Exploring the Use of LLMs for Agent Planning

Strengths and Weaknesses

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20/03/2025
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Context

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

Text Generation
Their Scope

Math Reasoning
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Planning Abilities
Emerging Behavior

More

LLM-based Planning

Chain of Thought

Reasoning[1]

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

LLM-based Planning

Chain of Thought

Reasoning[1]

Few-Shots

Prompting[2]

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LLM-based Planning

Chain of Thought
Reasoning[1]

Few-Shots
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Fine-Tuning
Models[3]

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

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LLM-based Planning

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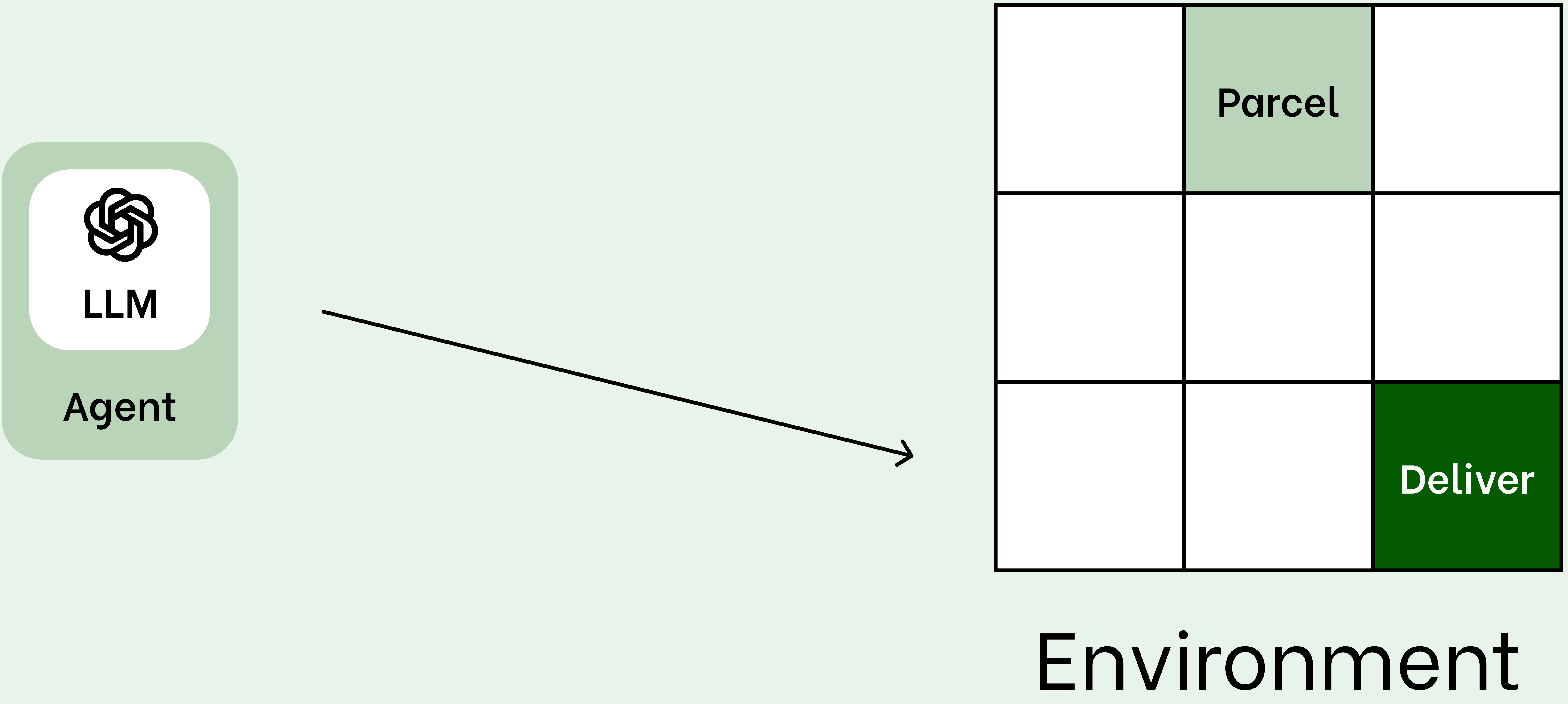
But what happens if we strip anything prior away?

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

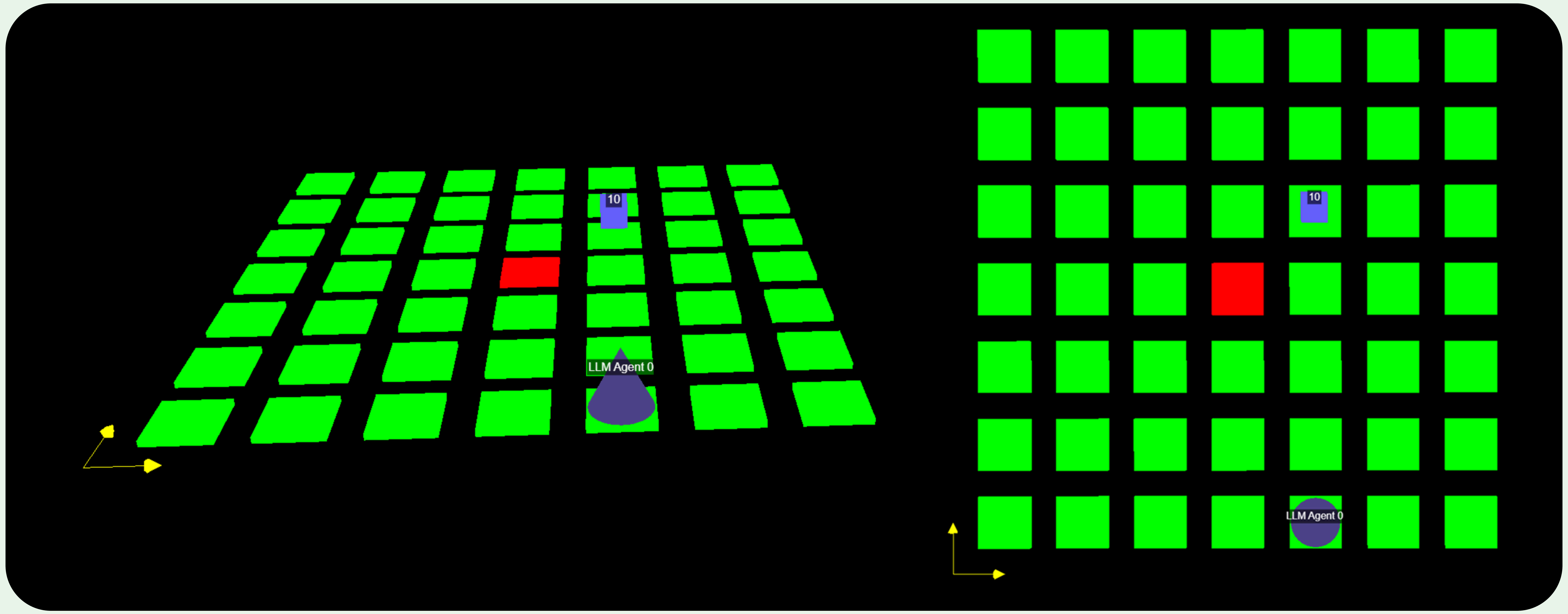
How well can LLMs make sequential decisions in such environments?

Idea



Setting

Deliveroo.js



Educational Game

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

KnowNo Uncertainty Framework

Prompt

Environment description

A) action 1
B) action 2
C) action 3
D) action 4

E) none of the above

— *Bias towards A, B, C, D, E* →

LogProbs

```
"A" -> -0.01
"B" -> -11.1
"C" -> -0.1
"D" -> -5.3
"E" -> -4.0
```

— *Softmax + Flitering* →

Result

"A" -> 60%
~~"B" -> 1%~~
"C" -> 30%
~~"D" -> 4%~~
~~"E" -> 5%~~

Prompting Strategy

Role	Delivery agent
↓	↓
Map	Without JSON syntax
↓	↓
Request	Best next action?

Model

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

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

Data Collection

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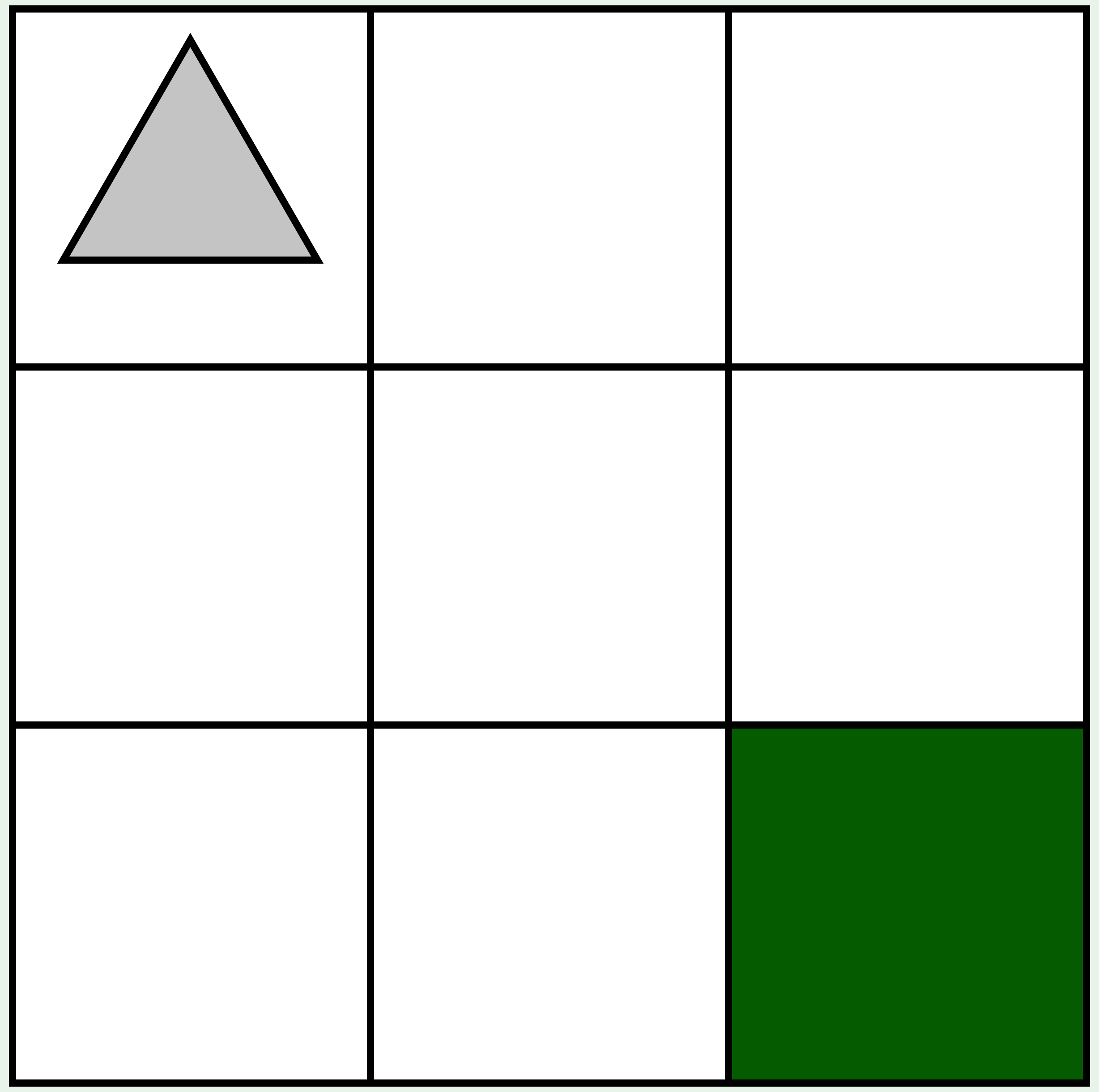
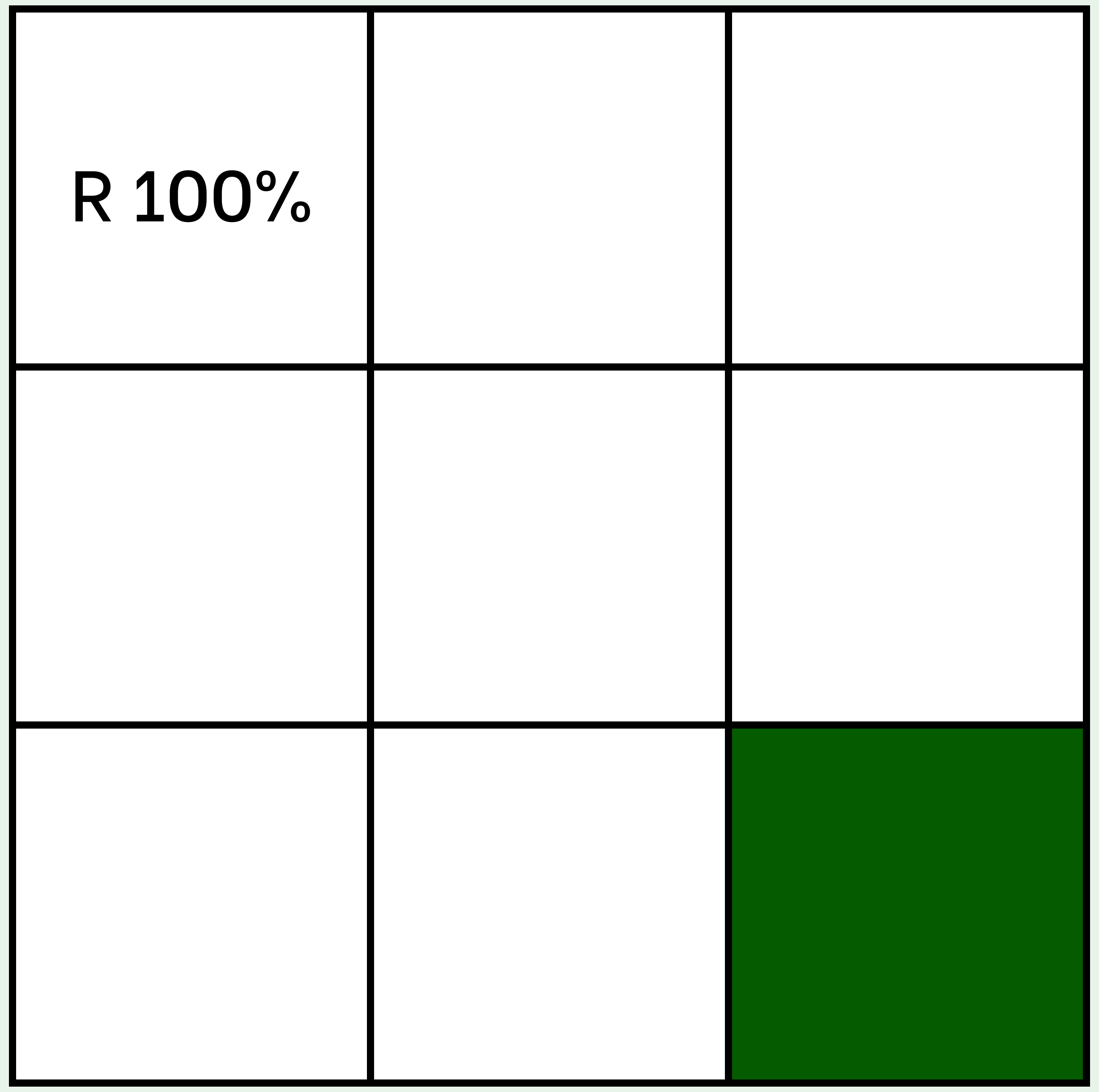
Heatmaps Creation #1





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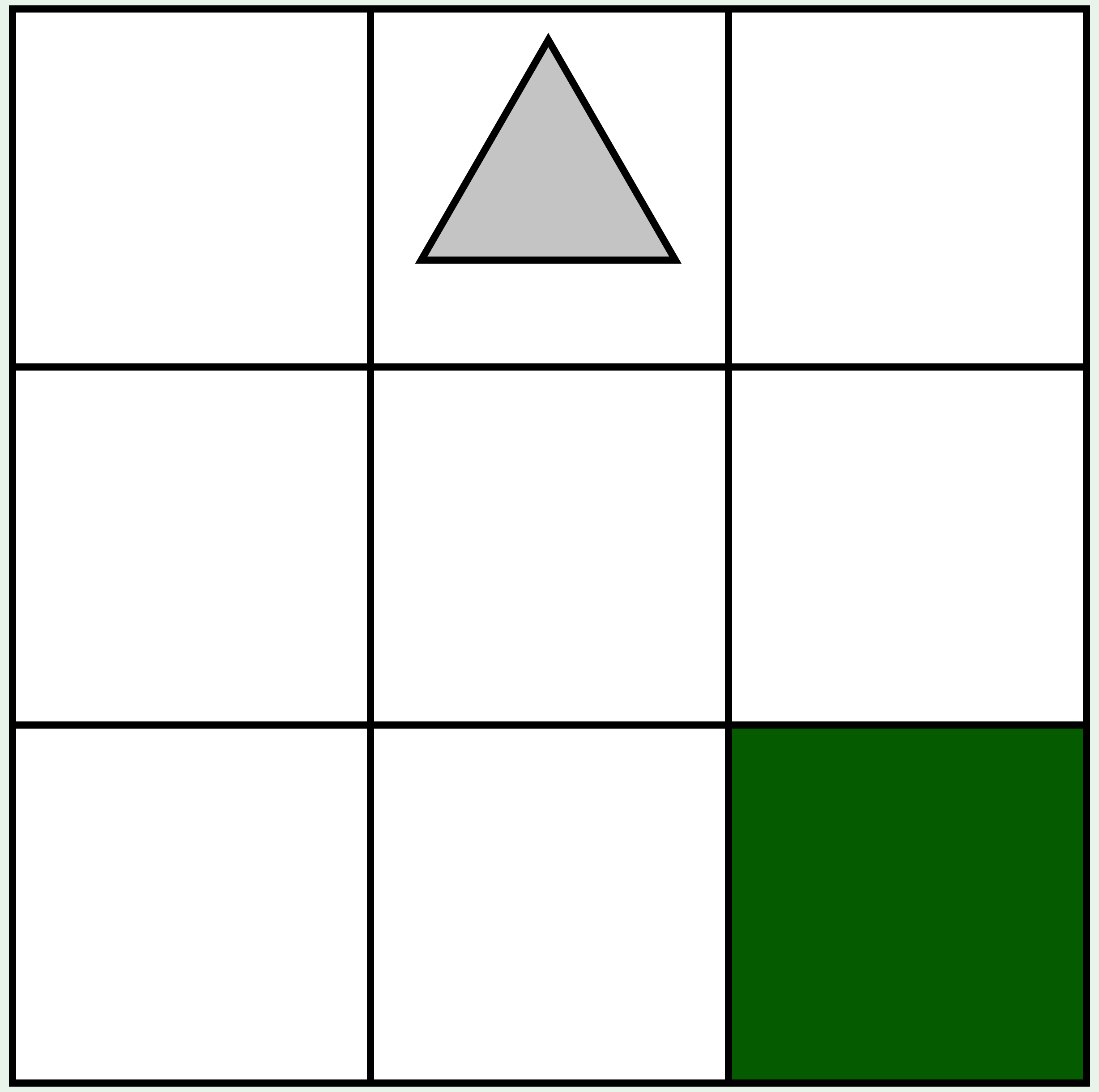

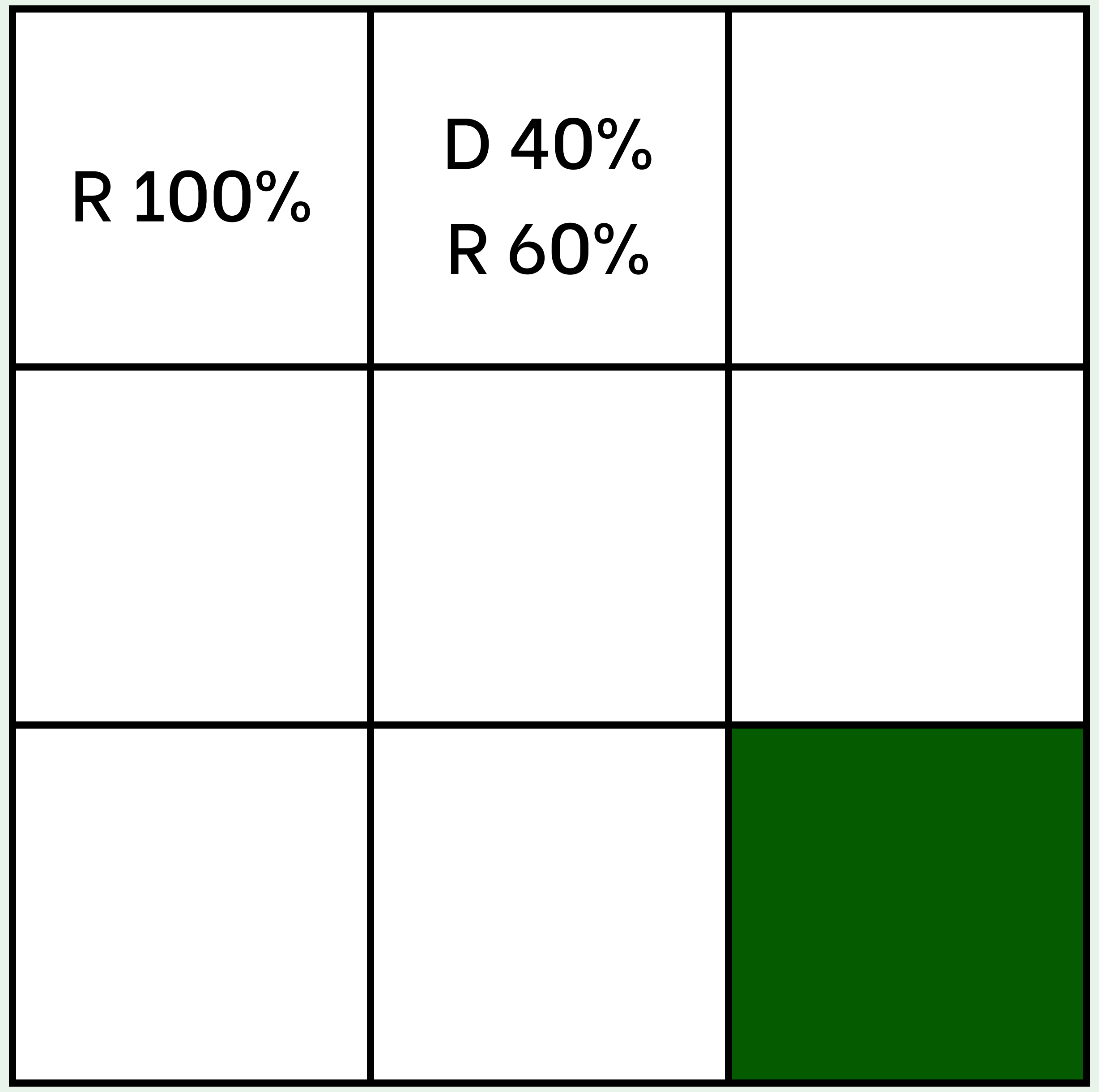

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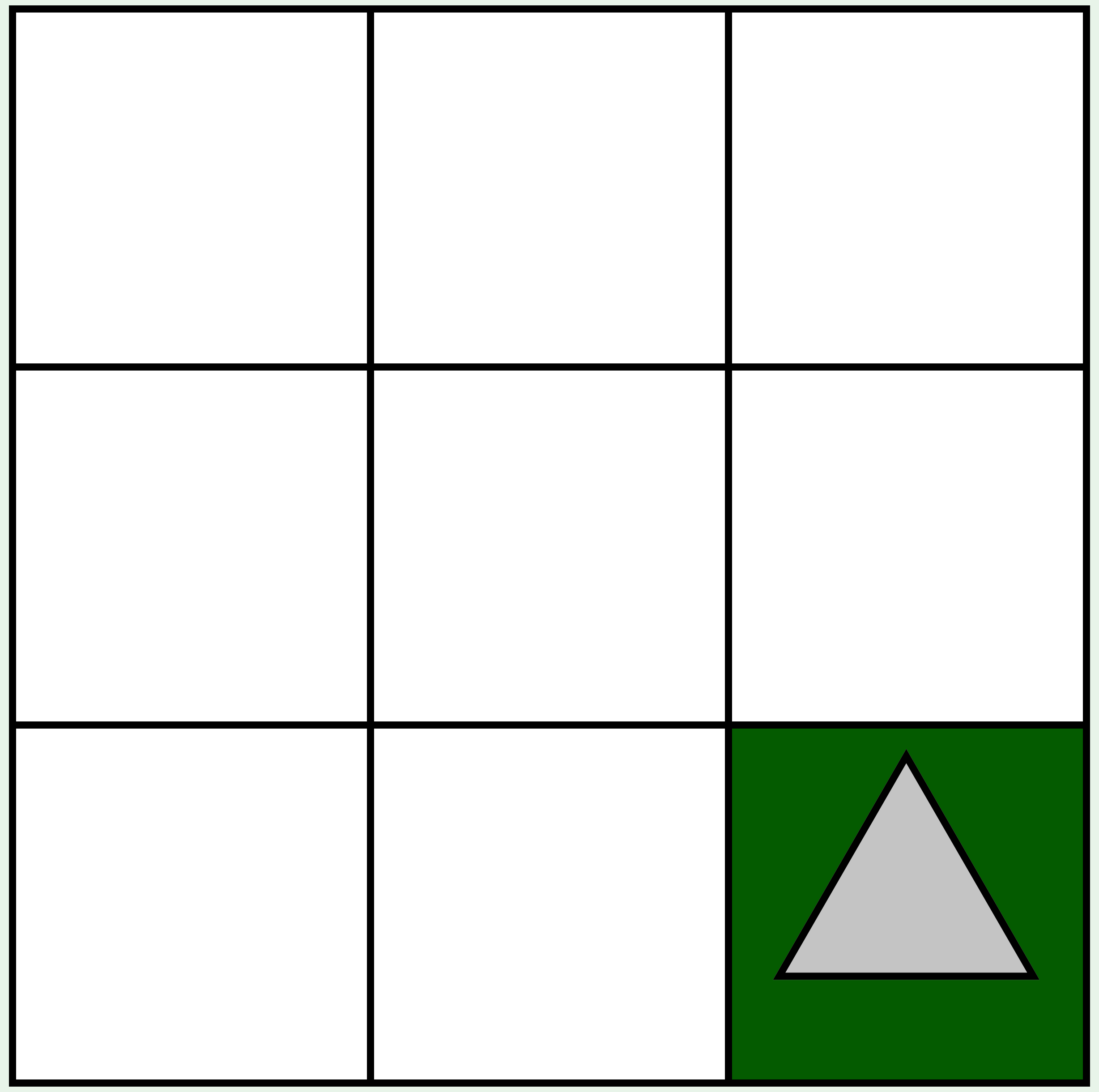


R 100%	D 40% R 60%	D 35% R 65%
D 5% R 95%	D 5% R 95%	D 30% R 70%
D 5% U 7% R 88%	D 5% R 95%	

Heatmaps Creation #2

R 100%	D 40% R 60%	D 35% R 65%
D 5% R 95%	D 5% R 95%	D 30% R 70%
D 5% U 7% R 88%	D 5% R 95%	

100%	100%	35%
100%	100%	30%
88%	95%	

Testing Strategy

Goals

Deliver

Goal tile identified in map description

Pickup

Goal tile identified in map description

Testing Strategy

Agents

Stateless

Each iteration a new instance

Stateful

Retains the Conversation History

Our Findings

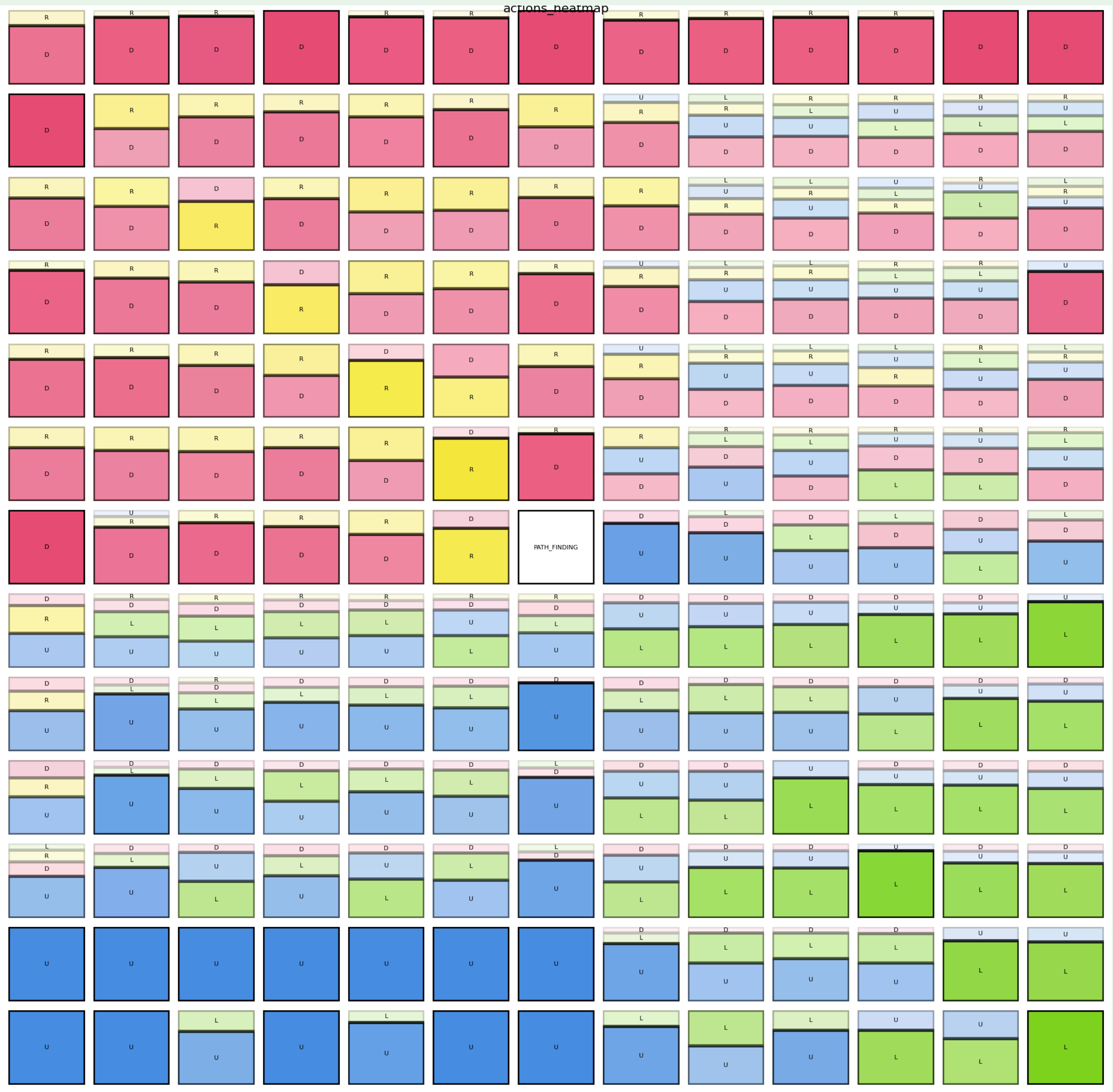
Map Orientation

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

Map Orientation

(0,0)

(0,0)



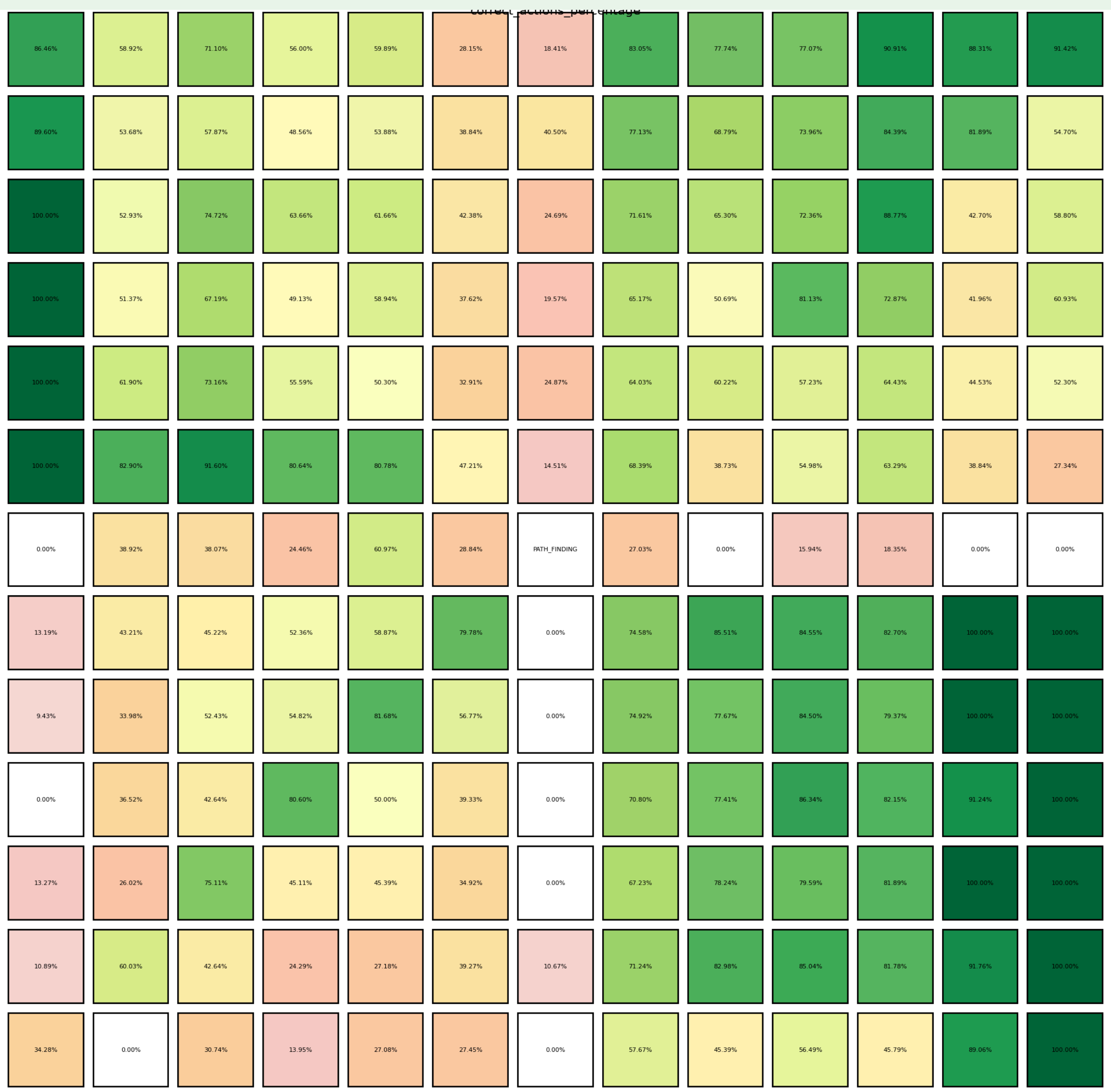
Up

Down

Left

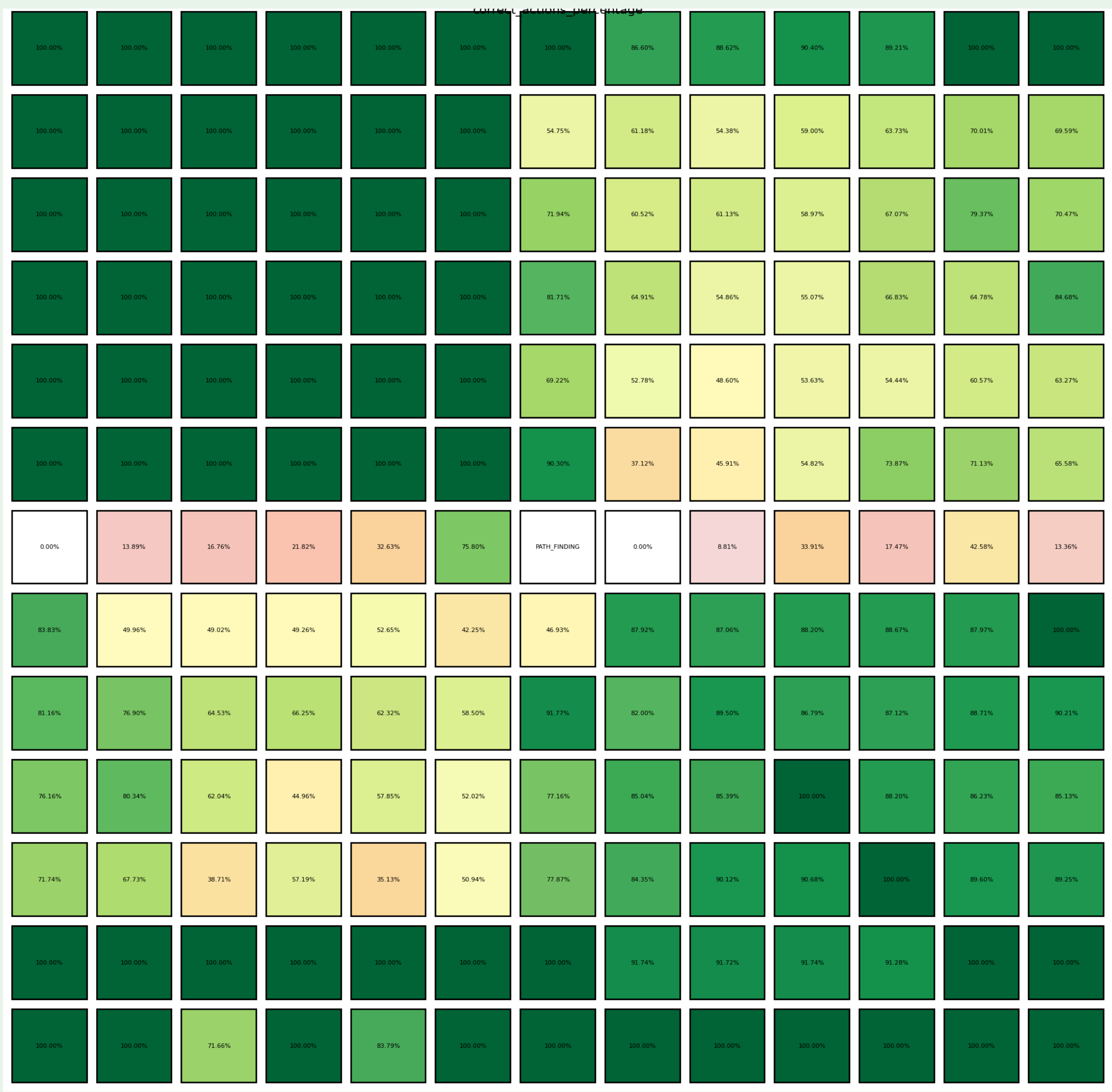
Right

Map Orientation



(0,0)

(0,0)



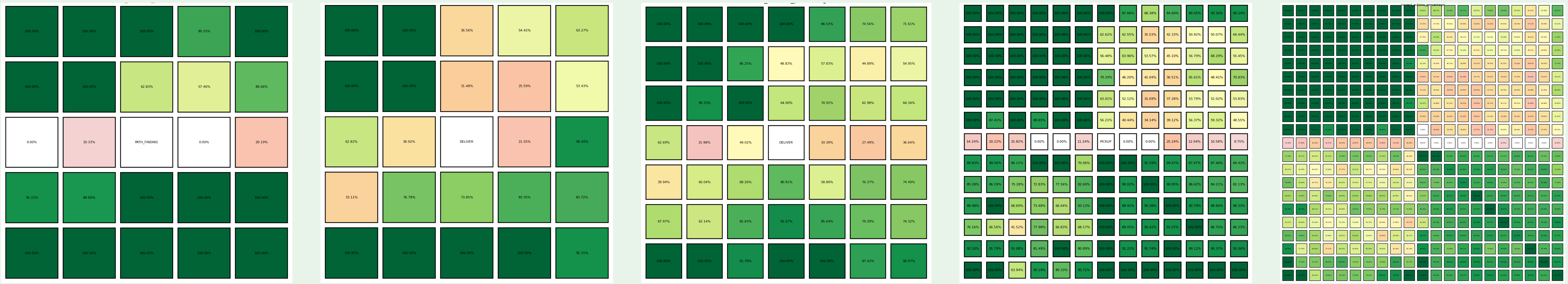
100%

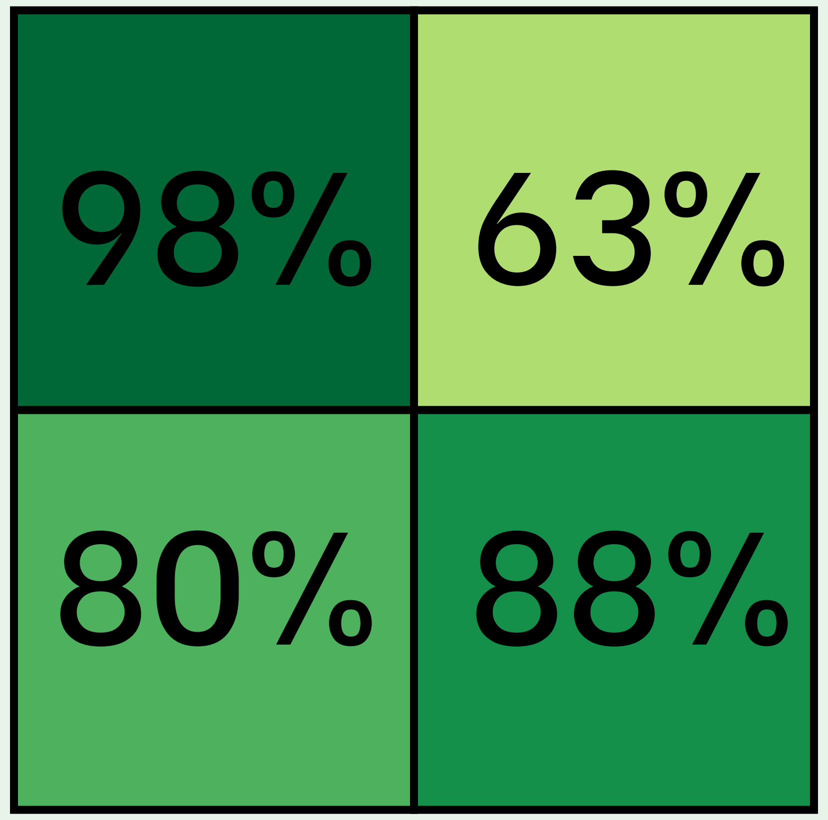
0%

Map Orientation

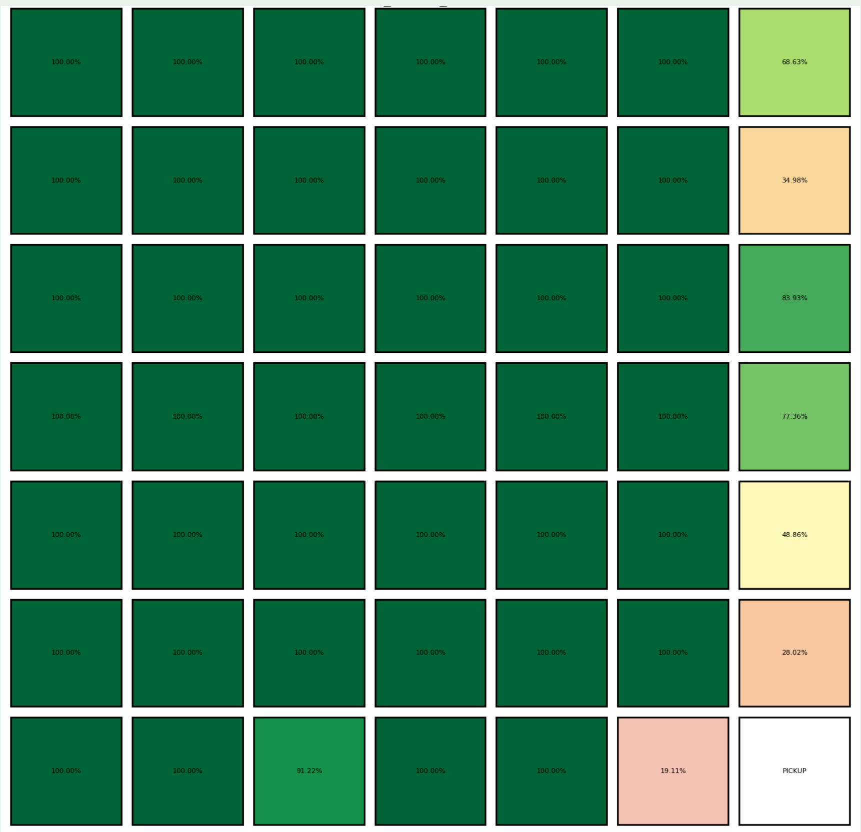
	Bottom-Left Origin	Top-Left Origin
top1%	62%	92%
top2%	92%	97%
top3%	93%	99%

Common Uncertainty Patterns #1

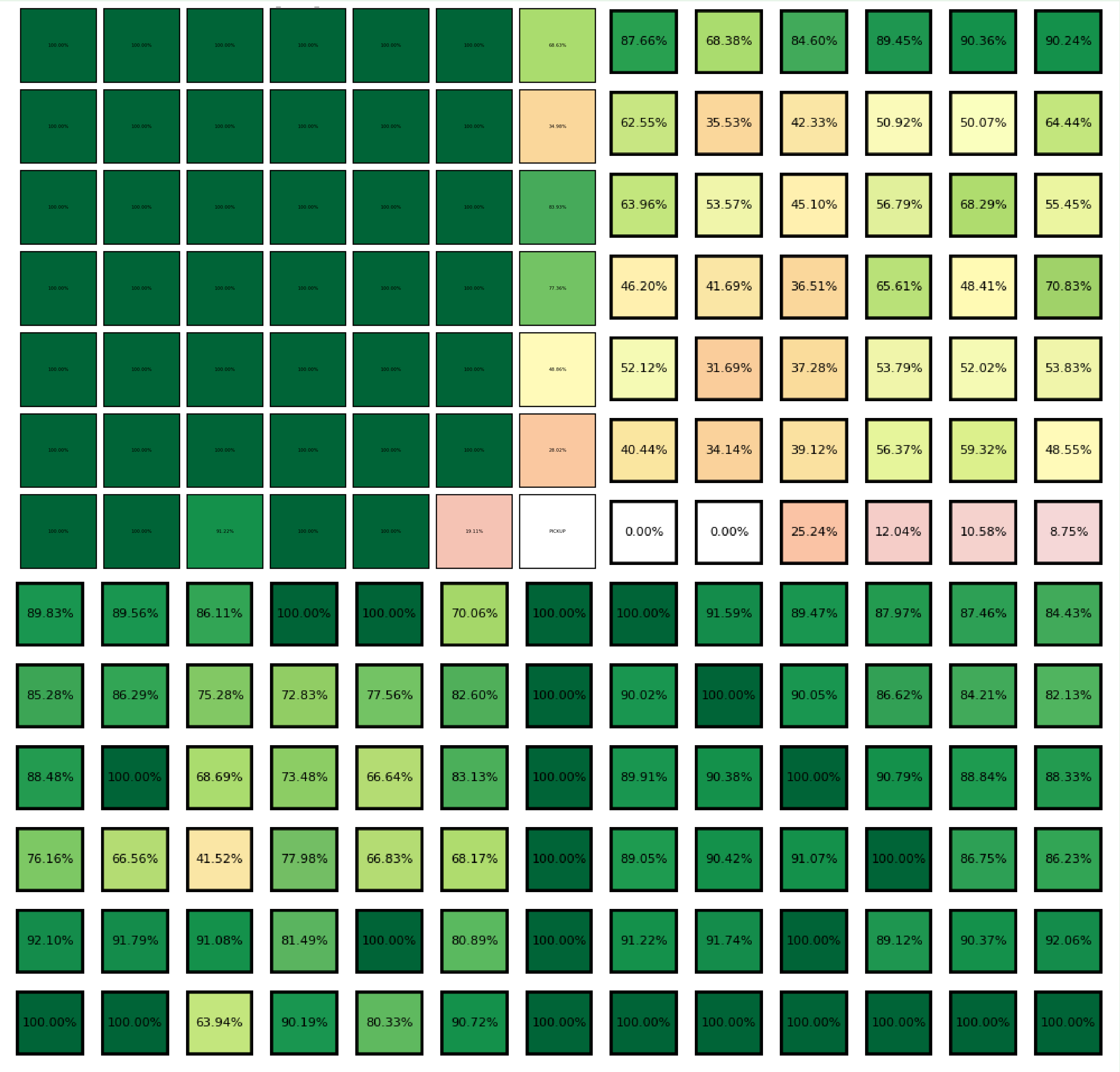




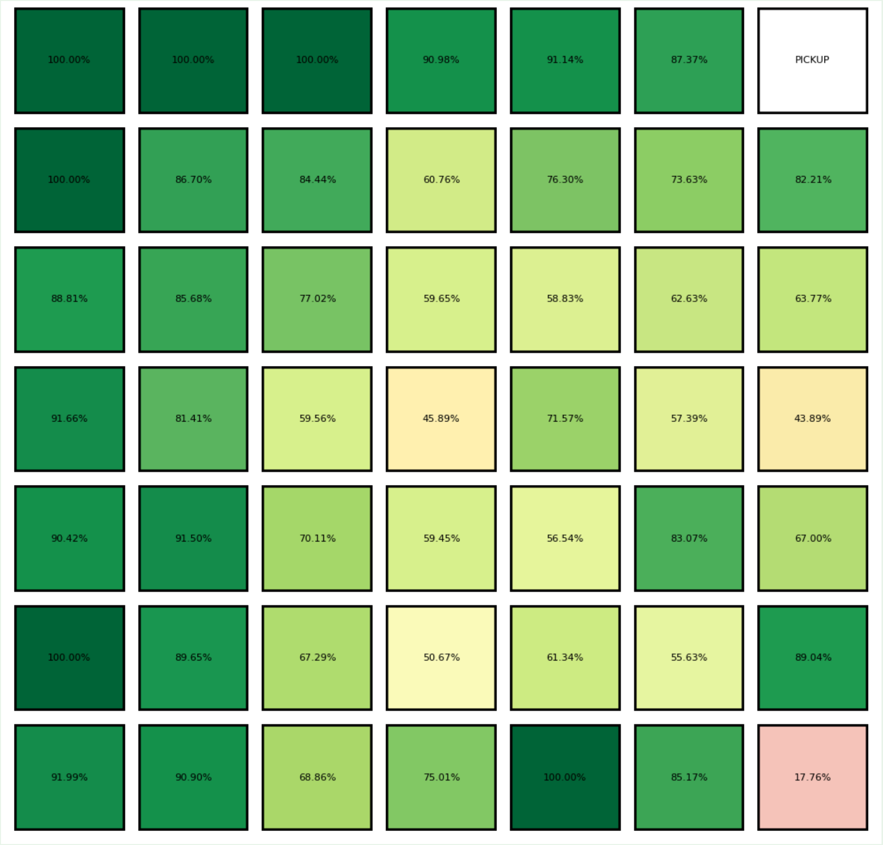
Common Uncertainty Patterns #1.1



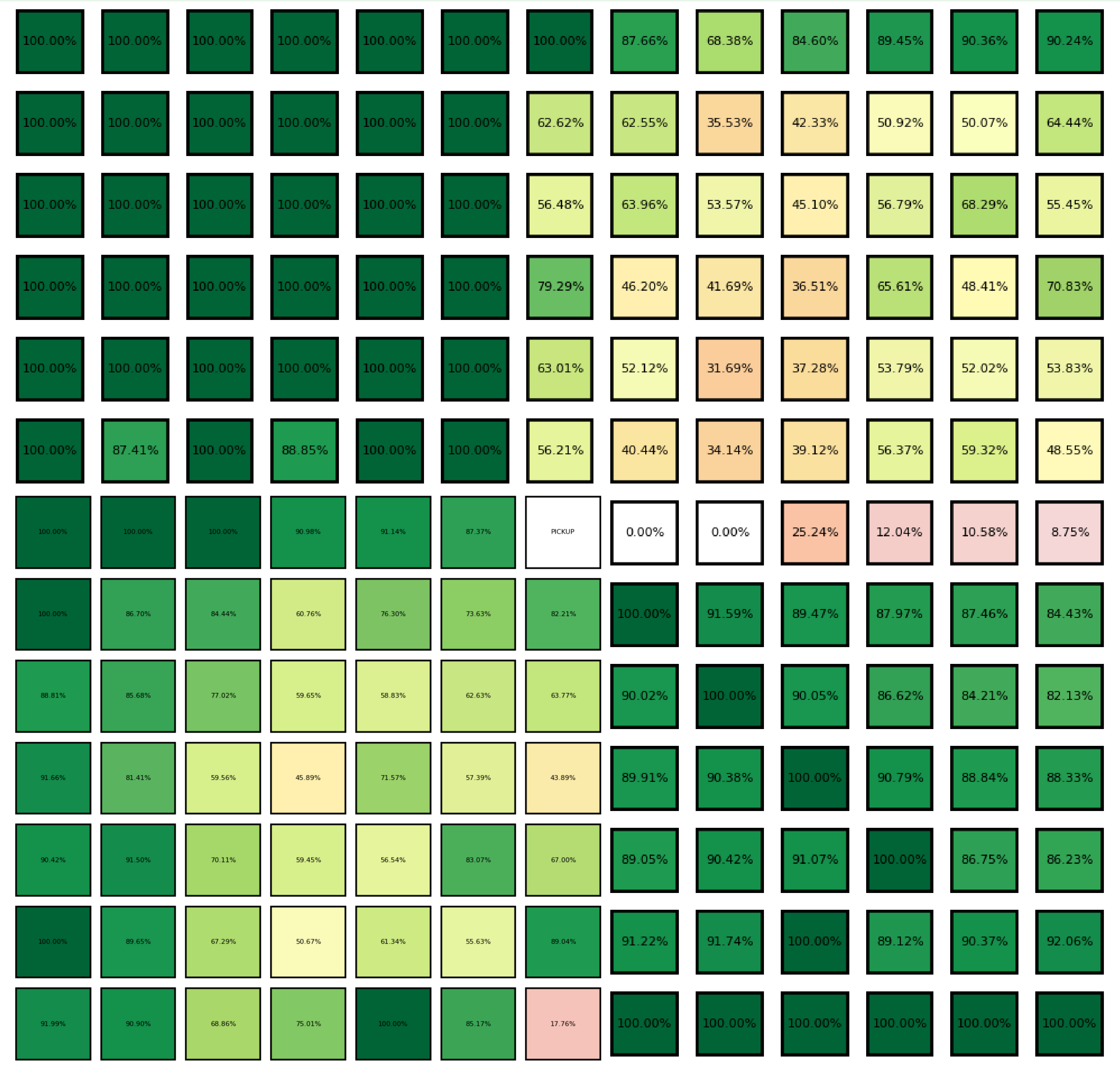
Common Uncertainty Patterns #1.1



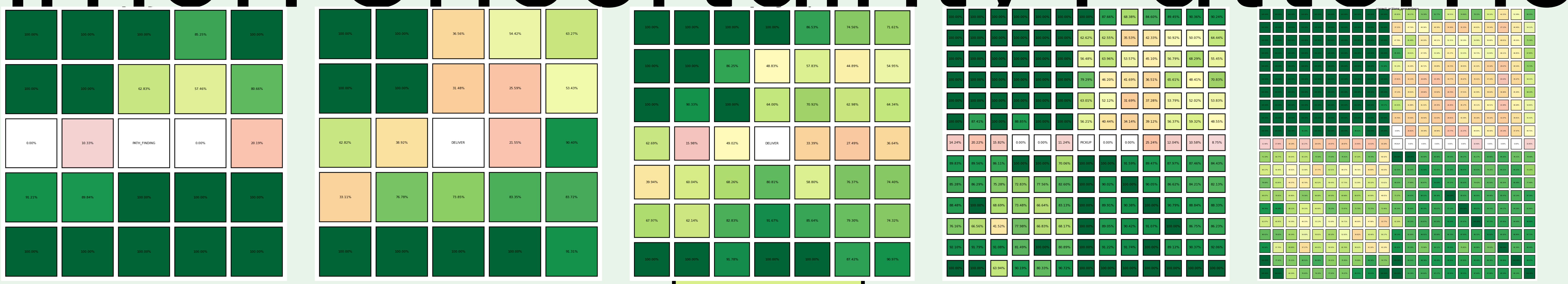
Common Uncertainty Patterns #1.2

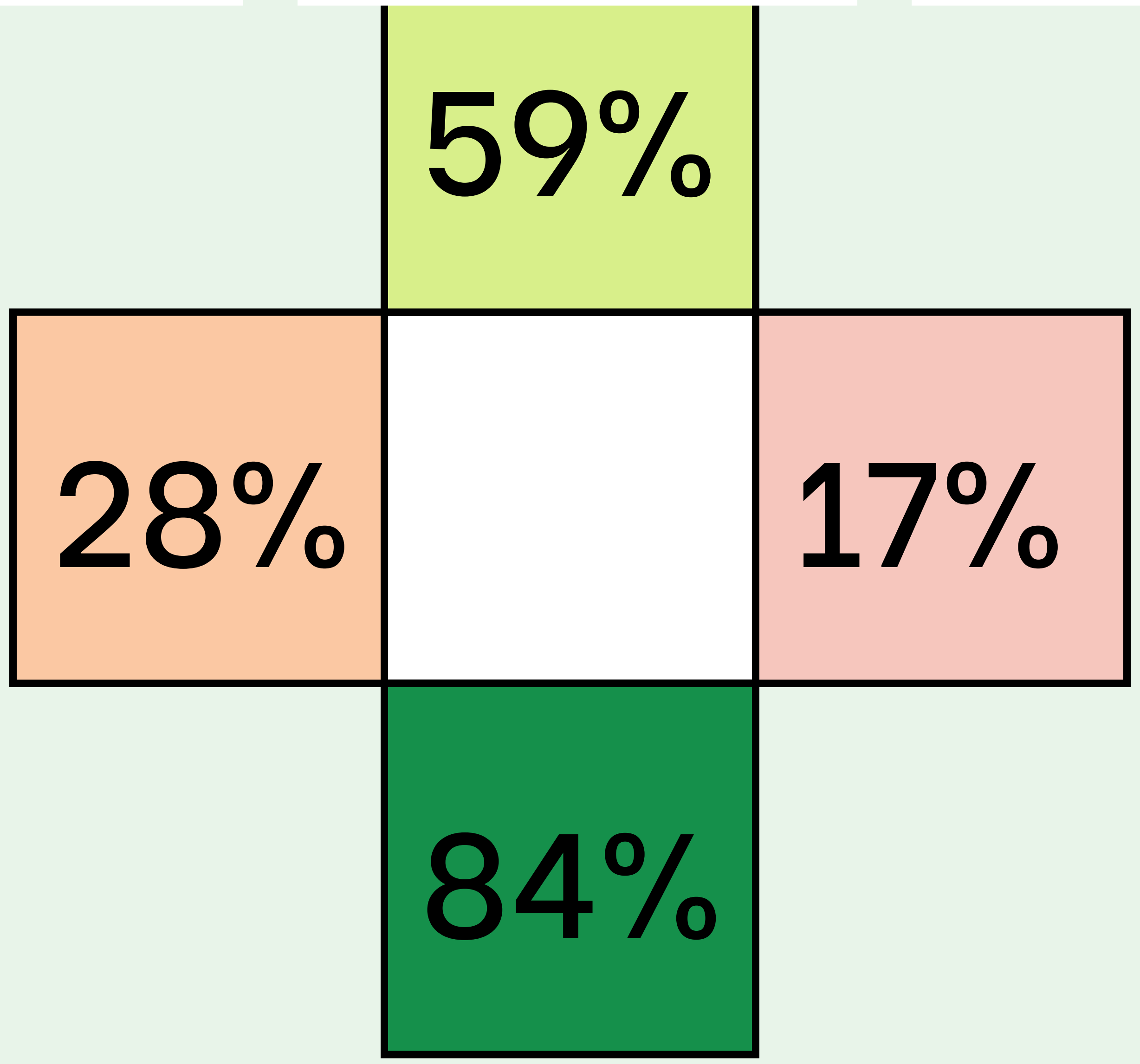


Common Uncertainty Patterns #1.2

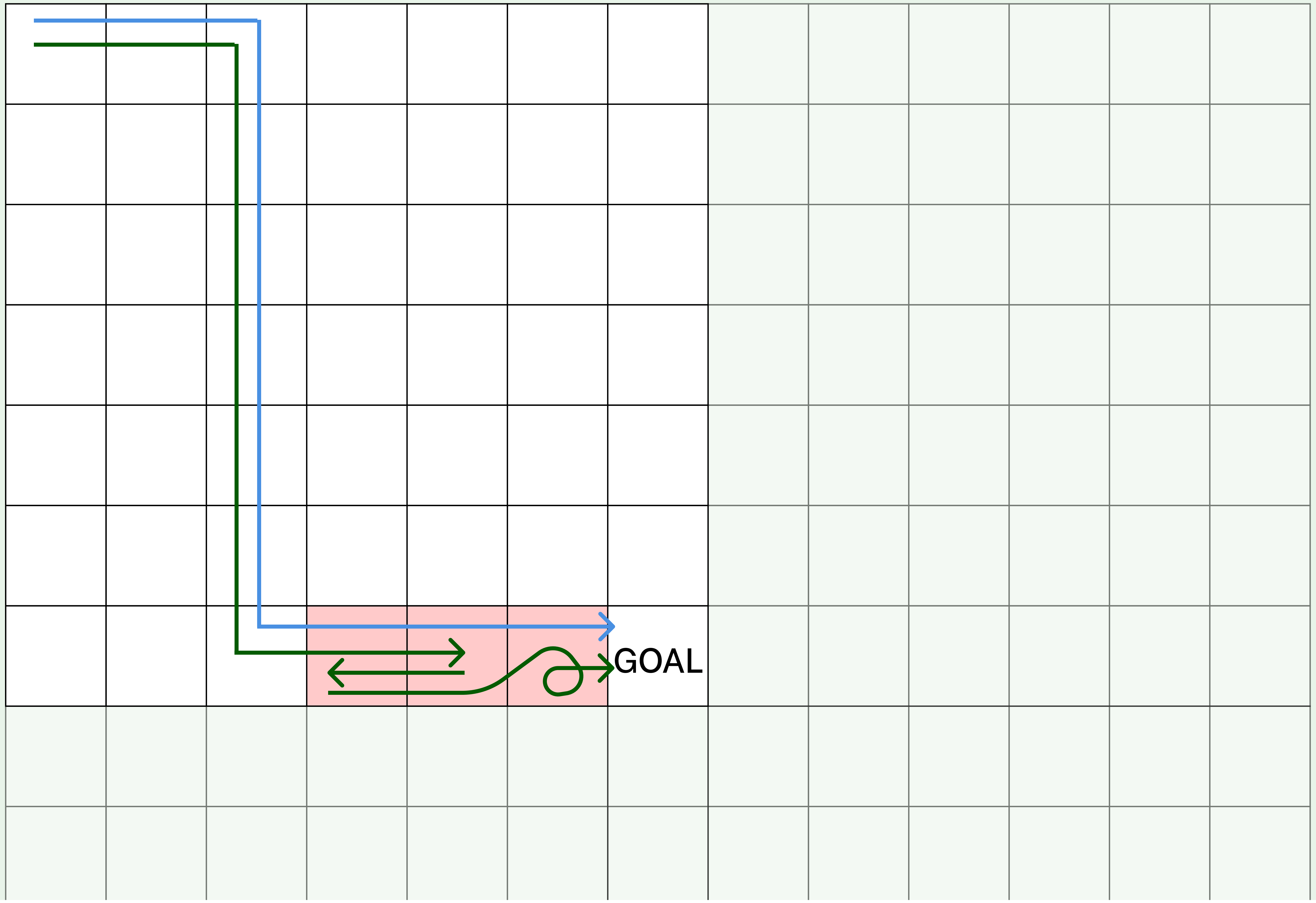


Common Uncertainty Patterns #2





Stateful Example



Optimal path

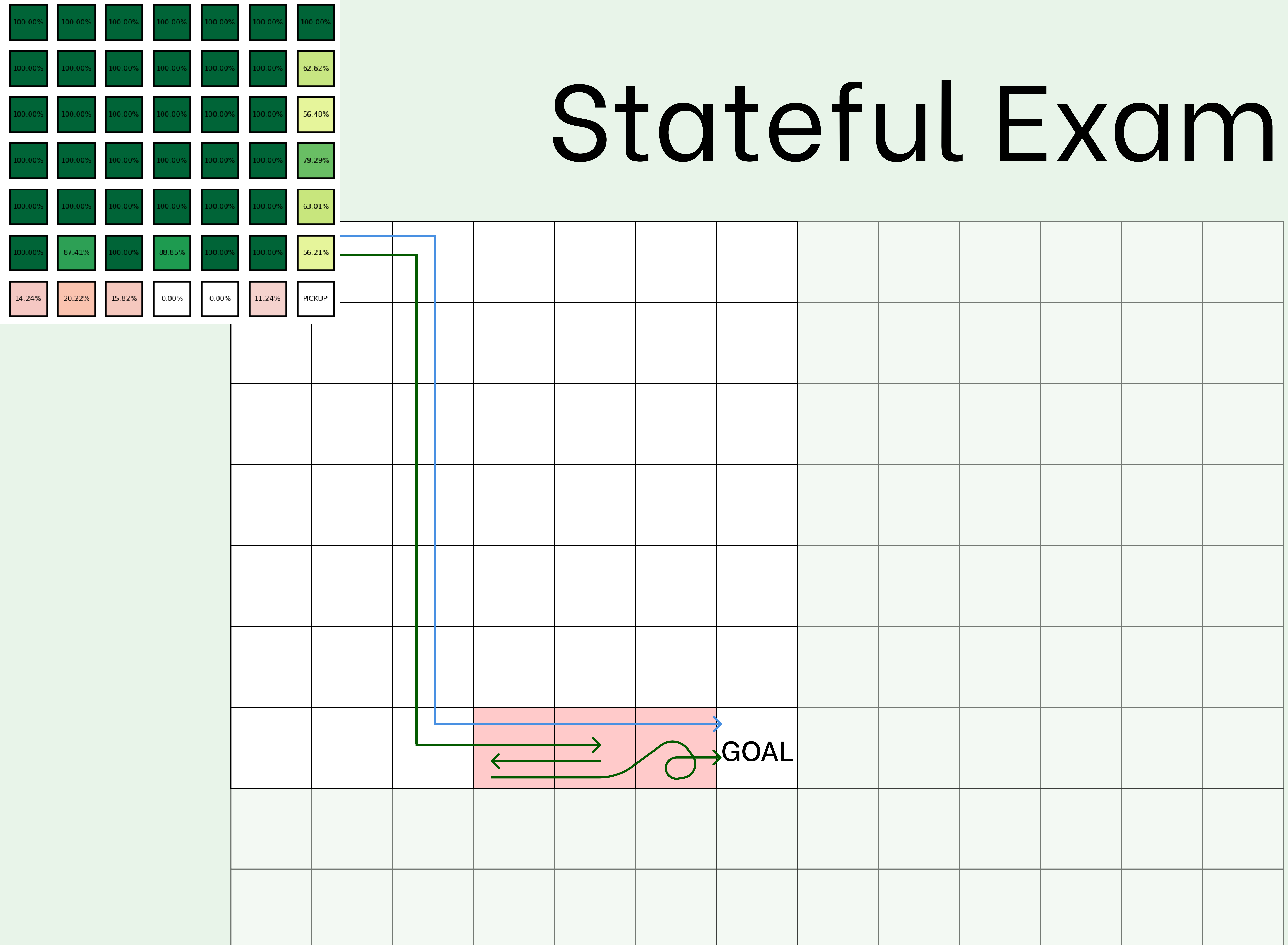
Our path

Repeated cells

Shared Nodes: 100%

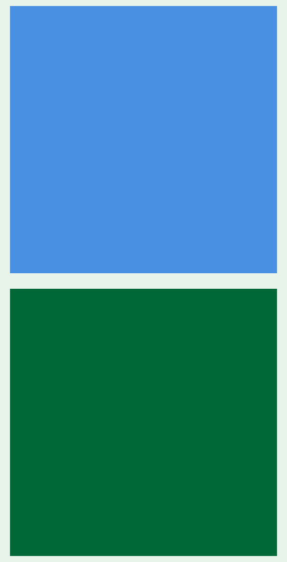
Ratio: 81%

Stateful Example



Shared Nodes: 100%

Ratio: 81%



Optimal path

Our path

Central difference

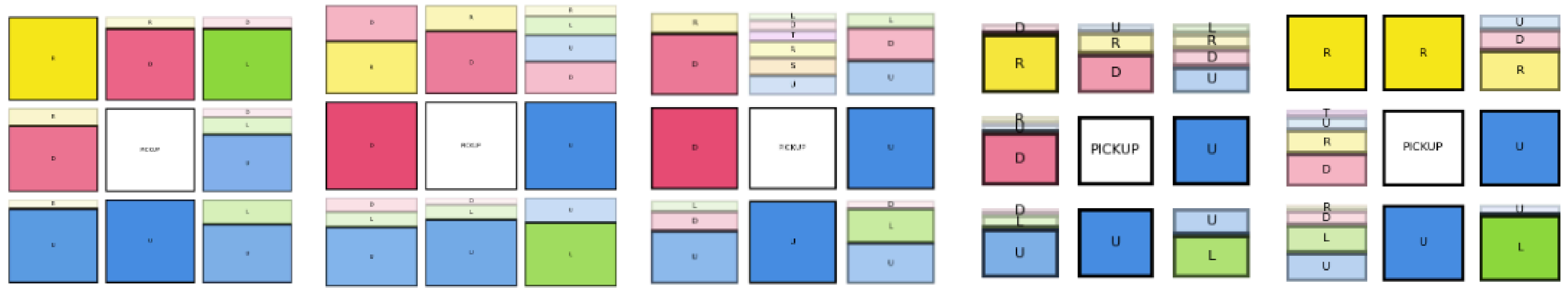


Figure 6.35: 3x3 Figure 6.36: 5 × 5 Figure 6.37: 7 × 7 Figure 6.38: 13×13 Figure 6.39: 21x21

79% 59% 53% 59% 50%

100%	45%	57%
13%	GOAL	4%
69%	95%	98%

Strengths & Weaknesses

it's possible

history helps - 20% less actions

correctly identify goal in a big map definition

Better models, better results

prone to error near the goal

consistent problematic zones

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

Context size is a big limitation

Thank You

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