Exploring the Use of LLMs for Agent Planning

Strengths and Weaknesses

DAVIDE MODOLO
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Supervisor PAOLO GIORGINI

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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

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Text Generation

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Planning Abilities

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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

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Reasoning[1]

Few-Shots

Prompting[2]

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LLM-based Planning

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Few-Shots
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Fine-Tuning
Models[3]

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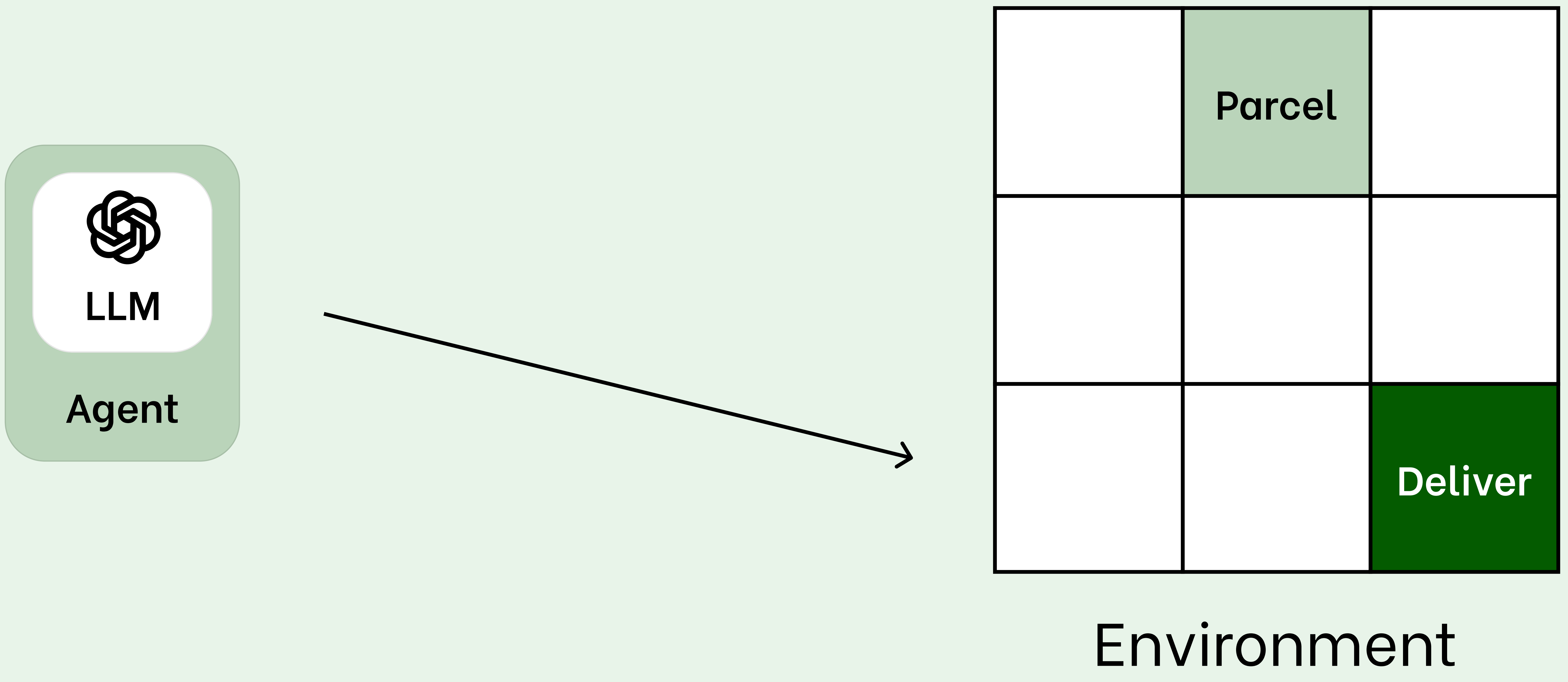
Research Questions

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's generative capabilites make sequential decisions in such environments?

Idea

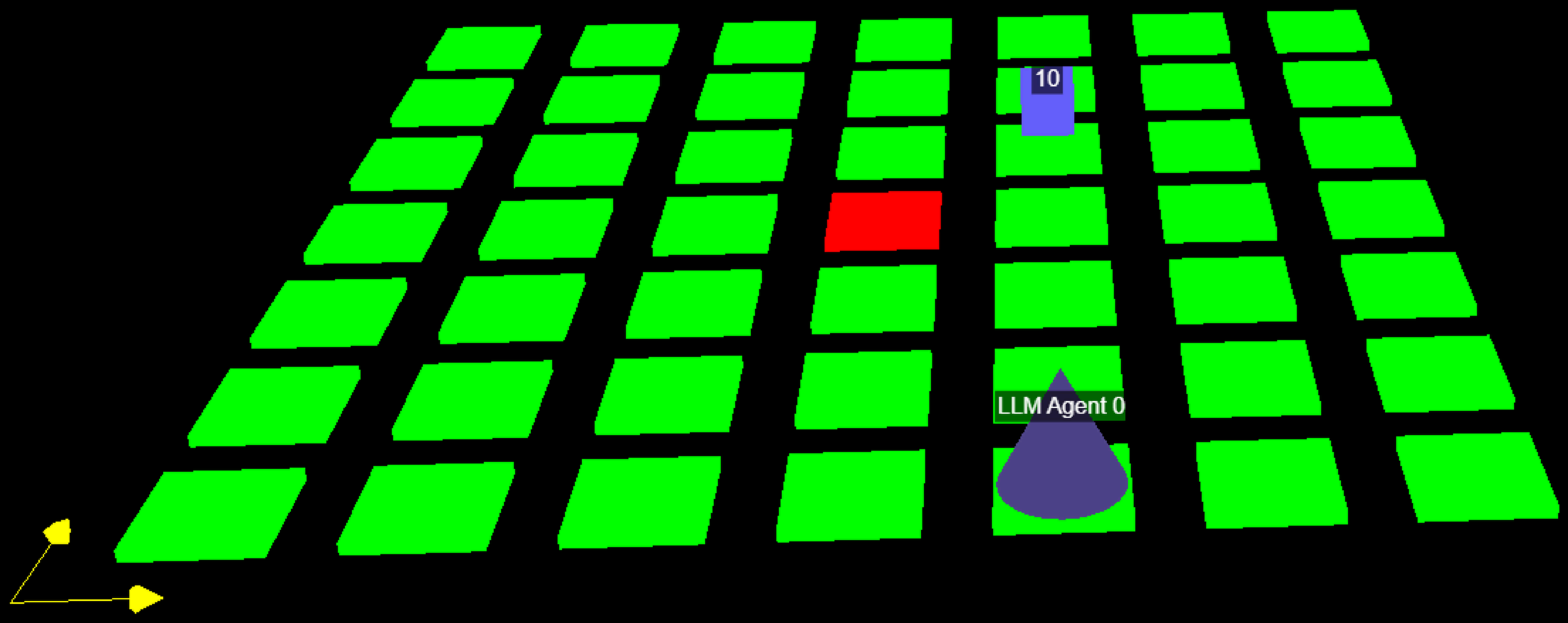


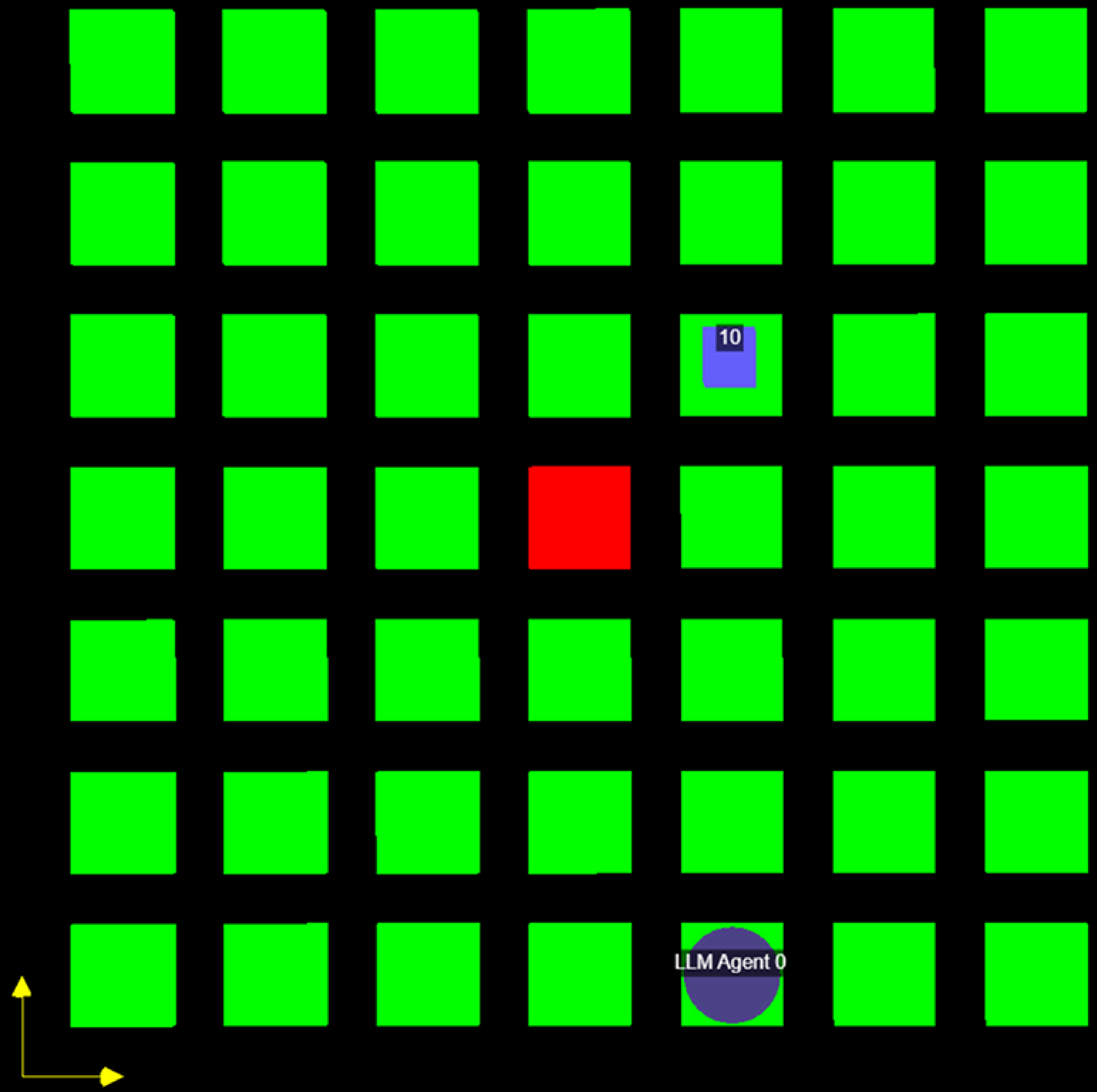
Setting

Deliveroo.js

Educational Game

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





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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?

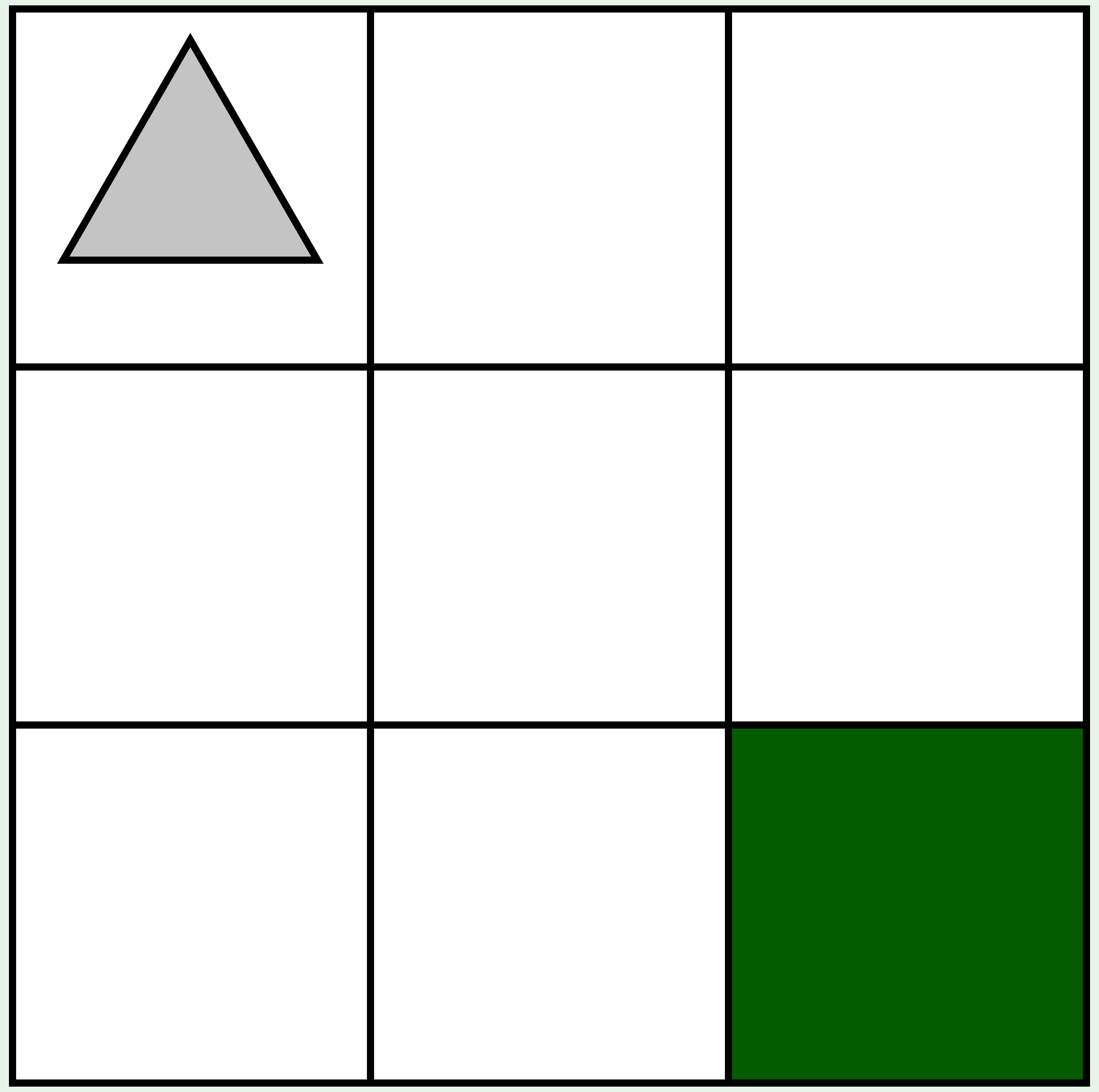
Model

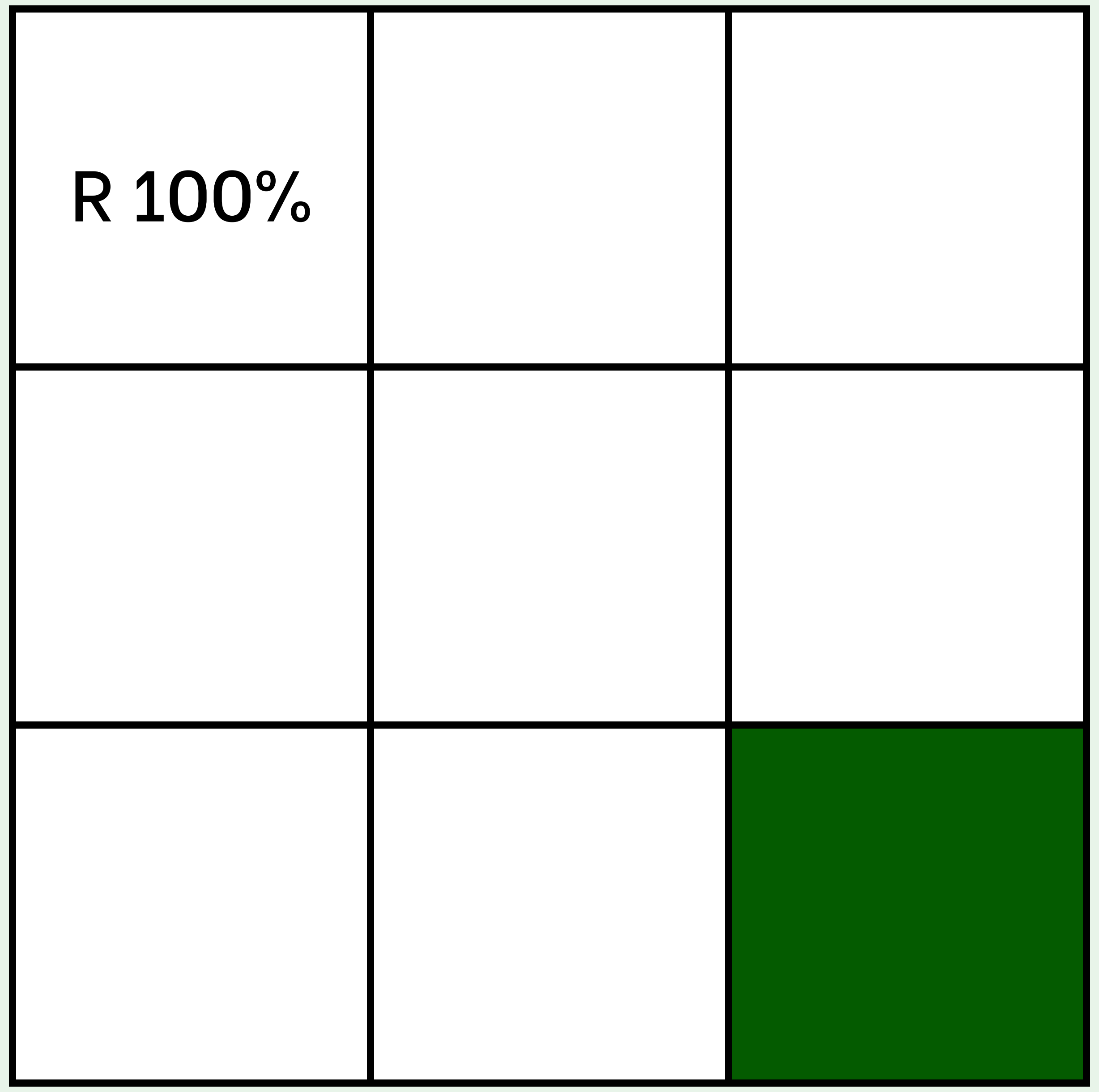
- OpenAI models
- GPT-4o was the best
- GPT-4o-mini selected for price/performance

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

Data Collection

Heatmaps Creation #1





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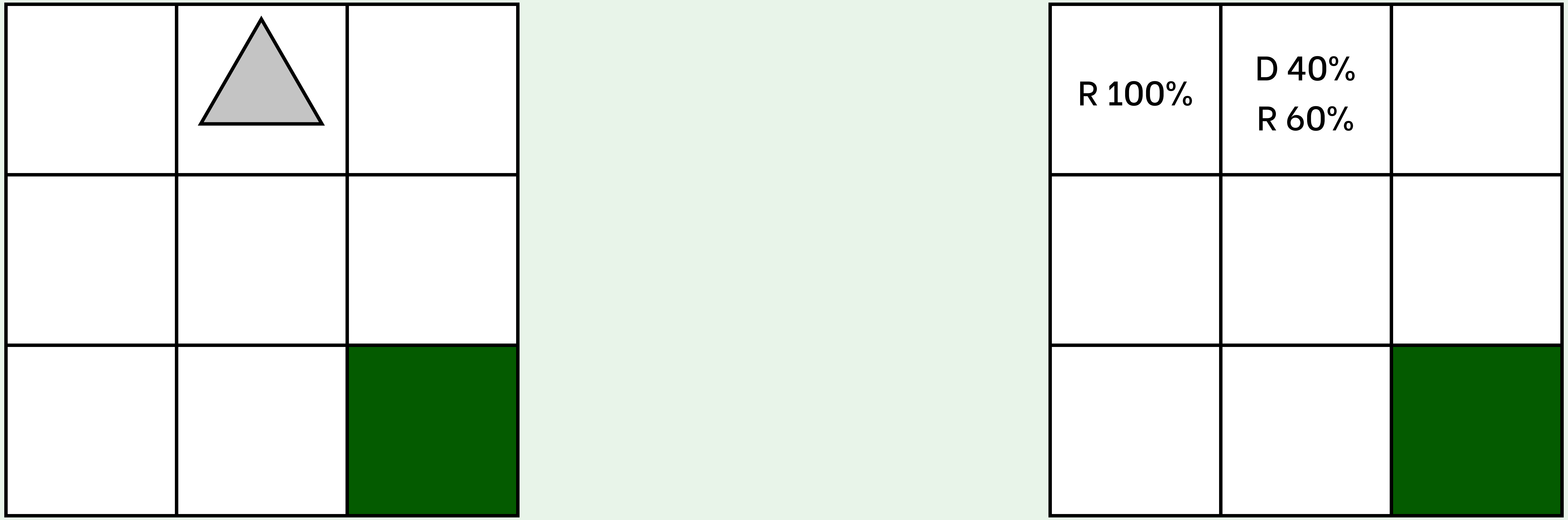

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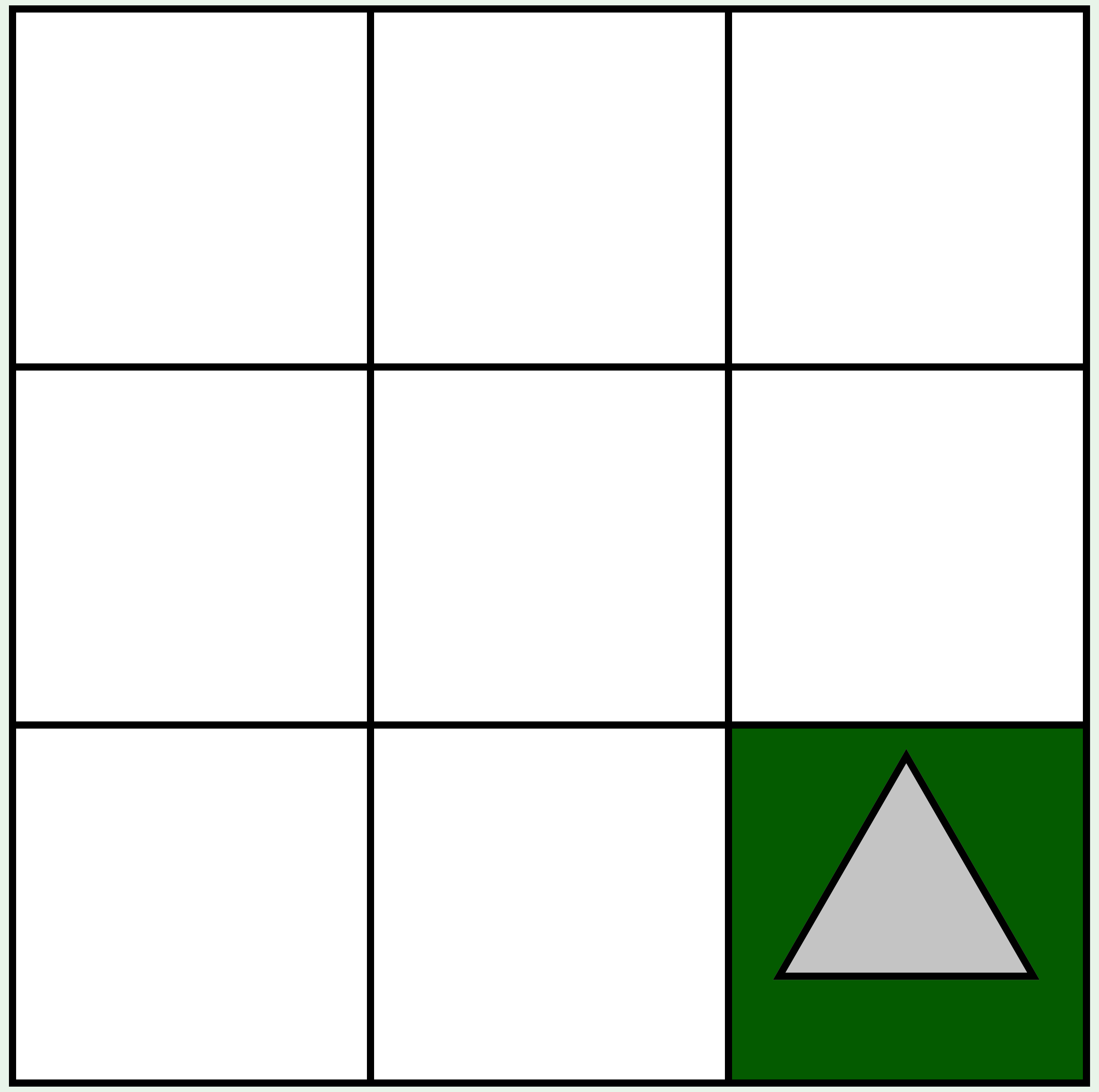


R 100%	D 40% R 60%	D 35% R 65%
D 5% R 95%	D 5% R 95%	D 30% R 70%
D 5% U 7% R 88%	D 5% R 95%	

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

Pickup

Goal tile identified in map description

Deliver

Goal tile identified in map description

Average top1%
87%

Average top1%
81%

Testing Strategy

Agents

Stateless

Each iteration a new instance

Stateful

Retains the Conversation History

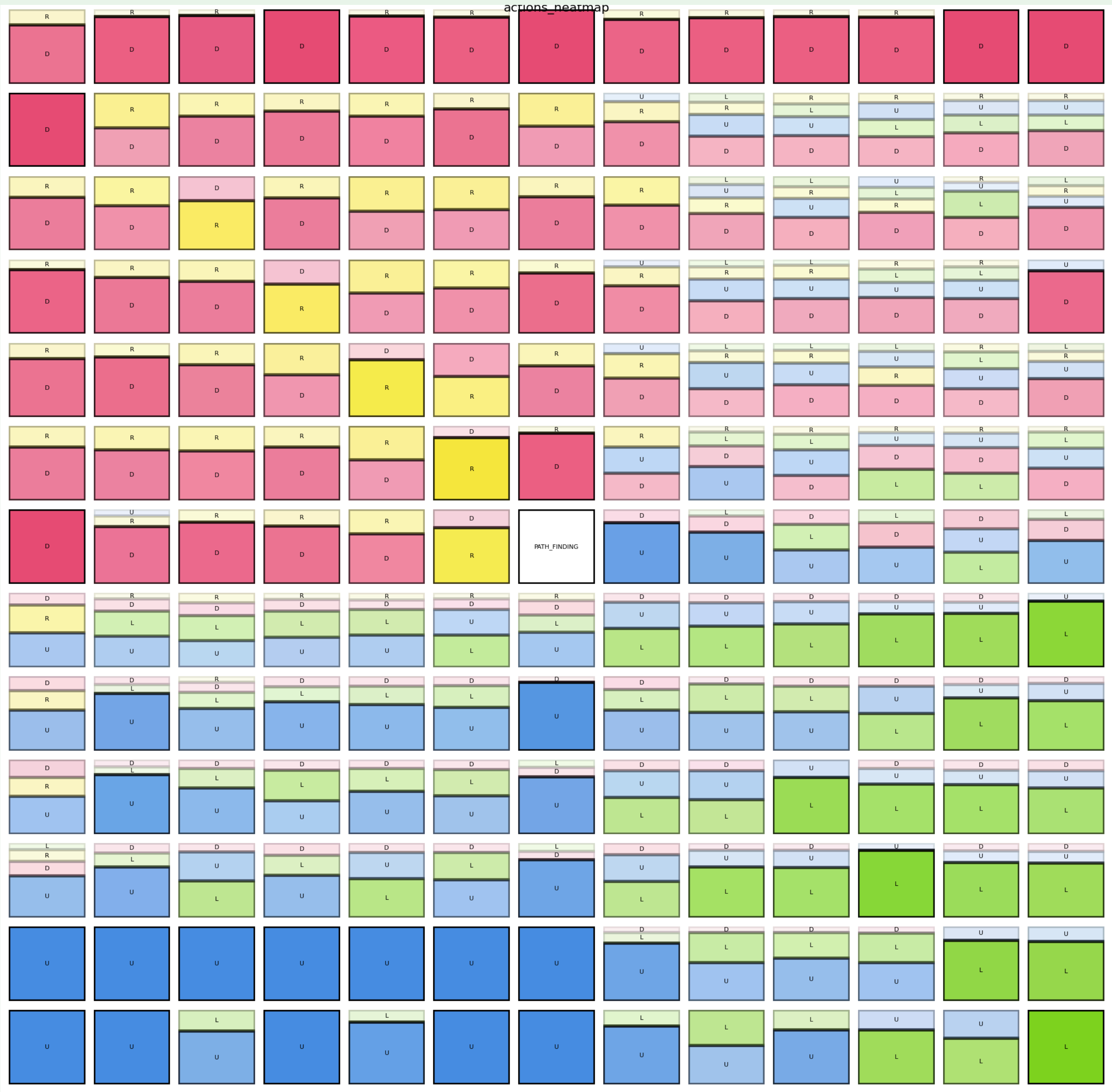
Our Findings

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

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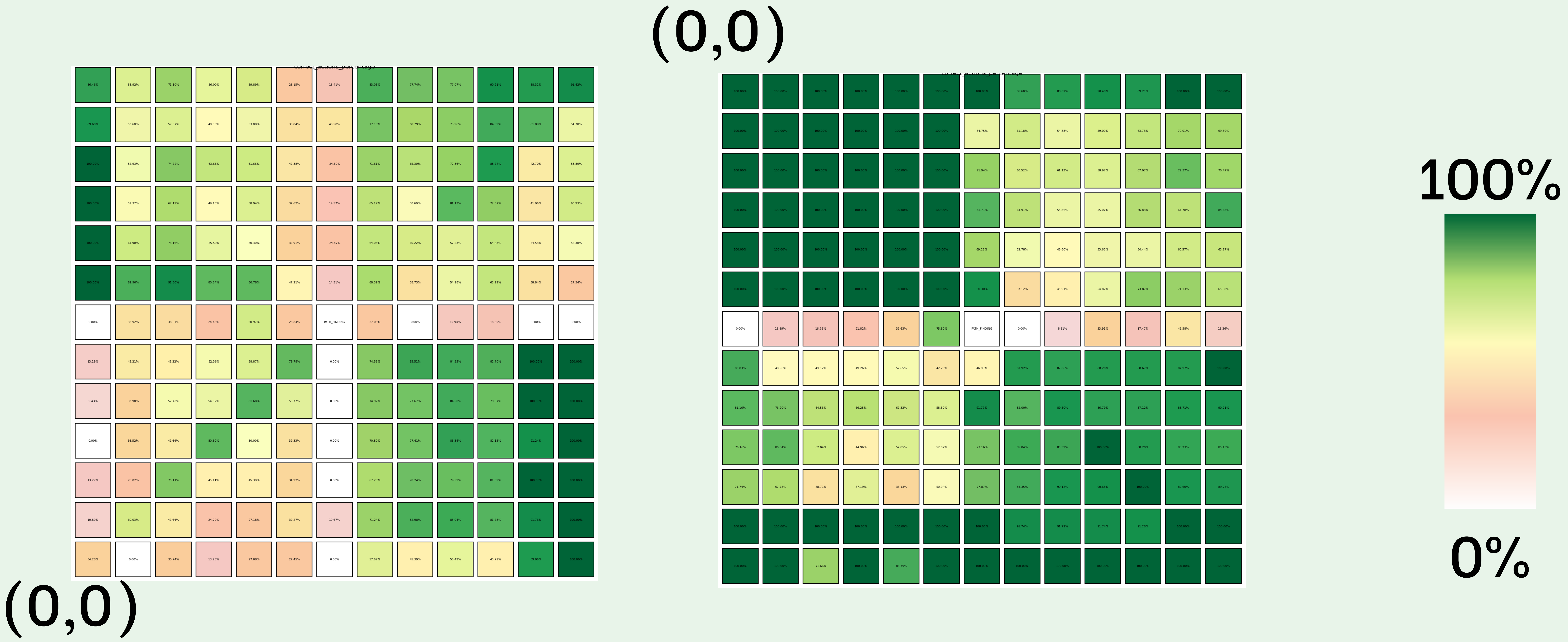
Map Orientation

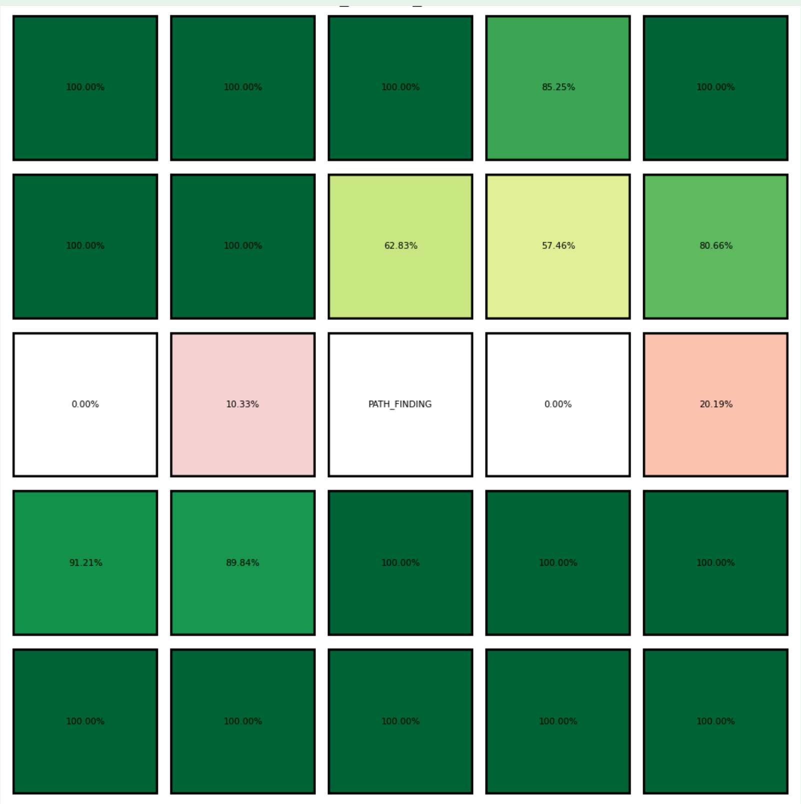


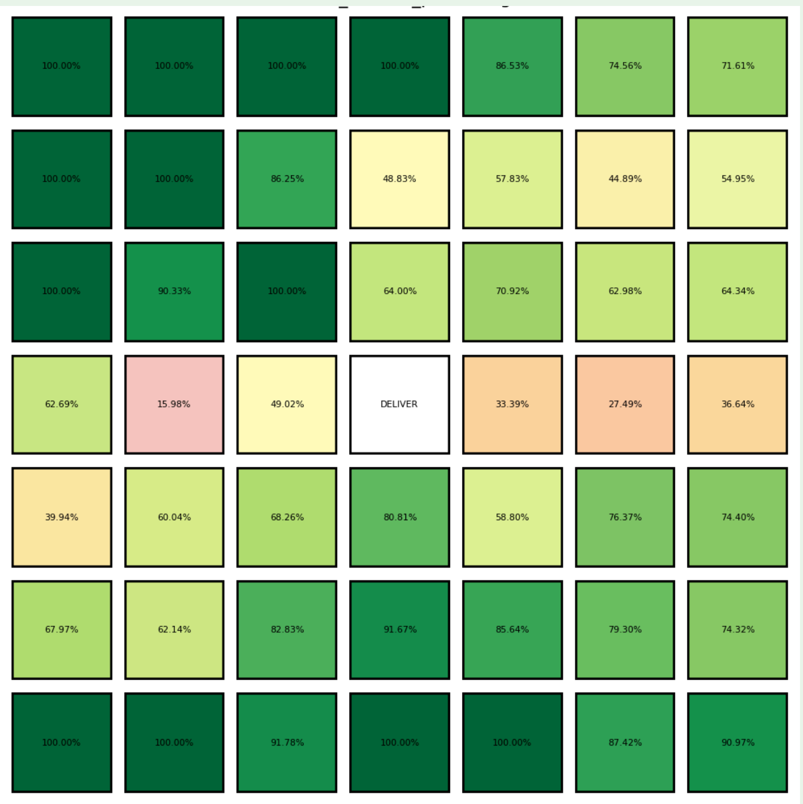
Map Orientation

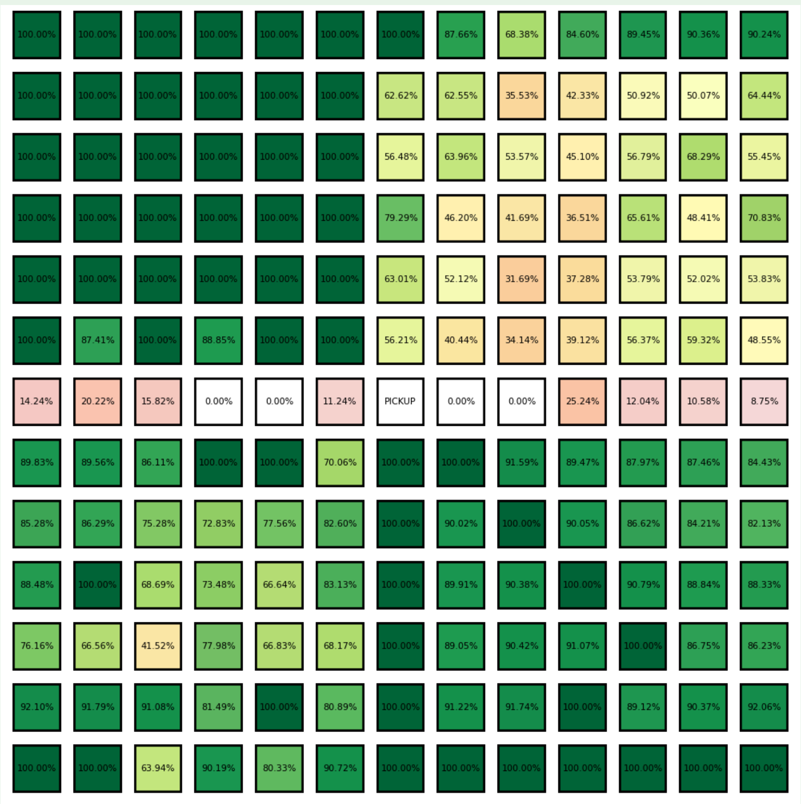
	Bottom-Left Origin	Top-Left Origin
top1%	62%	92%
top2%	92%	97%
top3%	93%	99%

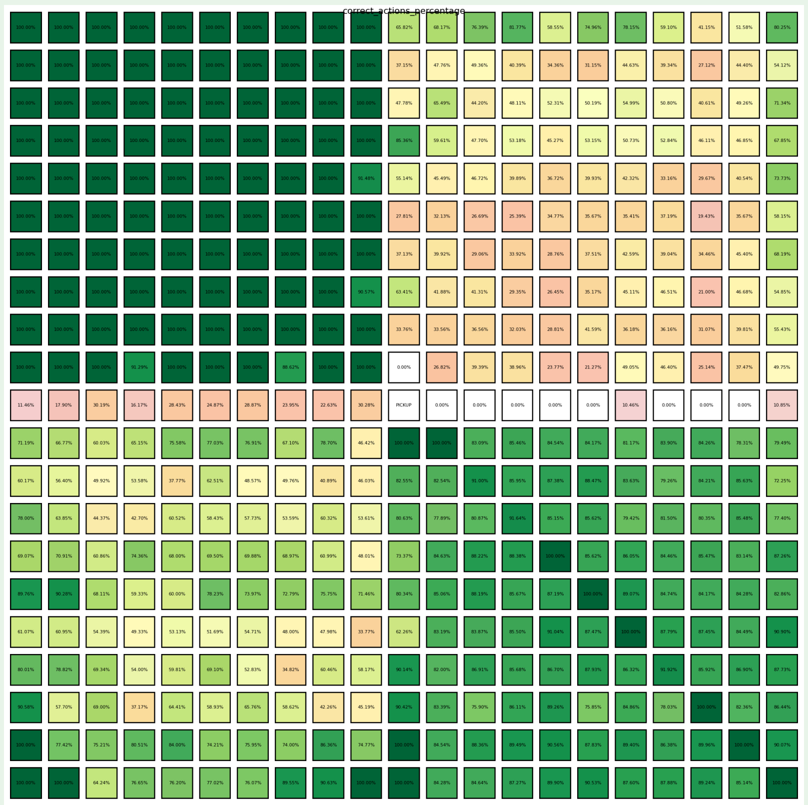
Common Uncertainty Patterns

Common Uncertainty Patterns #1









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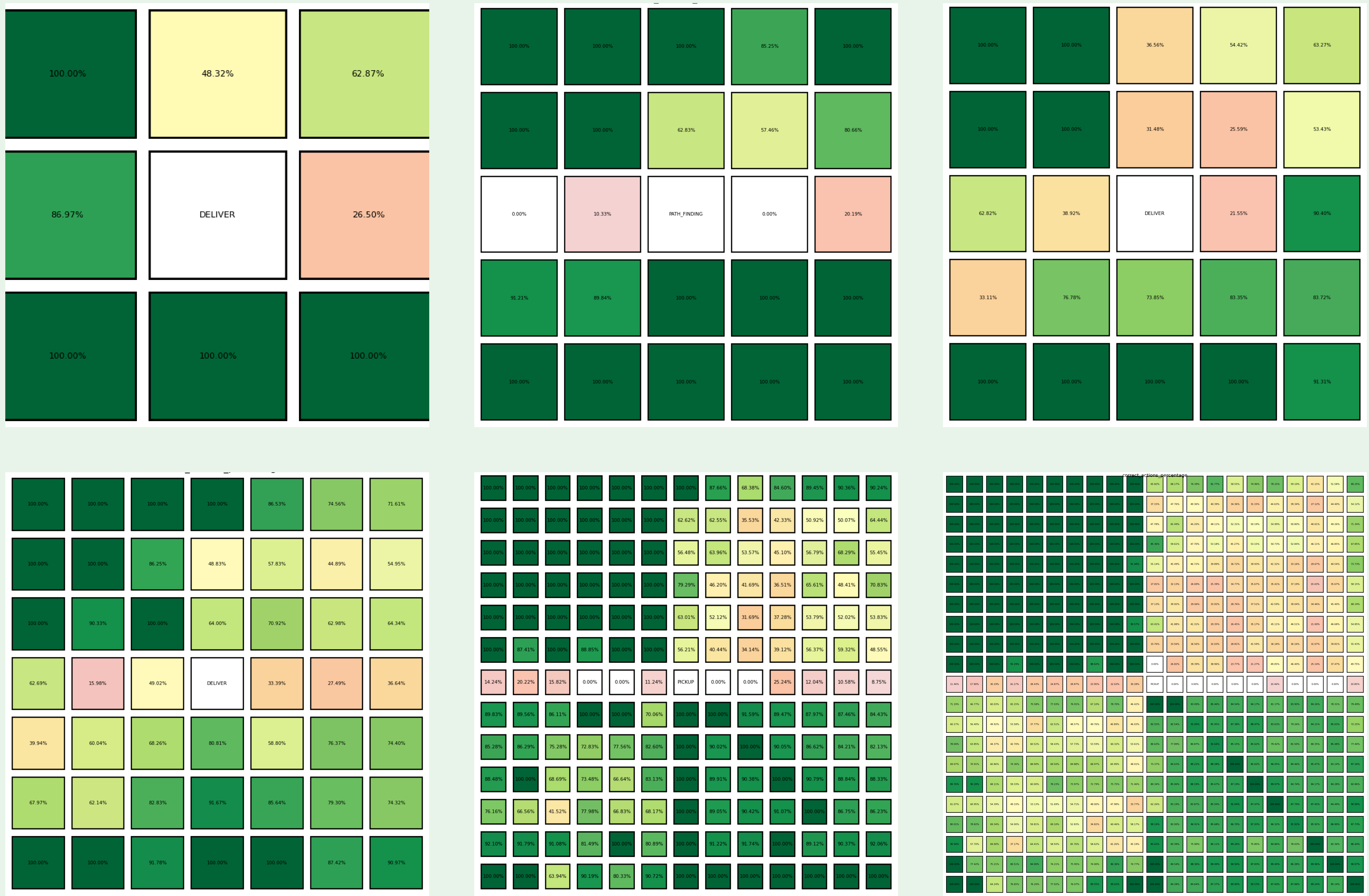
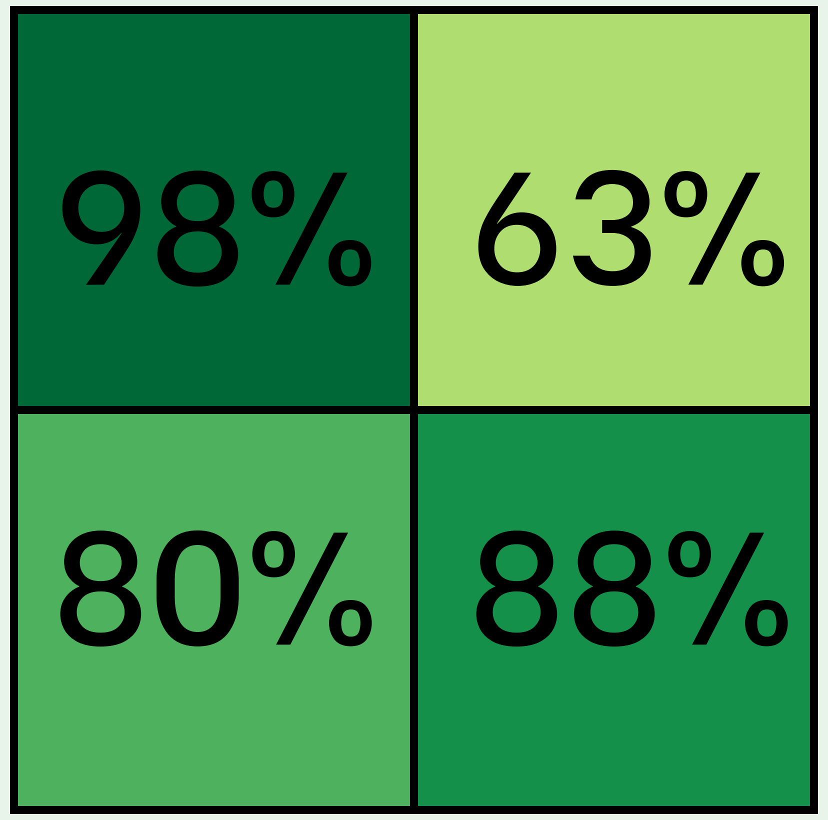
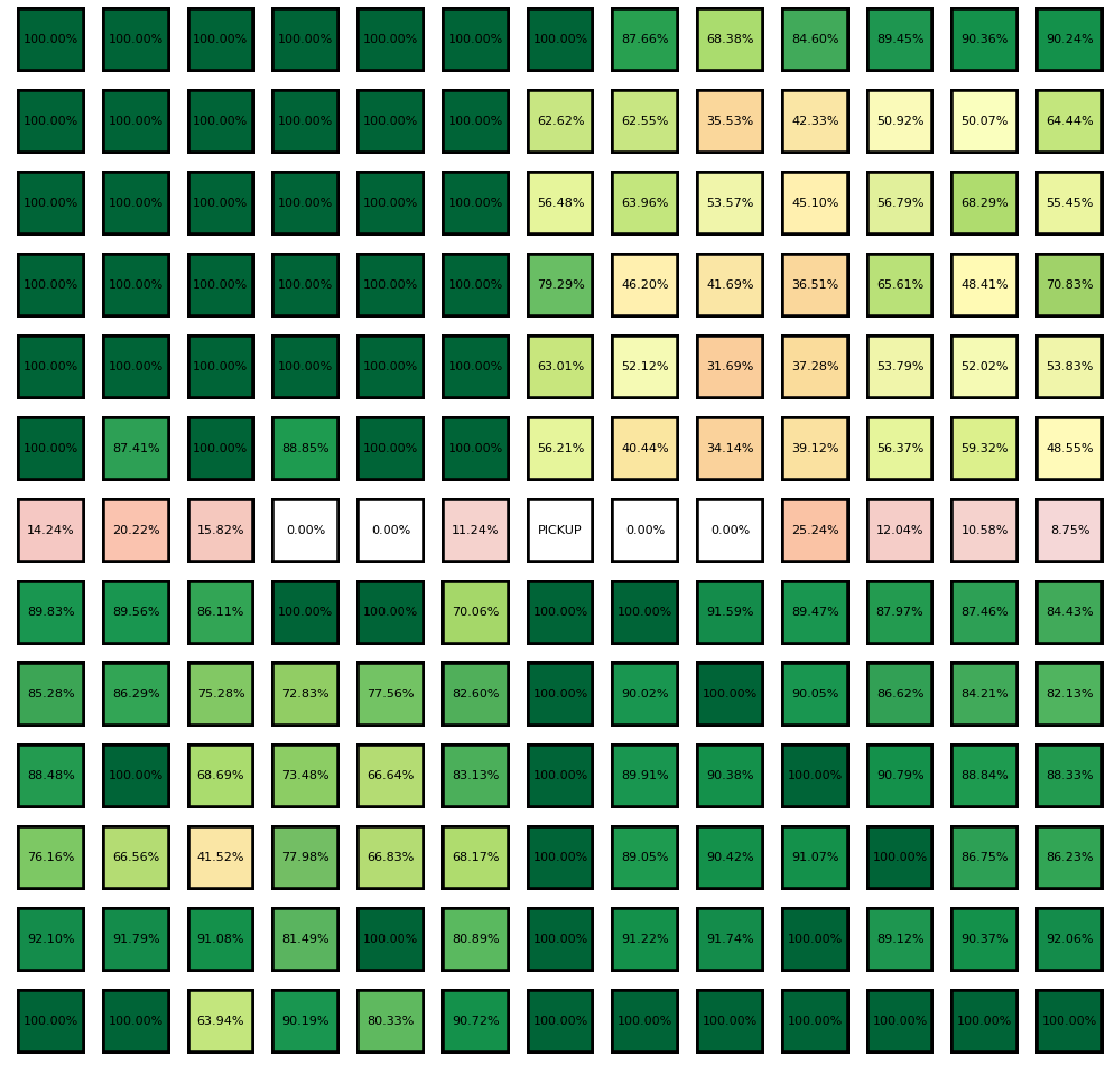


Average



Common Uncertainty Patterns #1.1



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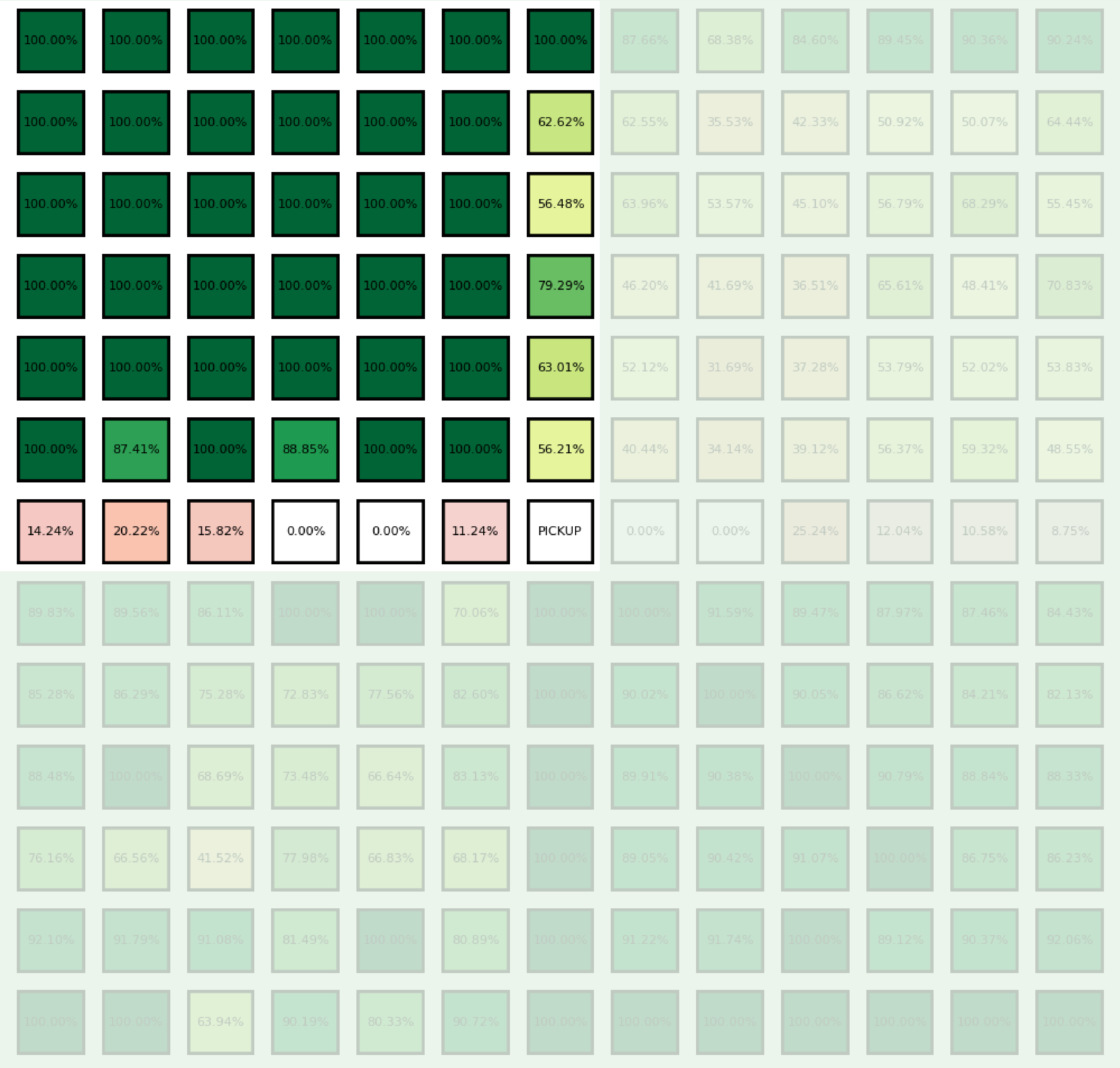

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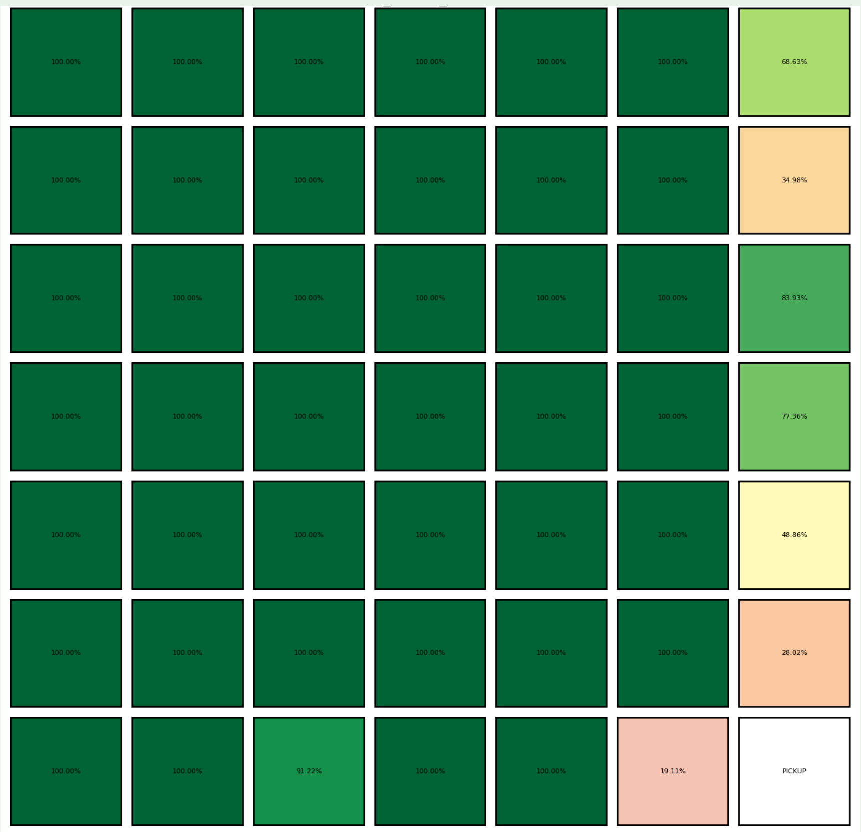
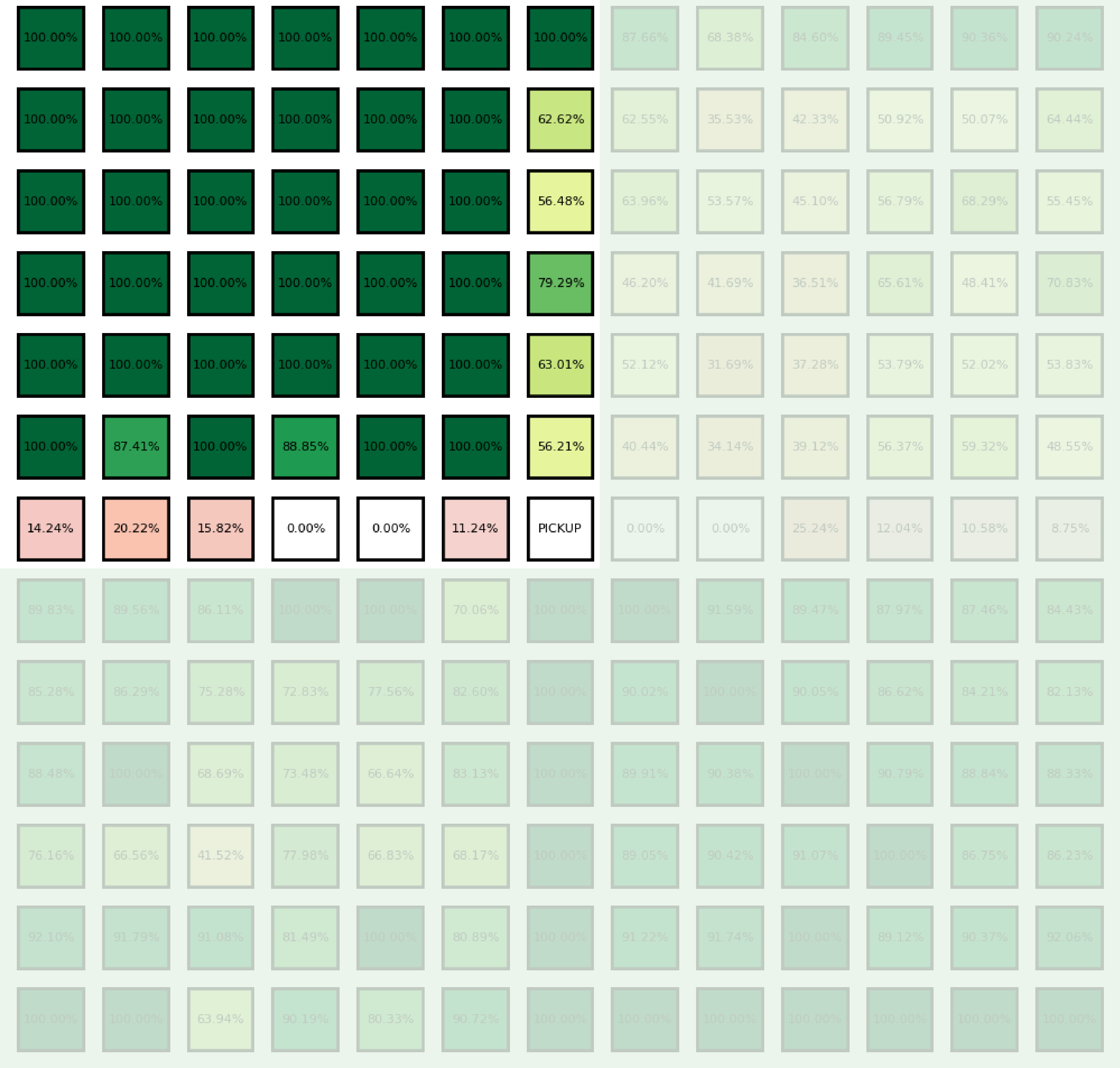
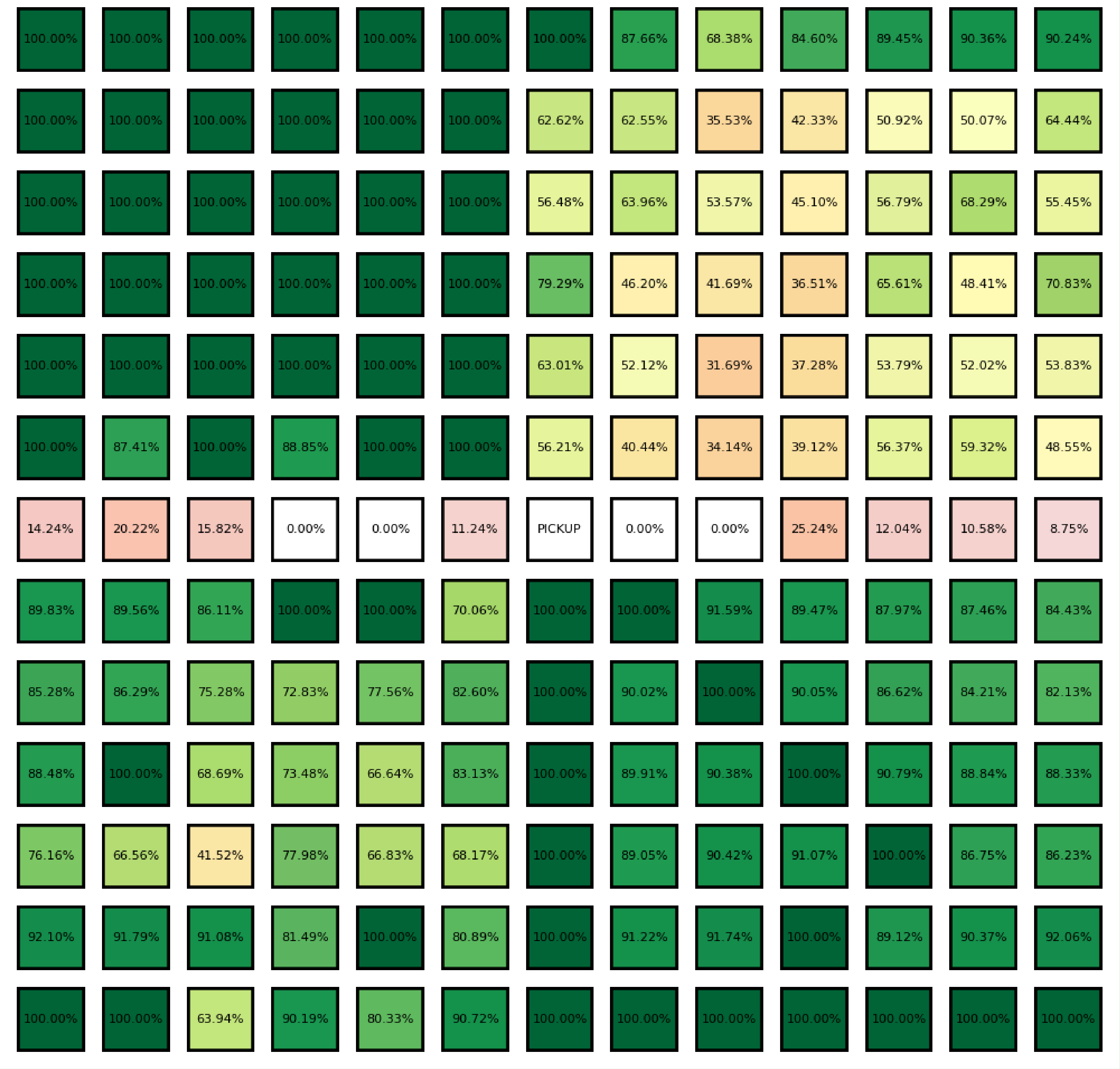




Common Uncertainty Patterns #1.2



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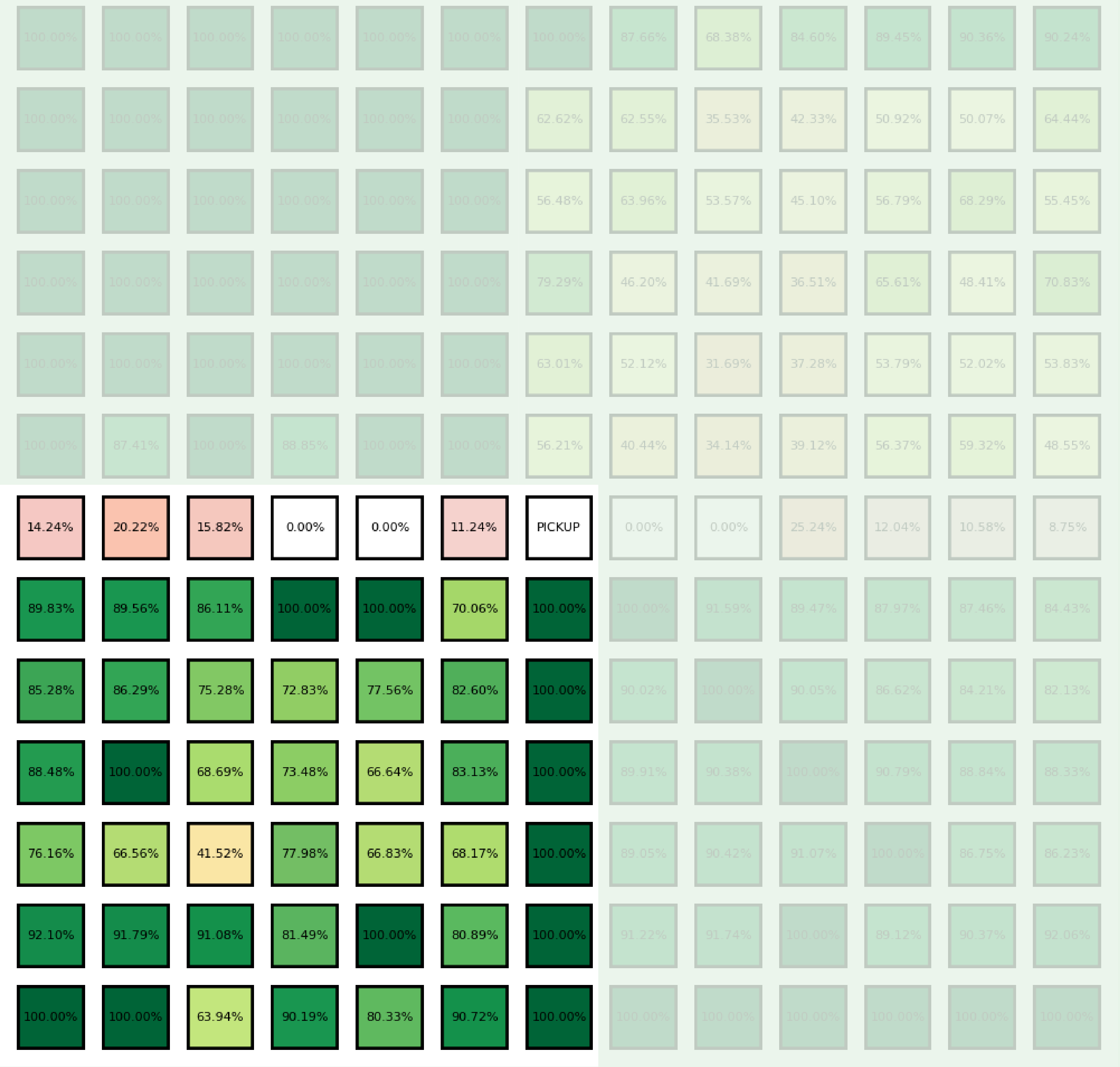

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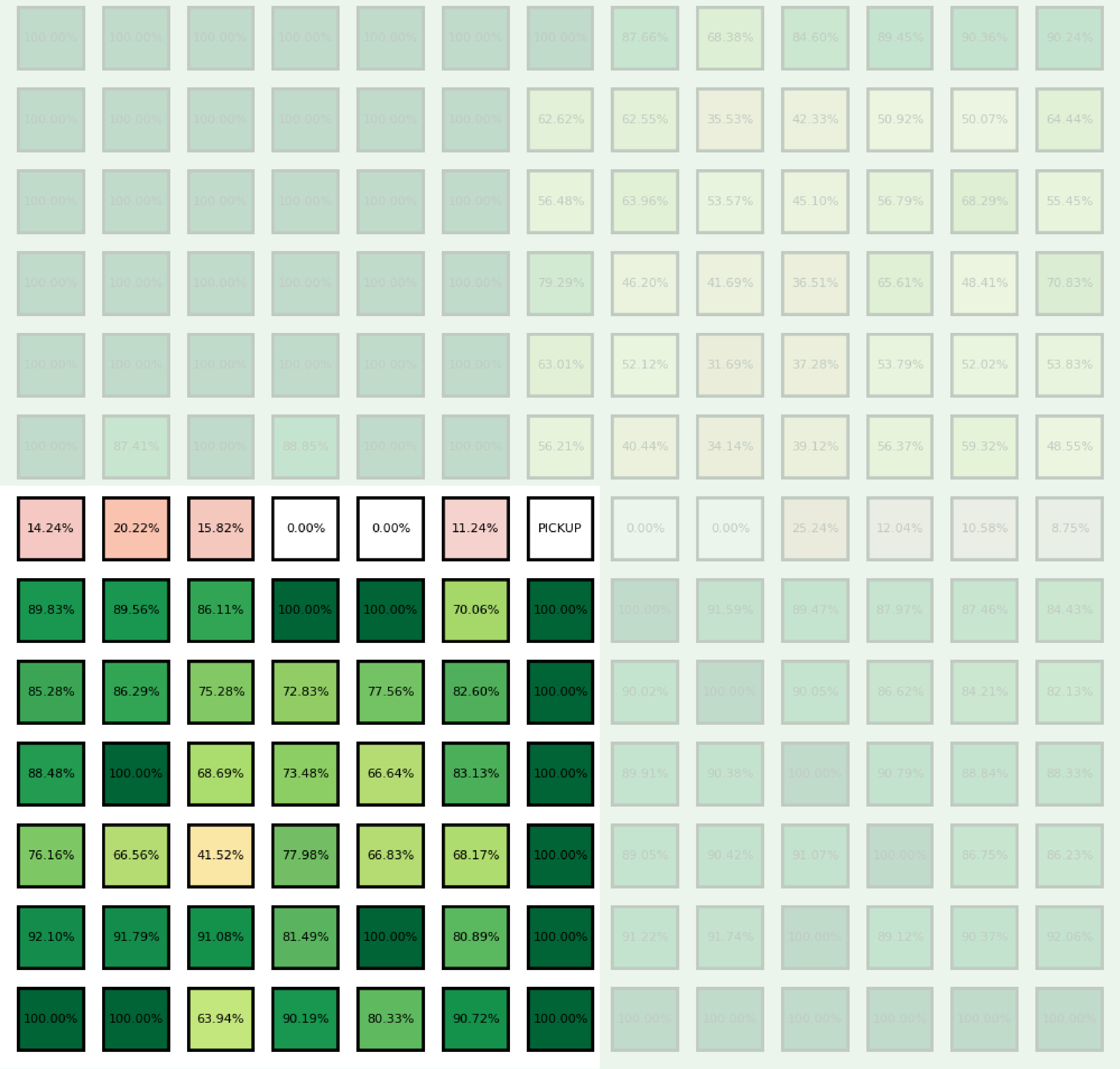
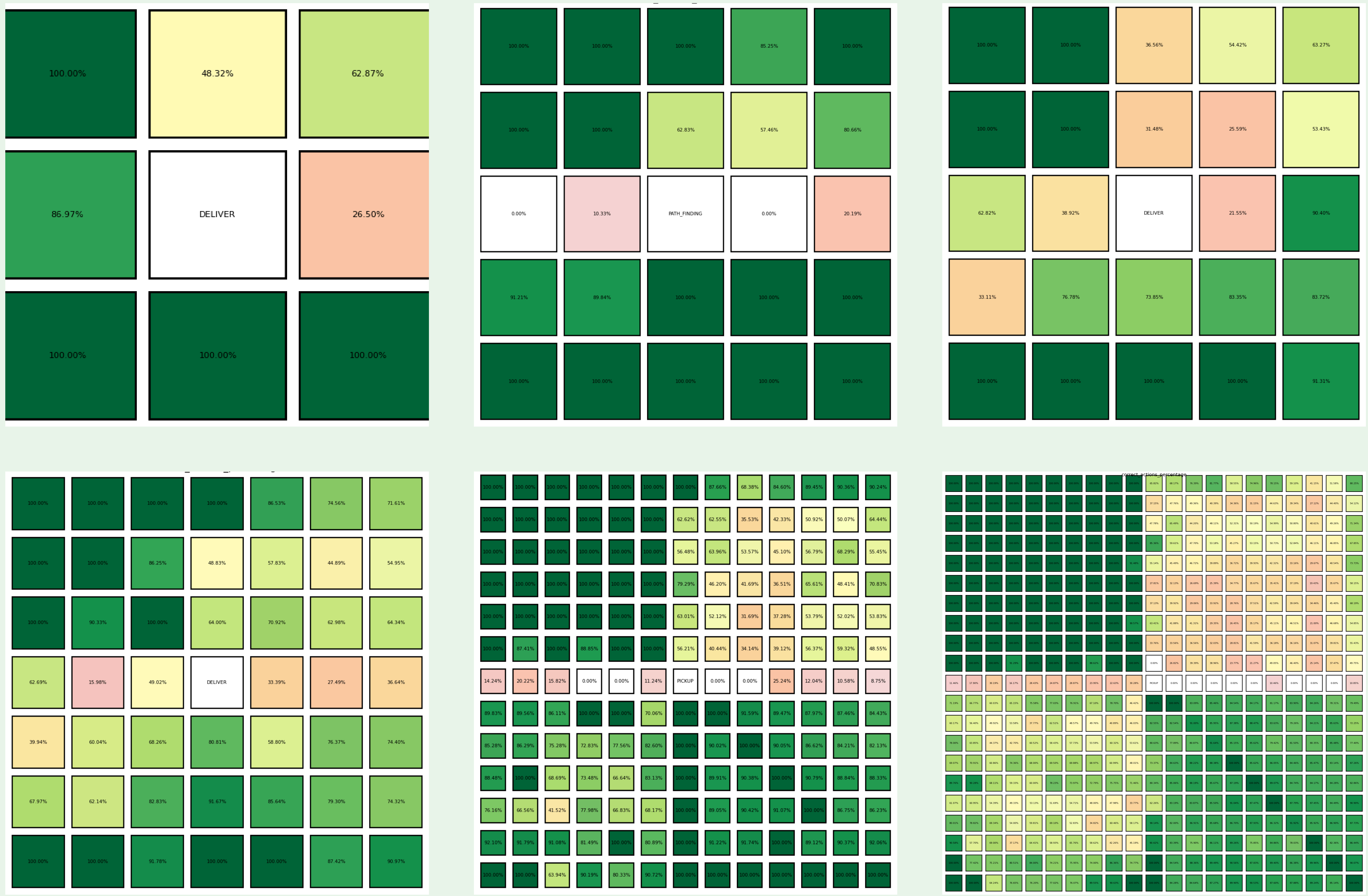
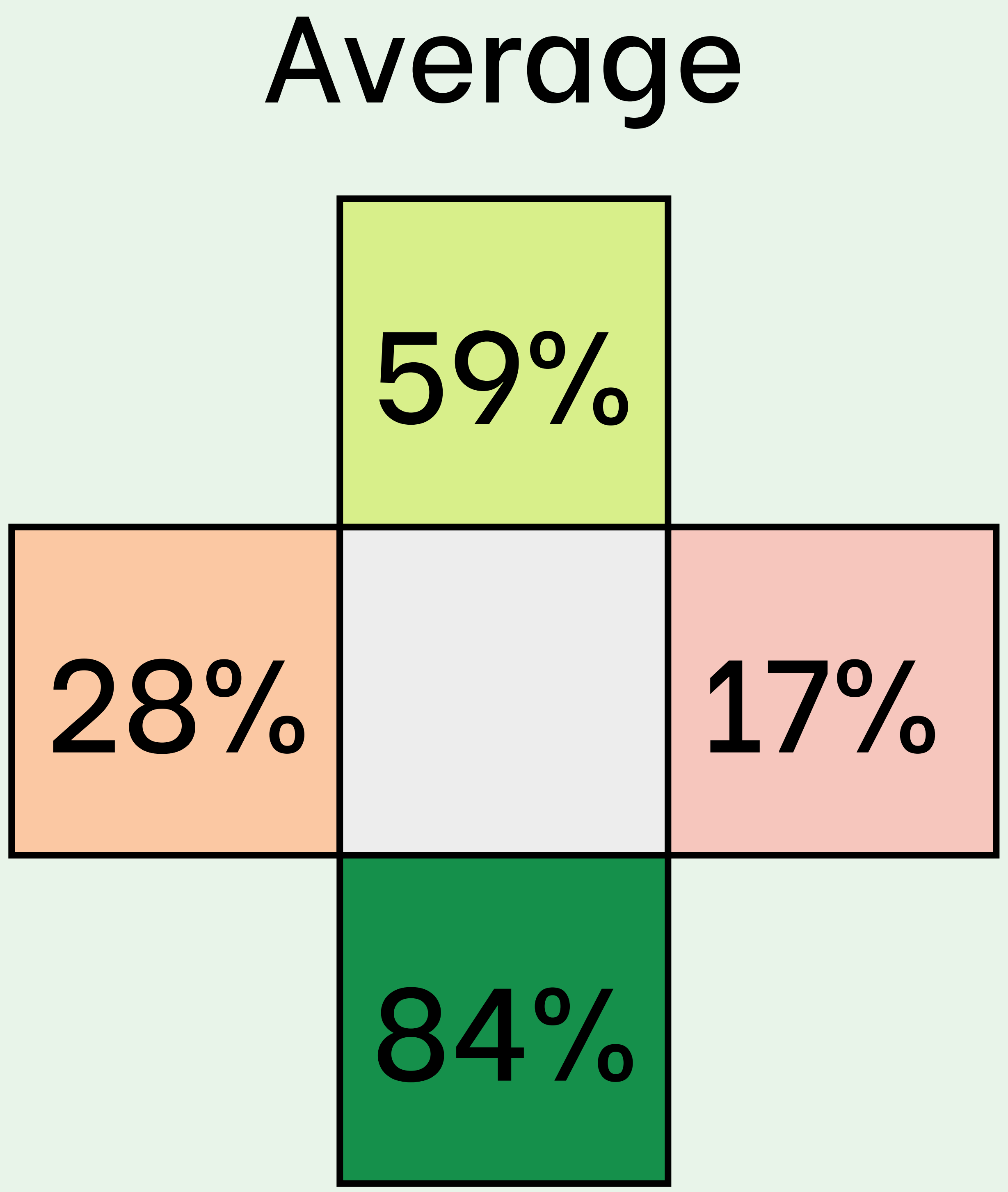
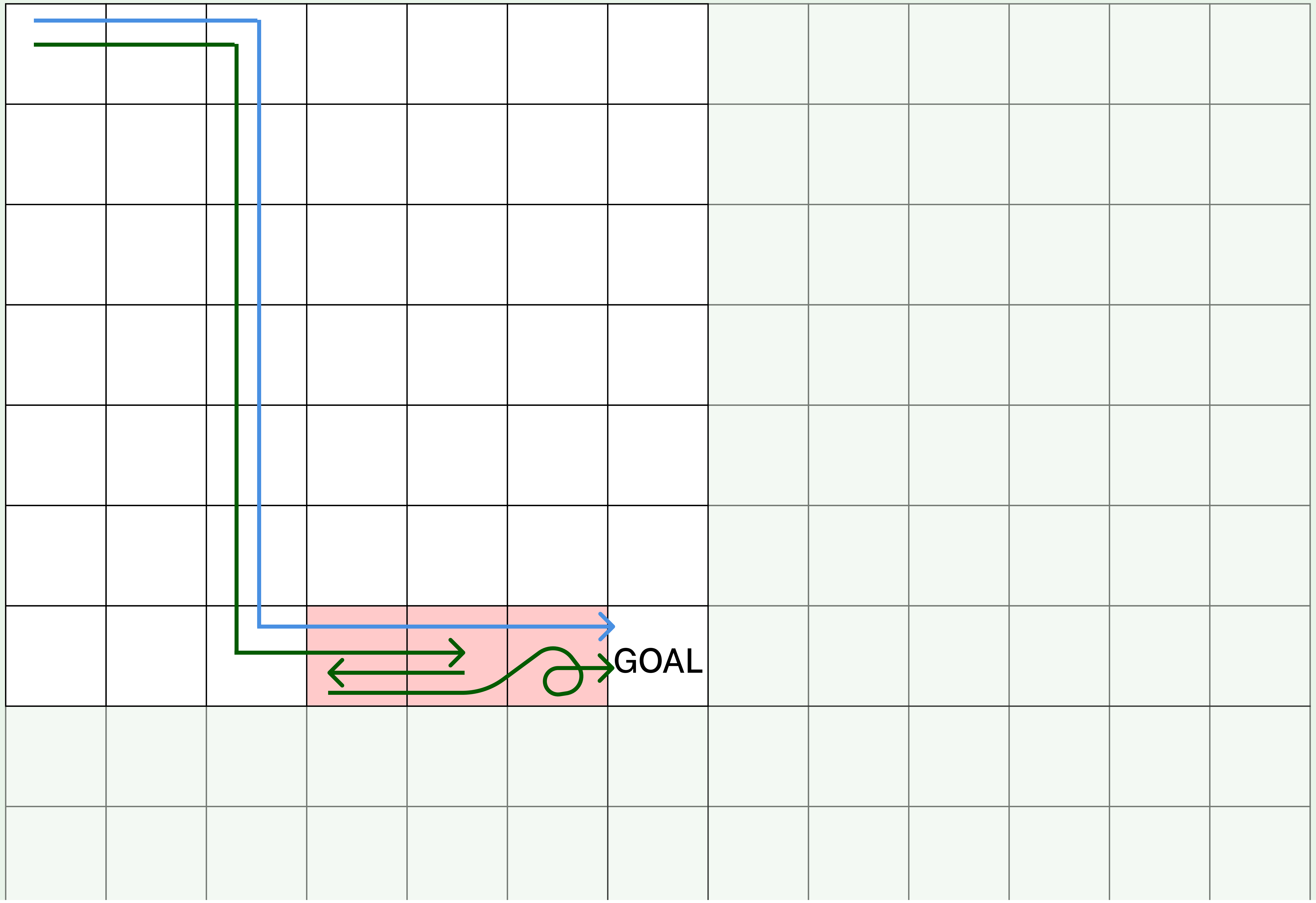


Common Uncertainty Patterns #2





Stateful Example



Optimal path

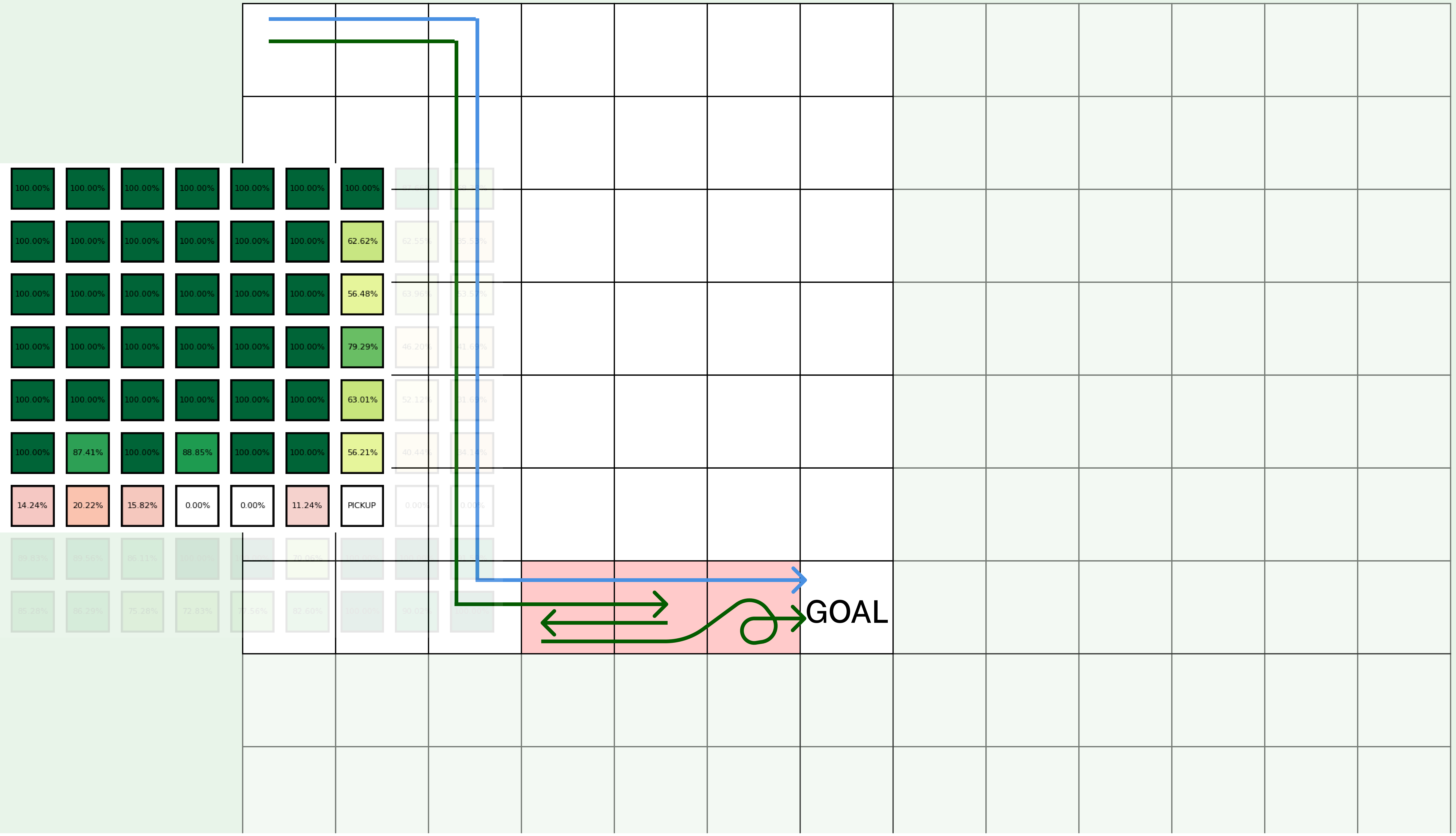
Our path

Repeated cells

Shared Nodes: 100%

Ratio: 81%

Stateful Example



- Optimal path
- Our path
- Repeated cells

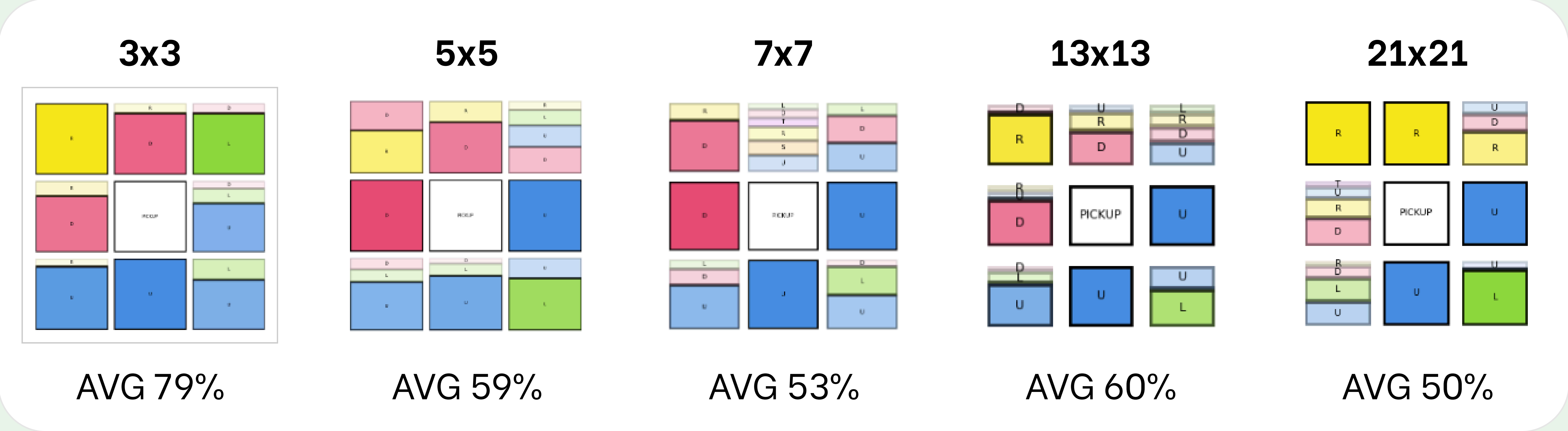
Shared Nodes: 100%

Ratio: 81%

Stateful

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

Central difference



- Up
- Down
- Left
- Right
- Pick Up
- Put Down

Average

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

Standard Deviation

0	33	24
12	GOAL	8
17	10	4

Conclusions

Strengths

Effective

History helps ~ 20% less actions

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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