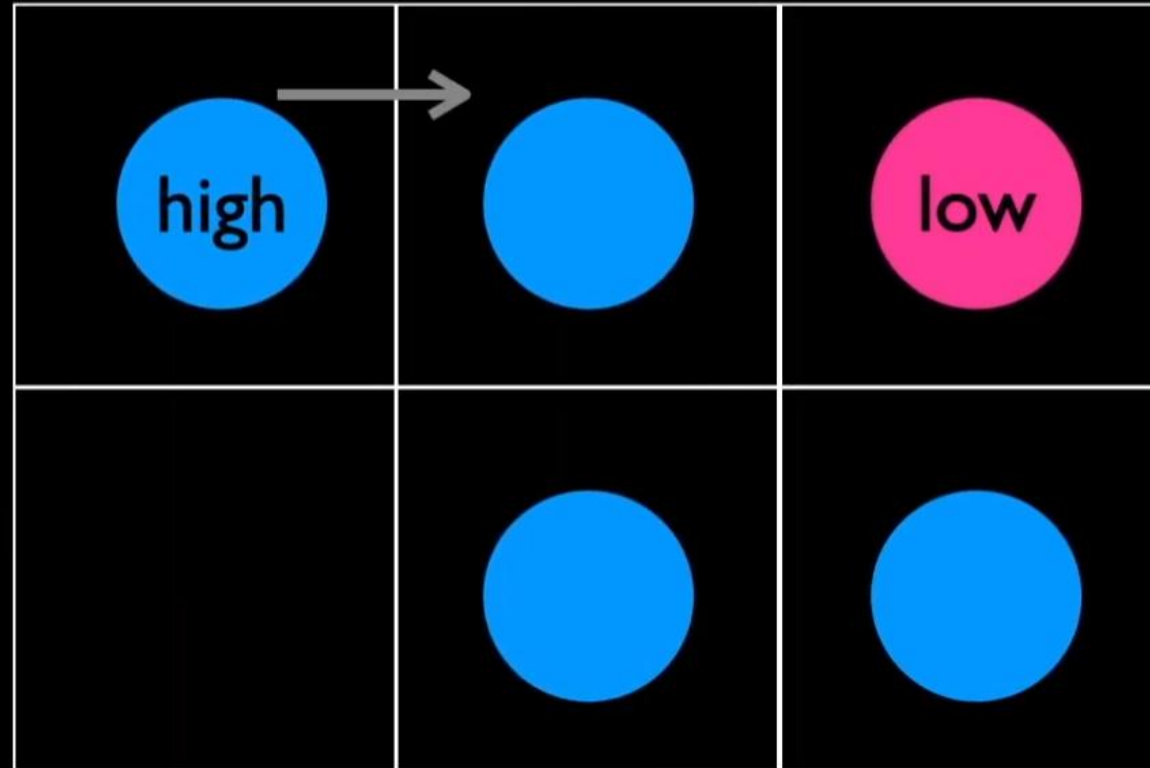
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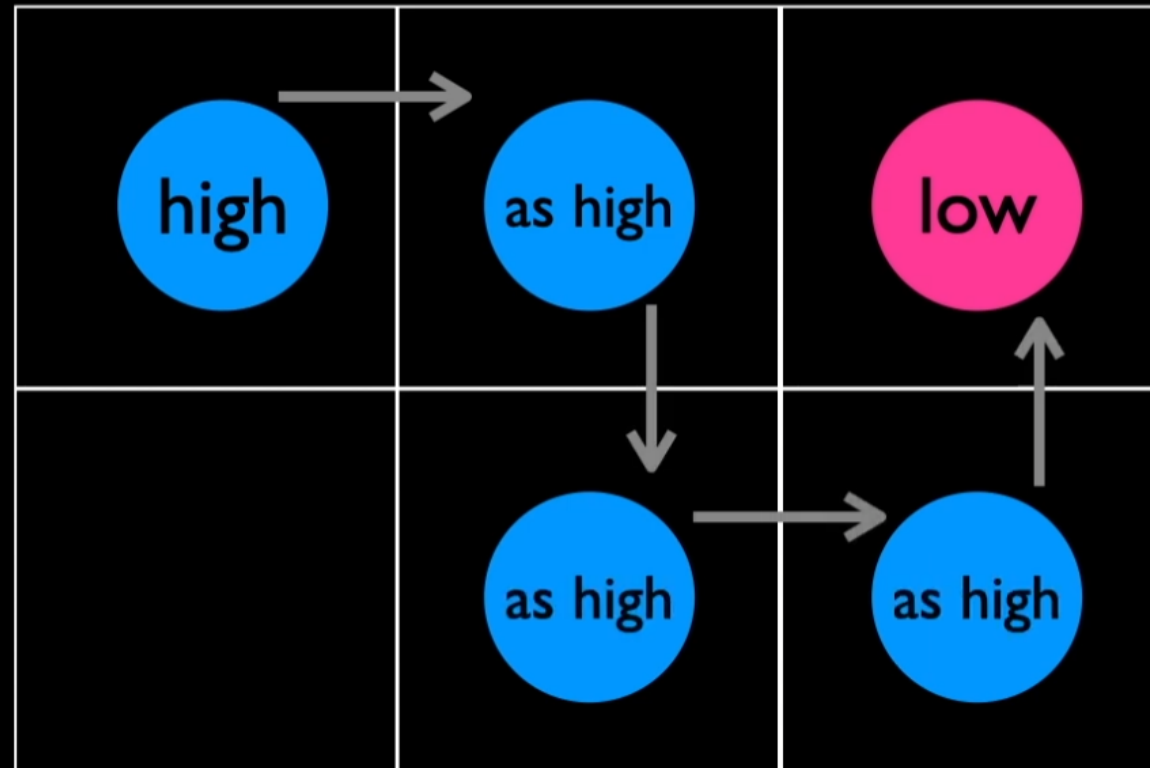
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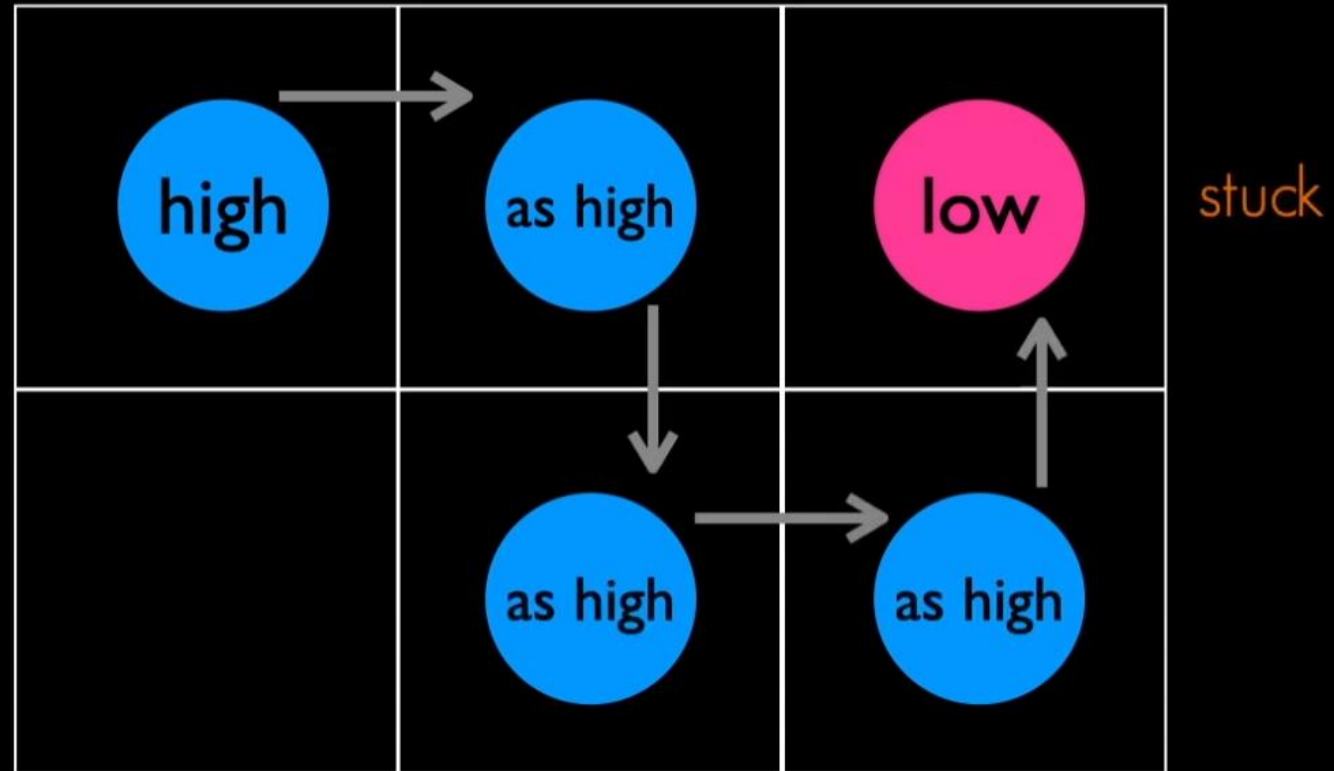
but still not deadlock-free



but still not deadlock-free



but still not deadlock-free



introduce *backtracking*



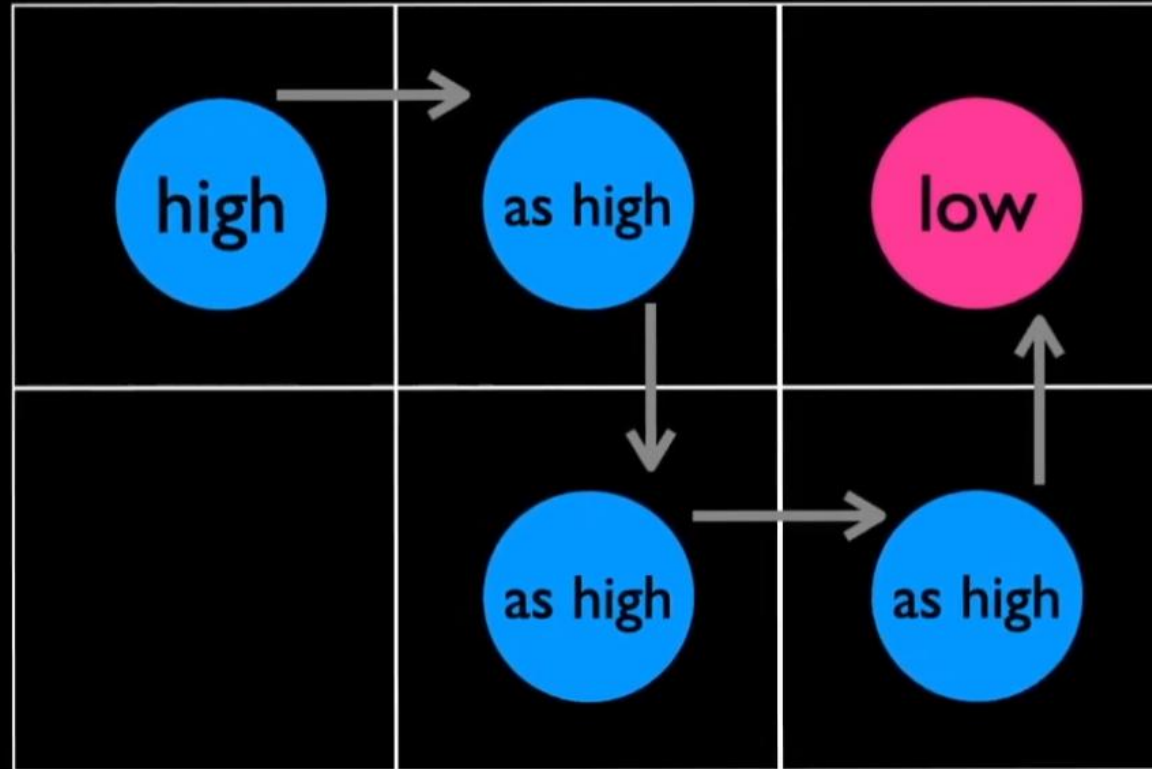
valid

"You can move"



invalid

"You must re-plan, I will stay"



introduce *backtracking*



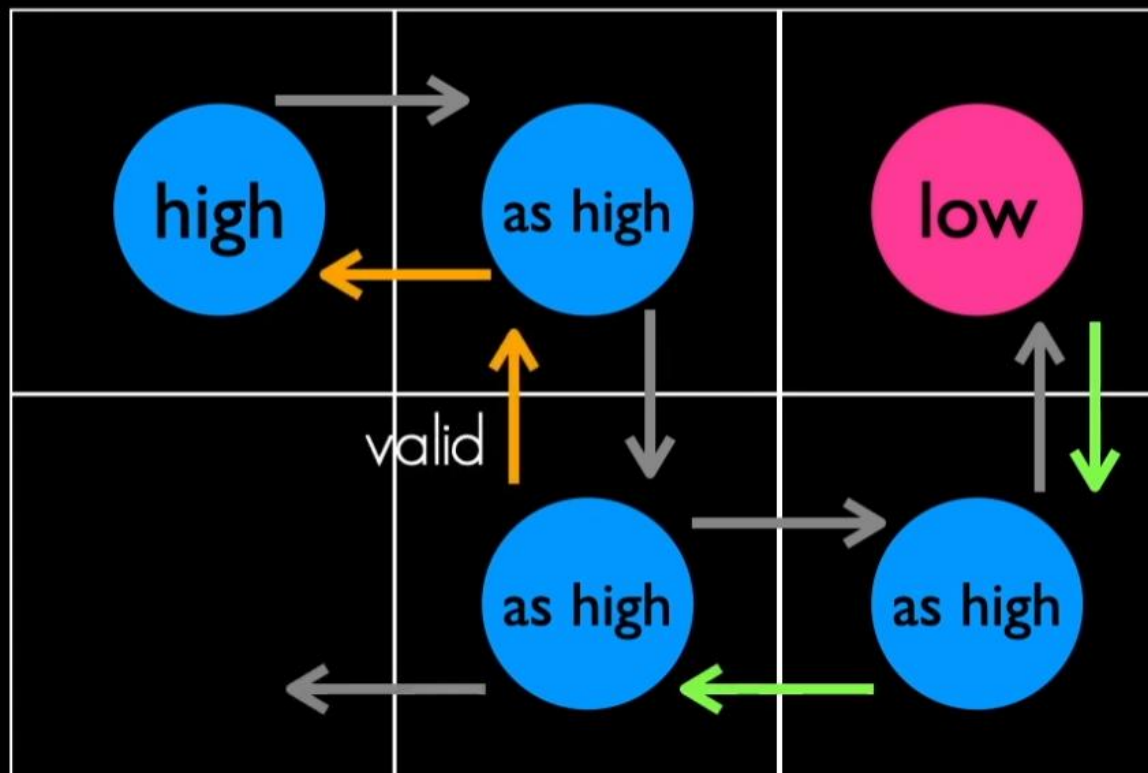
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invalid

re-plan

re-plan

introduce *backtracking*



valid "You can move"



invalid "You must re-plan, I will stay"

high	as high	low
	as high	as high

introduce *backtracking*



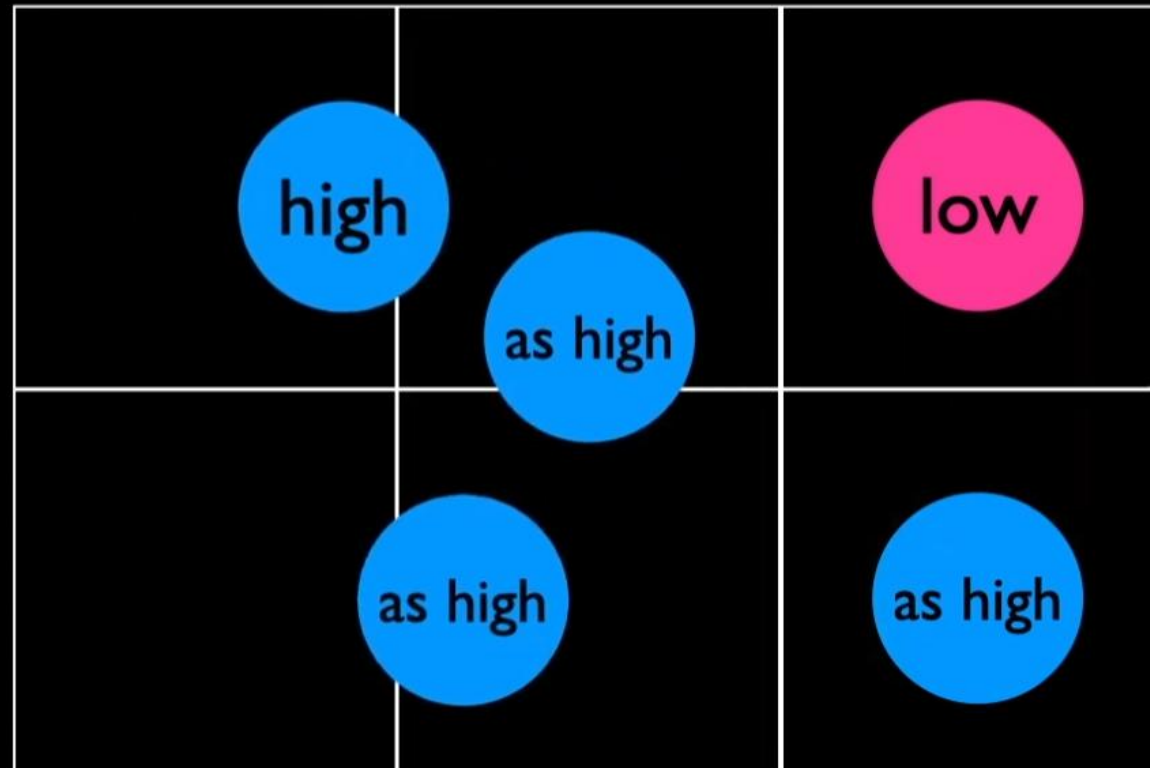
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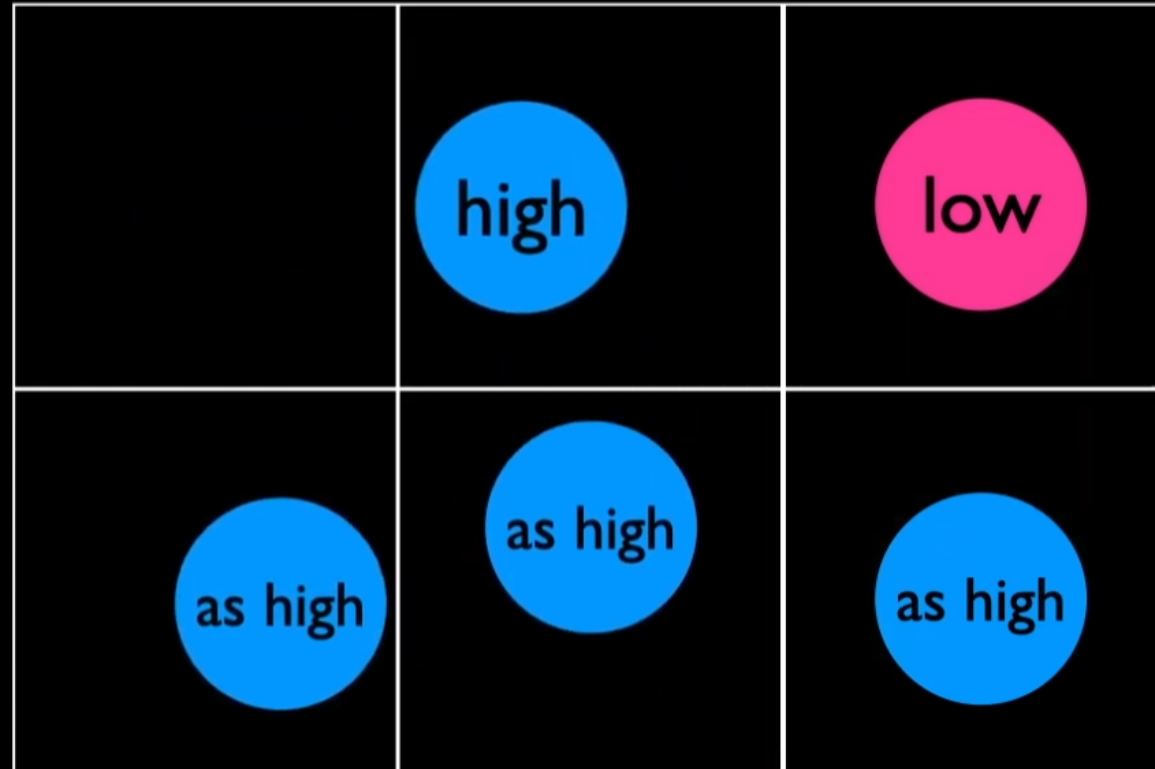
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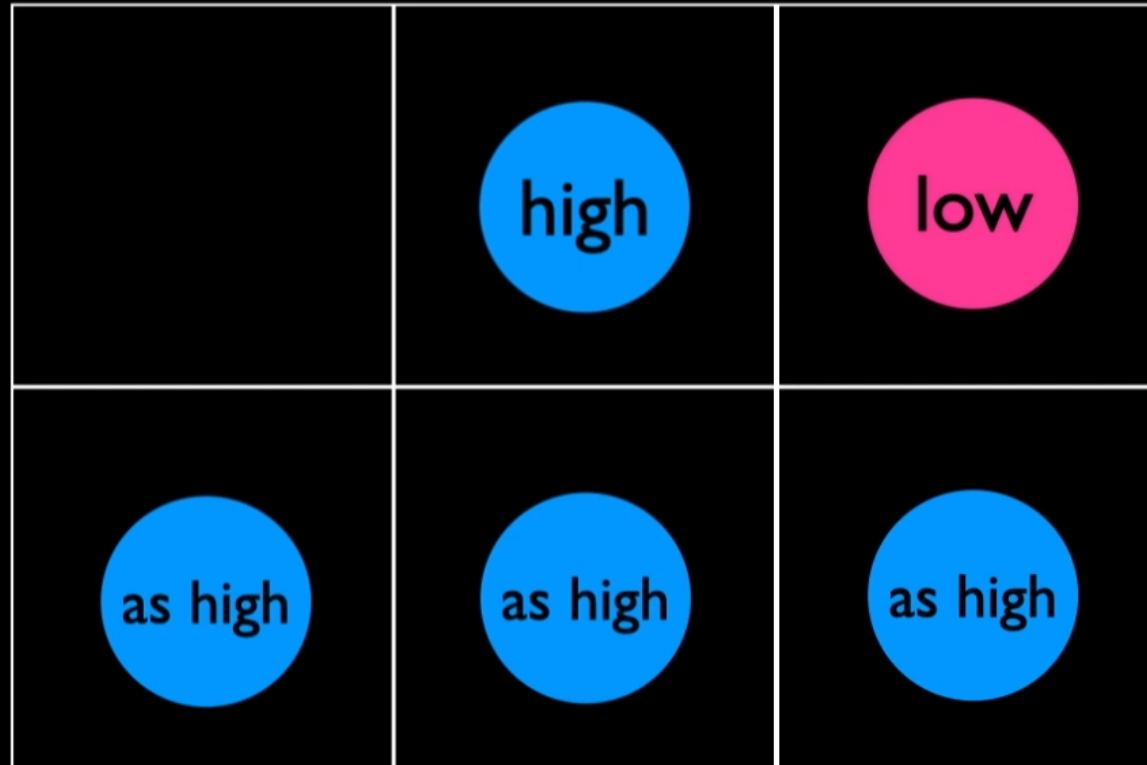
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Thank you!