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

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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]

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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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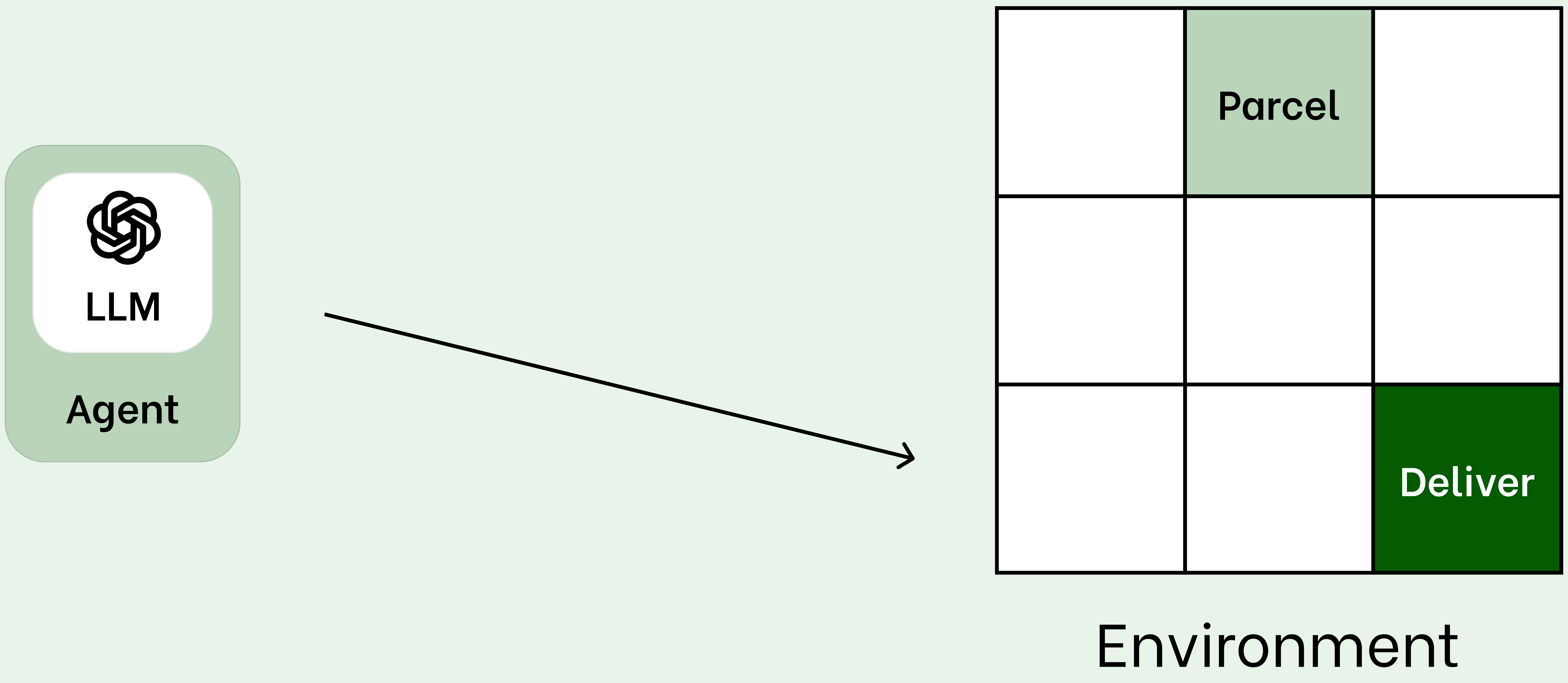
Research Questions

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

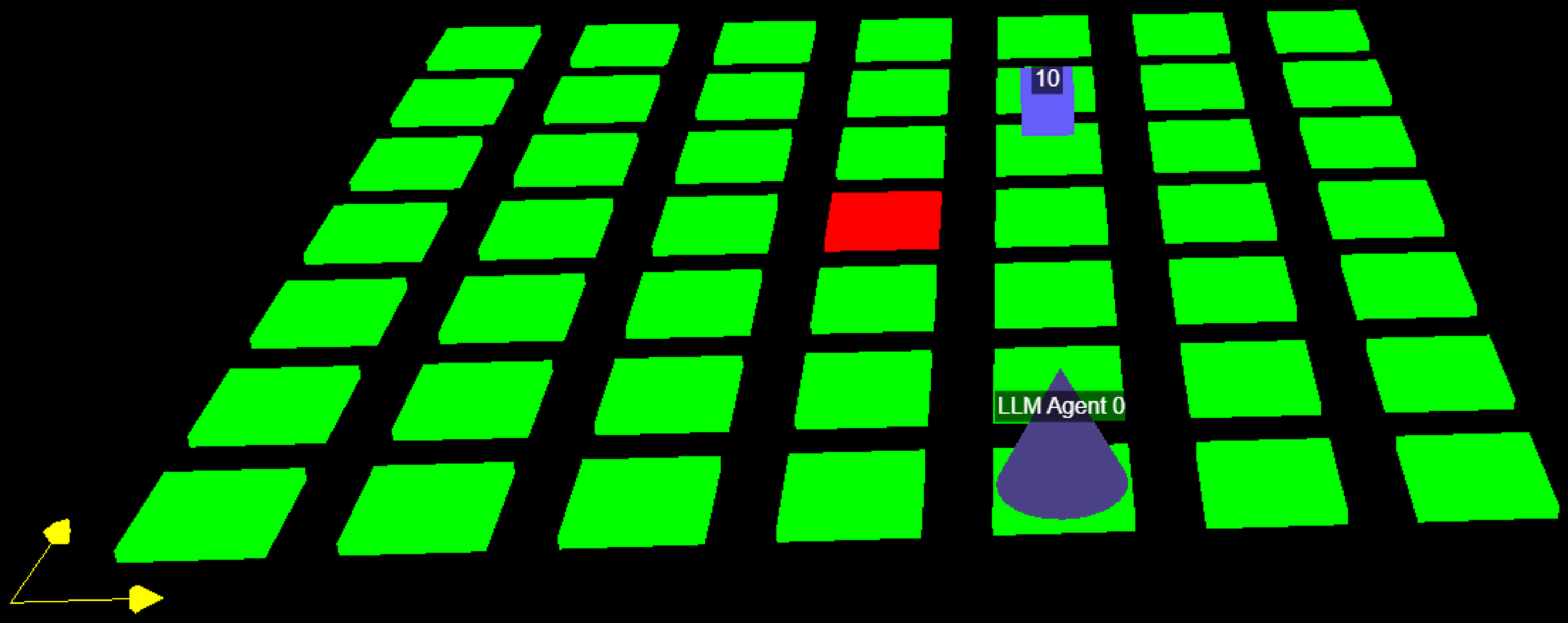


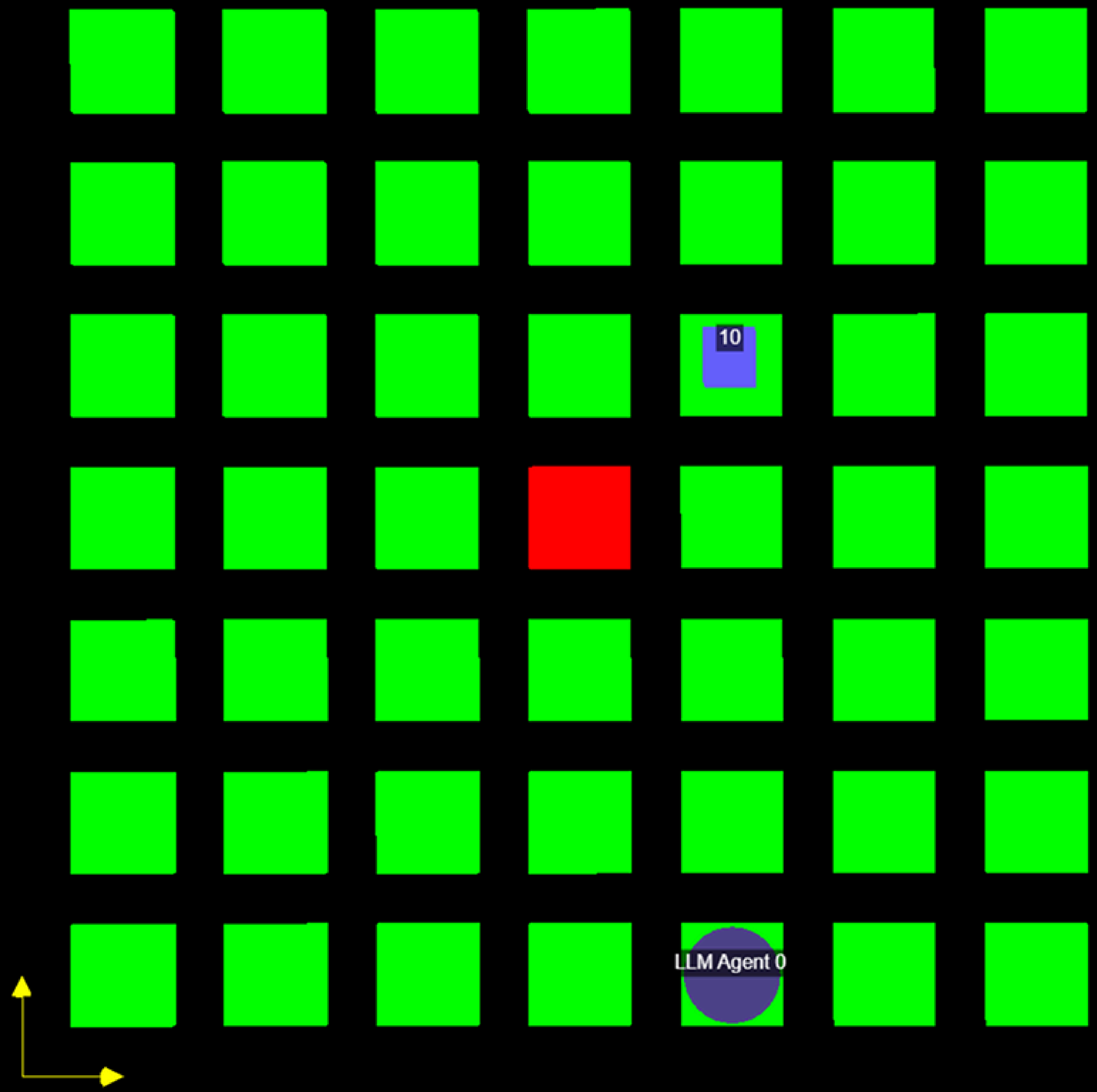
Setting

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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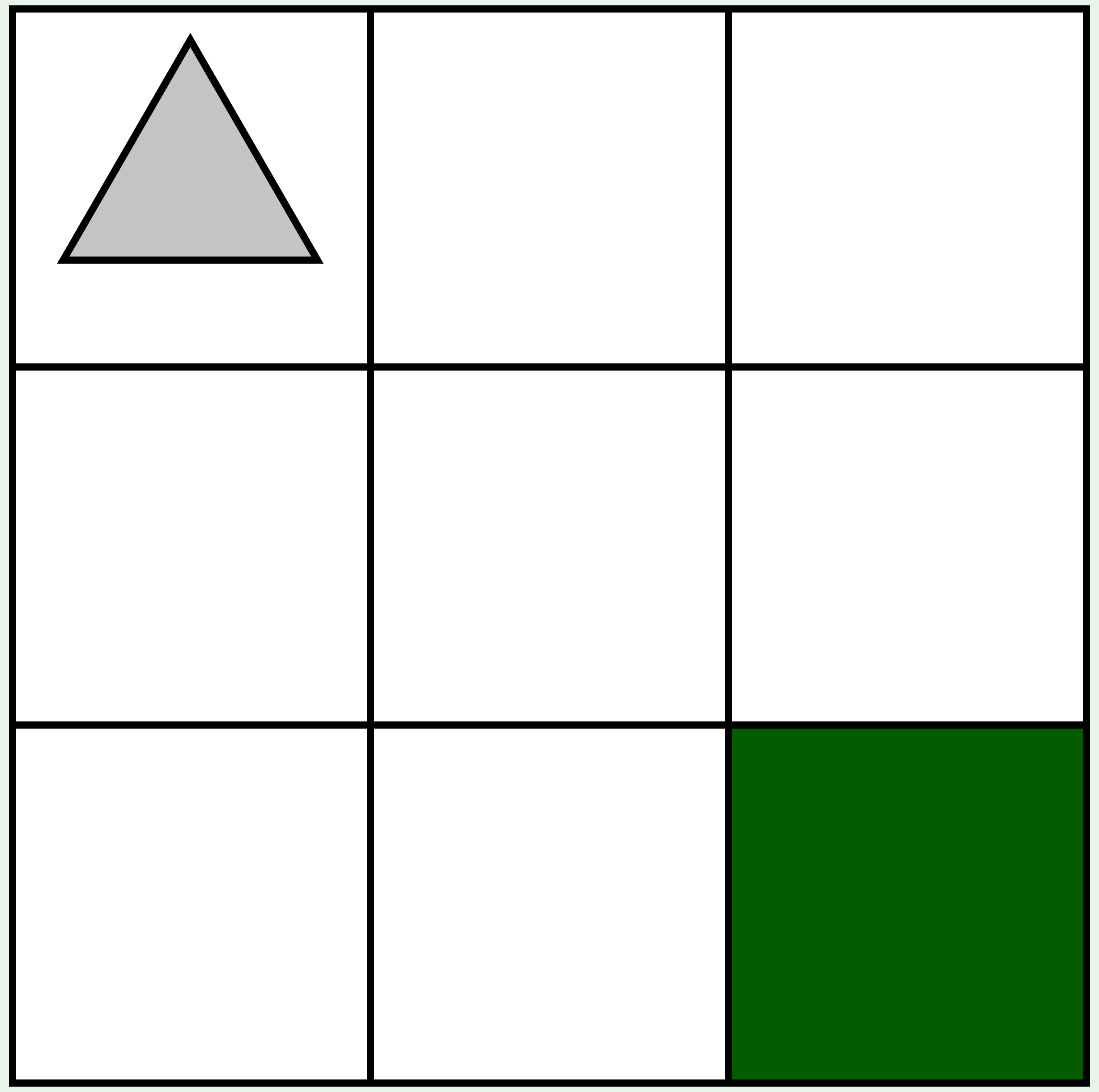
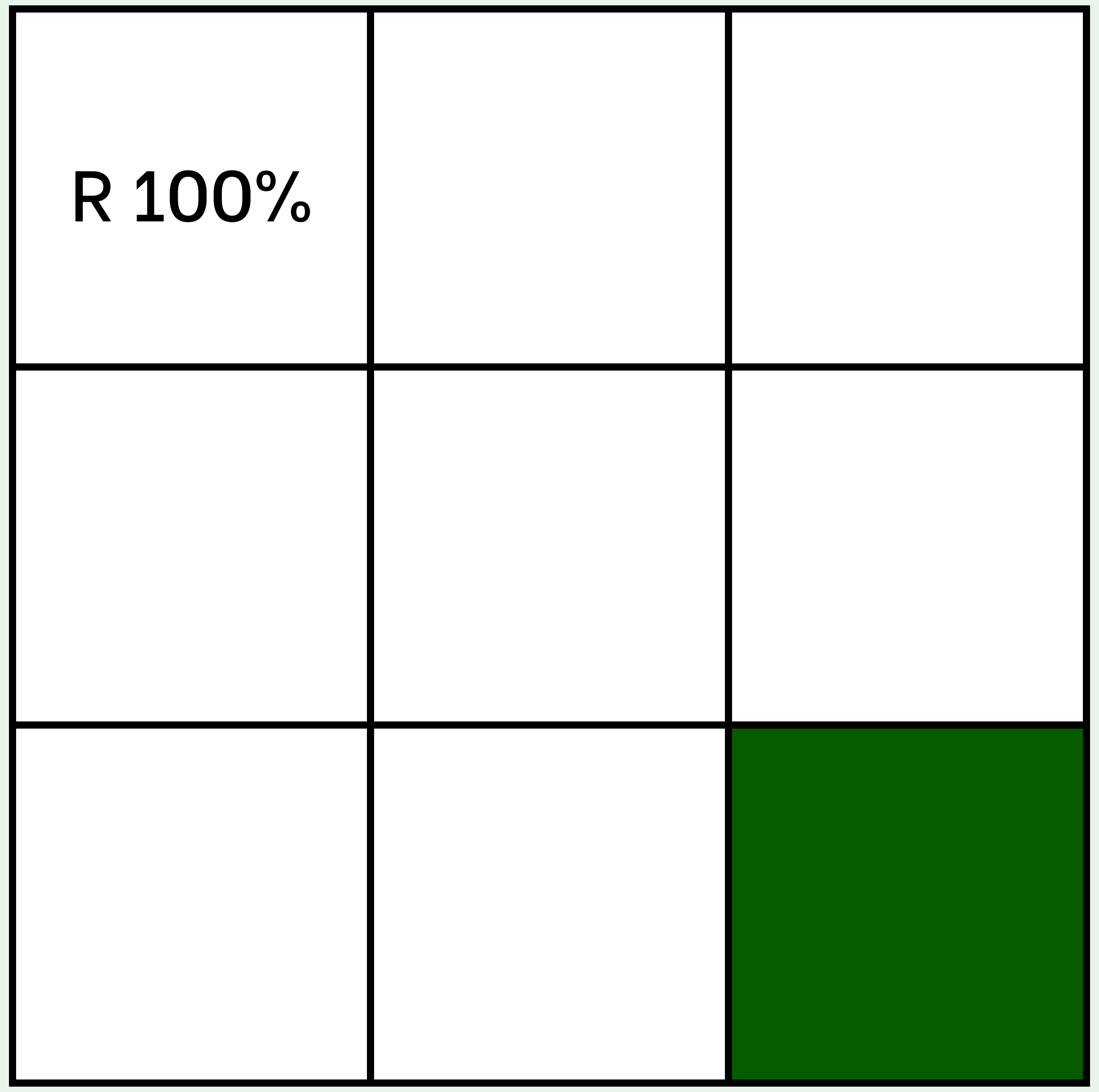
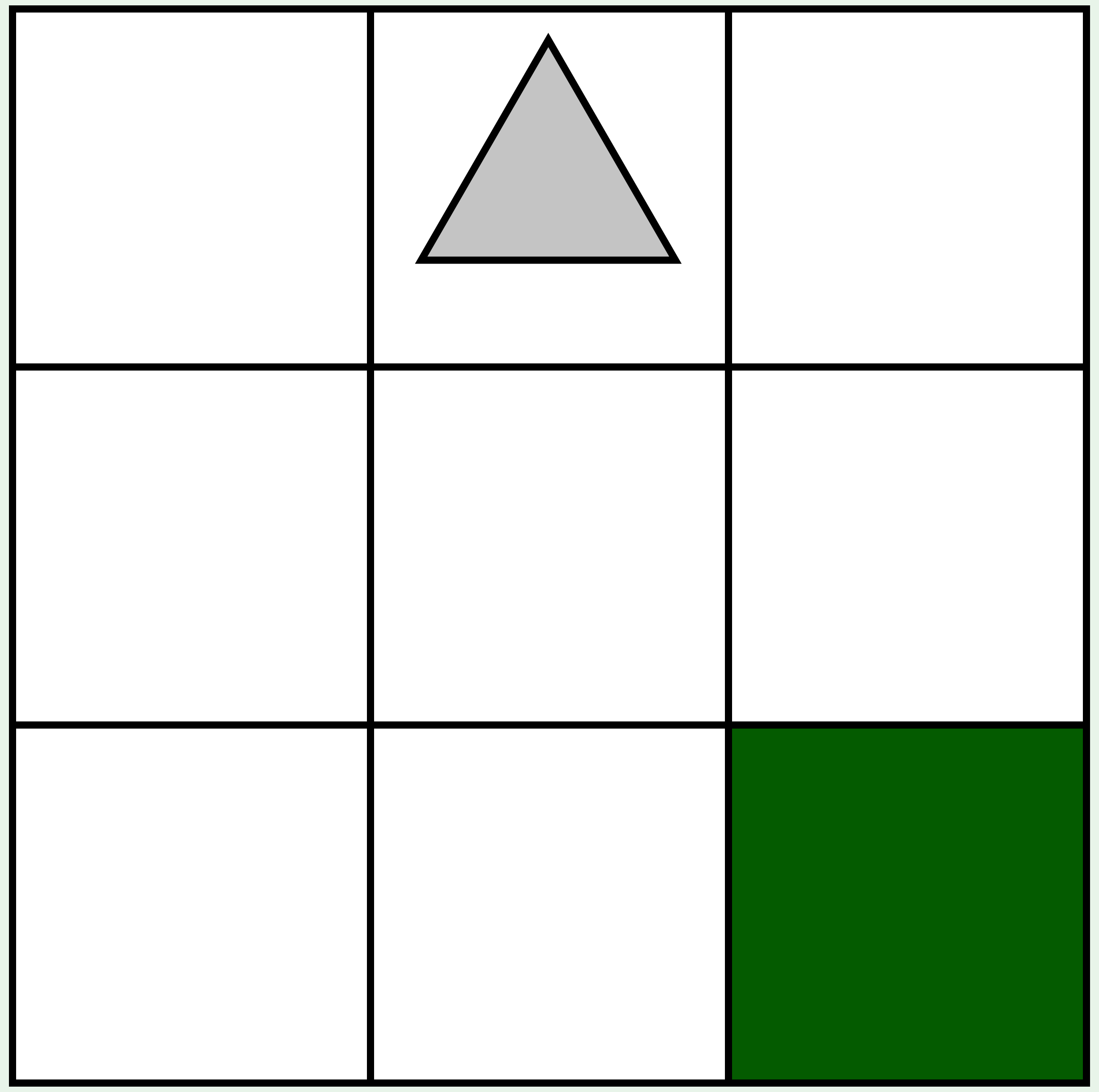
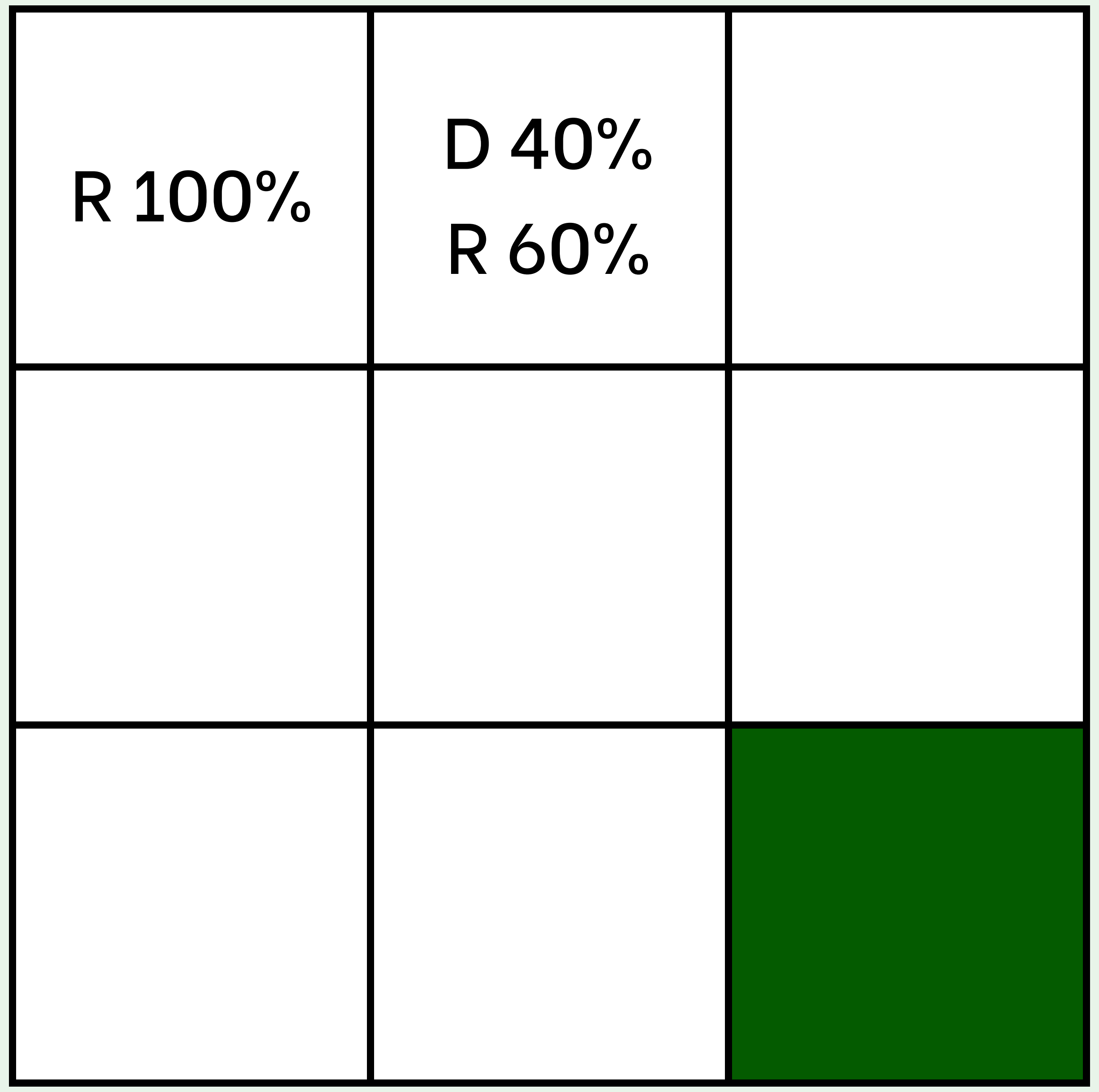
Heatmaps Creation #1





Heatmaps Creation #1





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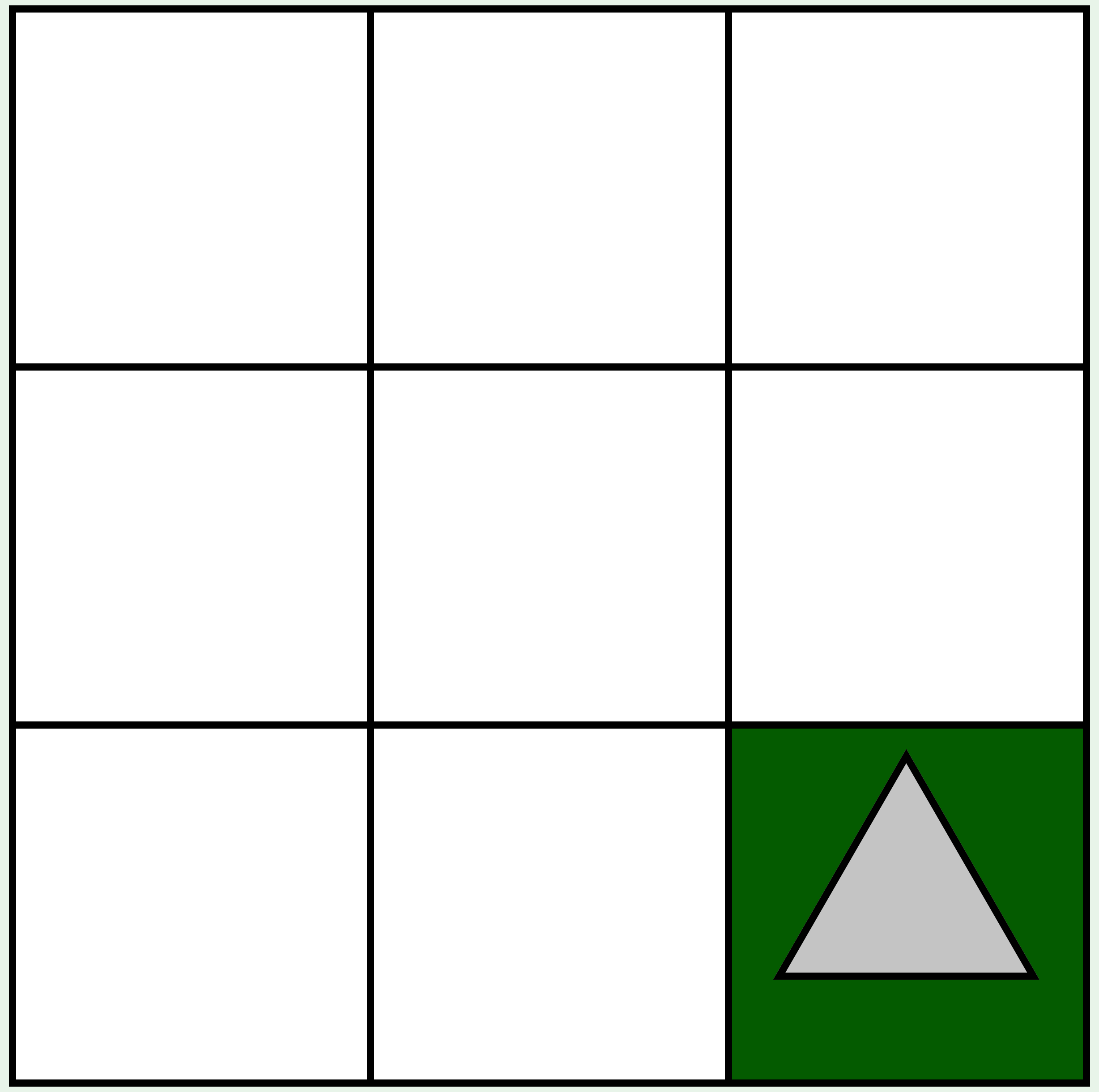


R 100%	D 40% R 60%	D 35% R 65%
D 5% R 95%	D 5% R 95%	D 30% R 70%
D 5% U 7% R 88%	D 5% R 95%	

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

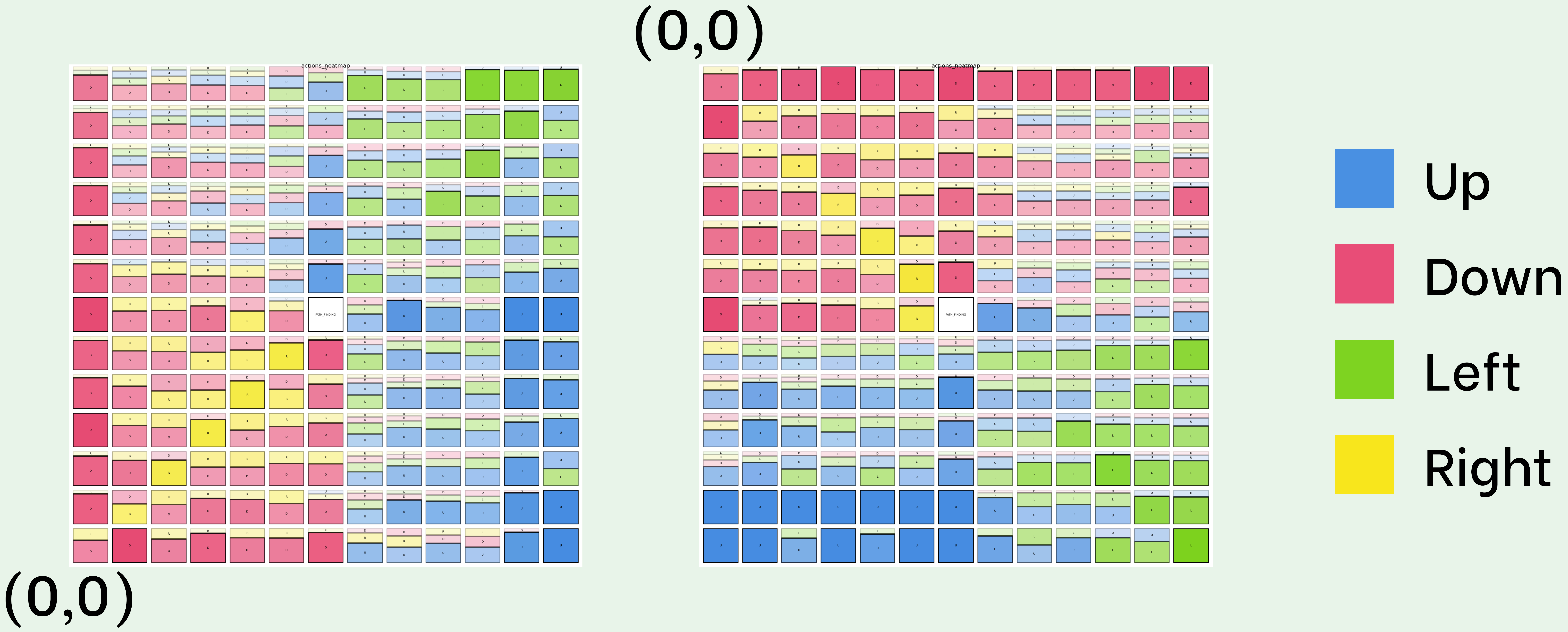
Retains the Conversation History

Our Findings

Map Orientation

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

Map Orientation



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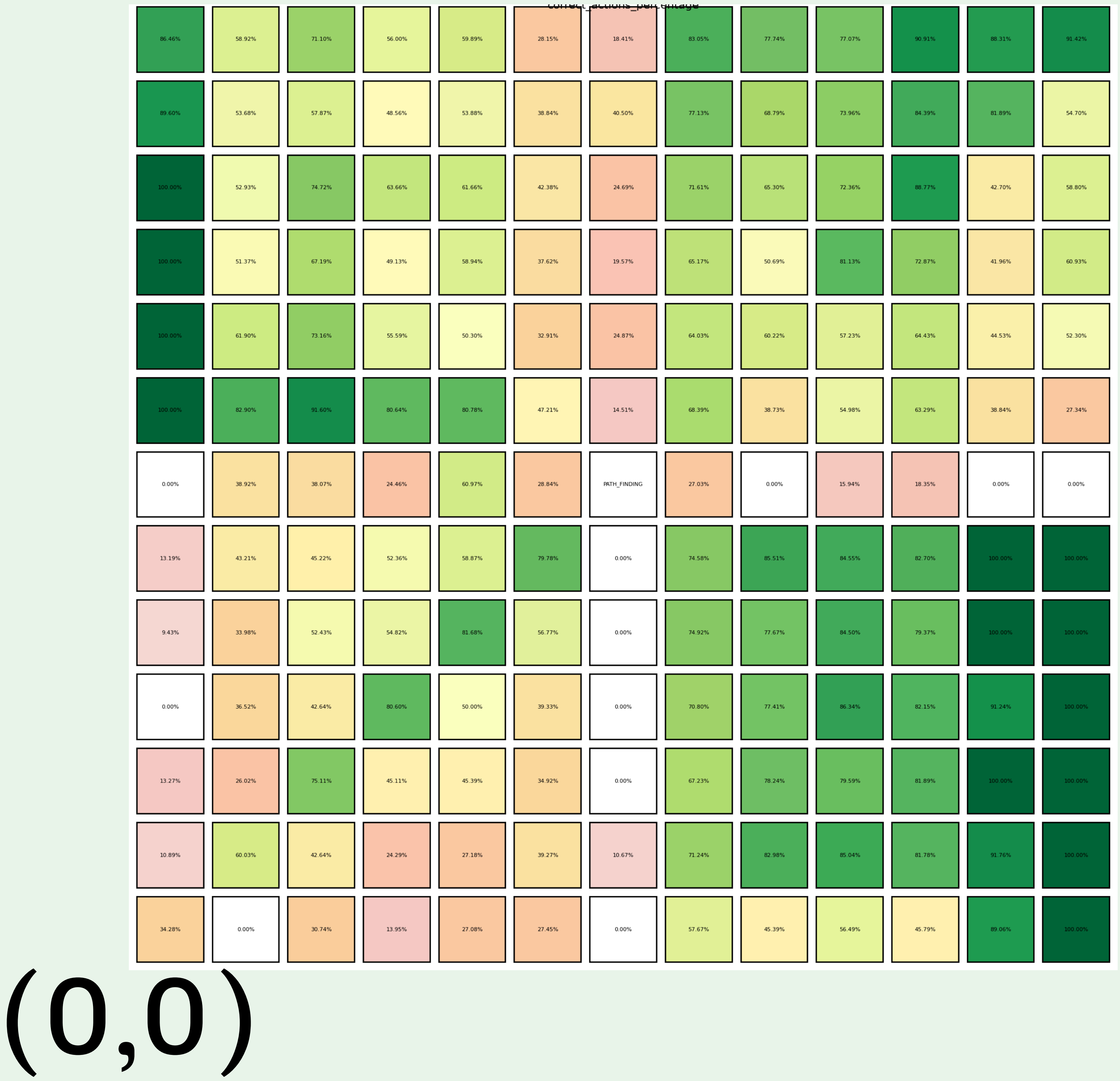
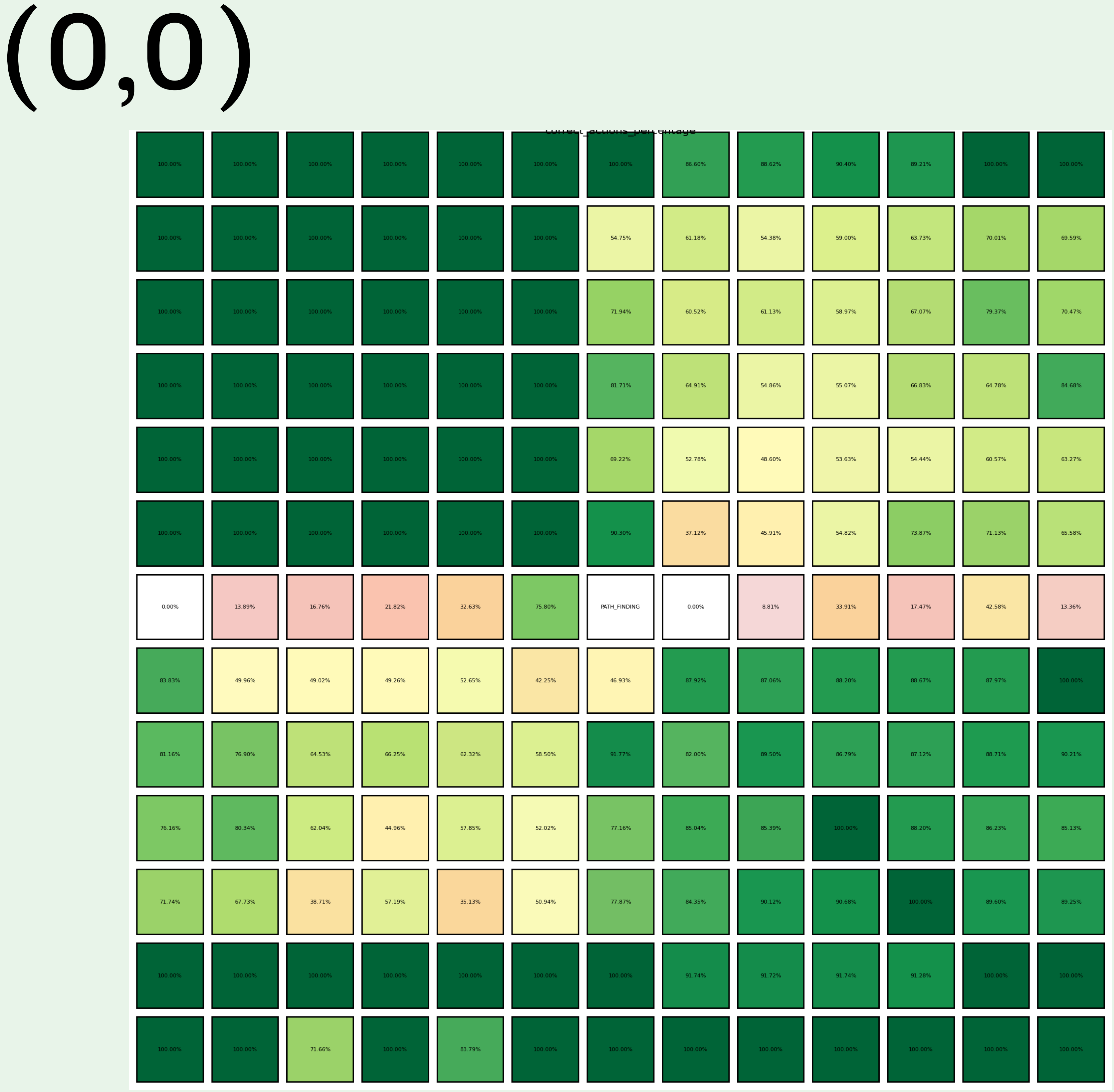
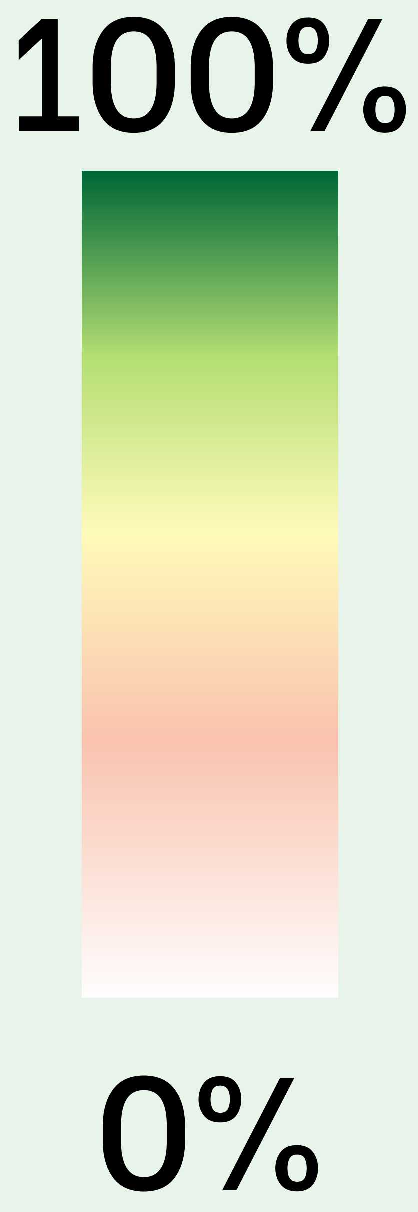
Map Orientation



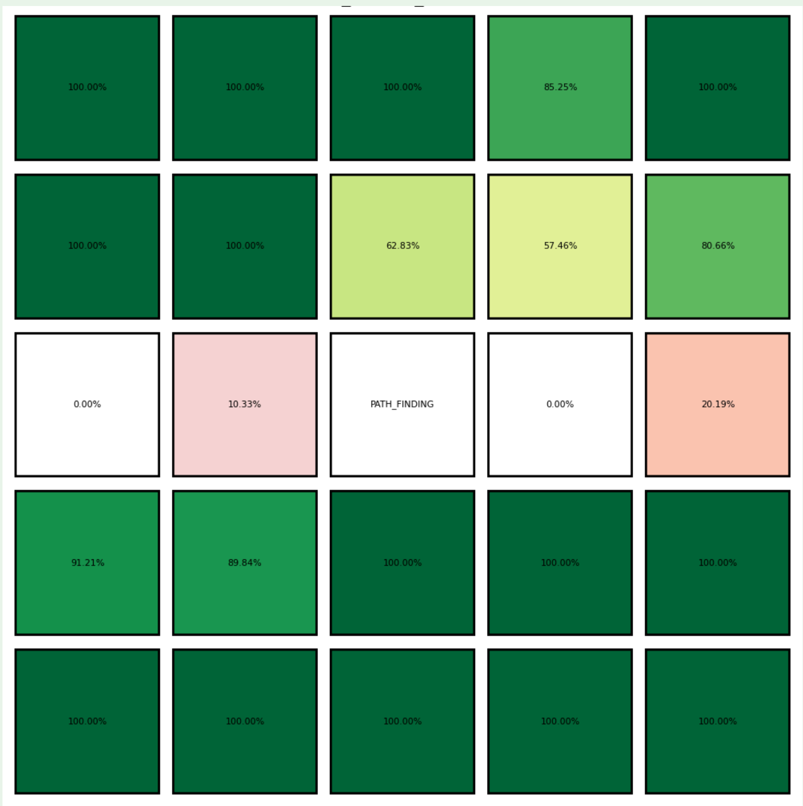


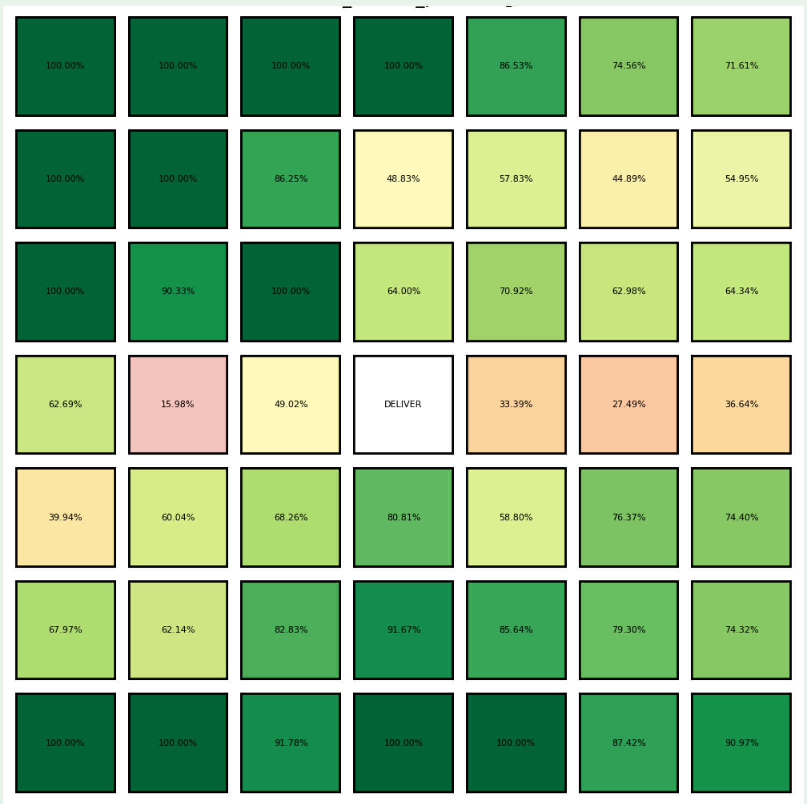


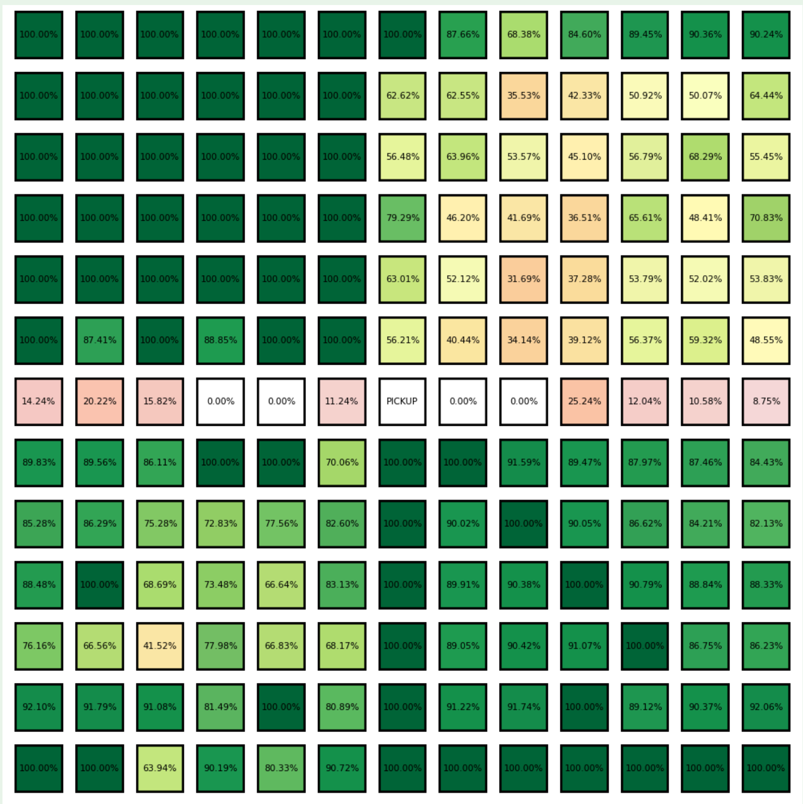
Map Orientation

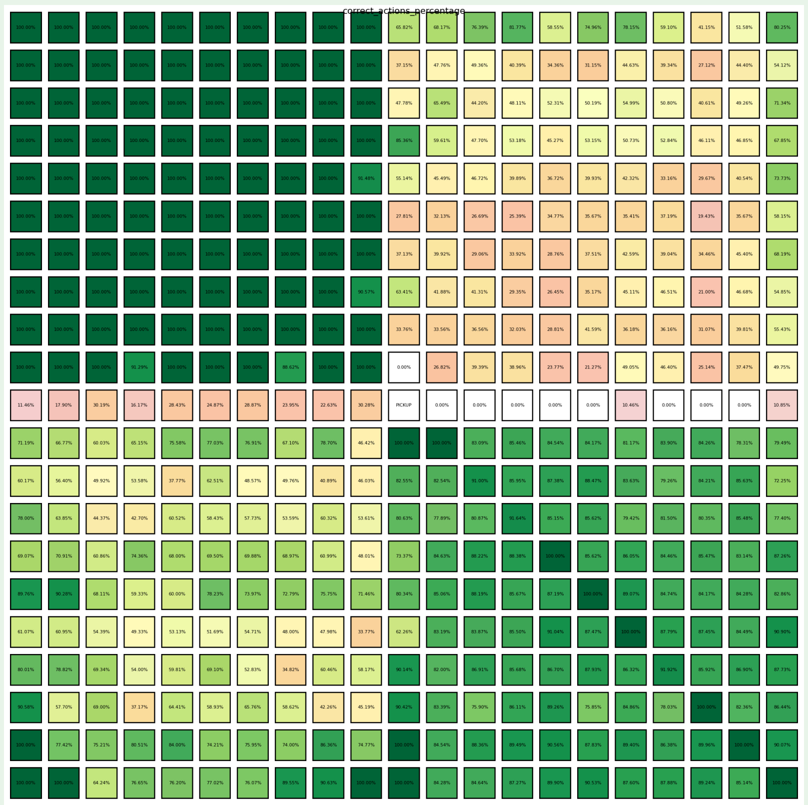
	Bottom-Left Origin	Top-Left Origin
top1%	62%	92%
top2%	92%	97%
top3%	93%	99%

Common Uncertainty Patterns #1









Common Uncertainty Patterns #1

→

Average

98%	63%
80%	88%

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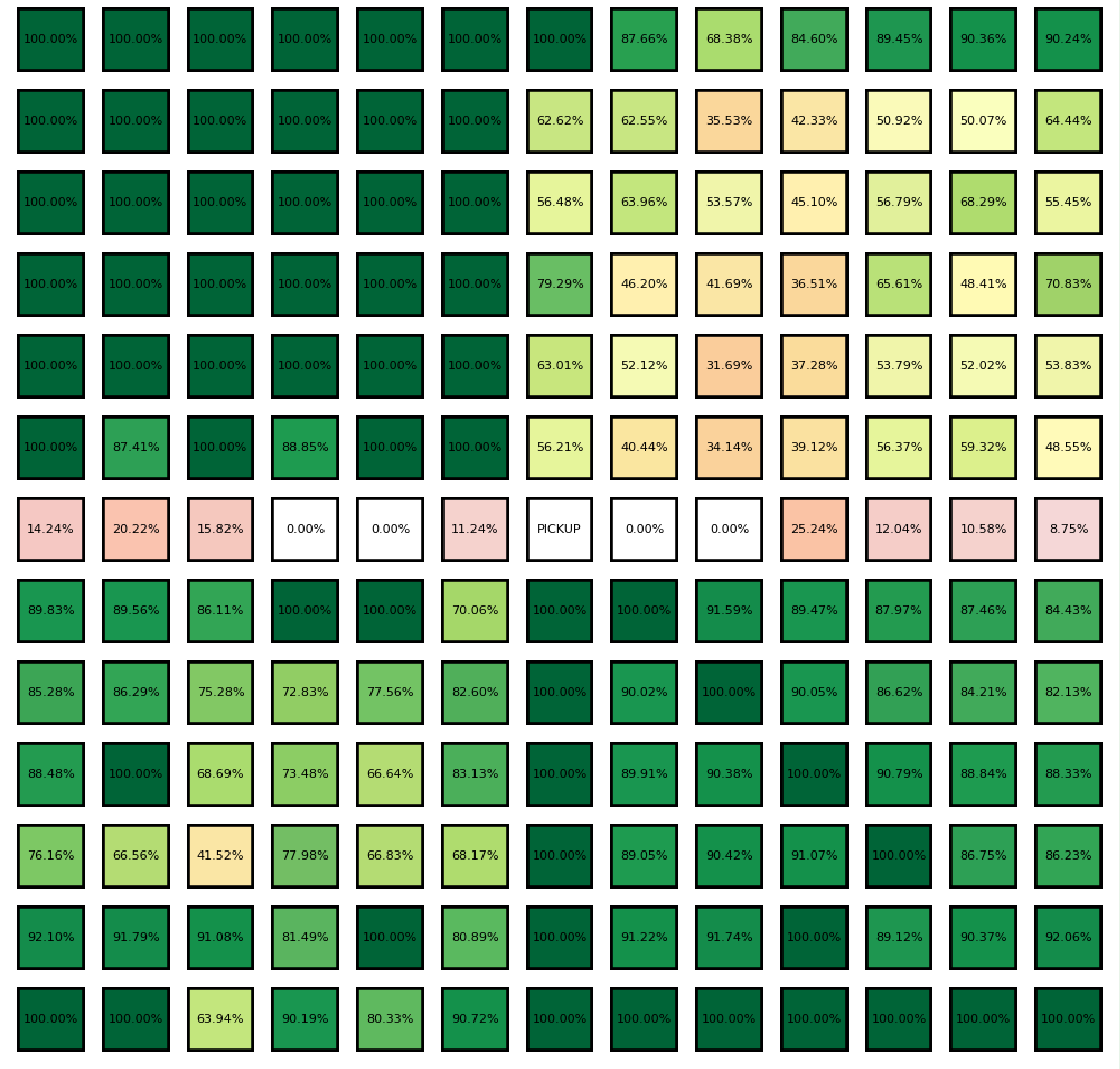
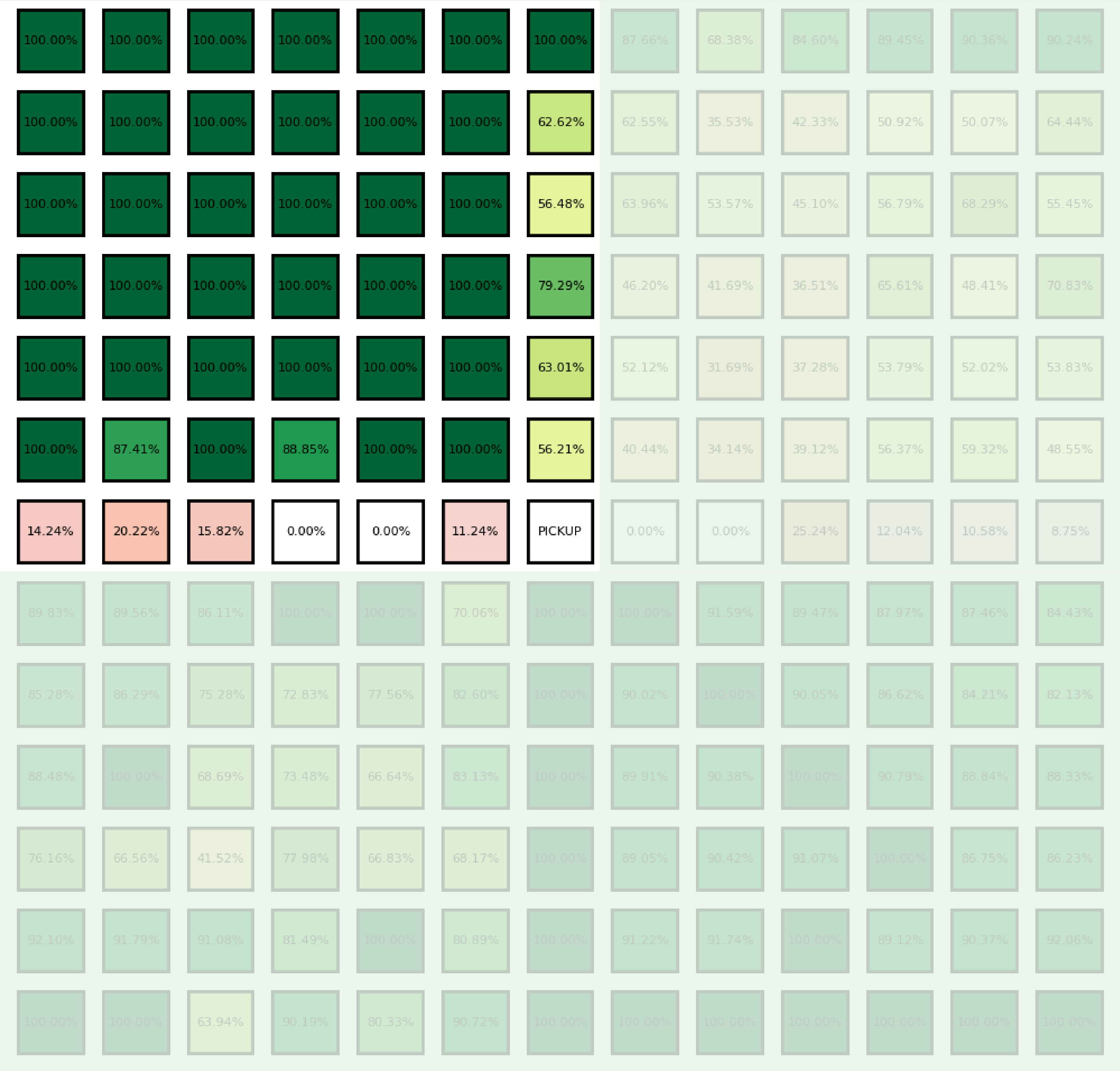
Common Uncertainty Patterns #1.1



Common Uncertainty Patterns #1.1



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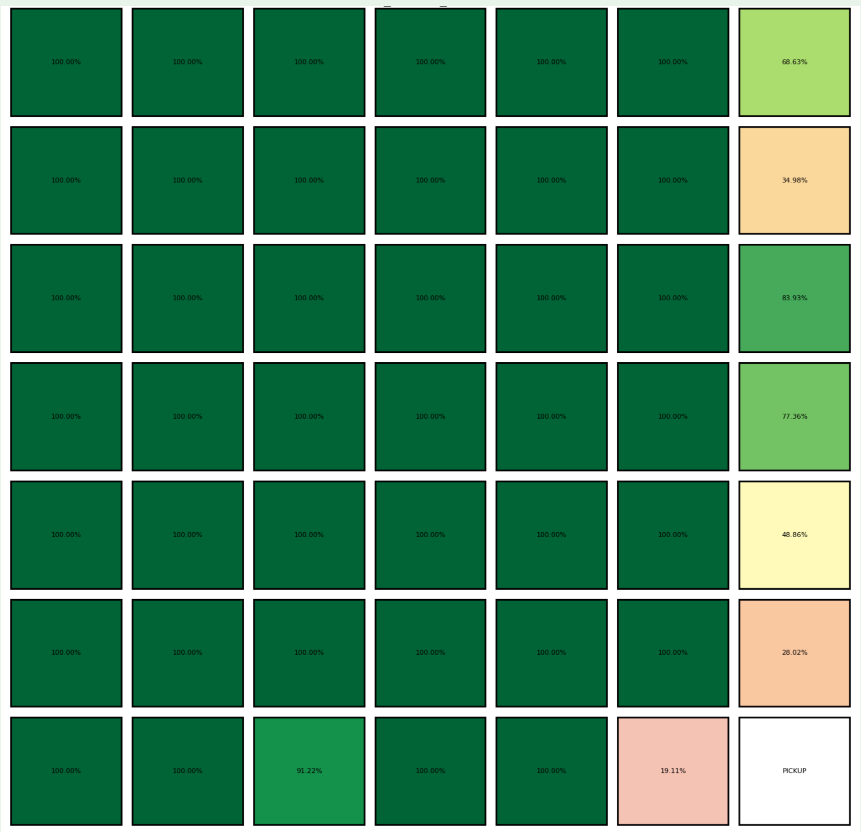

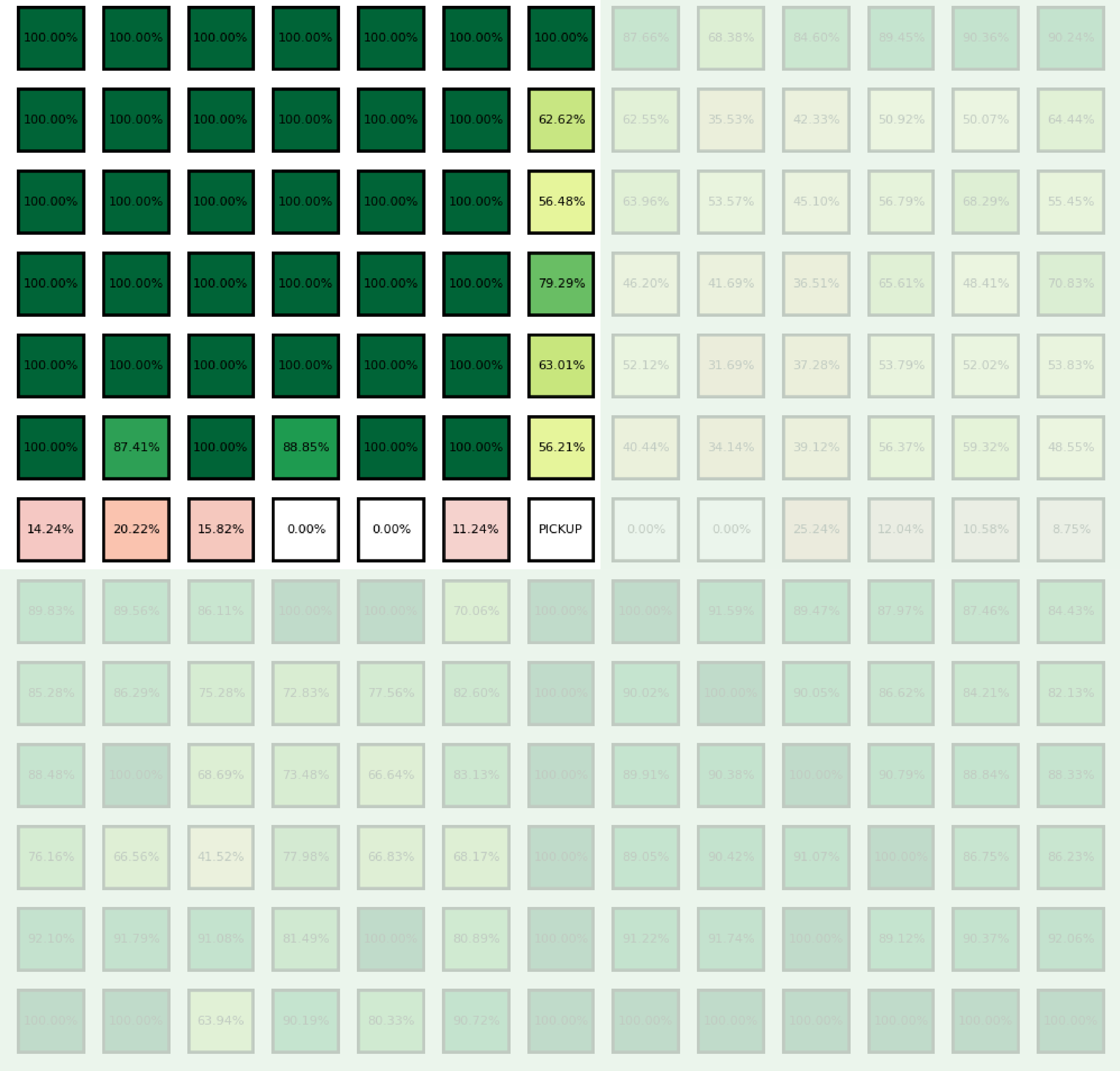

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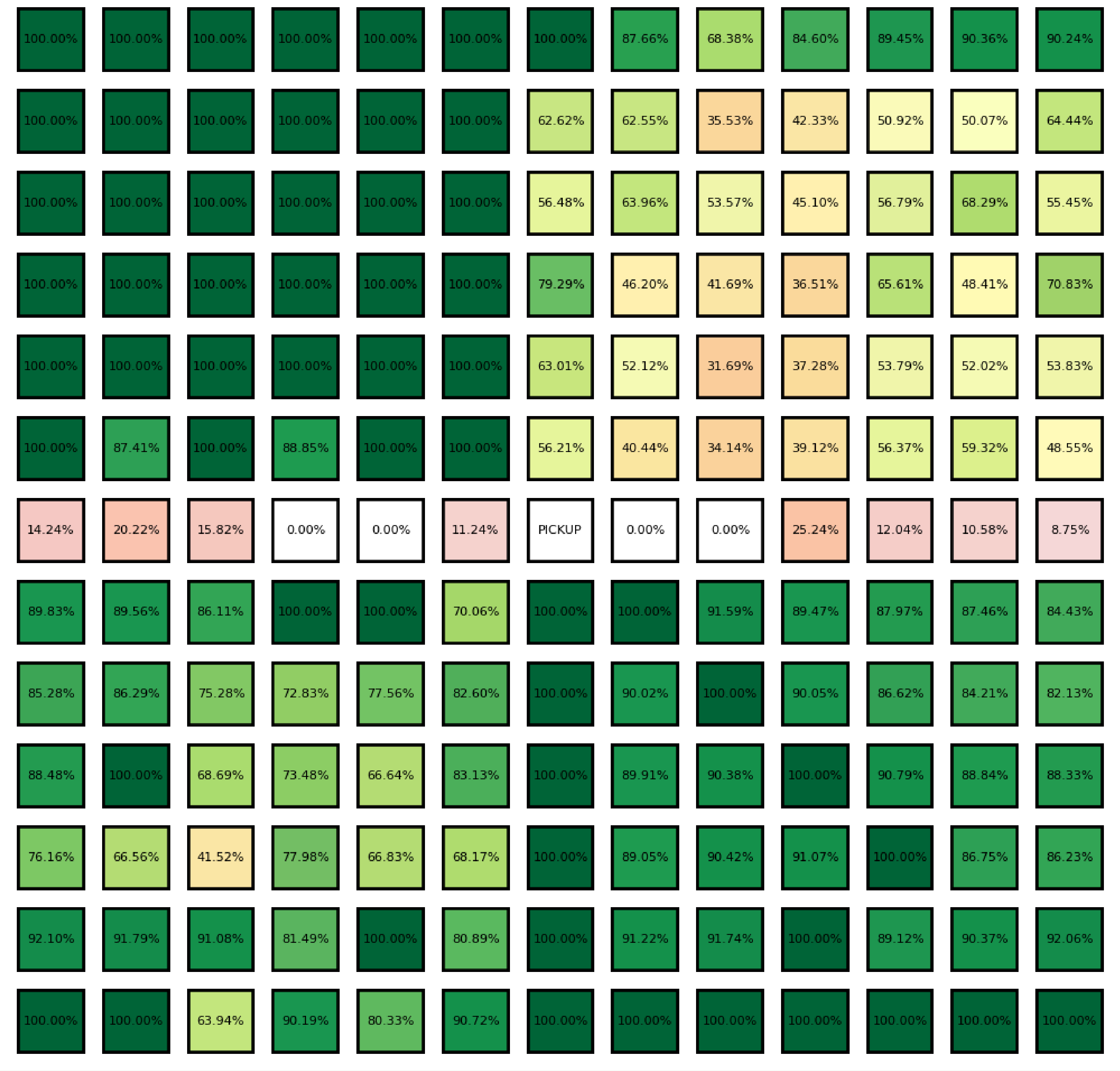
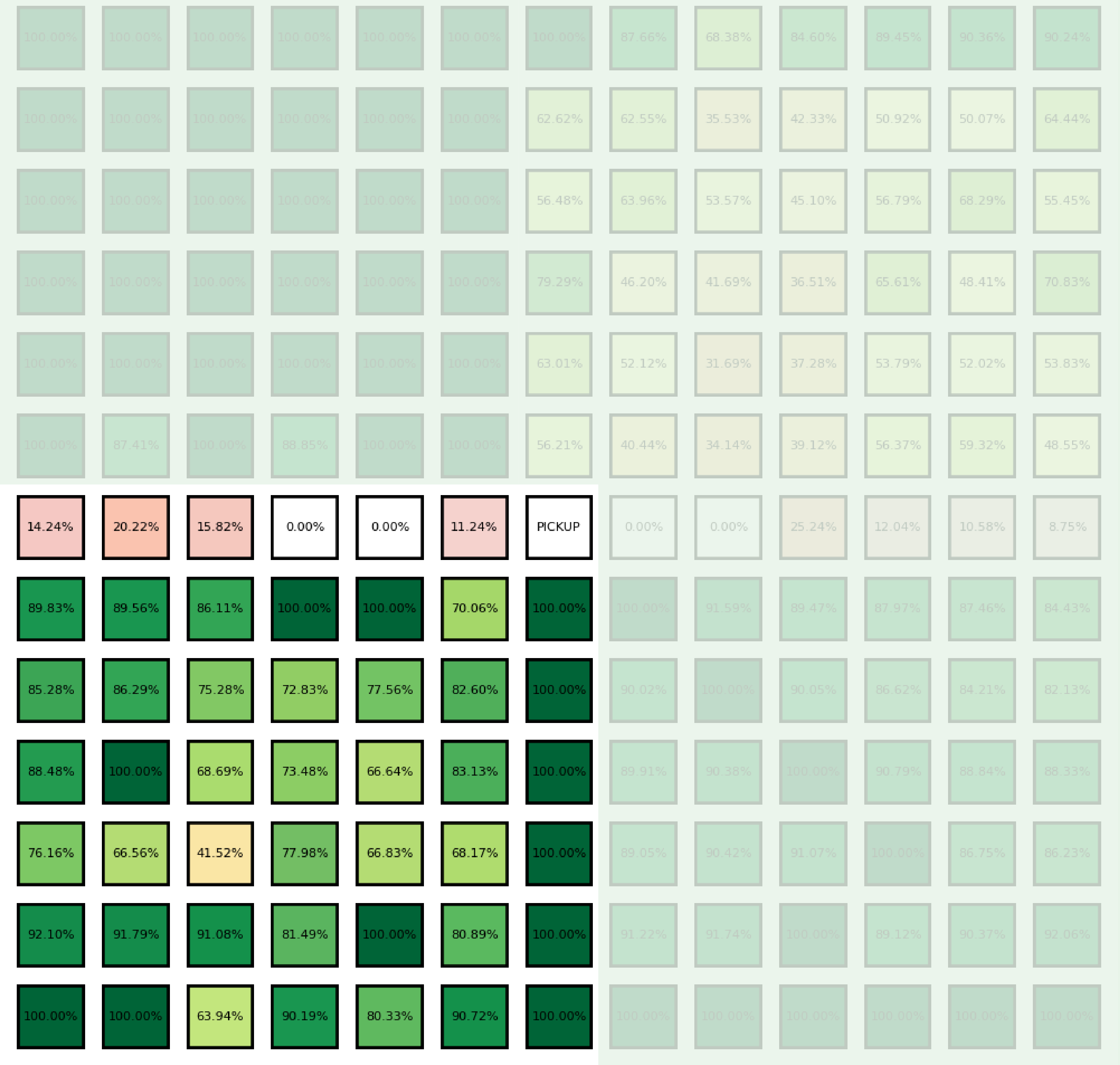
Common Uncertainty Patterns #1.2



Common Uncertainty Patterns #1.2



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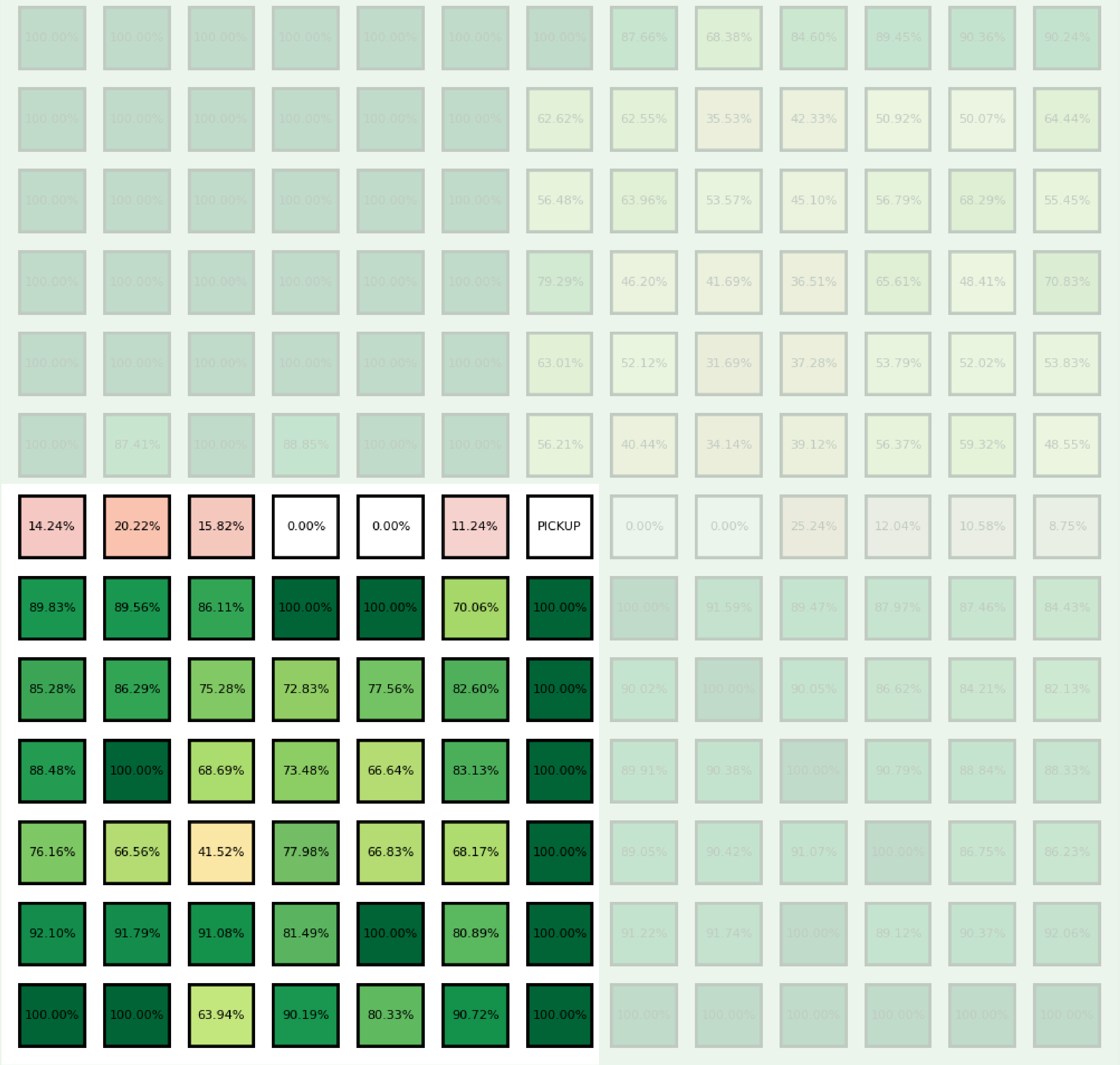
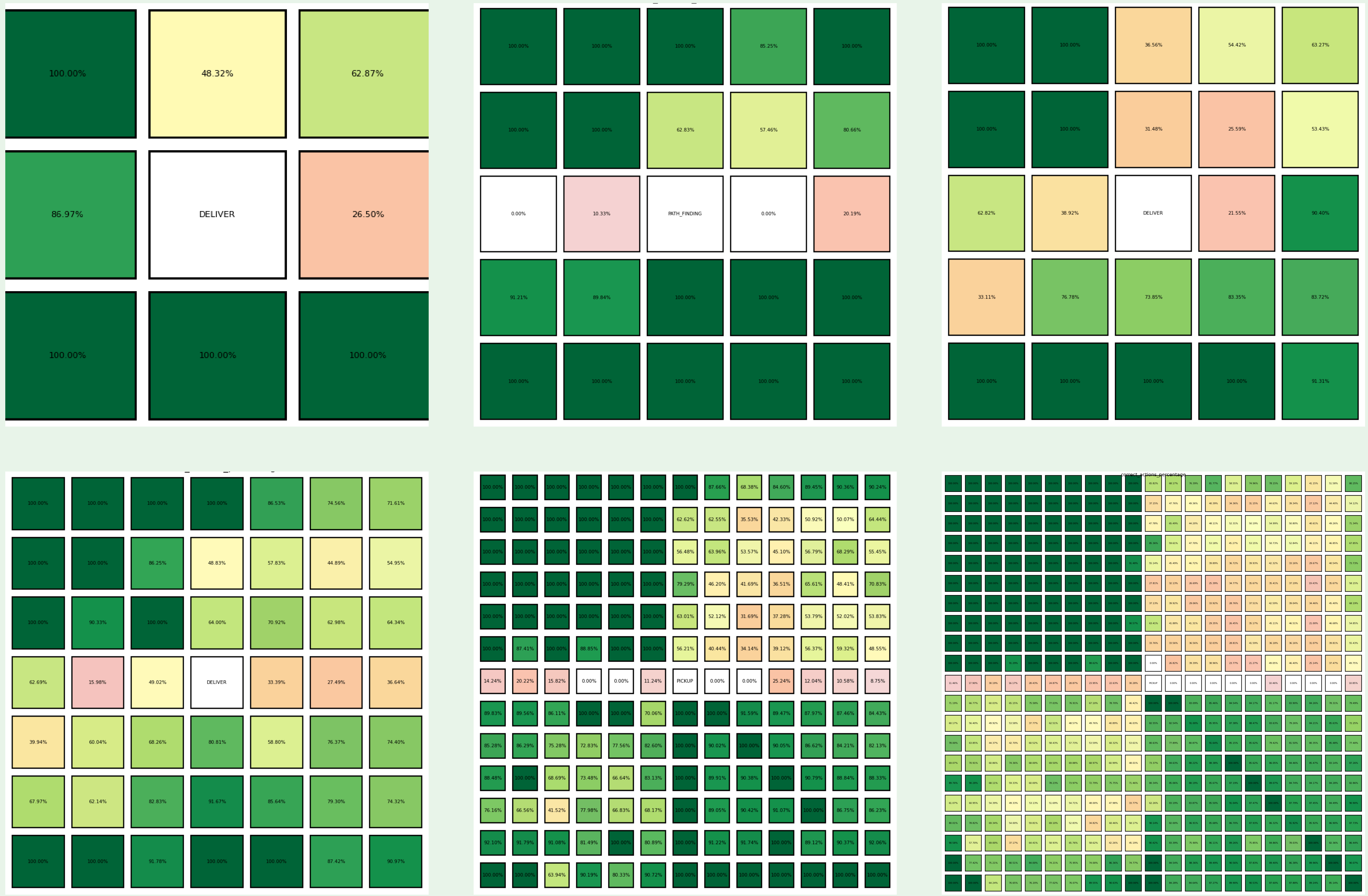
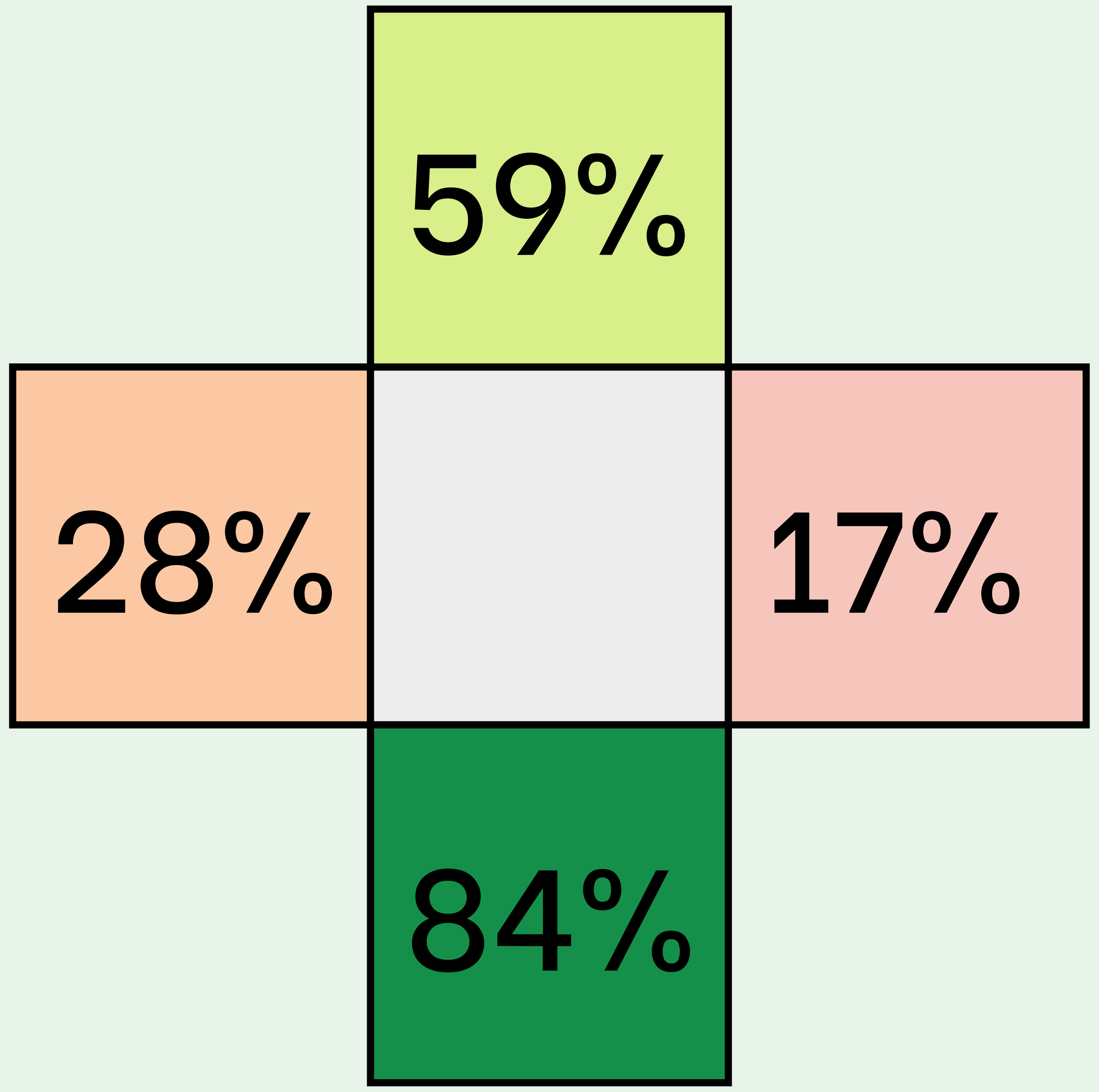


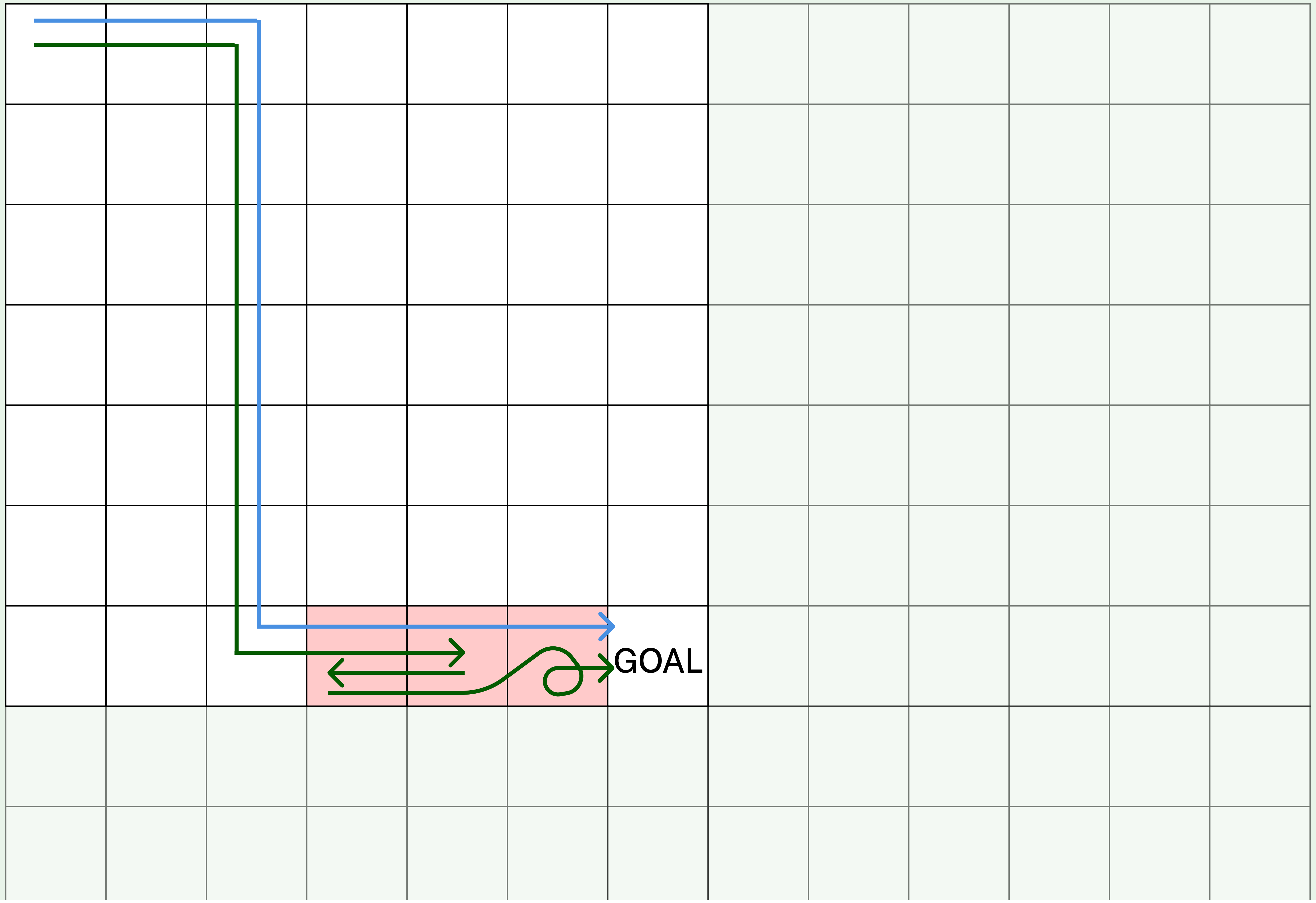
Common Uncertainty Patterns #2



Average



Stateful Example



Optimal path

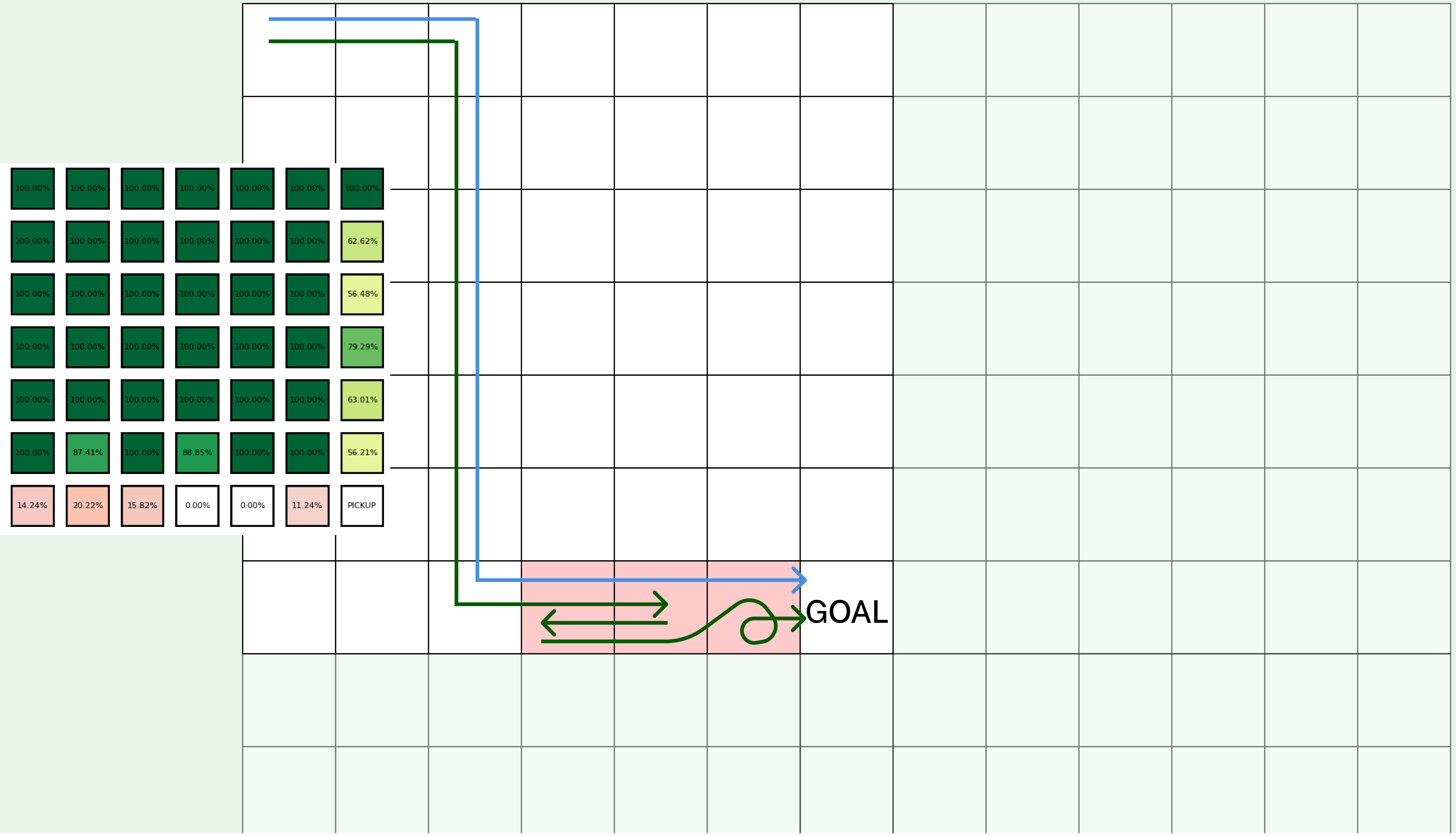
Our path

Repeated cells

Shared Nodes: 100%

Ratio: 81%

Stateful Example



Optimal path

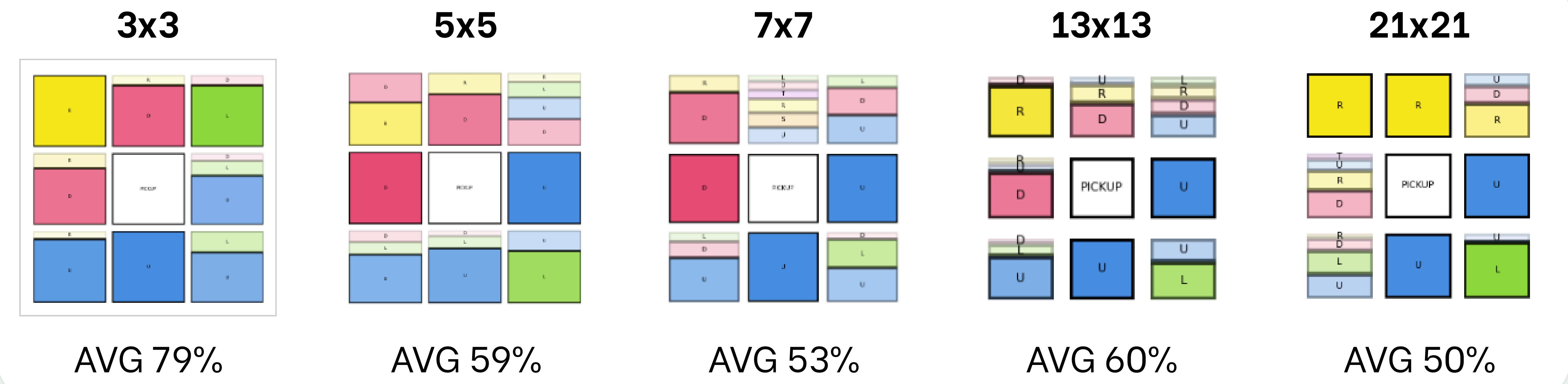
Our path

Repeated cells

Shared Nodes: 100%

Ratio: 81%

Central difference



Average

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

Standard Deviation

0	33	24
12	GOAL	8
17	10	4

Conclusions

Strengths

Feasibility

History helps ~ 20% less actions

Retrieving goals in big maps

Better models, better results

Same % error as the size increase

Weaknesses

Limited Explainability

Prone to error near the goal

Consistent problematic zones

Context size is a limitation

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

Thank You

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