Exploring the Use of LLMs for Agent Planning

Strengths and Weaknesses

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Context

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Large Language Models’ Capabilities

Text Generation

Their Scope

Large Language Models' Capabilities

Text Generation

Their Scope

Math Reasoning

Emerging Behavior

Large Language Models' Capabilities

Text Generation

Their Scope

Math Reasoning

Emerging Behavior

Planning Abilities

Emerging Behavior

Large Language Models' Capabilities

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Emerging Behavior

Planning Abilities

Emerging Behavior

More

LLM-based Planning

LLM-based Planning

Chain of Thought

Reasoning[1]

[1] *Chain-of-thought prompting elicits reasoning in large language models* - Wei et al., 2022

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LLM-based Planning

Chain of Thought

Reasoning[1]

Few-Shots

Prompting[2]

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[2] *PDDL planning with pretrained large language models* - Silver et al., 2022

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LLM-based Planning

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Fine-Tuning

Models[3]

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LLM-based Planning

Chain of Thought

Reasoning[1]

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Fine-Tuning

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More[4]

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[3] *Unlocking Large Language Model's Planning Capabilities with Maximum Diversity Fine-tuning* - Wenjun Li et al., 2024

[4] *Efficient Sequential Decision Making with Large Language Models* - Dingyang Chen et al., 2024

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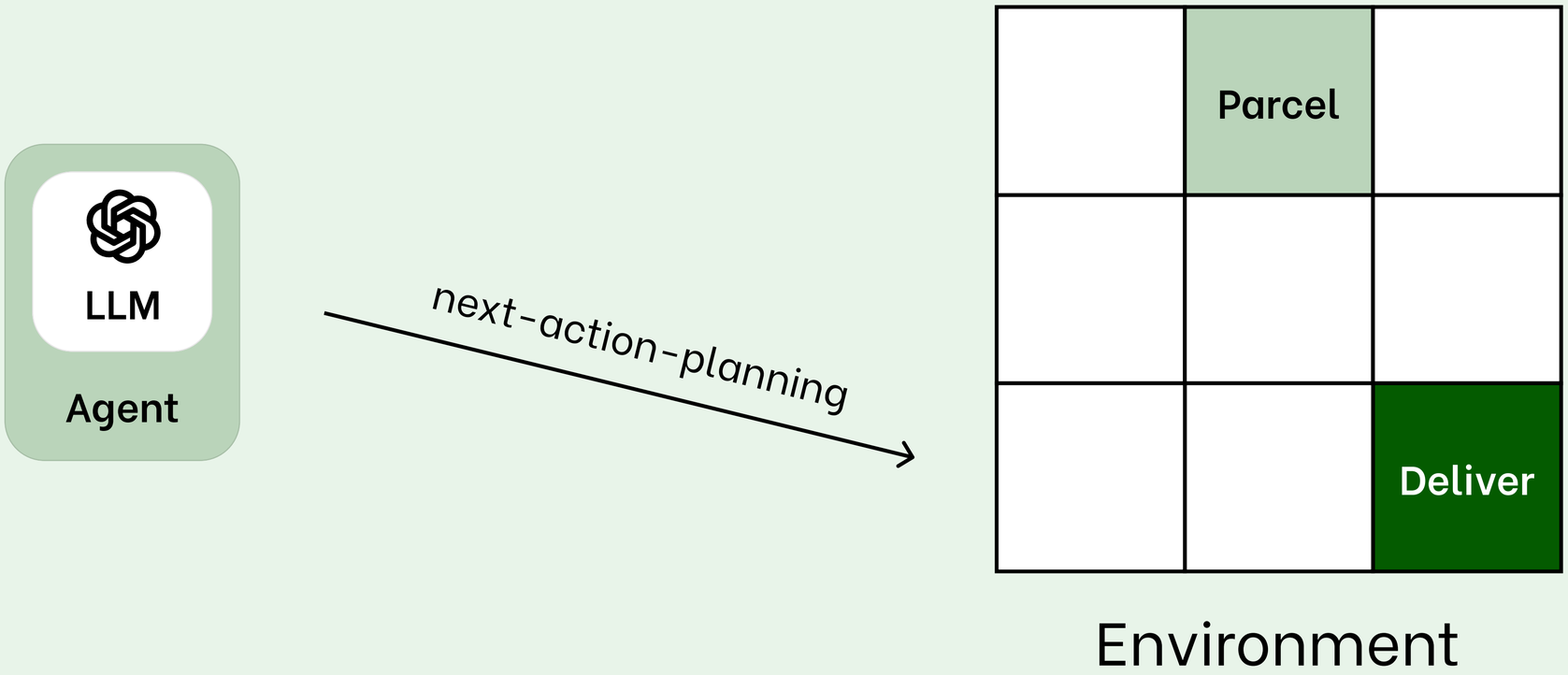
Research Questions

What happens if we strip everything prior away?

Can an LLM, without additional training or frameworks, effectively plan and navigate in an unknown environment?

How well can LLMs' generative capabilites make sequential decisions in such environments?

Idea

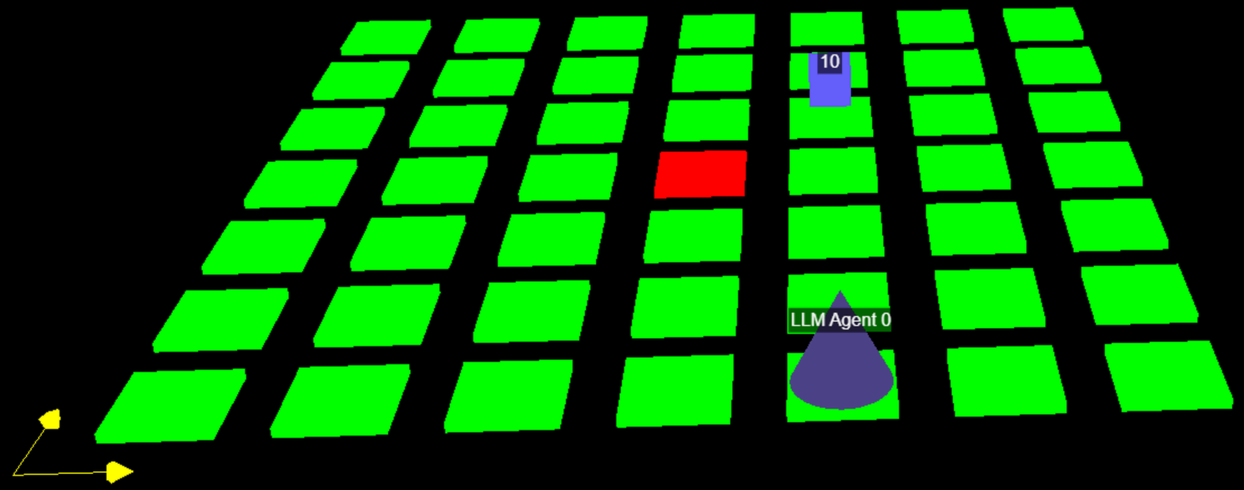

LLM
Agent
next-action-planning
Parcel
Deliver
Environment

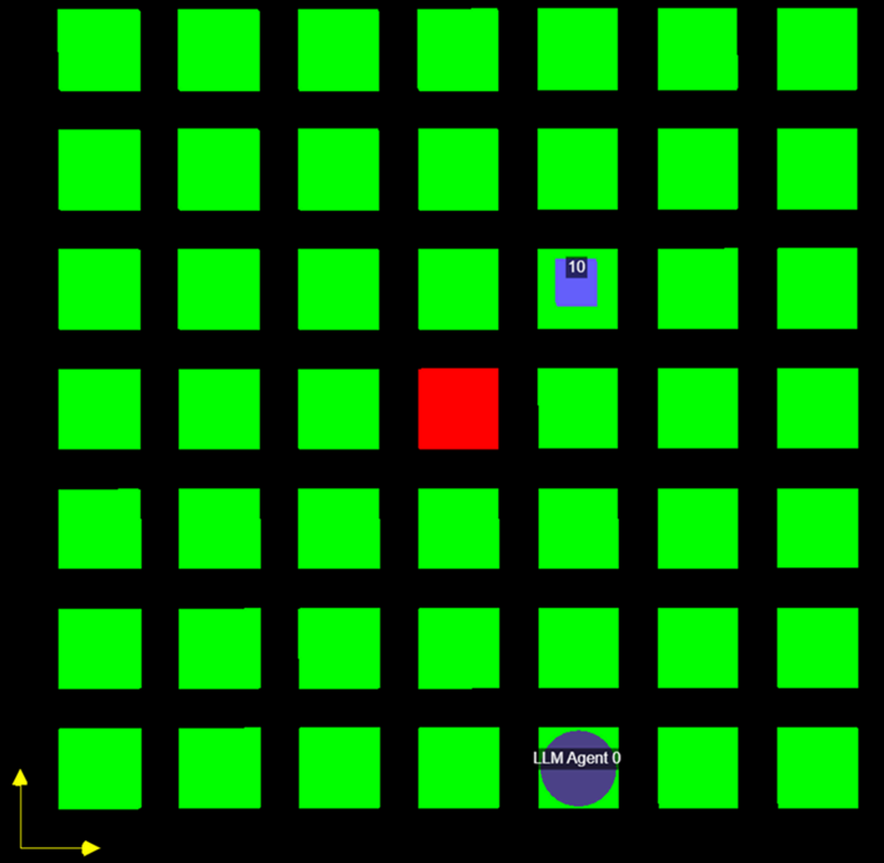
Setting

Deliveroo.js

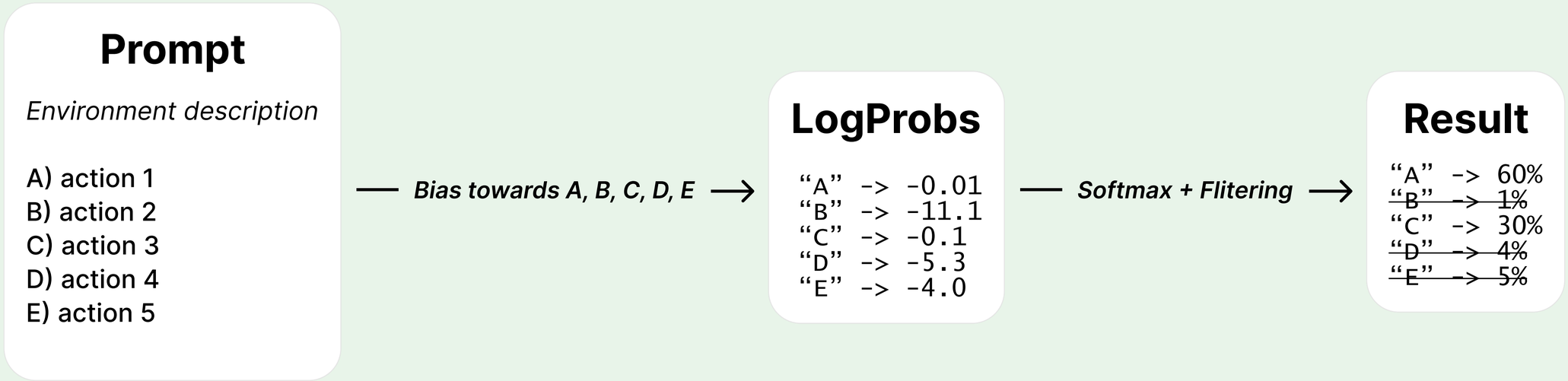
Educational Game

Parcels spawn all around the map. The goal is to pickup and deliver them.





KnowNo Uncertainty Framework[1]



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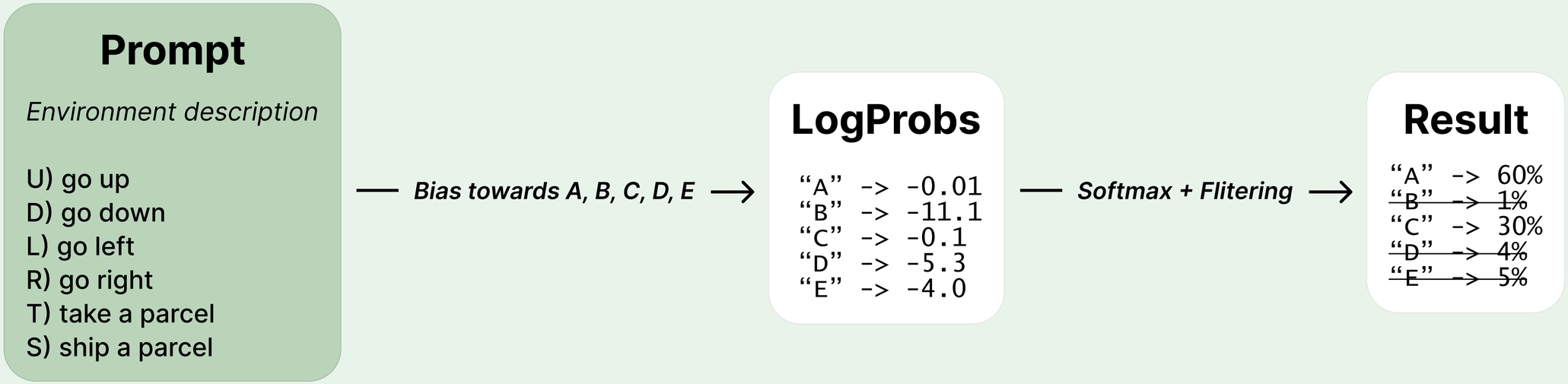

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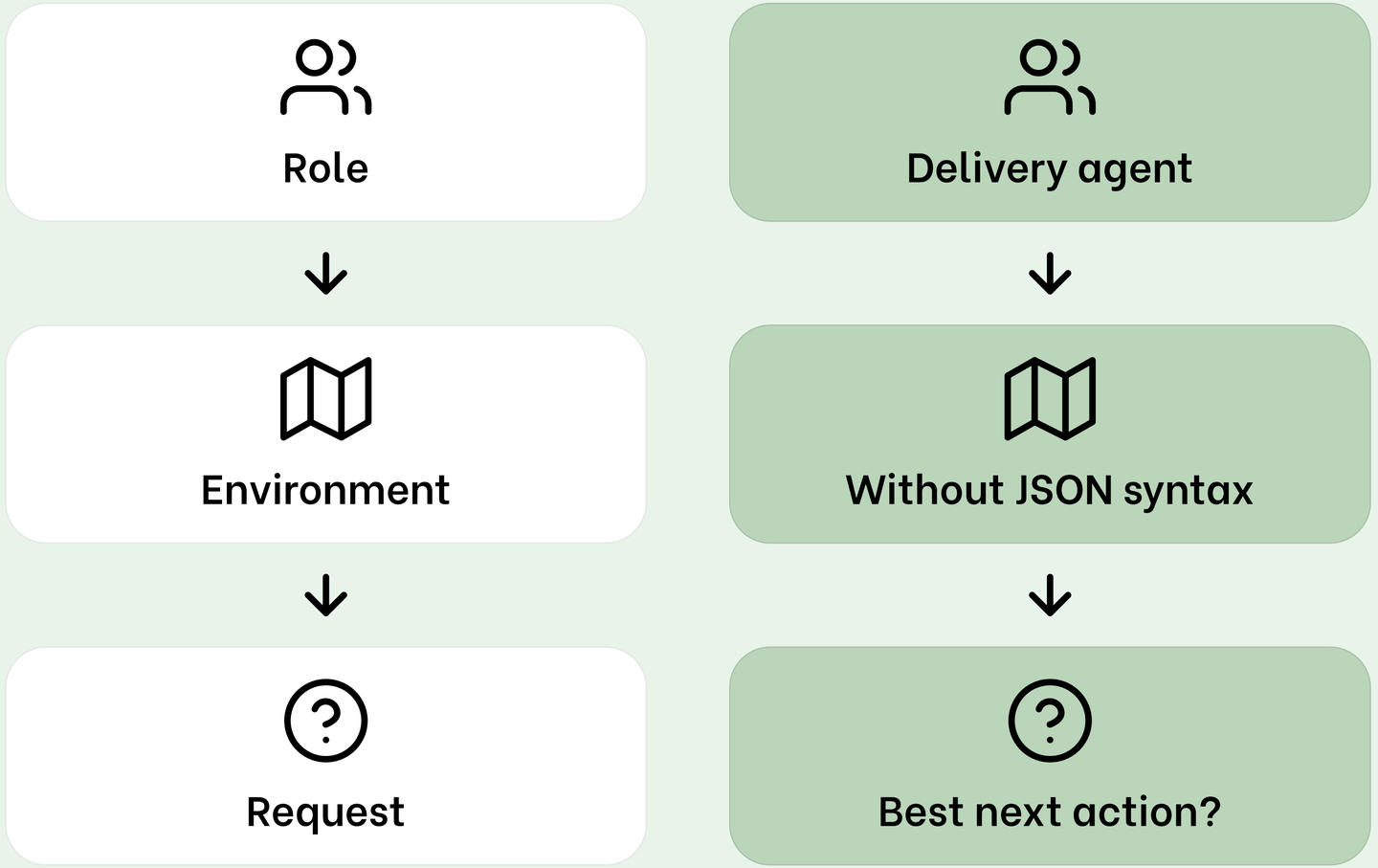
Prompting Strategy



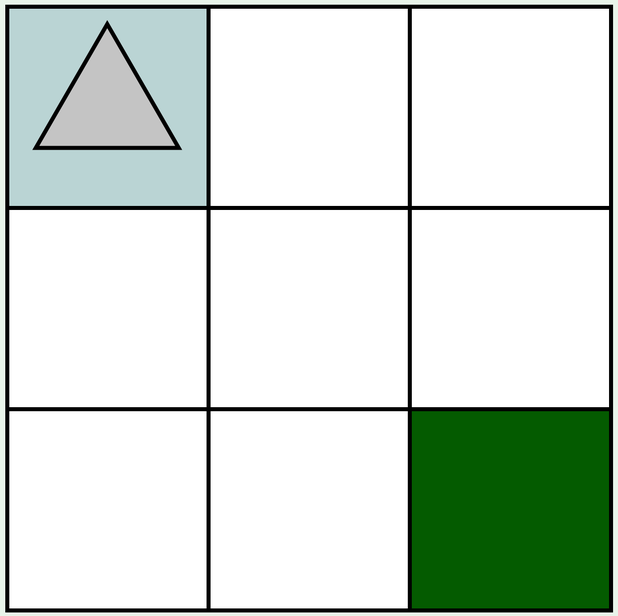
Model

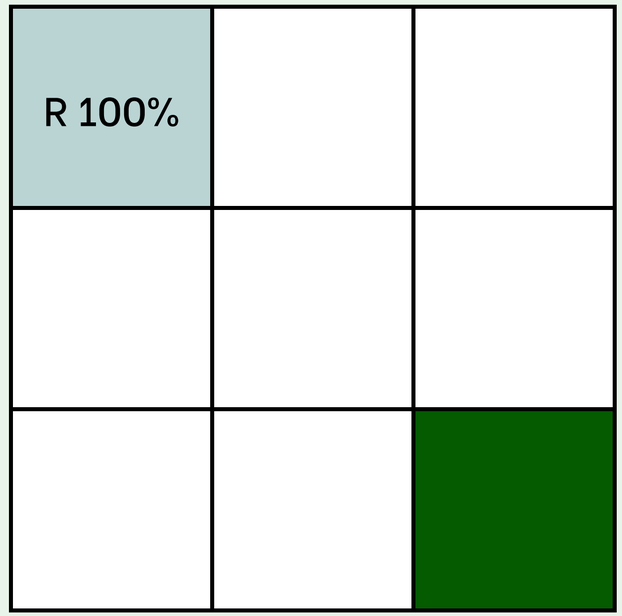
	GPT-4o	GPT-4o-mini
top1%	77%	84%
top2%	95%	91%
top3%	96%	92%

- OpenAI models
- GPT-4o was the best
- GPT-4o-mini selected for price/performance

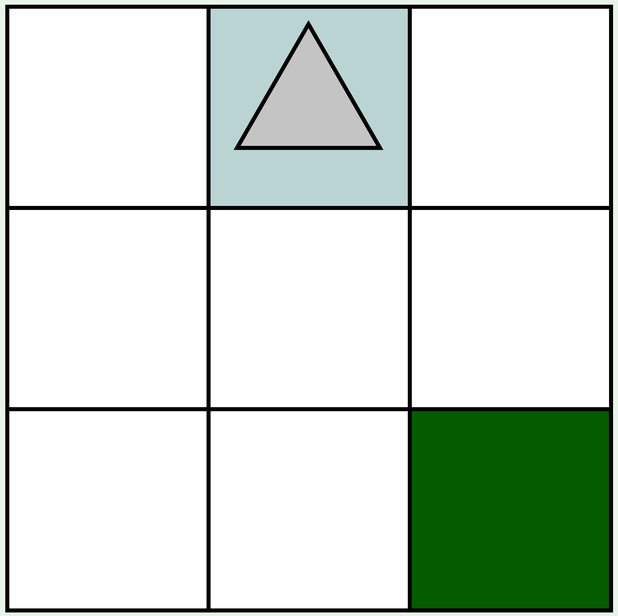
Data Collection

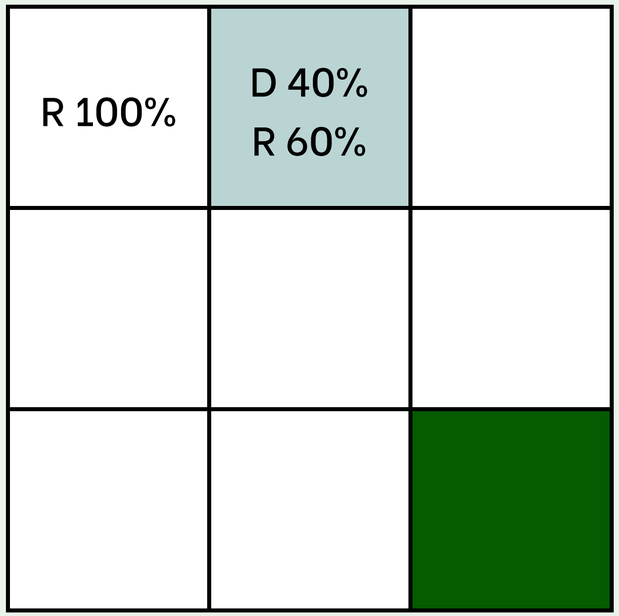
Heatmaps Creation #1





Heatmaps Creation #1





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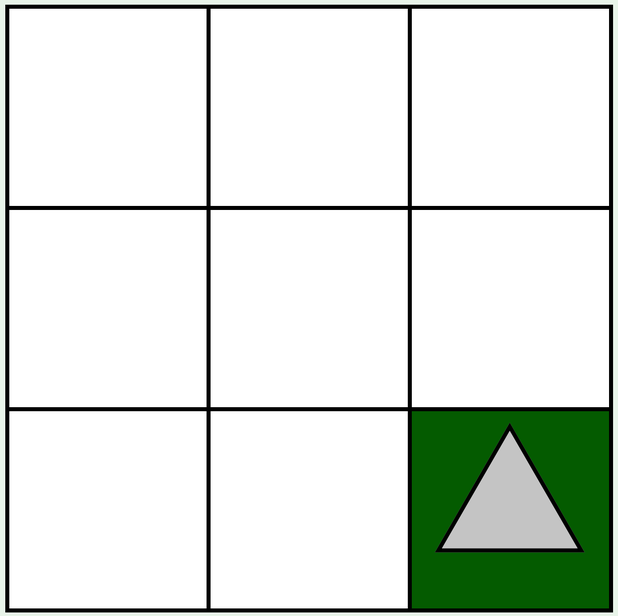
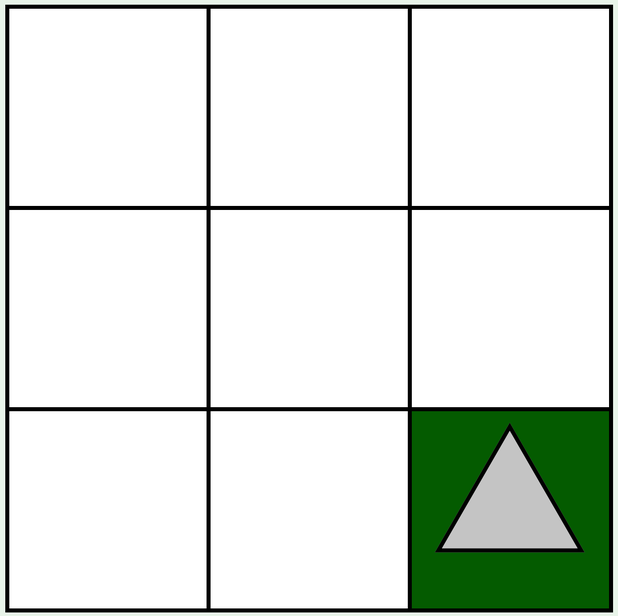
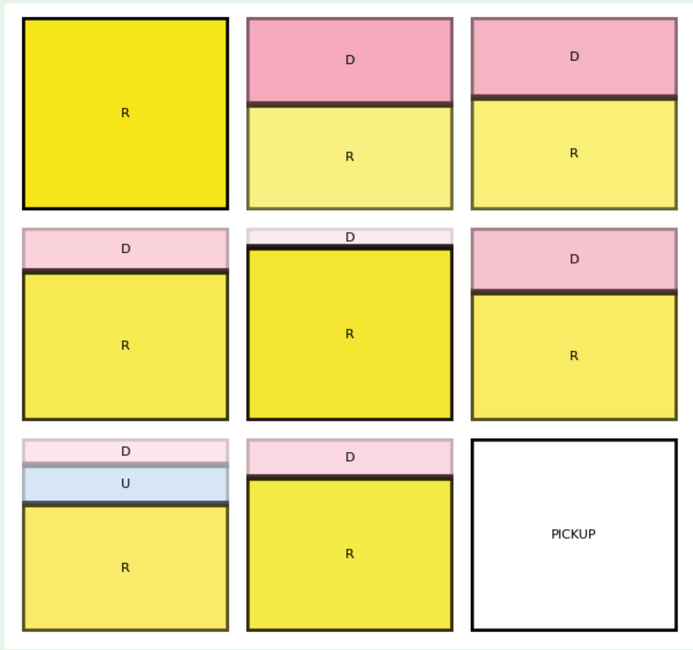


R 100%	D 40% R 60%	D 41% R 59%
D 5% R 95%	D 5% R 95%	D 33% R 67%
D 16% U 18% R 66%	D 20% R 80%	

Heatmaps Creation #1





Right Left Down Up

Heatmaps Creation #2

R 100%	D 40% R 60%	D 41% R 59%
D 5% R 95%	D 5% R 95%	D 33% R 67%
D 16% U 18% R 66%	D 20% R 80%	

100%	100%	41%
100%	100%	33%
66%	80%	

Heatmaps Creation #2

R 100%	D 40% R 60%	D 41% R 59%
D 5% R 95%	D 5% R 95%	D 33% R 67%
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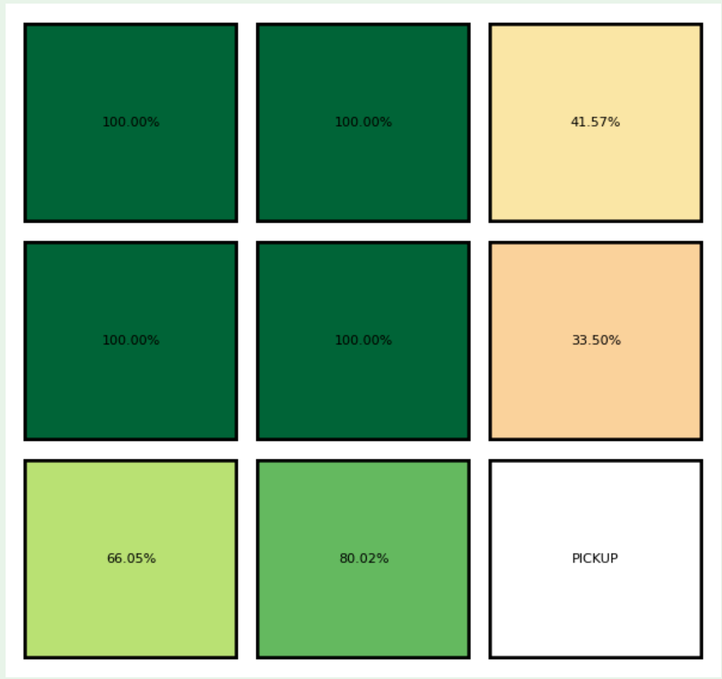


100%

0%

Testing Strategy

Goals

Pickup

Goal tile explicit

Average top1%
87%

Deliver

Goal tile identified in map description

Average top1%
81%

Testing Strategy

Agents

Stateless

Each iteration a new instance

Stateful

Retains the Conversation History

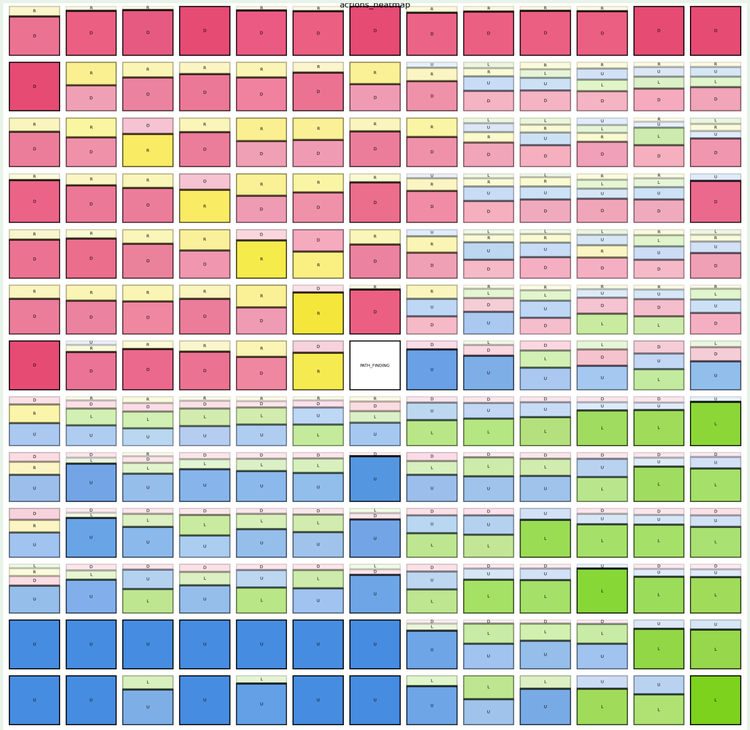
Our Findings

Map Orientation

“Since we did not provide any info about the orientation, how does the LLM perceive it?”

Map Orientation

(0,0)



(0,0)

Up

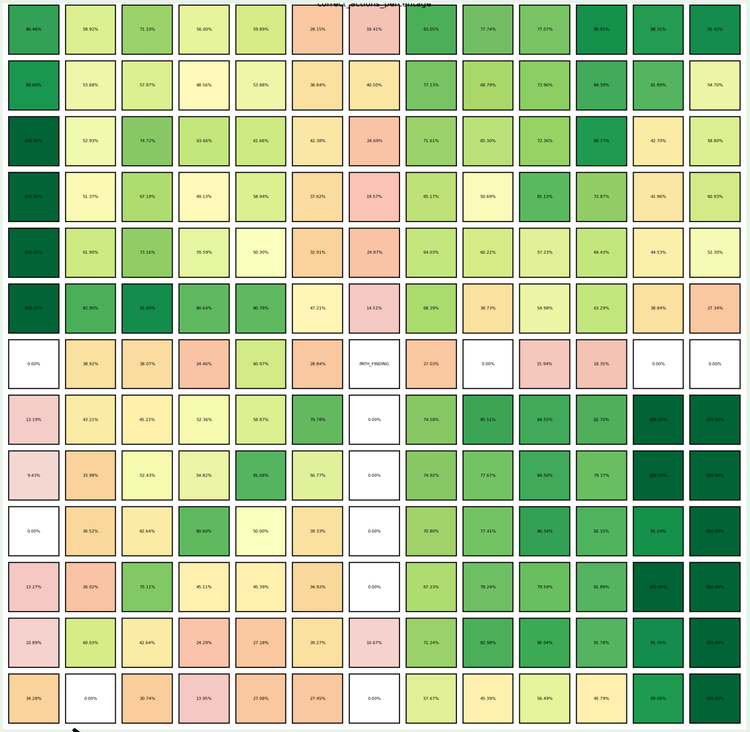
Down

Left

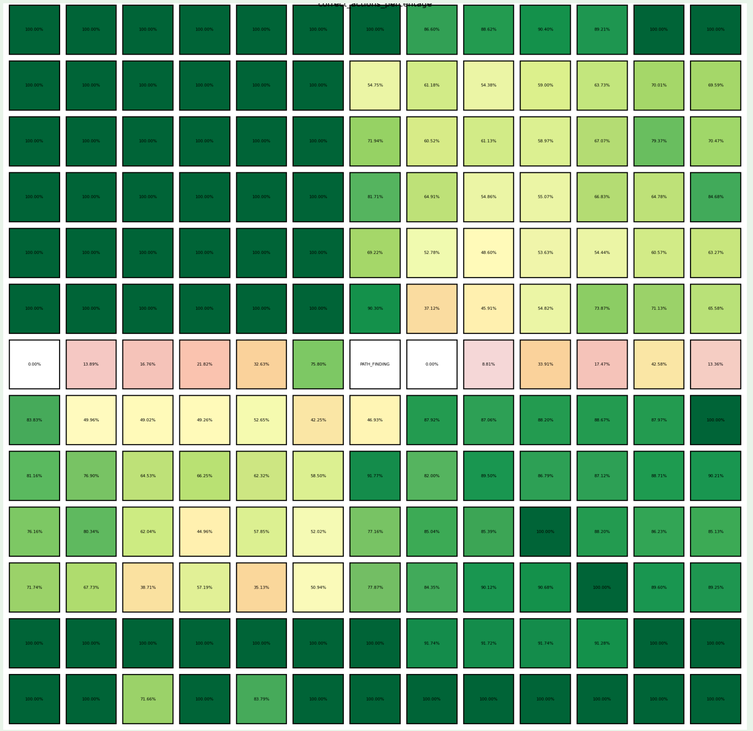
Right

Map Orientation

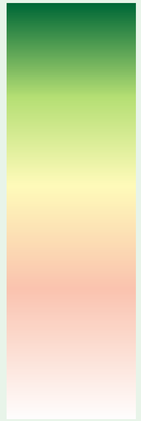
(0,0)



(0,0)



100%



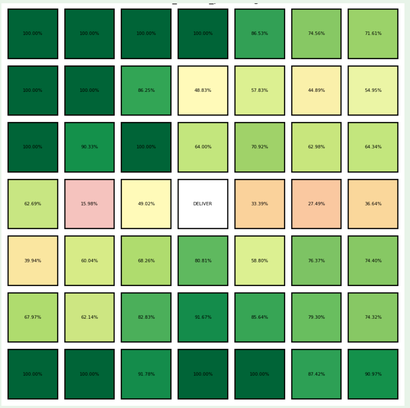
0%

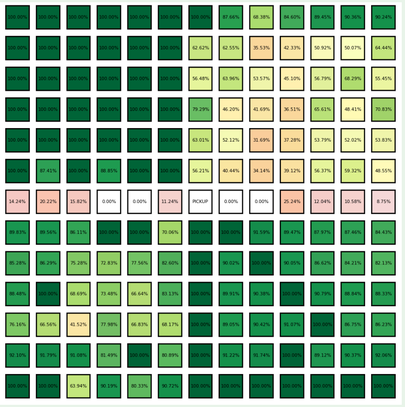
Map Orientation

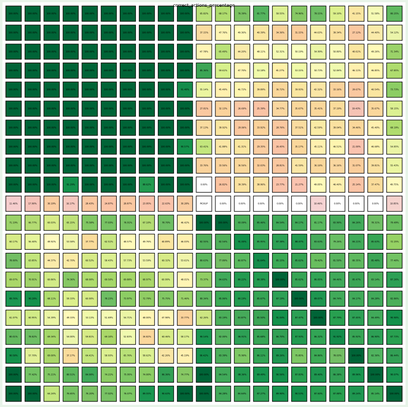
	Bottom-Left Origin	Top-Left Origin
top1%	62%	92%
top2%	92%	97%
top3%	93%	99%

Common Uncertainty Patterns

Common Uncertainty Patterns #1

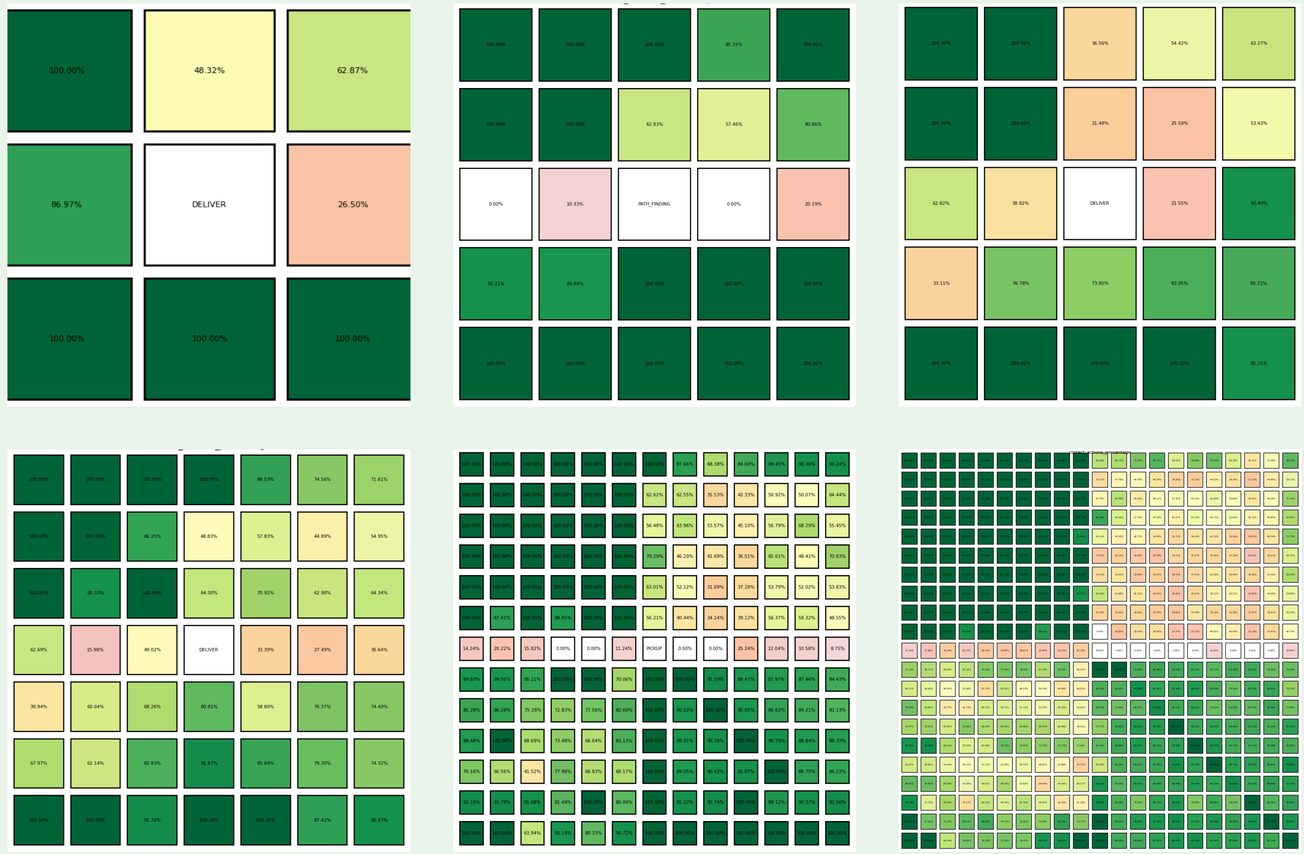




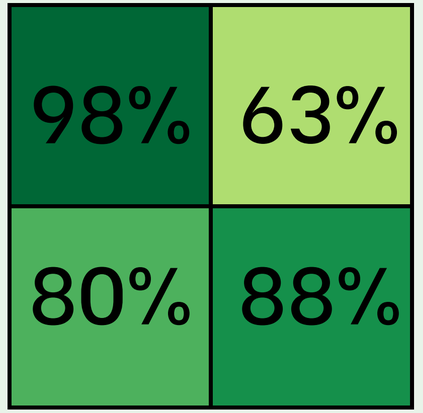


4. Findings

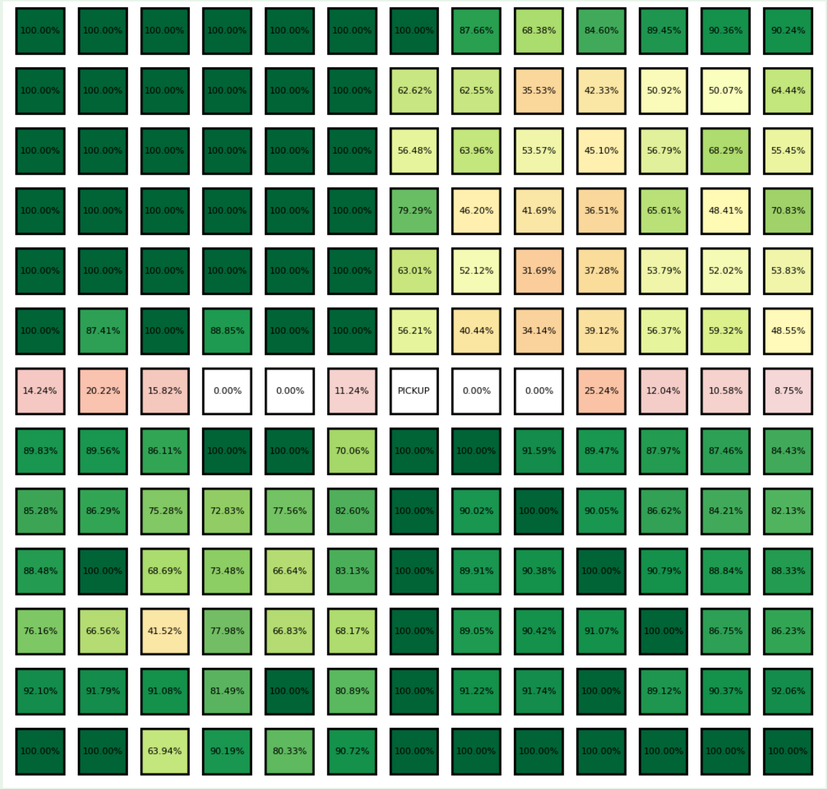
Common Uncertainty Patterns #1



Average



Common Uncertainty Patterns #1.1



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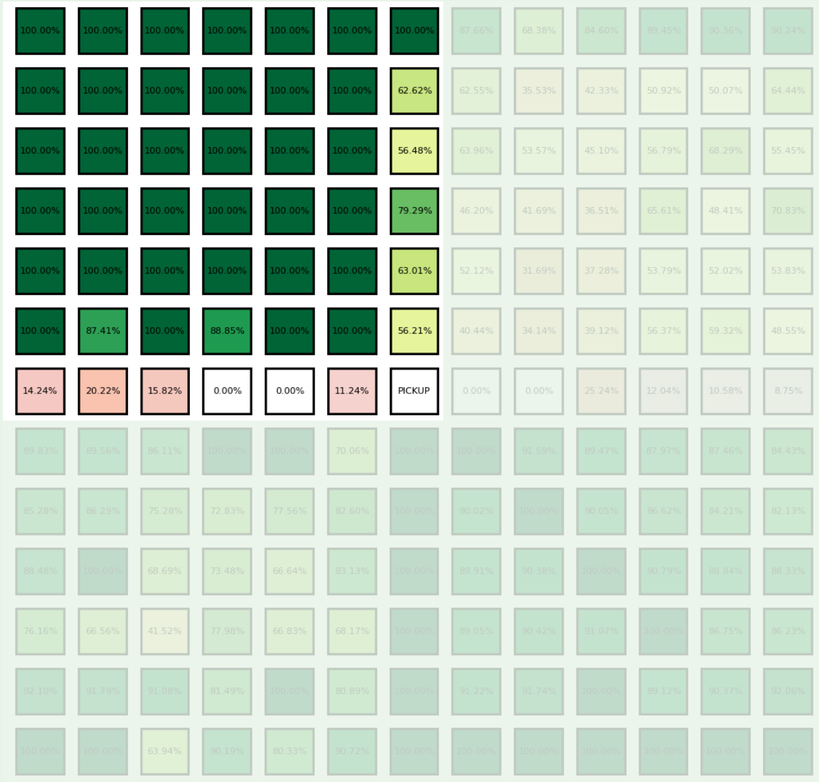

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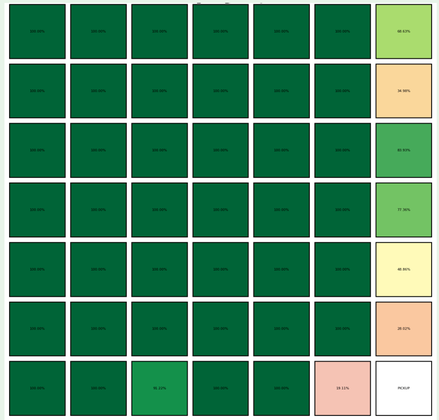
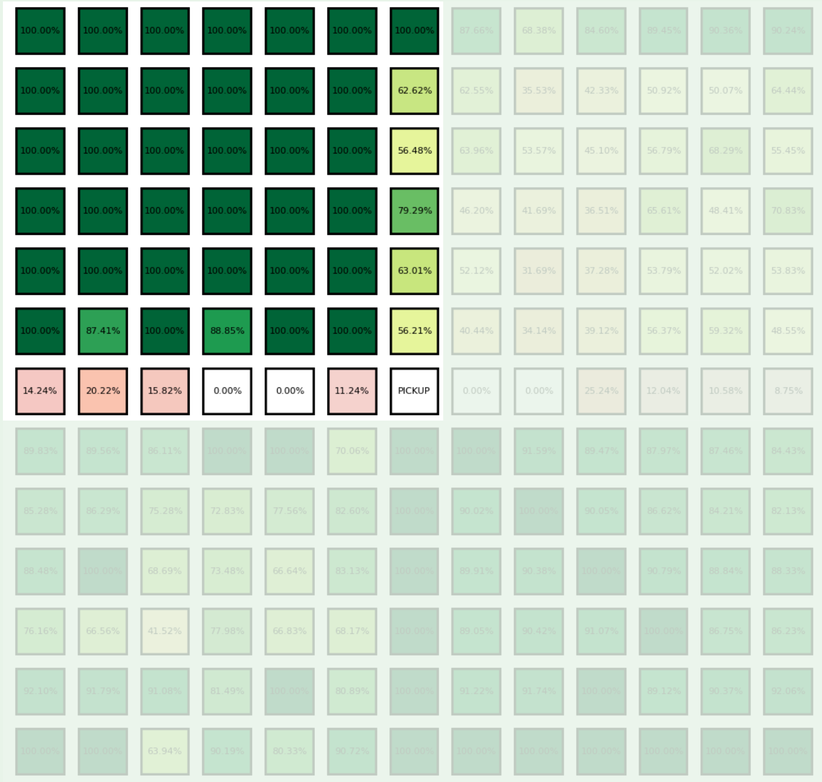
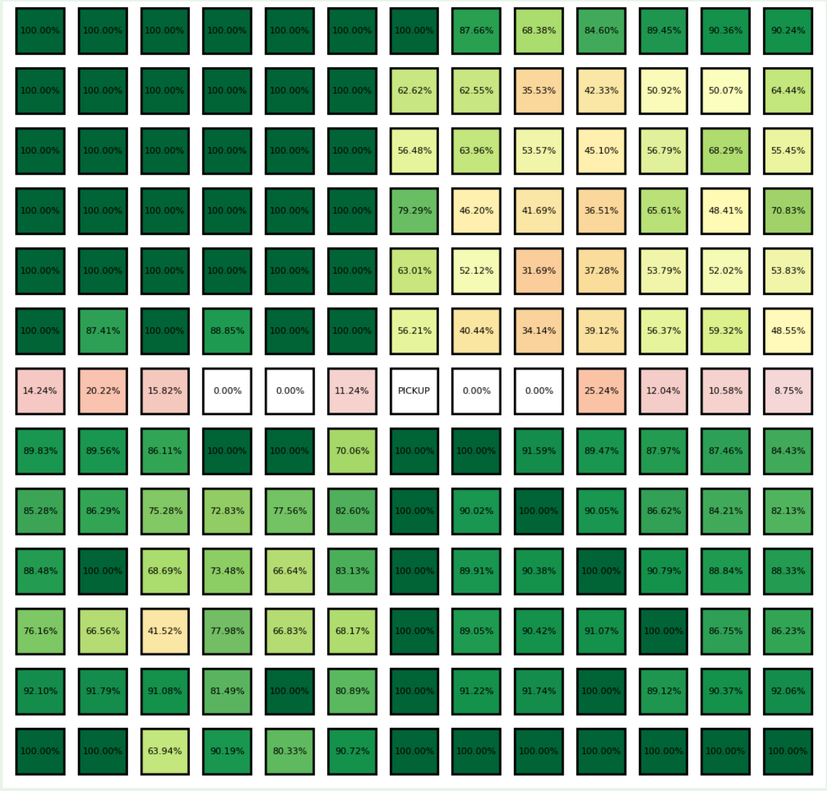


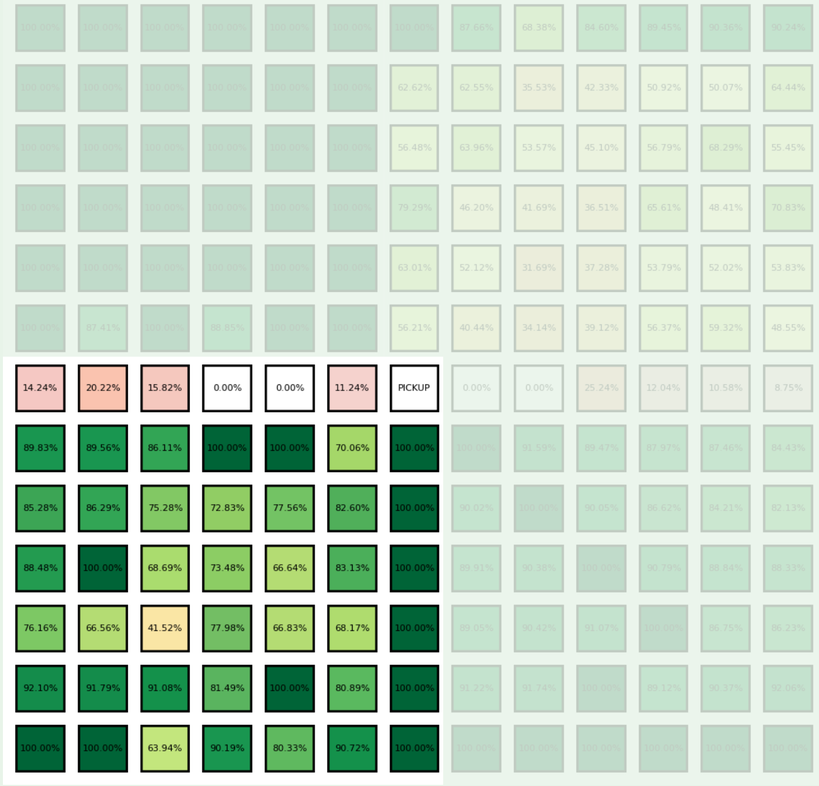


4. Findings

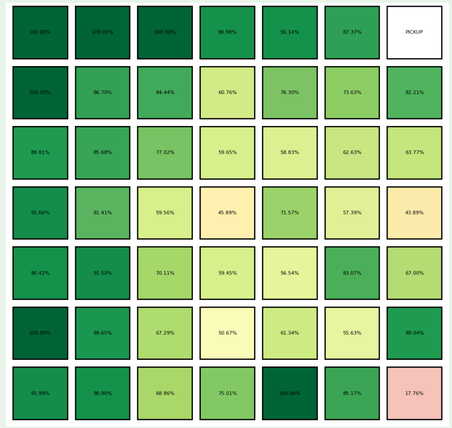
Common Uncertainty Patterns #1.2

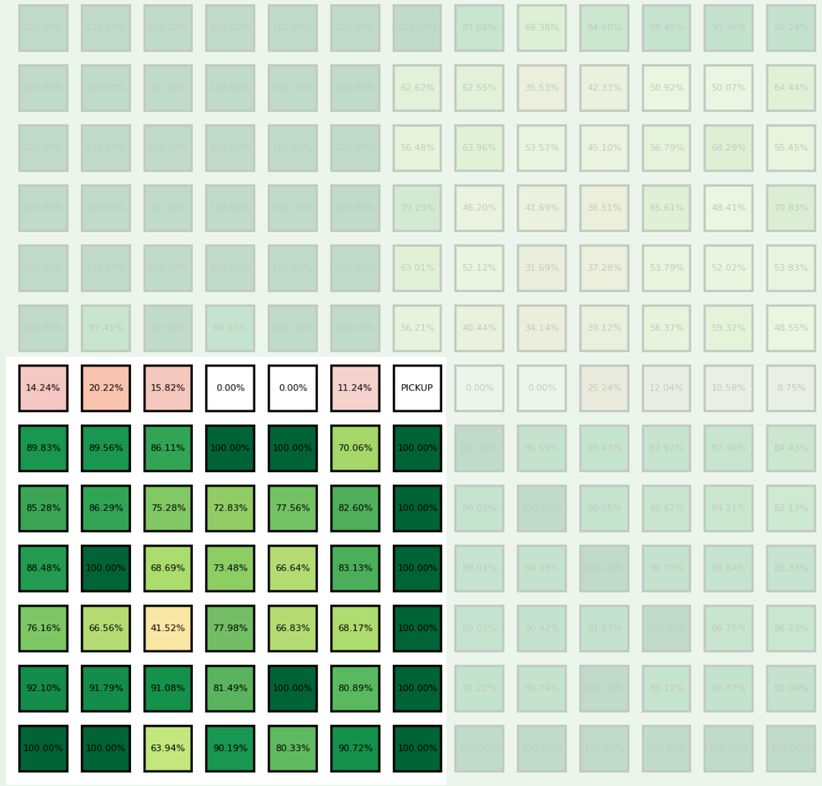


Common Uncertainty Patterns #1.2



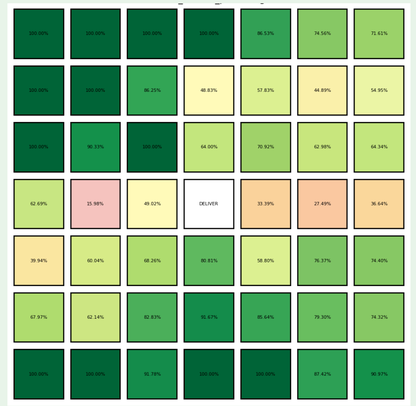
Common Uncertainty Patterns #1.2

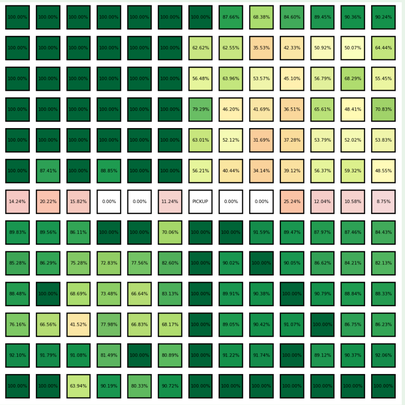


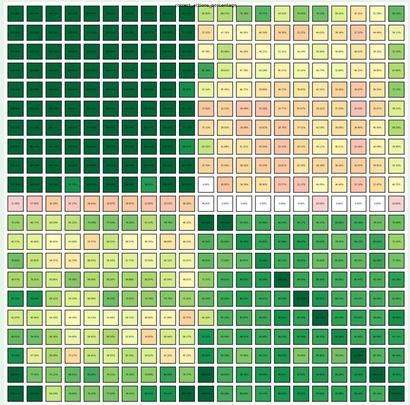


4. Findings

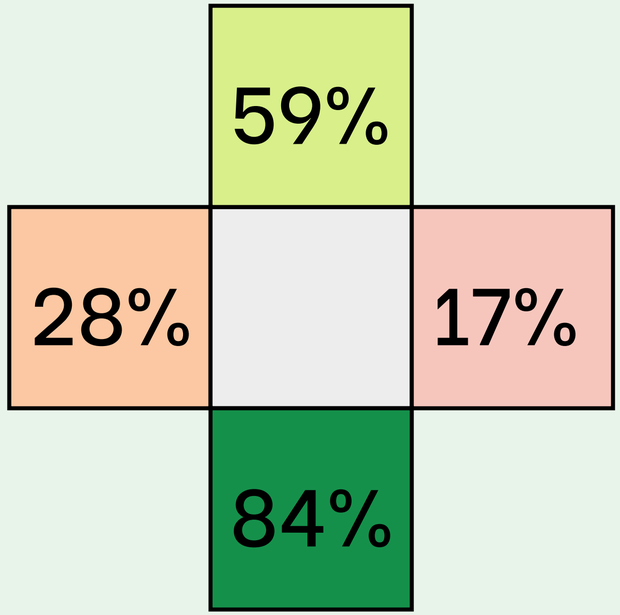
Common Uncertainty Patterns #2





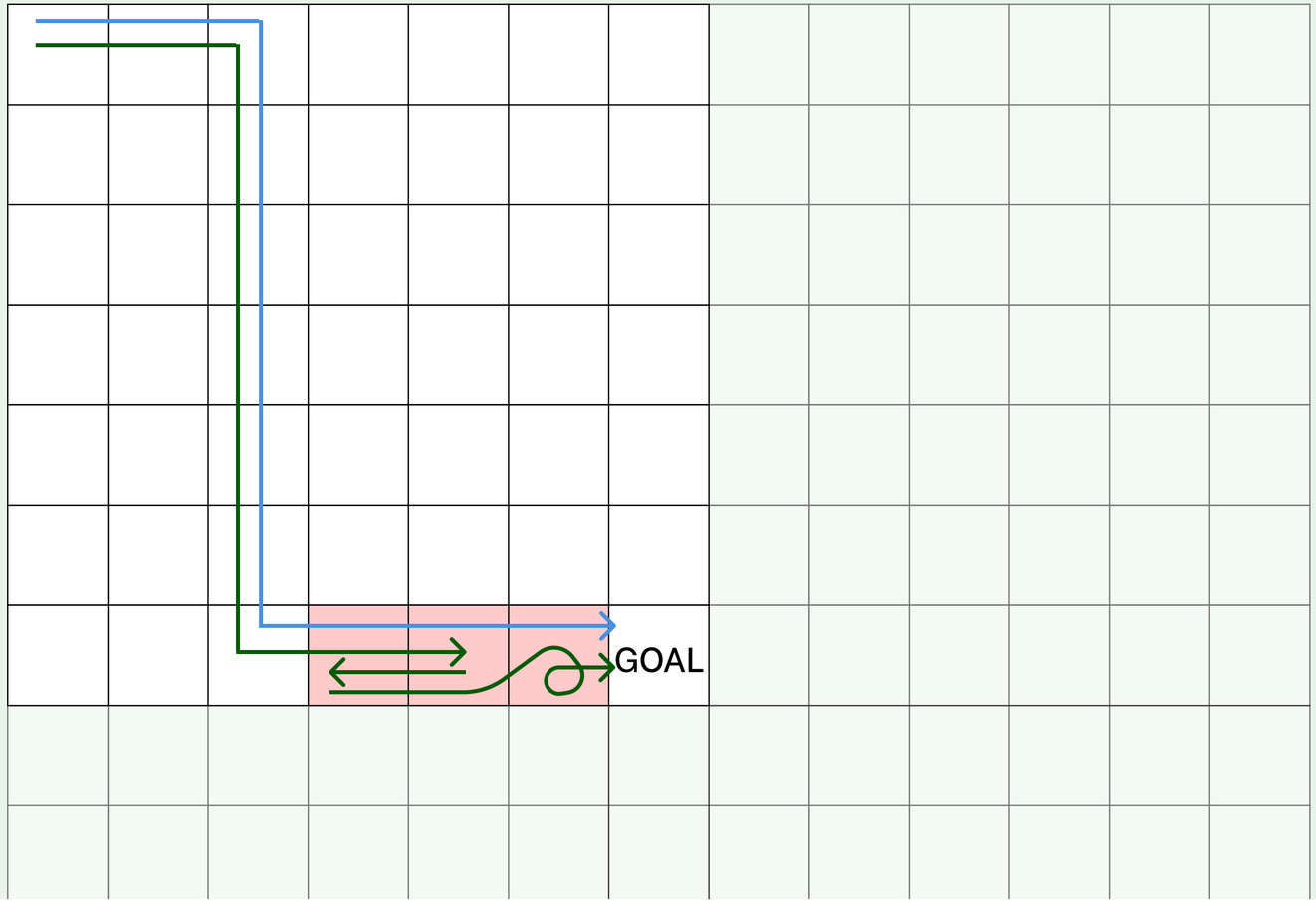


Average



4. Findings

Stateful Example



Optimal path

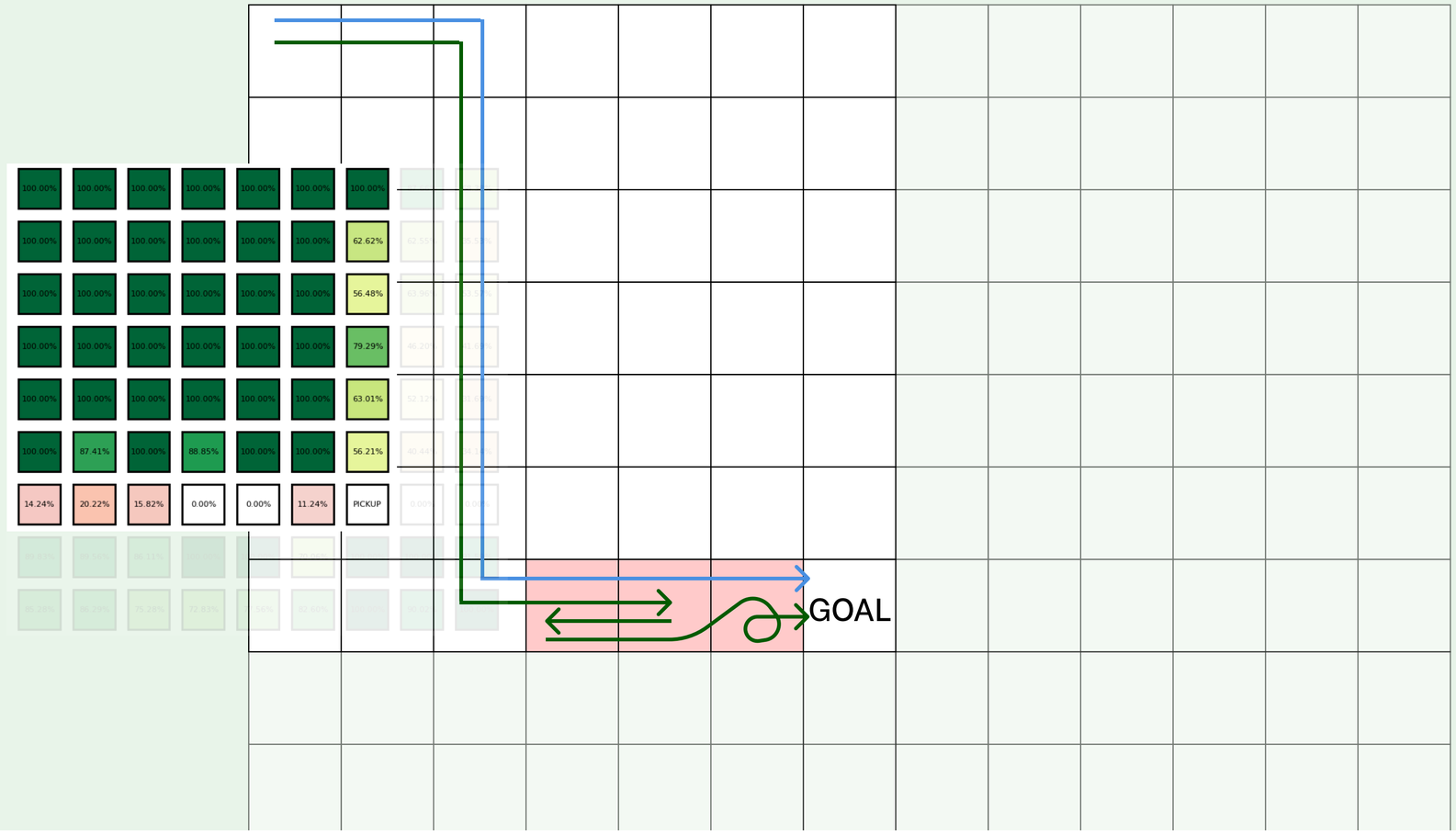
Our path

Repeated cells

Shared Nodes: 100%

Ratio: 81%

Stateful Example



Optimal path

Our path

Repeated cells

Shared Nodes: 100%

Ratio: 81%

Stateful

Map Size	Stateless	Stateful	Difference
13x13	41	39	-5%
7x7	27	21	-29%
5x5	14	11	-27%
3x3	11	9	-22%

Conclusions

Strengths

Effective

~ 20% Less action required with history

Retrieving goals in big maps

Better models, better results

Similar % error as the size increase

Weaknesses

Limited Explainability

Prone to error near the goal

Consistent problematic zones

Context size is a limitation

Similar % error as the size increase, but real number is a problem

Thank You

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Thank You

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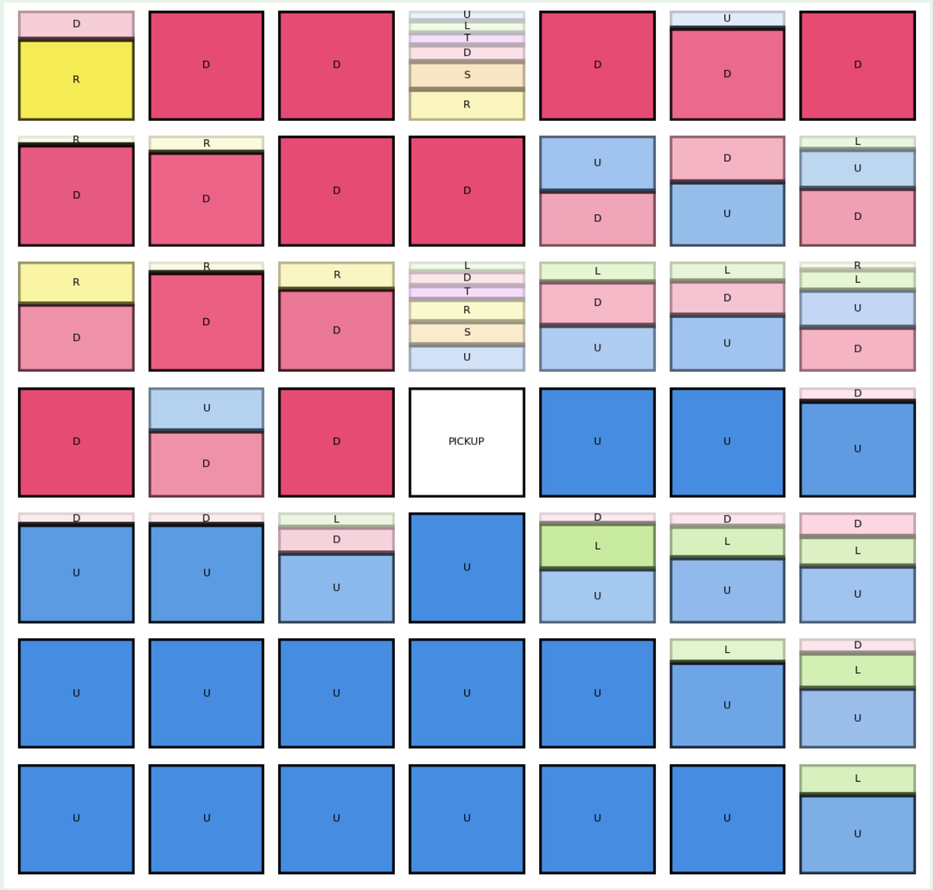
HM example where T and S were not always discarded



Example

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