Lecture 29: Machine Learning

Marvin Zhang
08/10/2015

(Some images borrowed from CS 188.)

Announcements

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  - Chris and Cale's 9:30-11am labs on Tuesday are NOT canceled.

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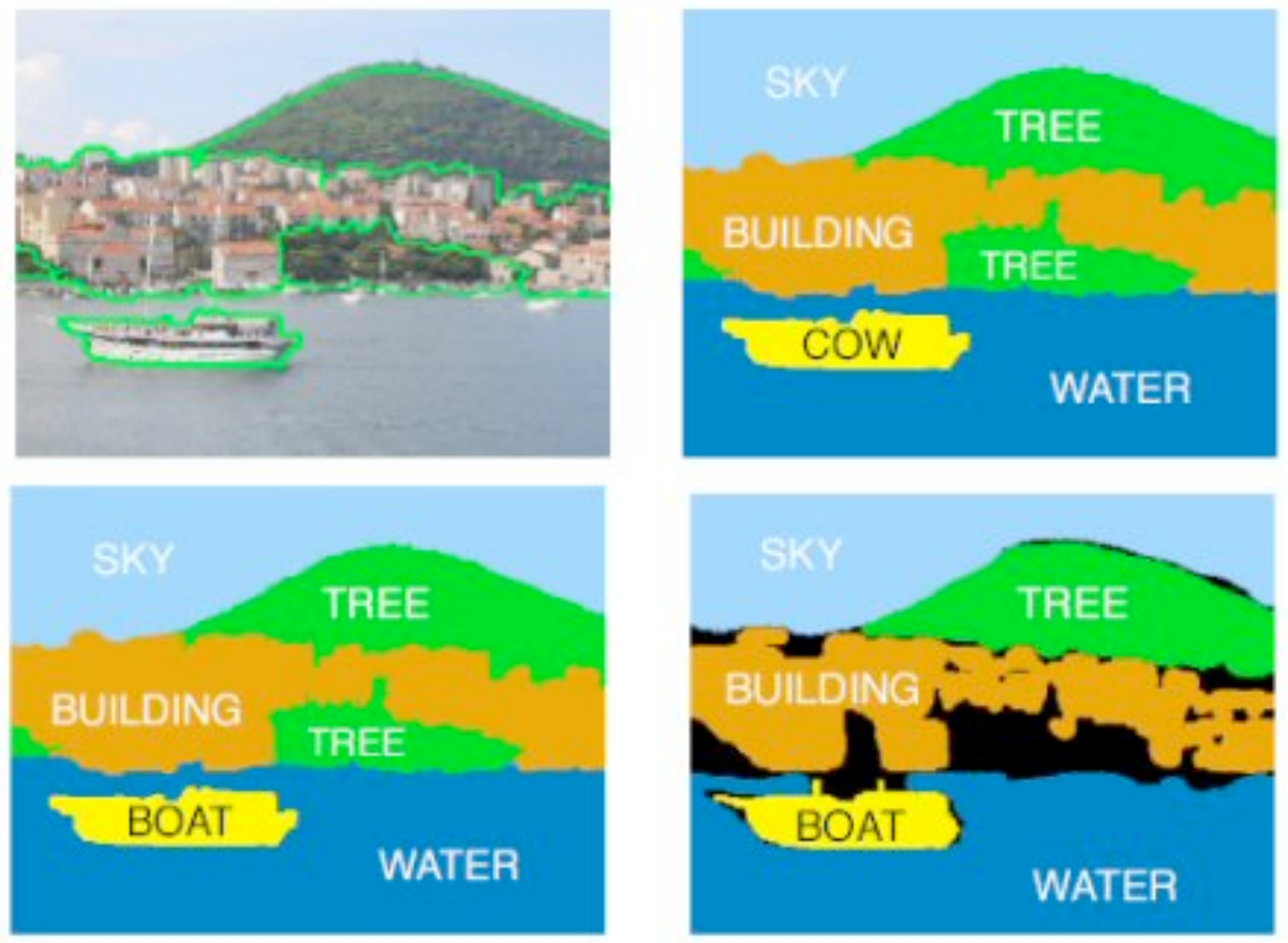

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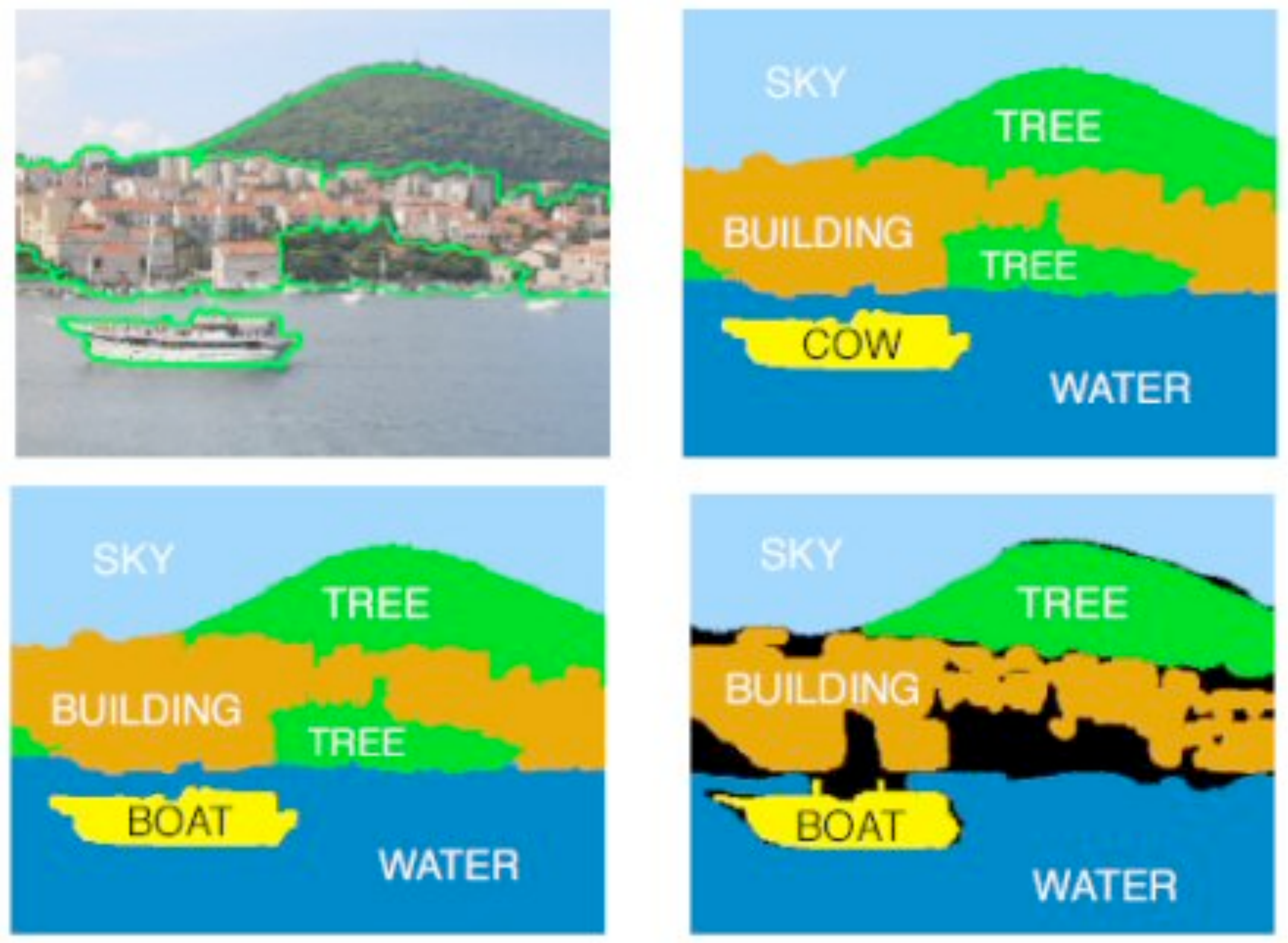

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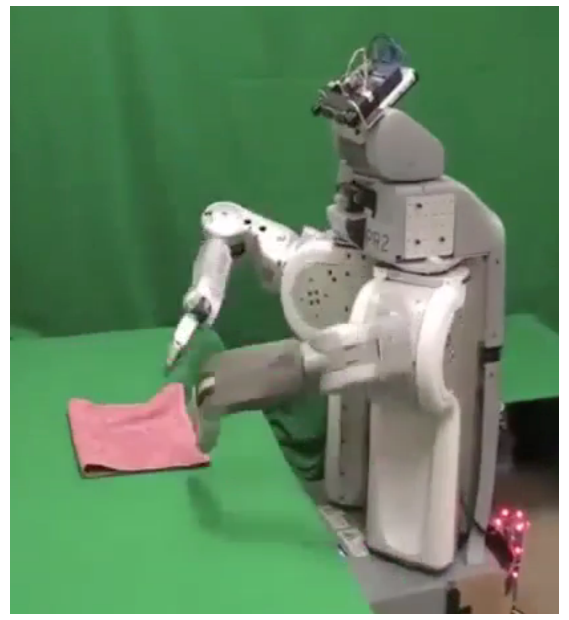

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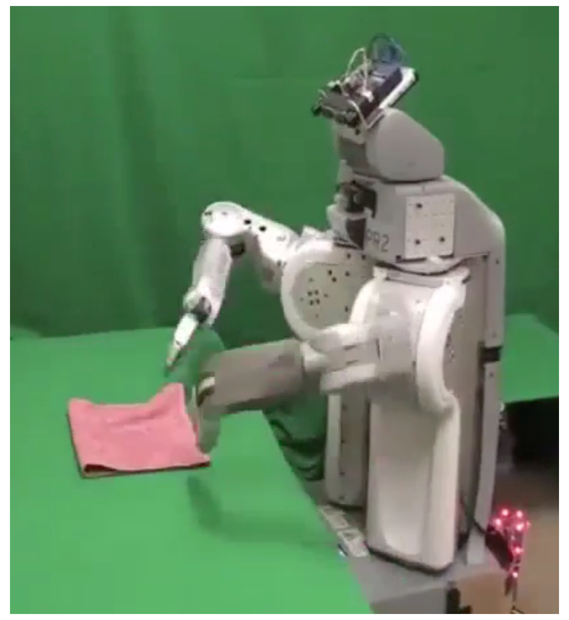


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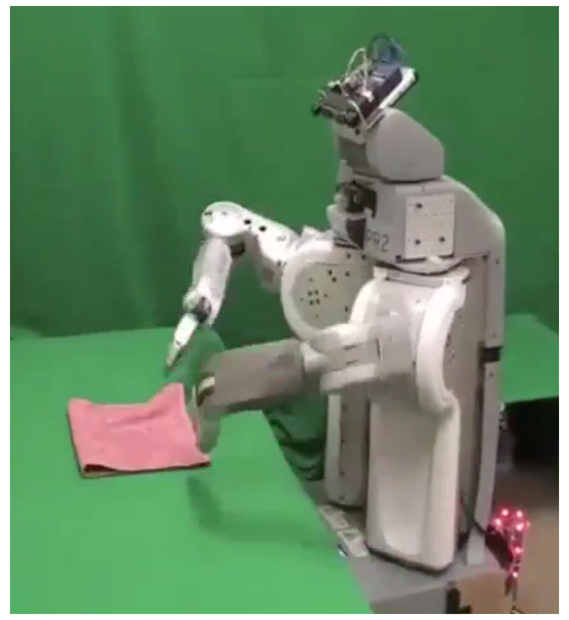

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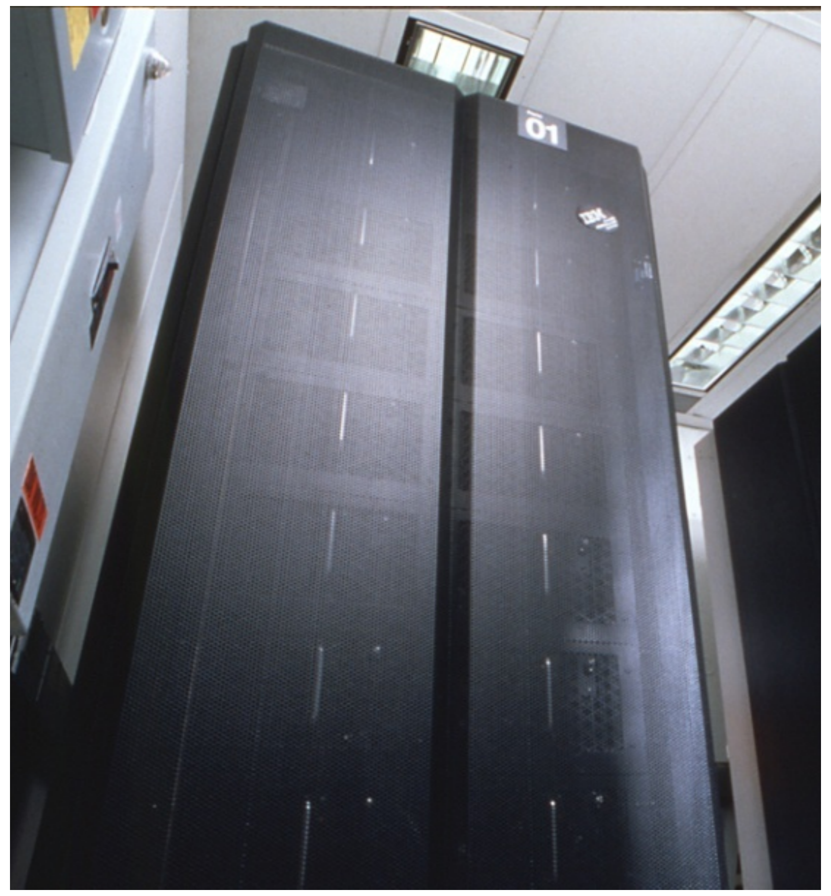

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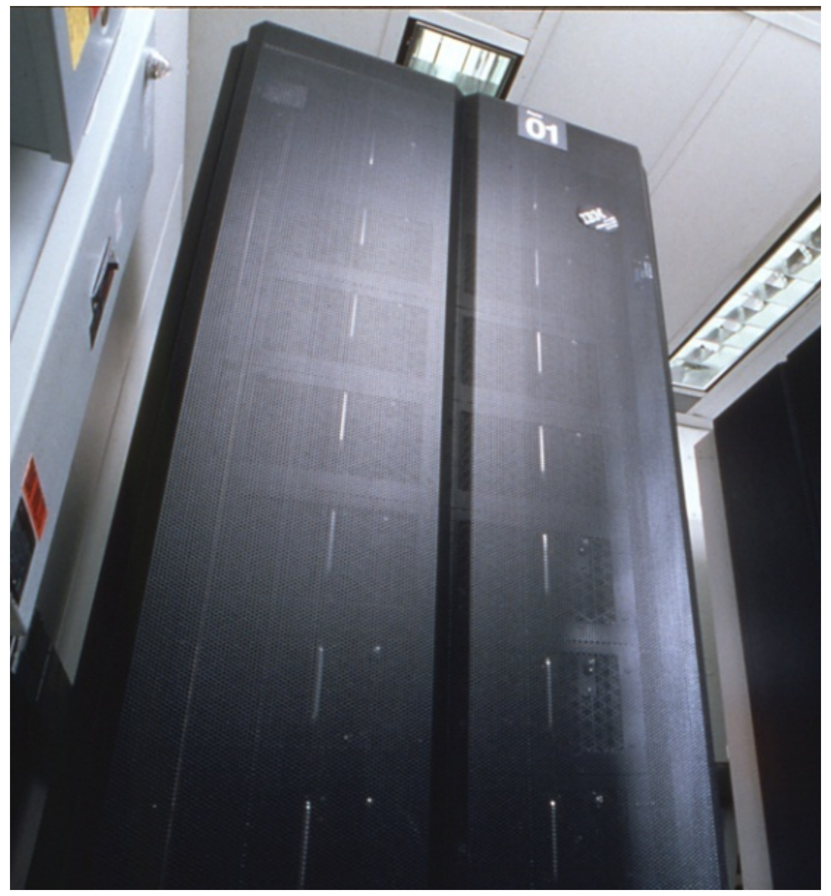
- Game Playing
- and much more!



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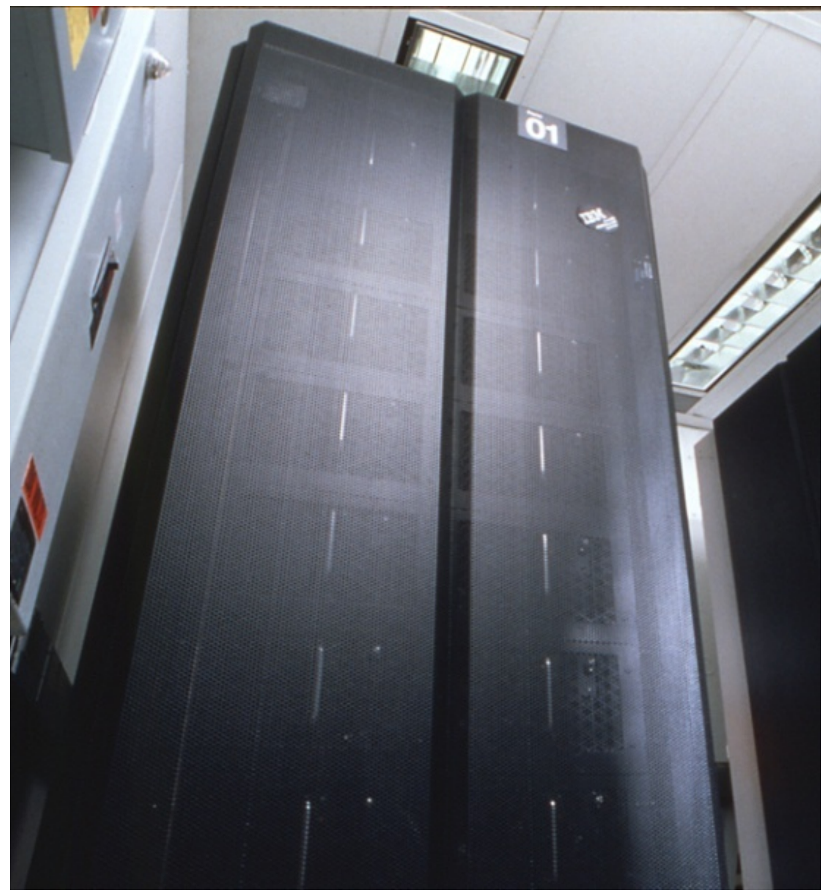

- What do these all have in common?

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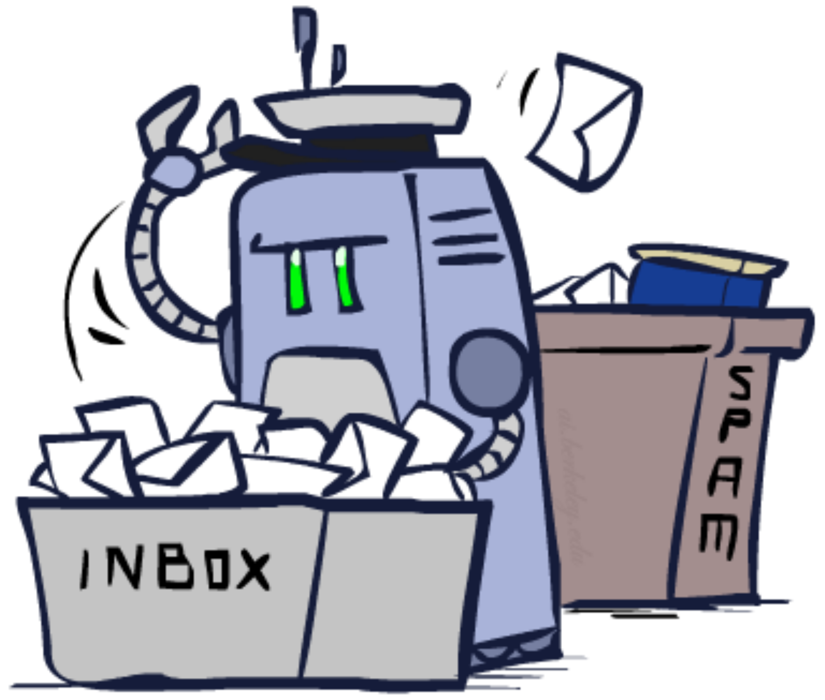

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  - Is this email ham or spam?
  - How do I translate this sentence?

"Il est impossible aux journalistes de rentrer dans les régions tibétaines"

Bruno Philip, correspondant du "Monde" en Chine, estime que les journalistes de l'AFP qui ont été expulsés de la province tibétaine du Qinghai "n'étaient pas dans l'illégalité".

Les faits Le dalaï-lama dénonce l'"enfer" imposé au Tibet depuis sa fuite, en 1959

Vidéo Anniversaire de la rébellion

"It is impossible for journalists to enter Tibetan areas"

Philip Bruno, correspondent for "World" in China, said that journalists of the AFP who have been deported from the Tibetan province of Qinghai "were not illegal."

Facts The Dalai Lama denounces the "hell" imposed since he fled Tibet in 1959

Video Anniversary of the Tibetan rebellion: China on guard

Machine Learning

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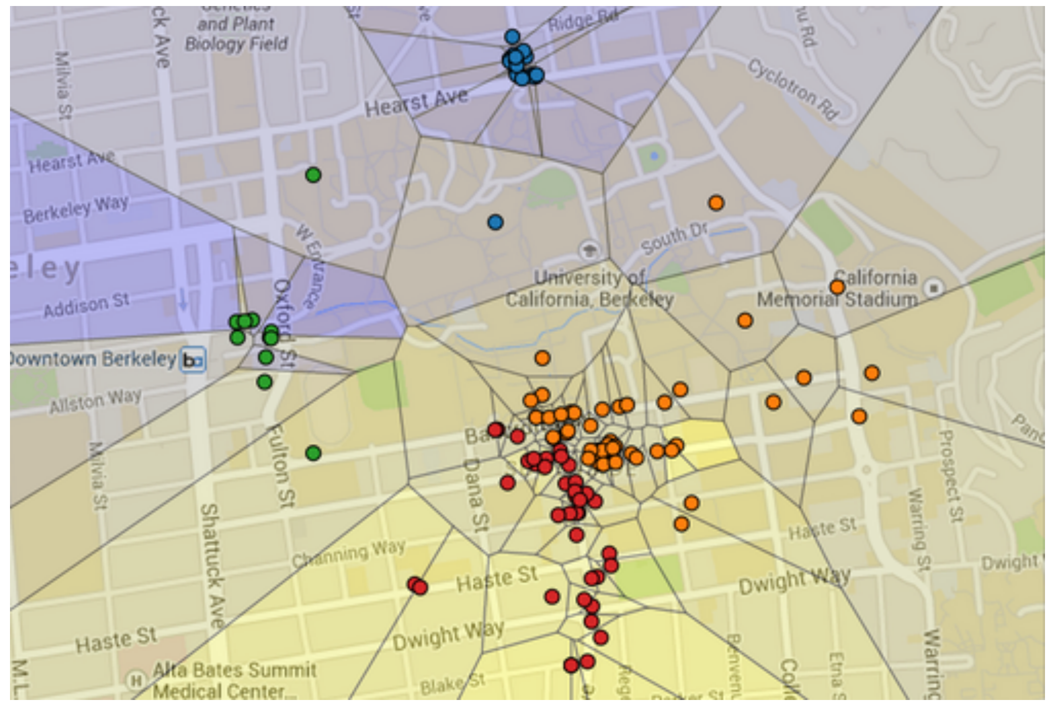
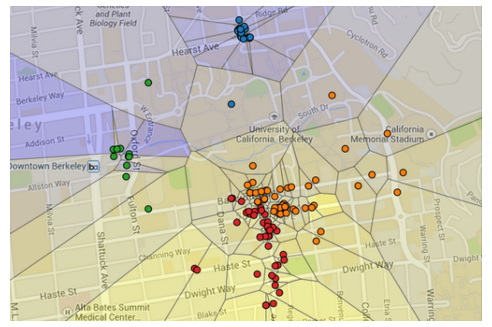
- A subfield of computer science.
- The study of algorithms that *analyze data to make decisions*.
- Examples of decisions:
  - Is this email ham or spam?
  - How do I translate this sentence?
  - Will this user like this restaurant?



Machine Learning Example: Maps



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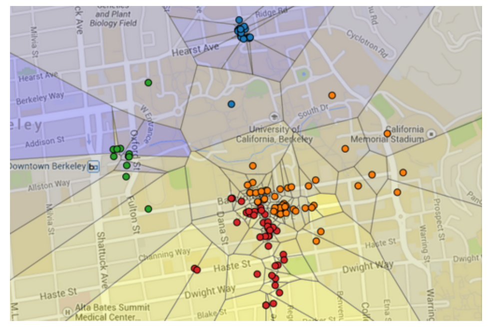

K-means Clustering

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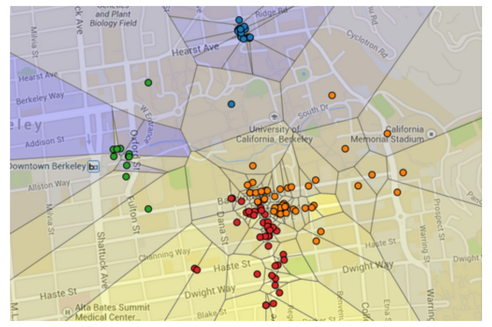

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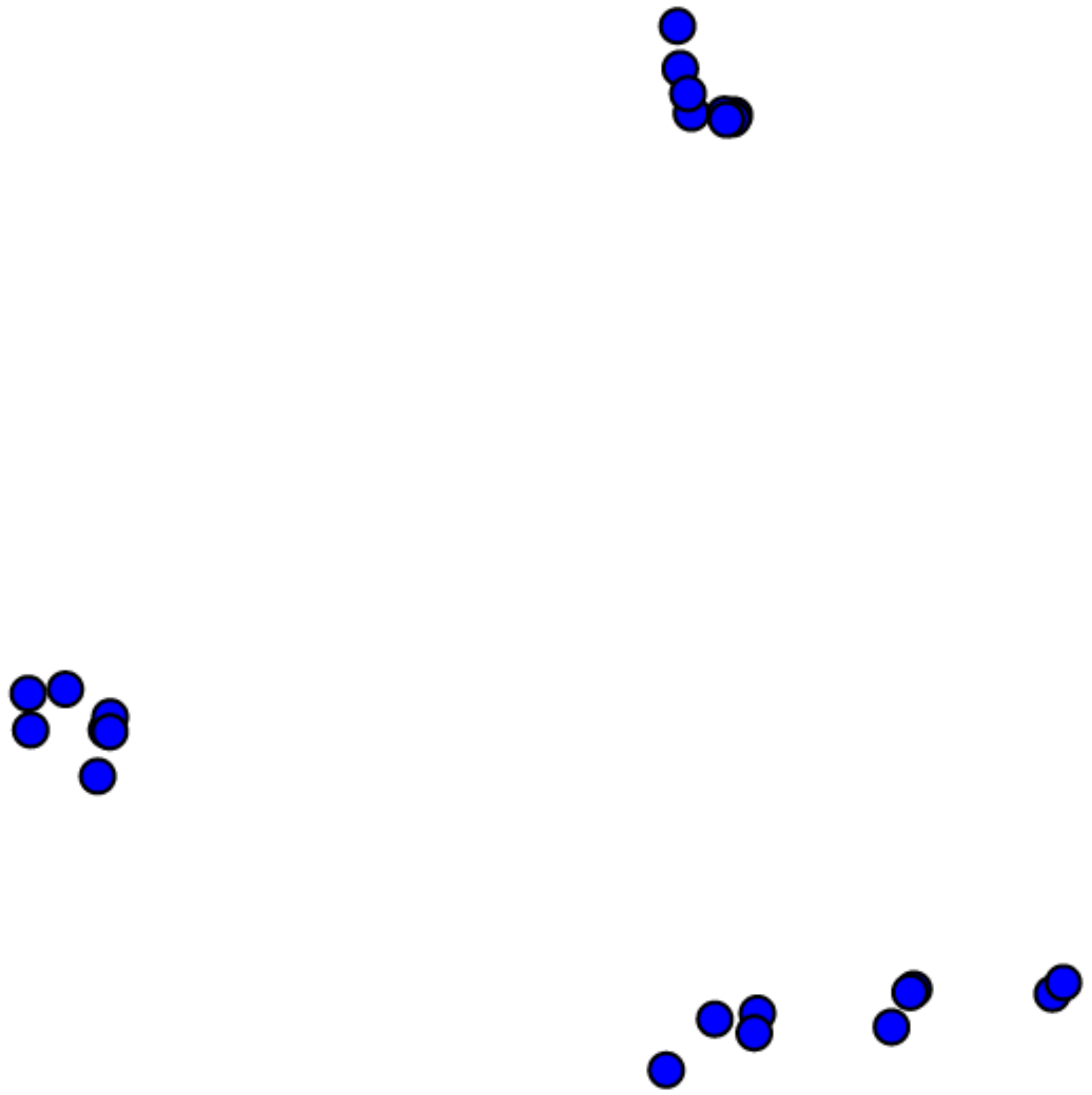

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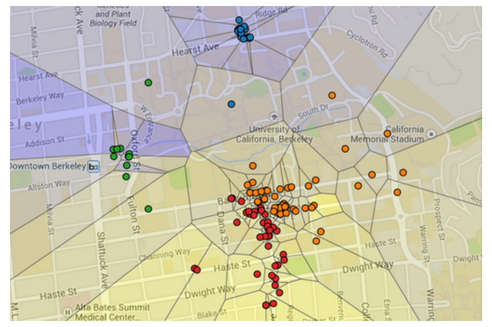

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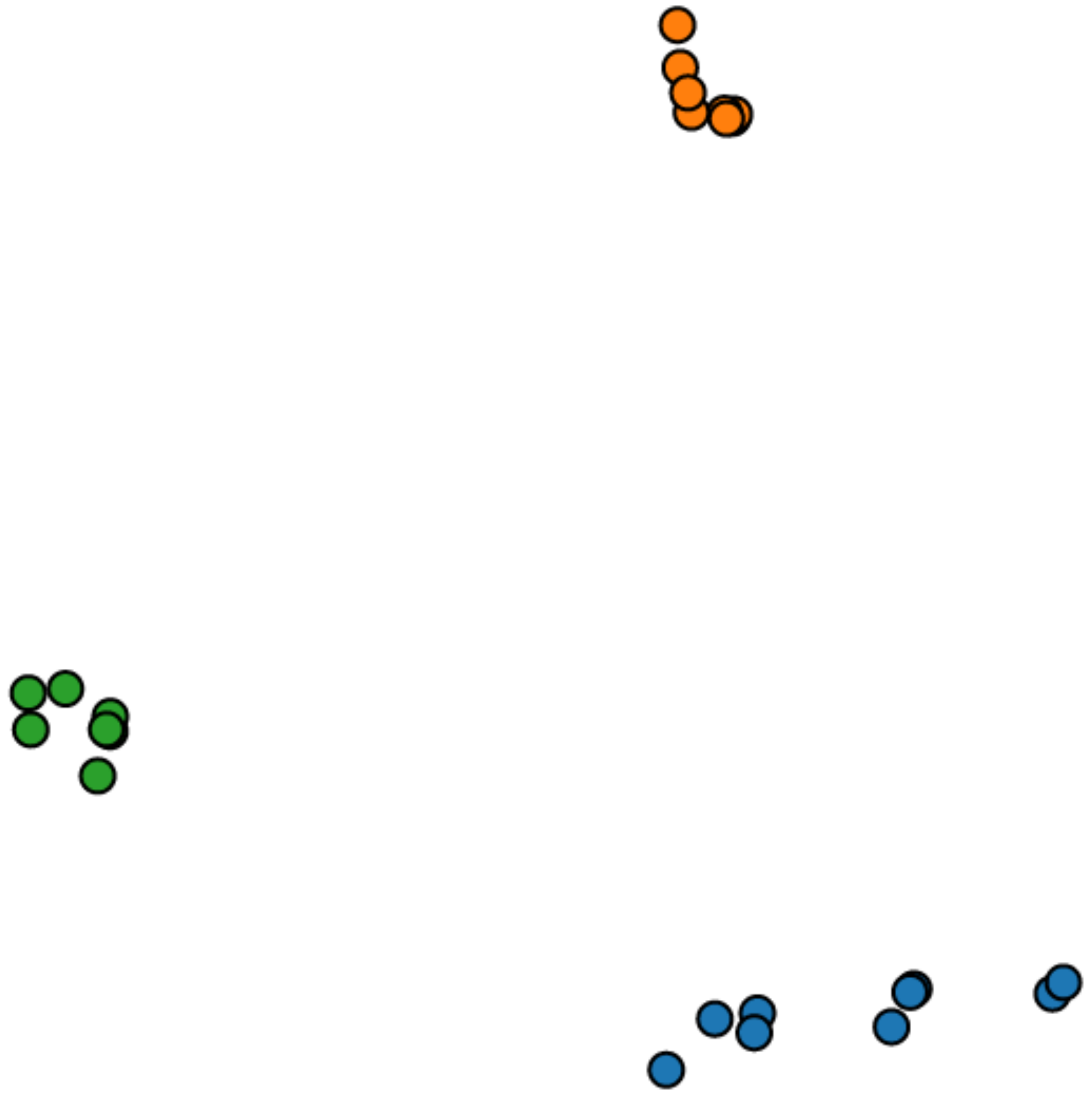

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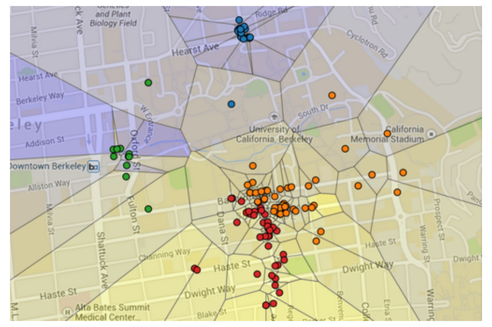

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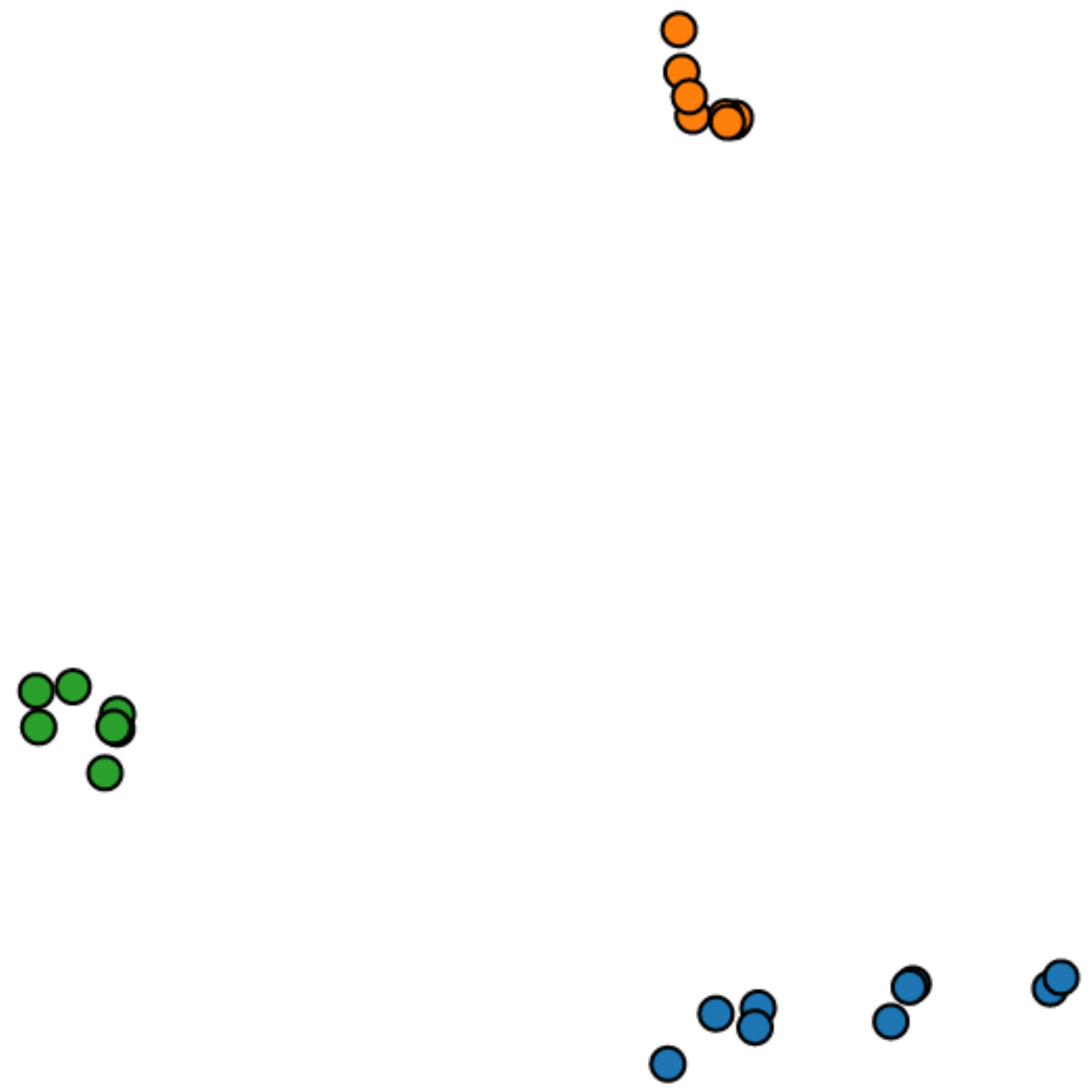
- The data: restaurant locations



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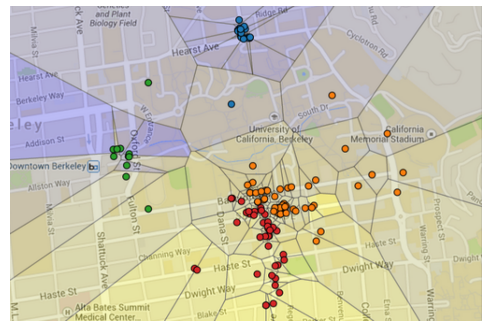

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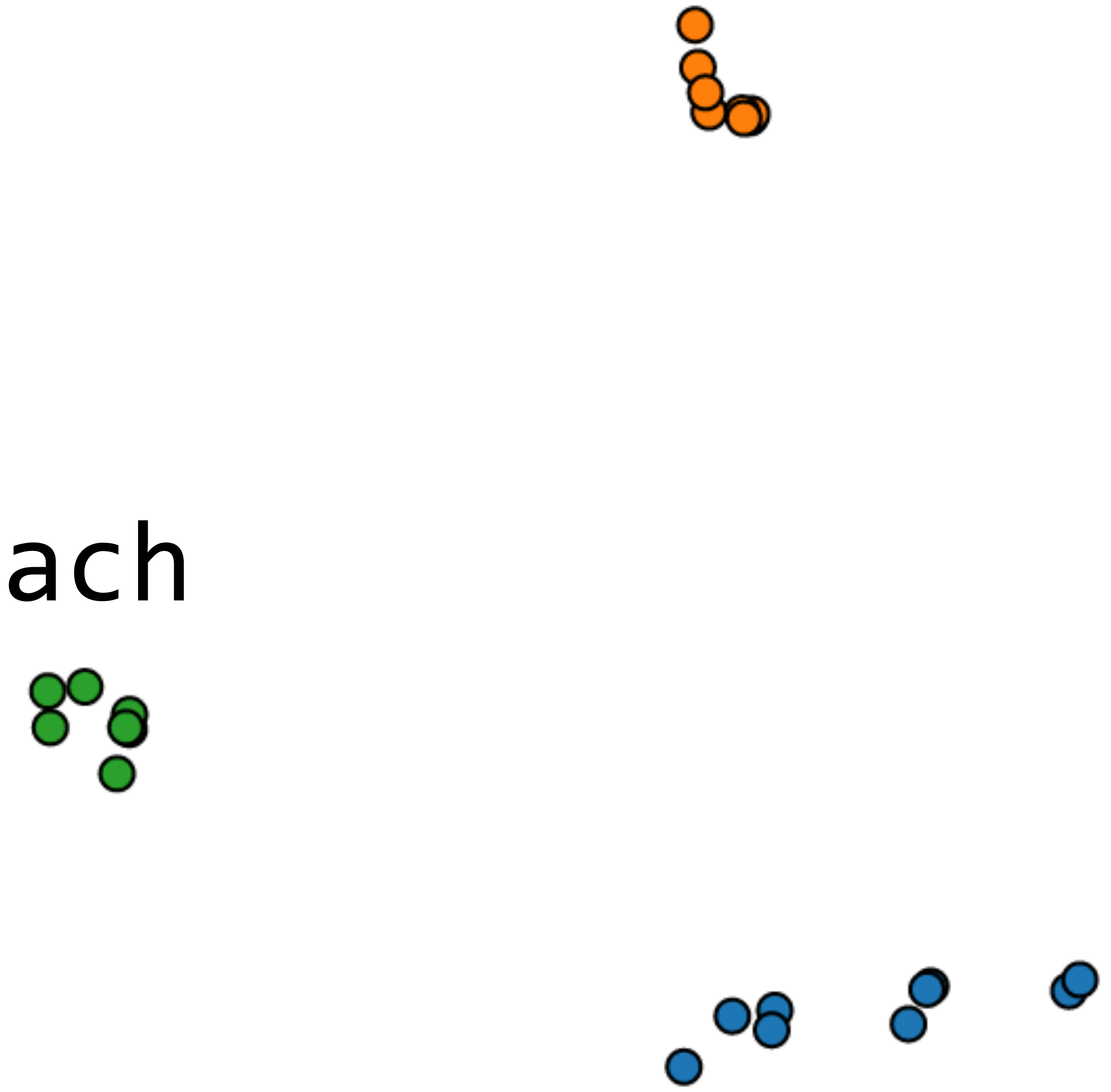

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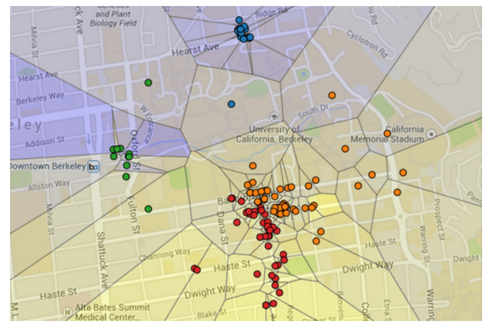

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Called *unsupervised learning*, because no one tells it what the correct decision is.

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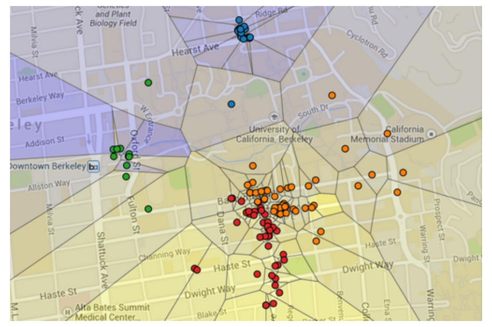

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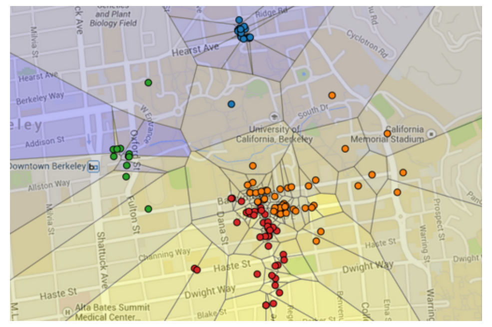
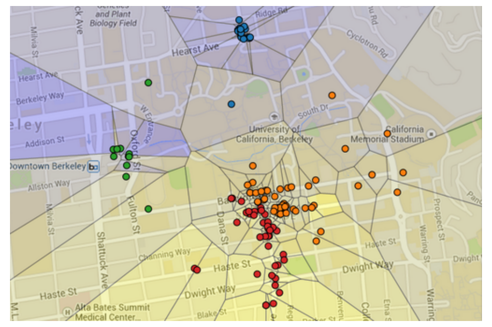


Linear Regression



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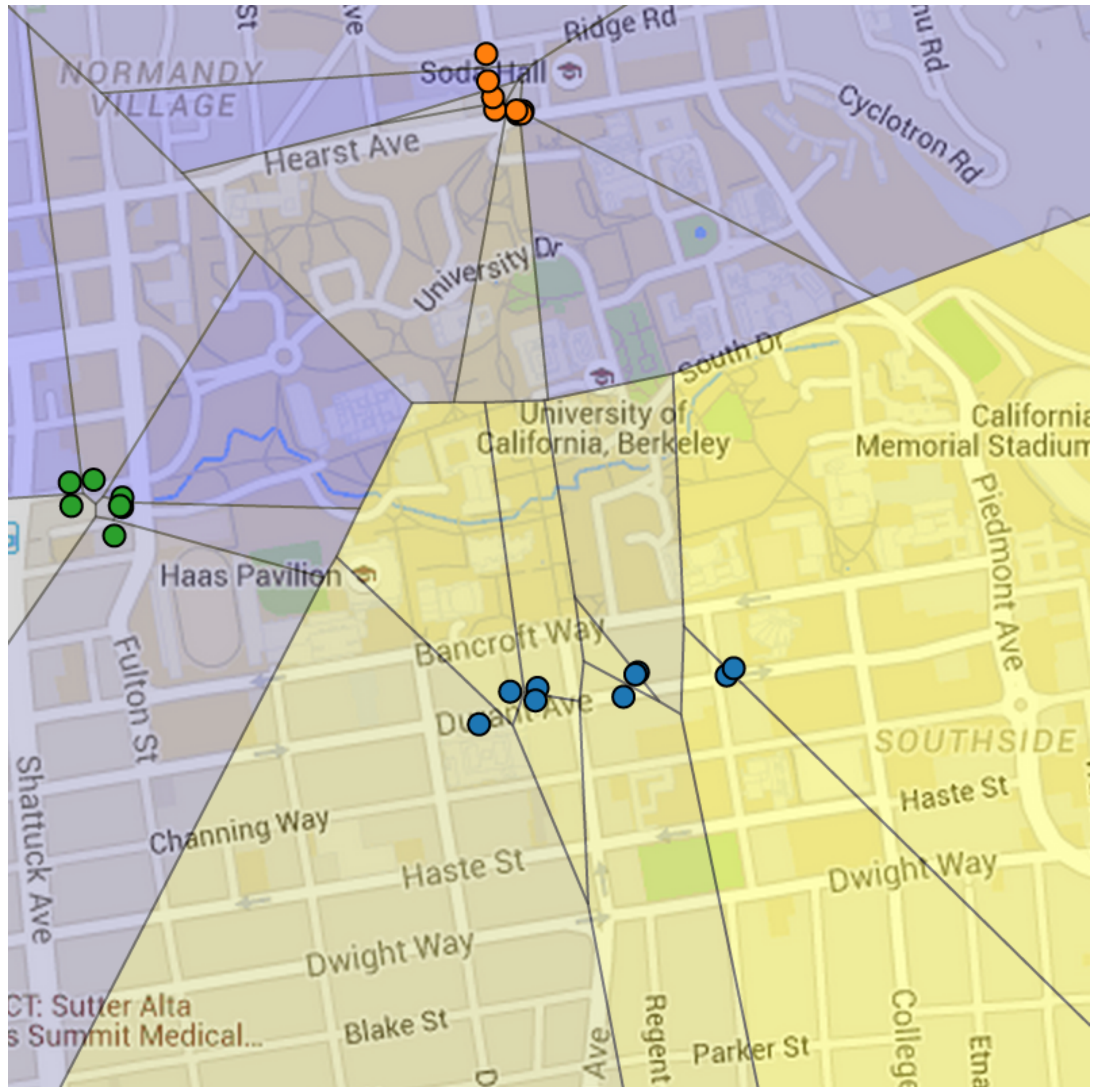

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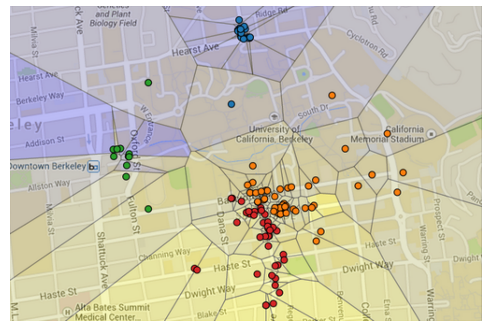

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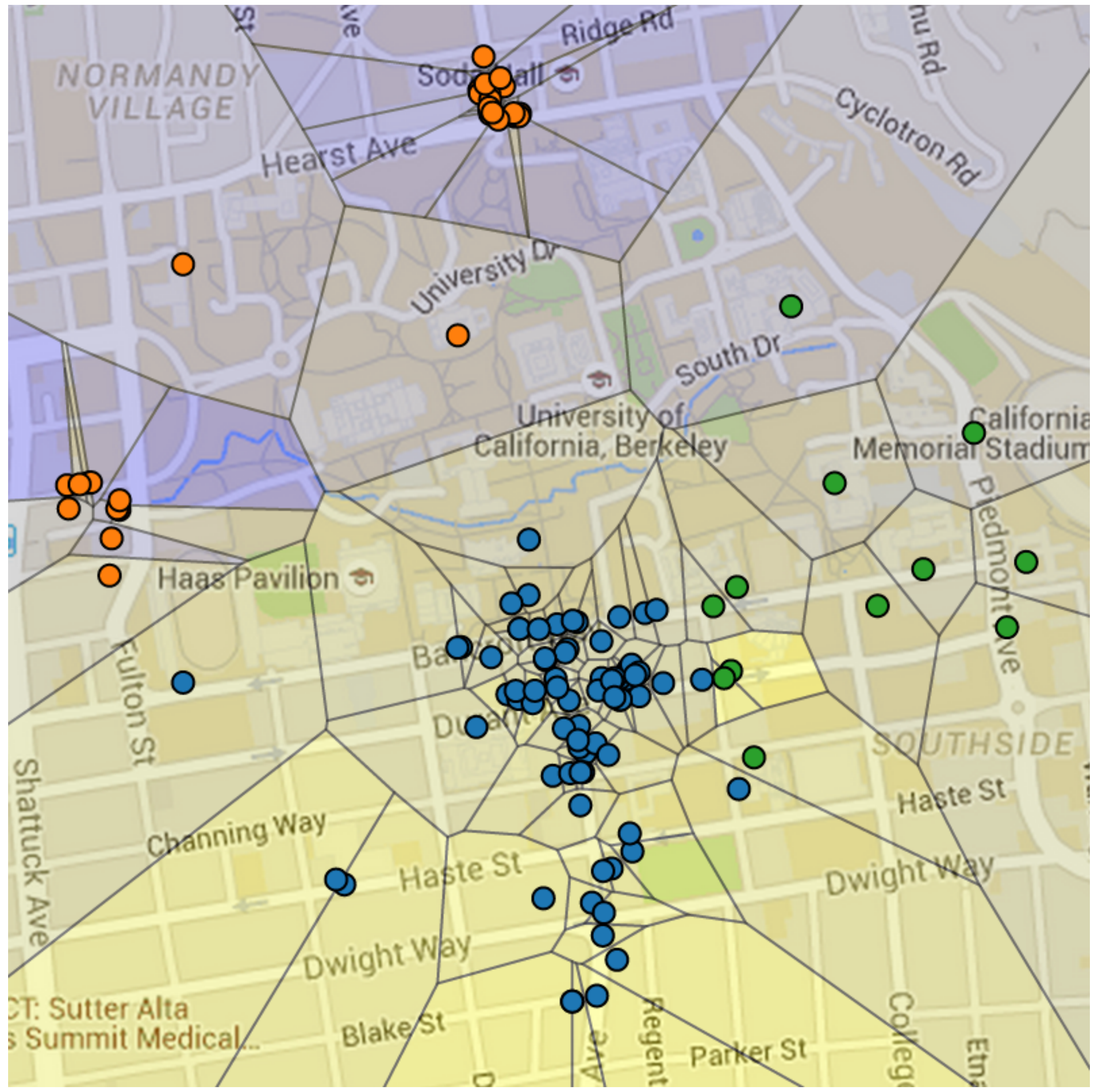

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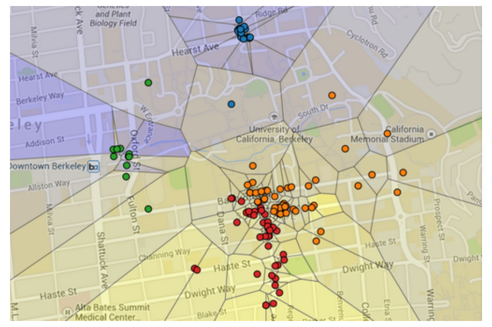

Linear Regression

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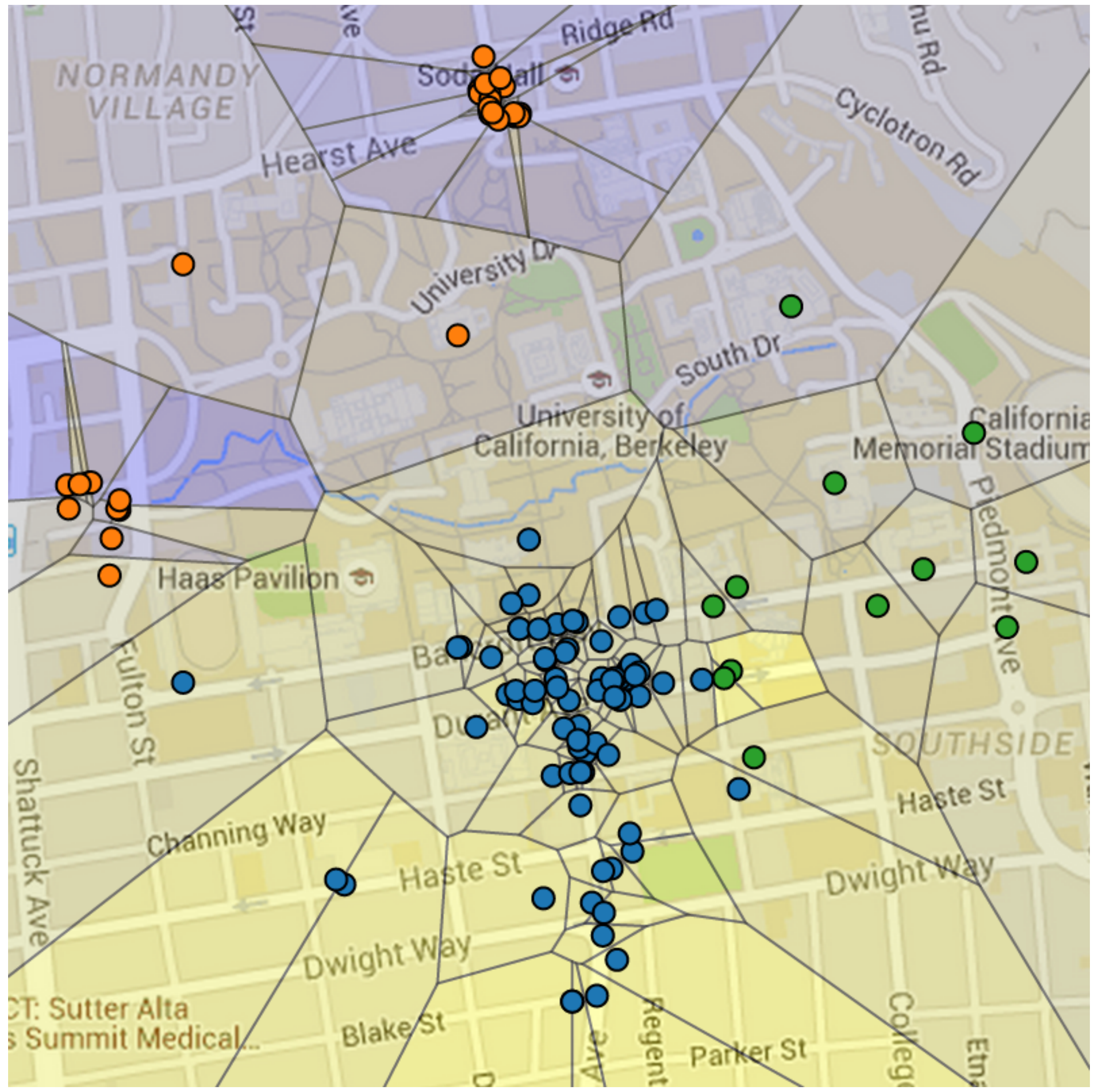

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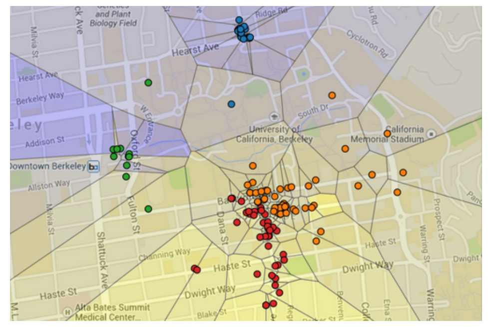

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- The data: user ratings
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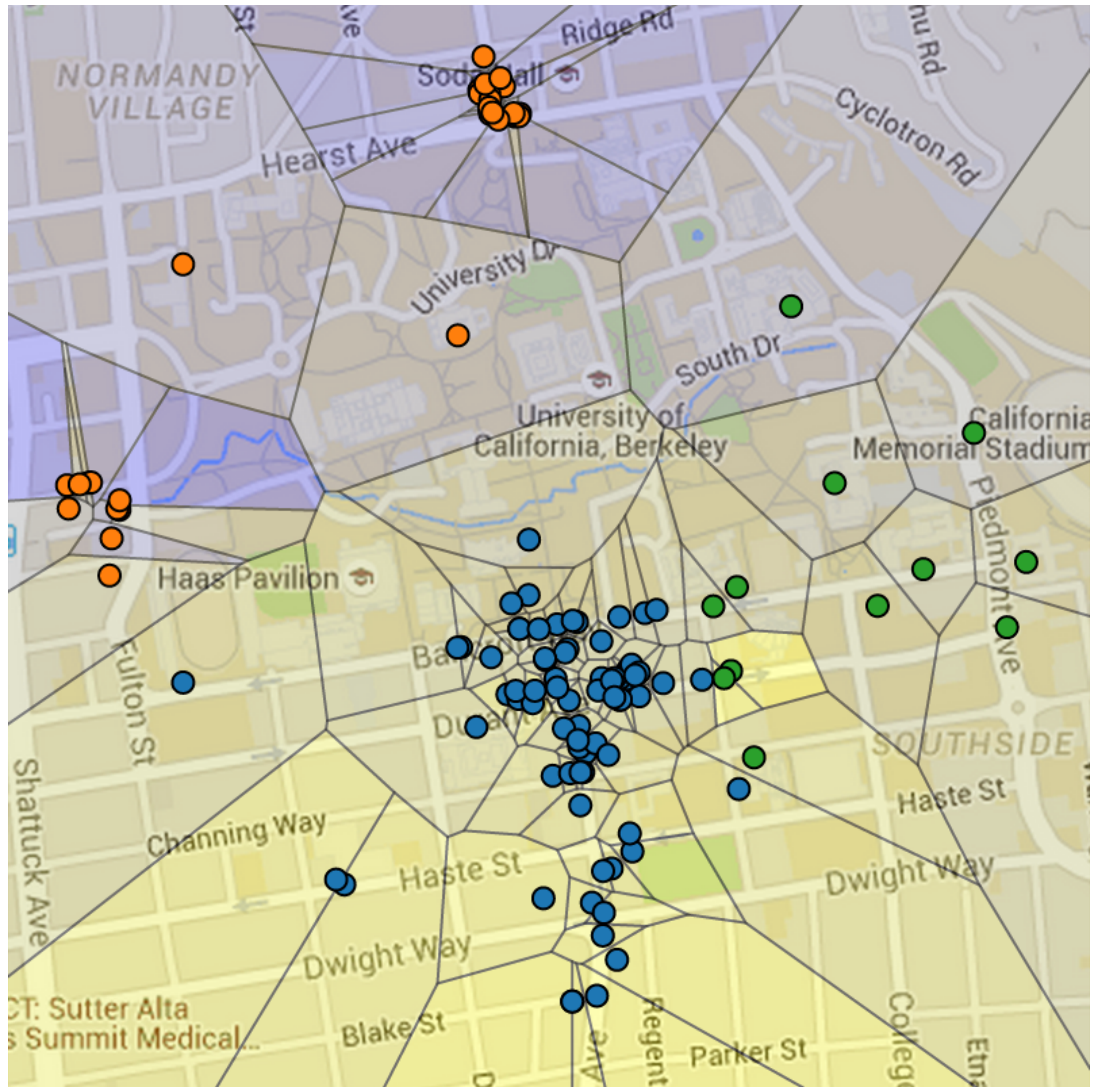

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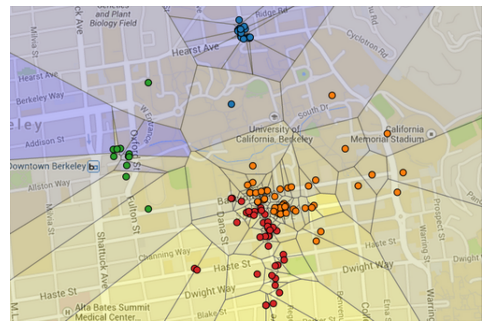

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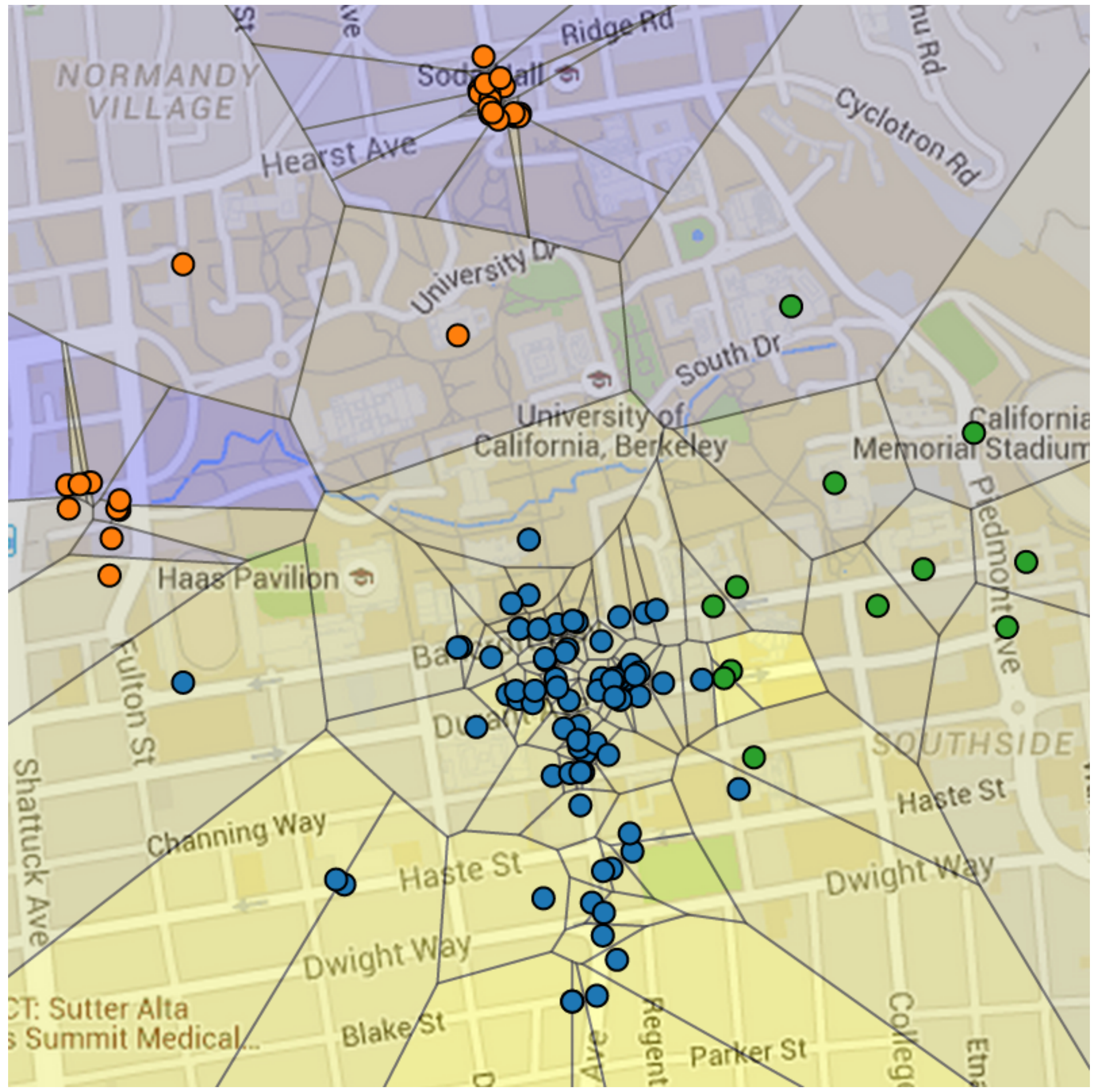
Called *supervised learning*, because some correct decisions are given.



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- Today, we will focus on a subclass of problems in machine learning, known as *reinforcement learning* problems, and algorithms for these problems.

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- Concerned with *learning behavior through experience*.
- Two main components: the *agent* and the *environment*.
- The agent lives in and interacts with the environment, and through this experience learns a good pattern of behavior.

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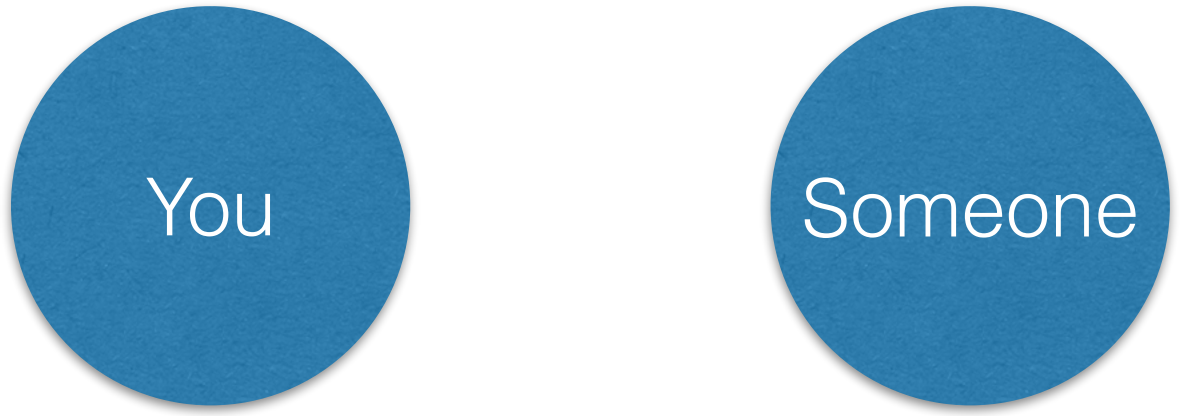

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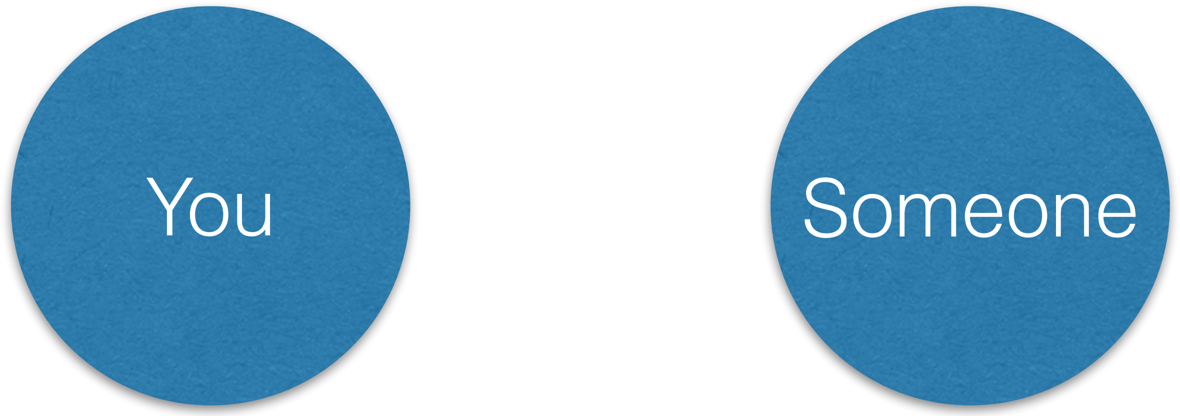

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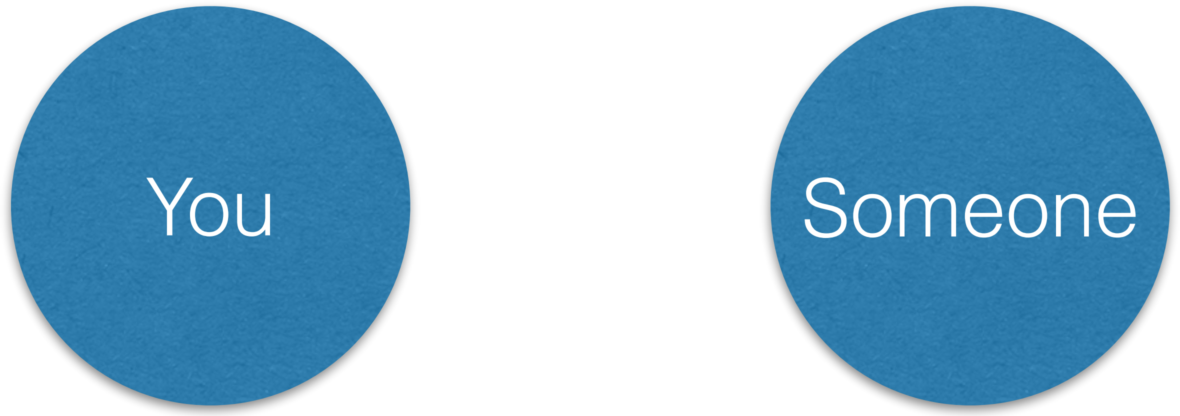

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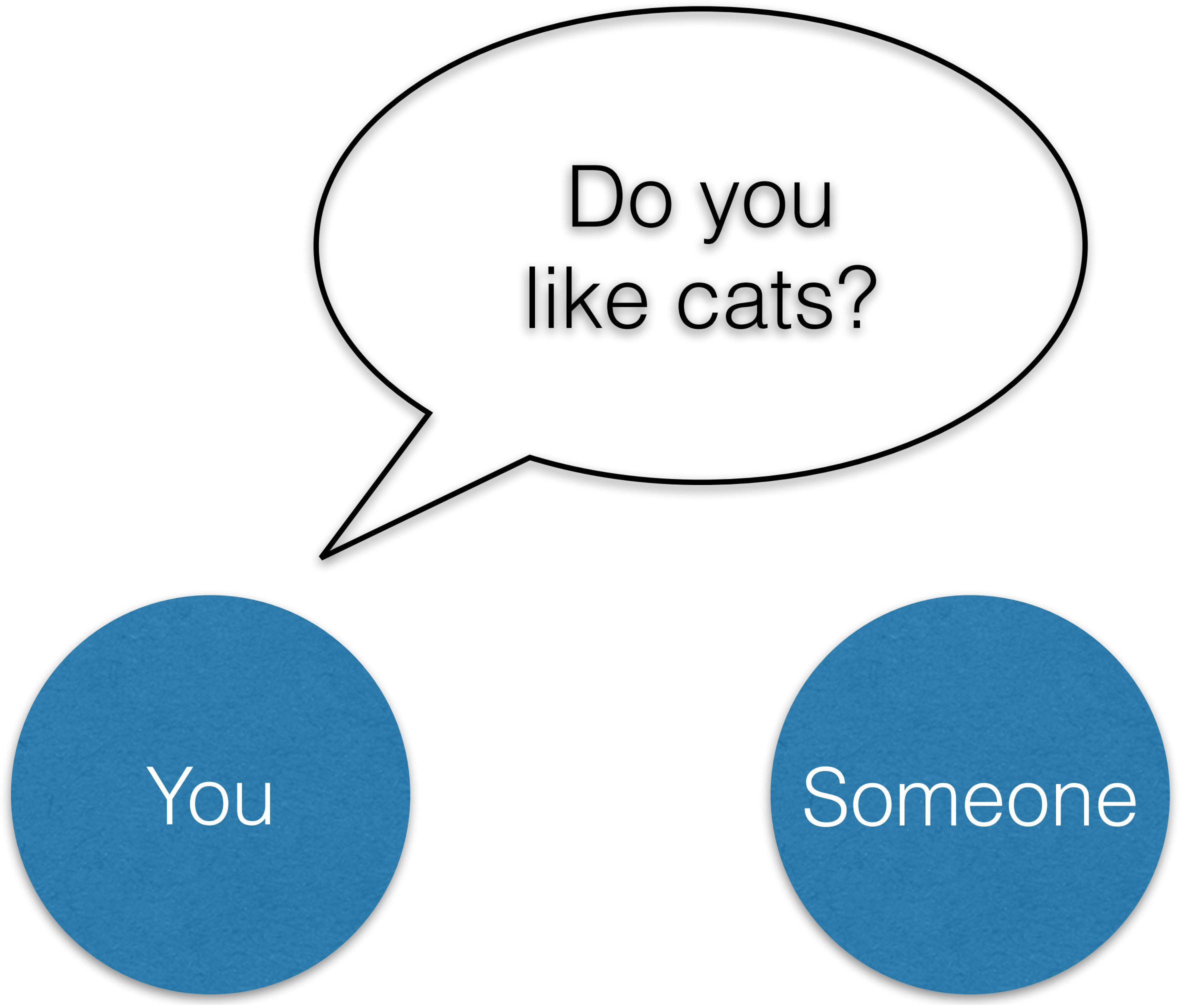

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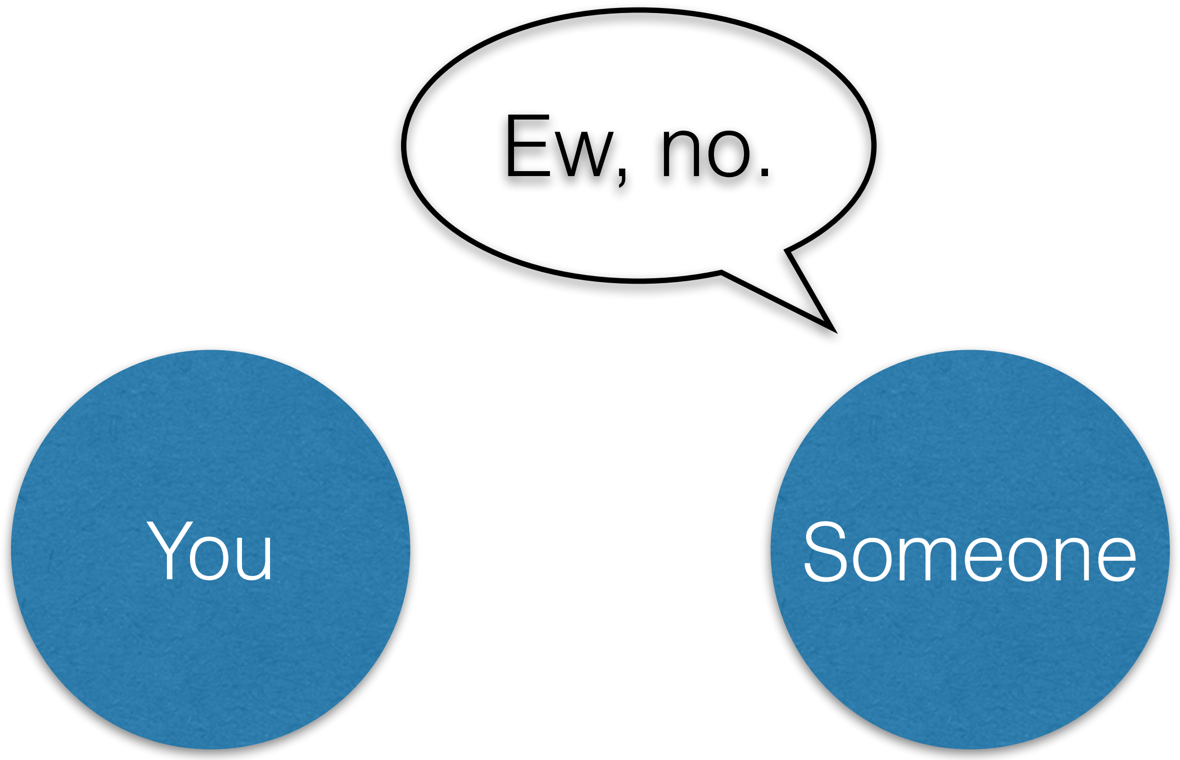

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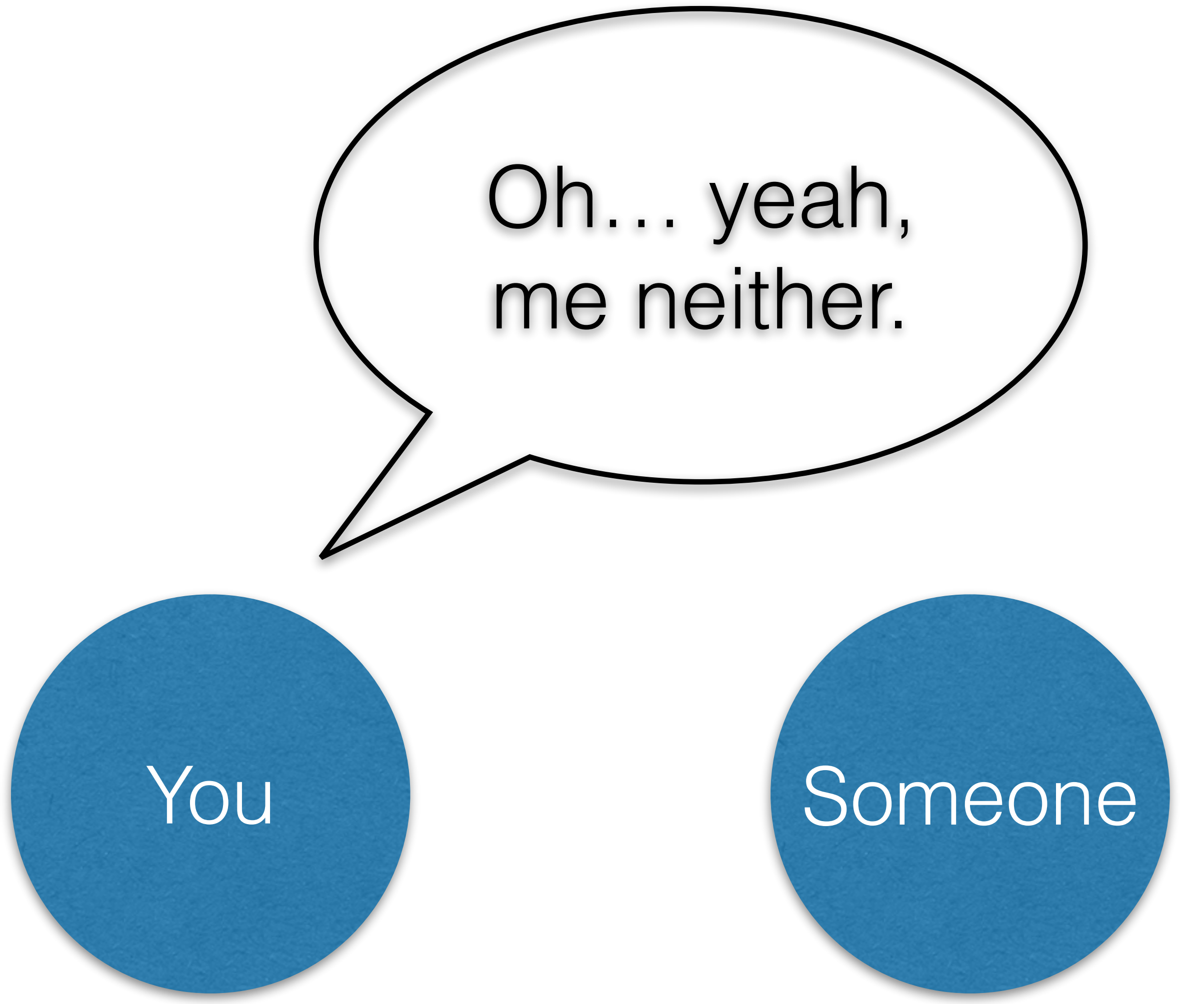

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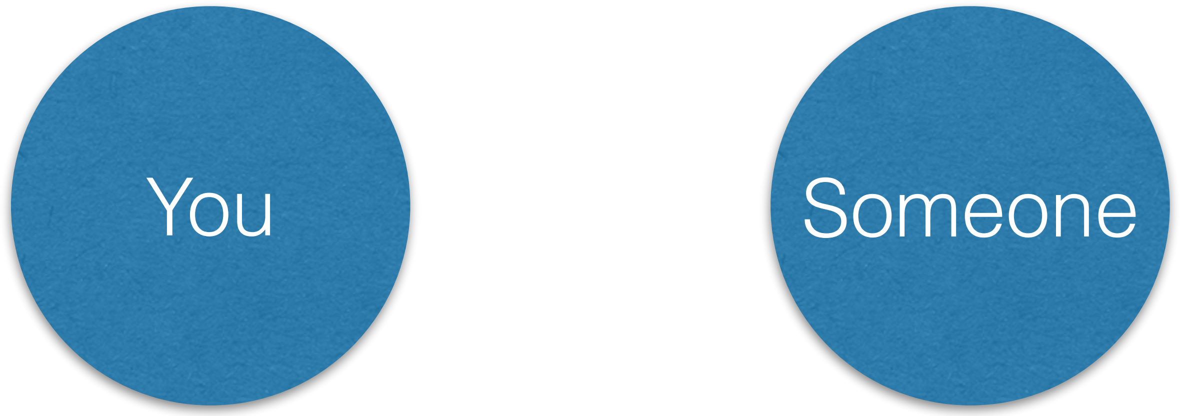
- As the date goes on, you slowly figure out how you should behave based on what you’ve tried so far, and how it went.



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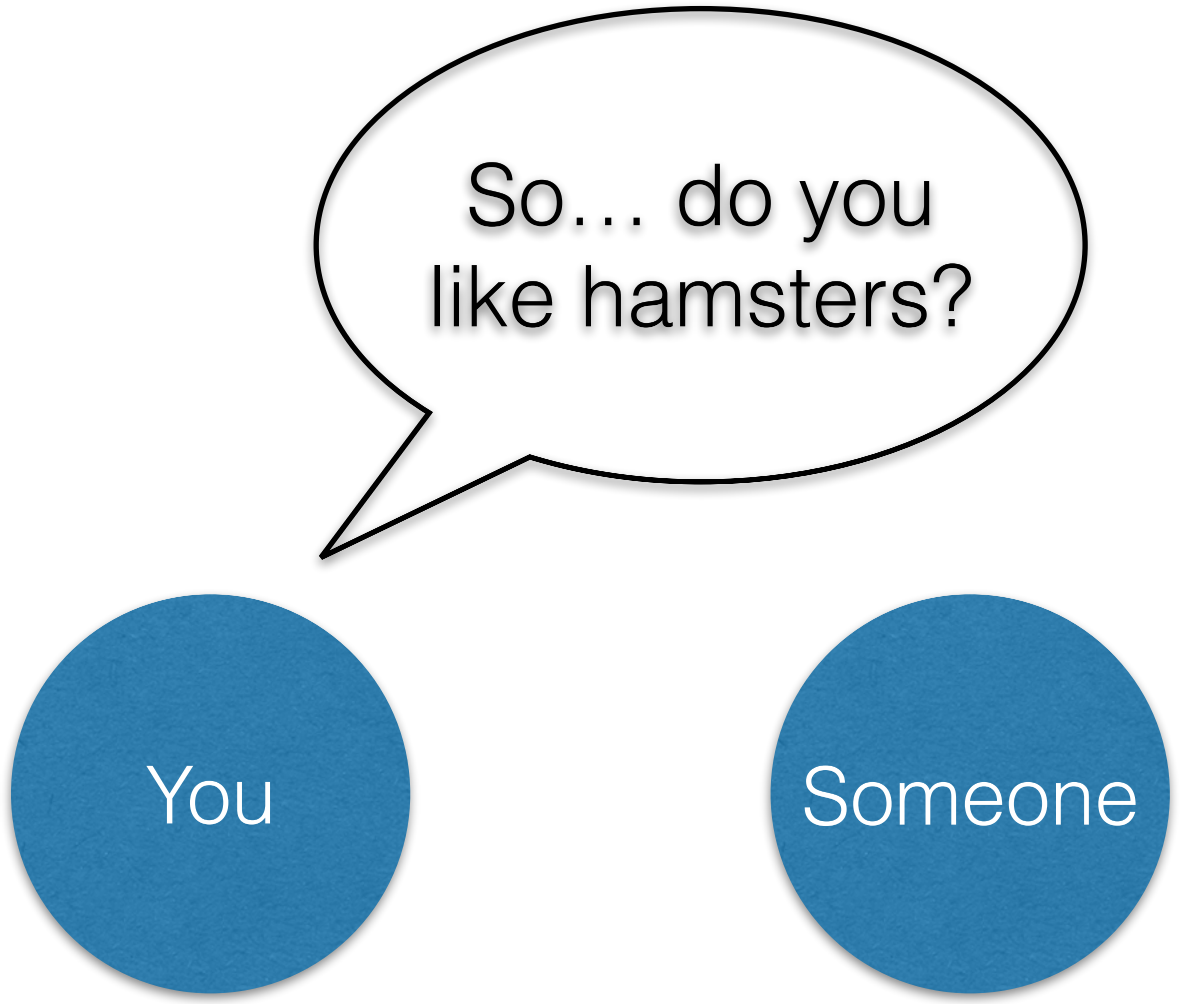

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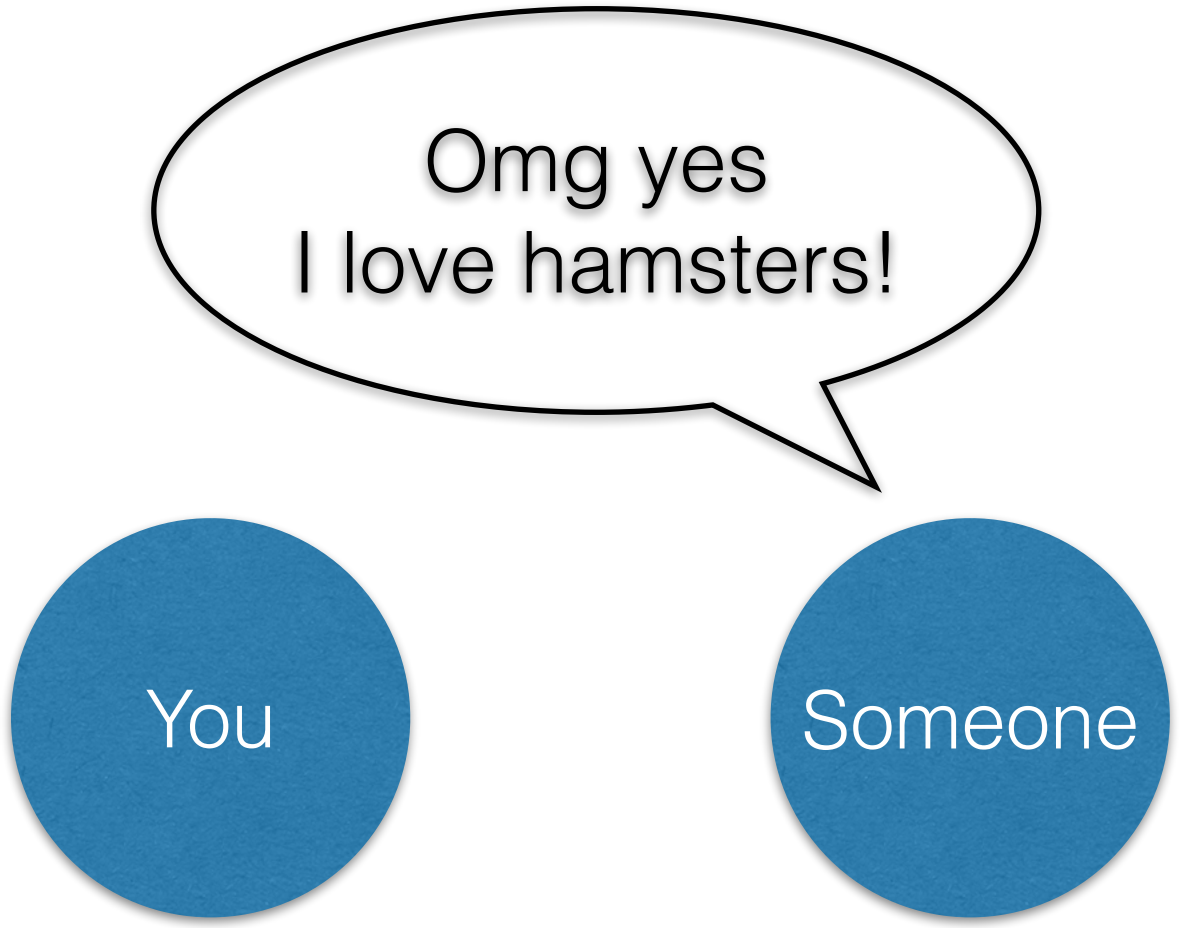

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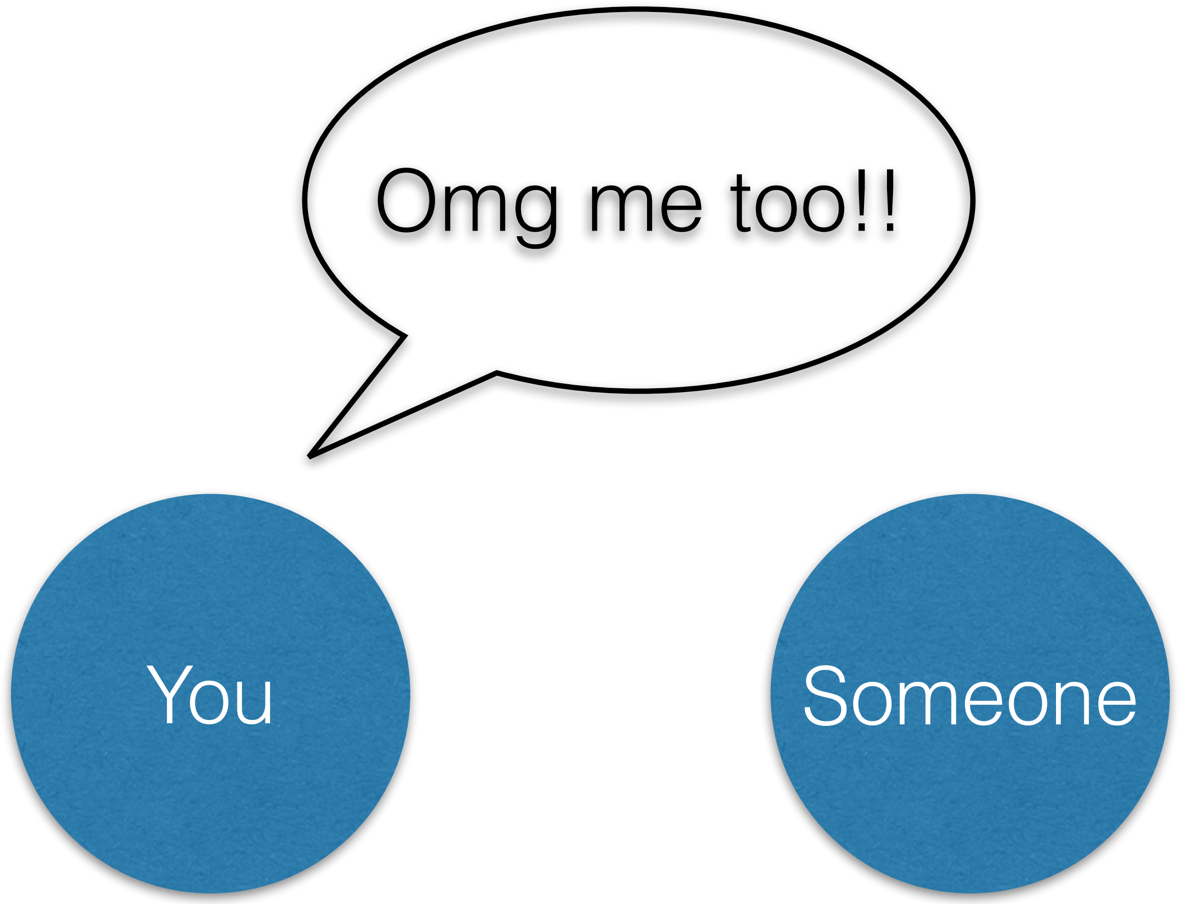

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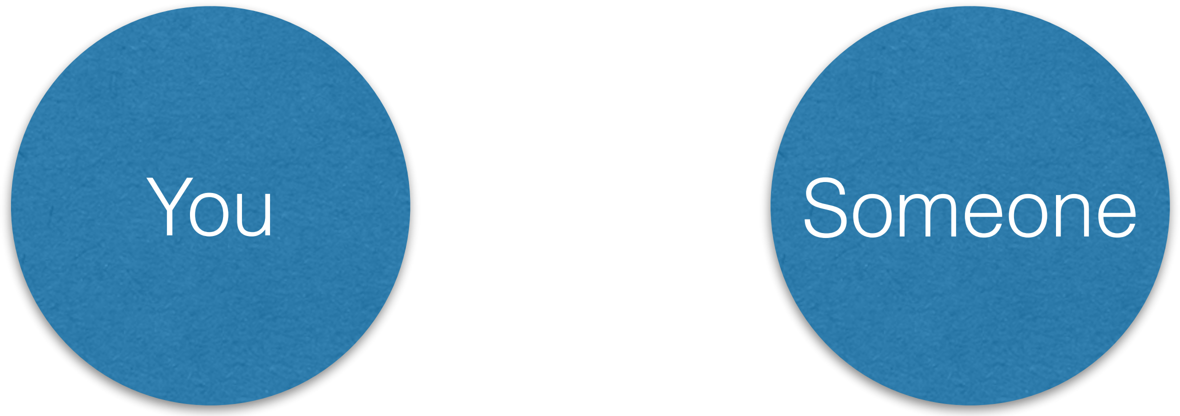
- If you're a good agent, you may even learn how to behave really, really well!



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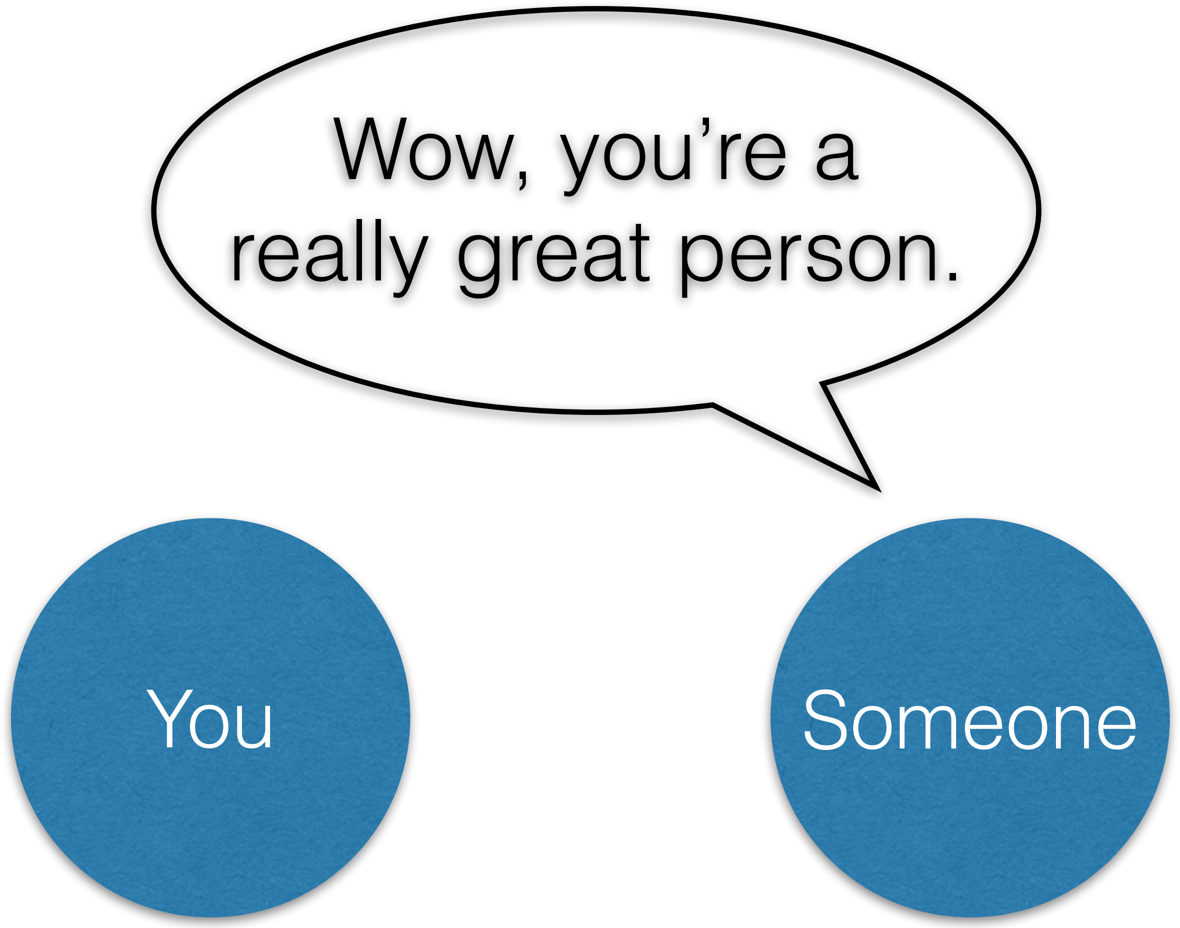

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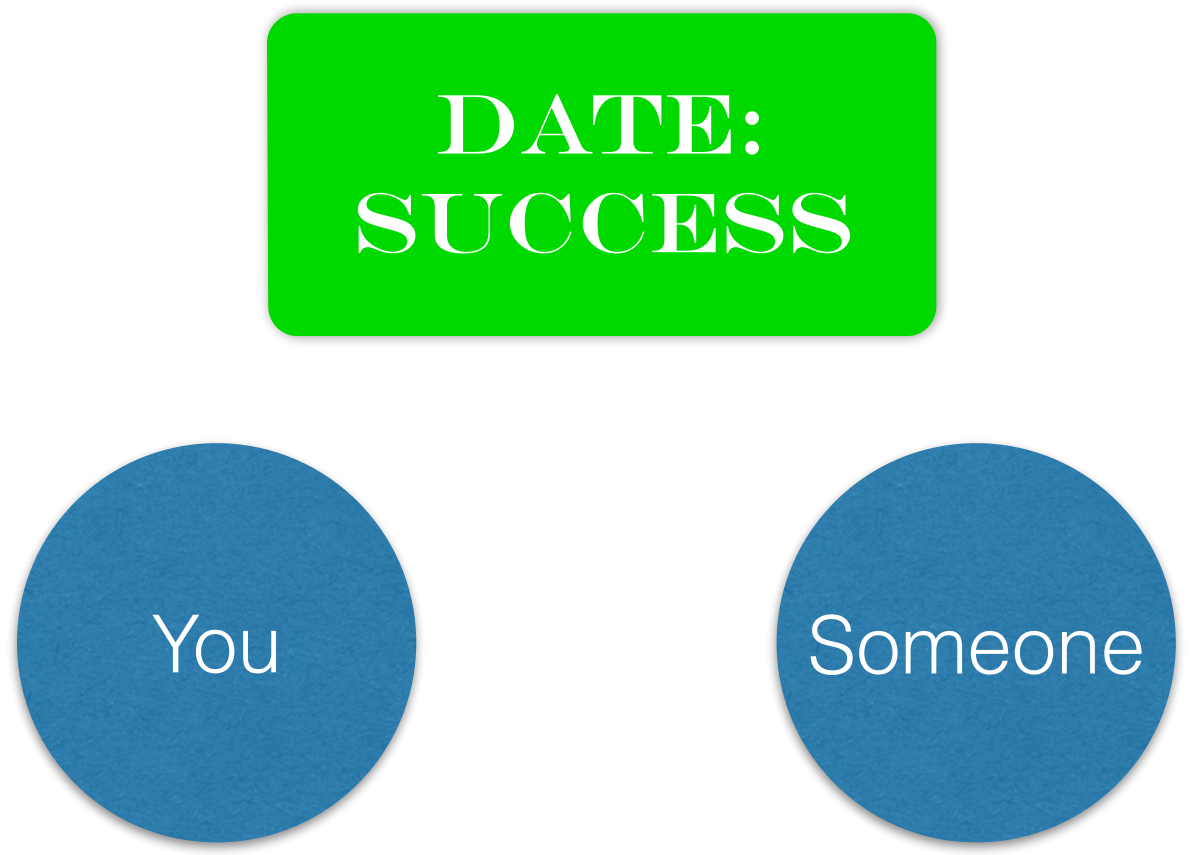
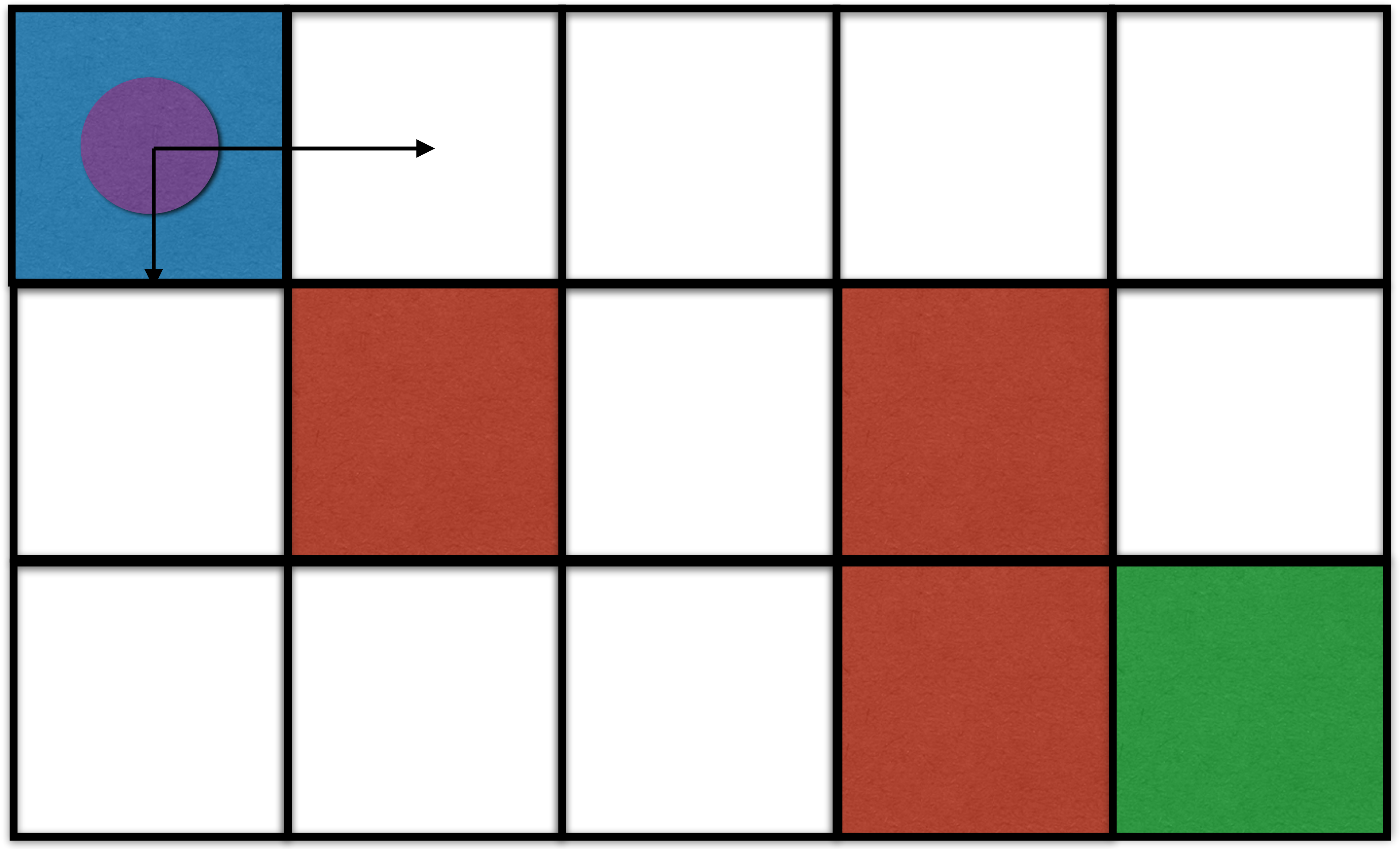


RL Example: Gridworld



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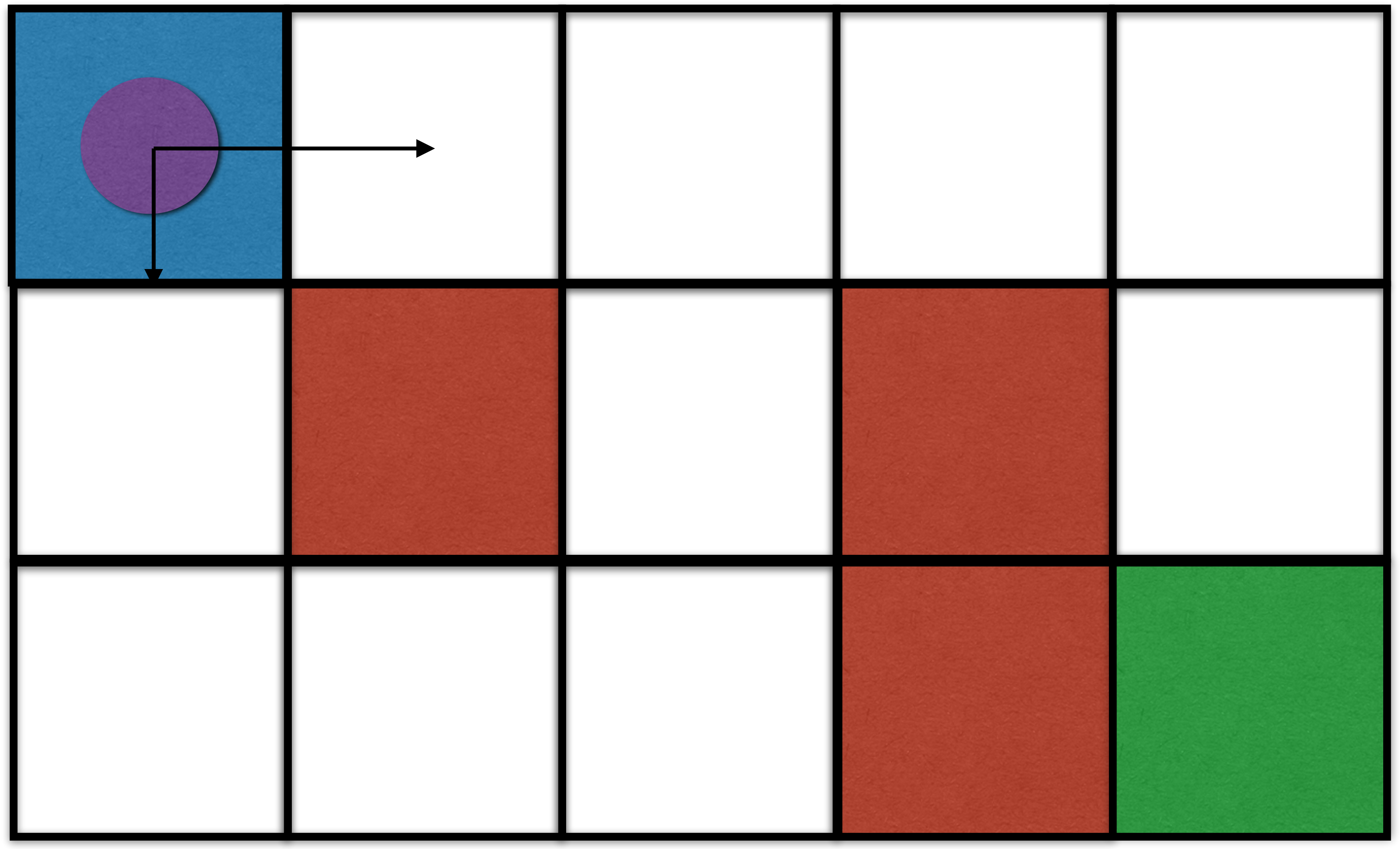

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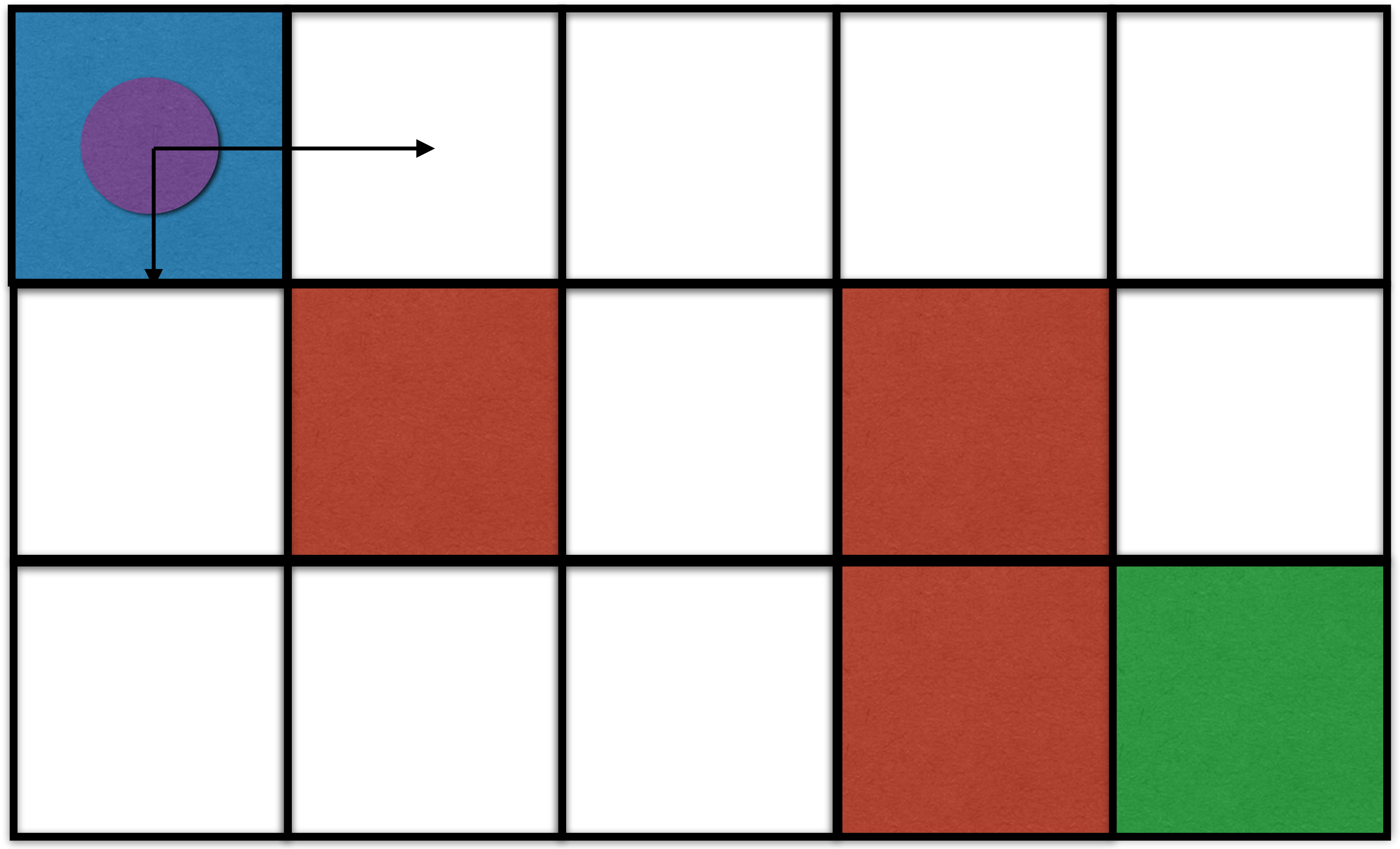

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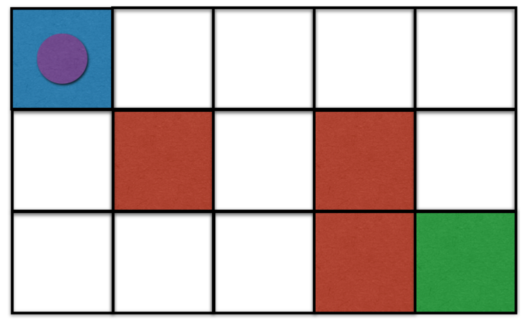

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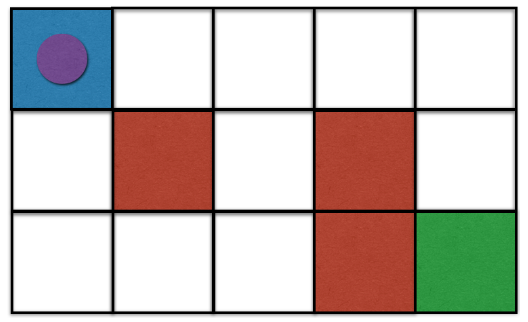

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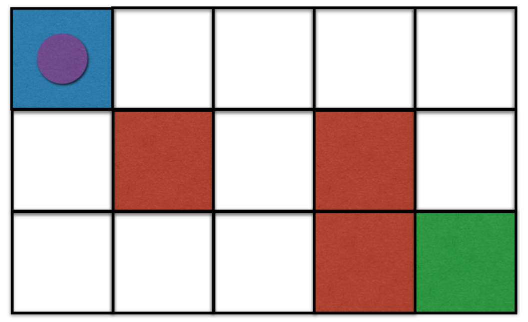

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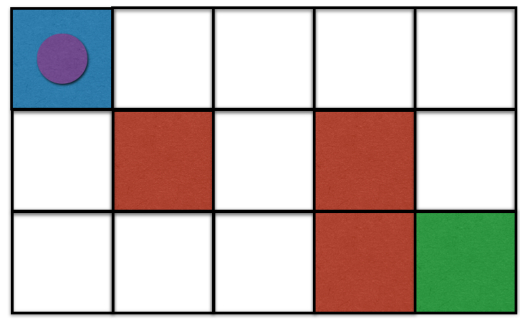

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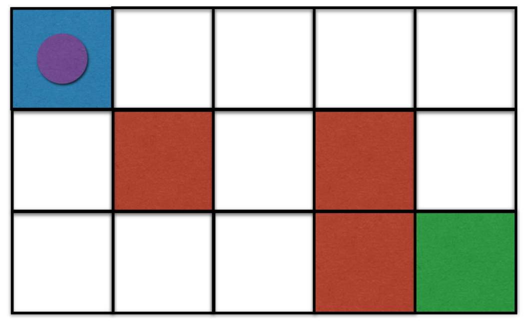

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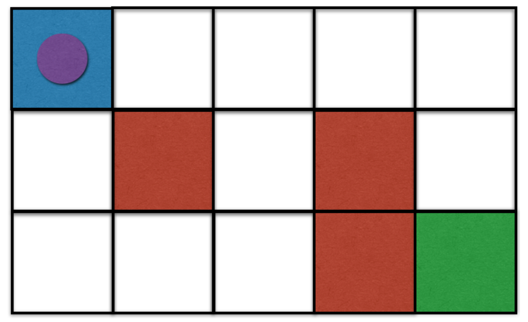

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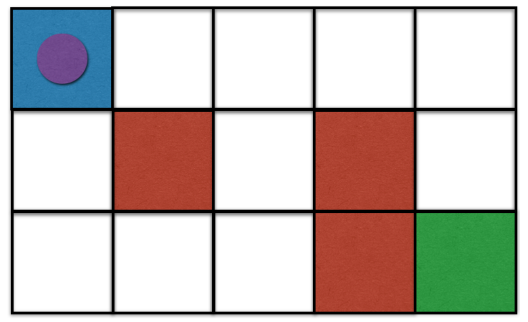

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- Policy (π):
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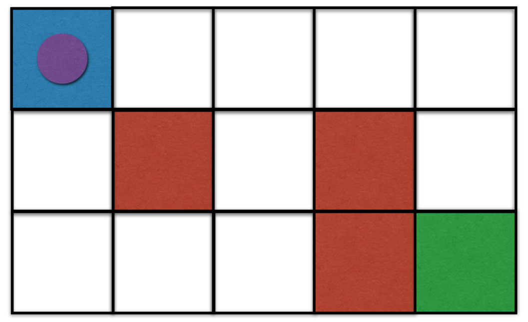

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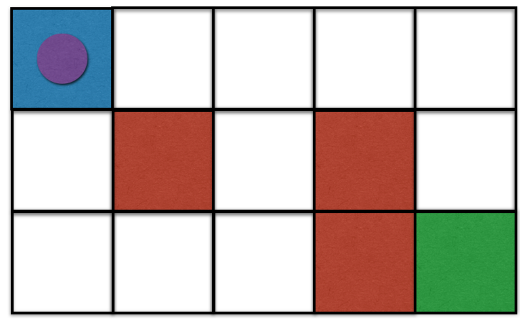

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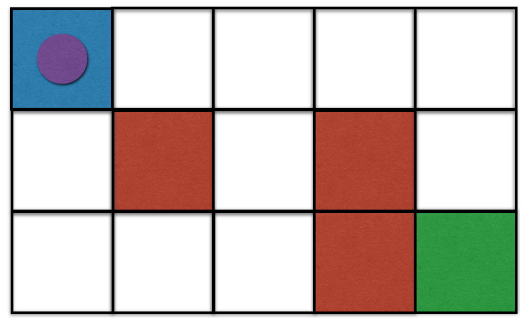

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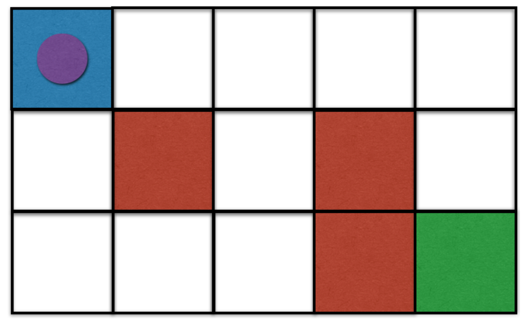

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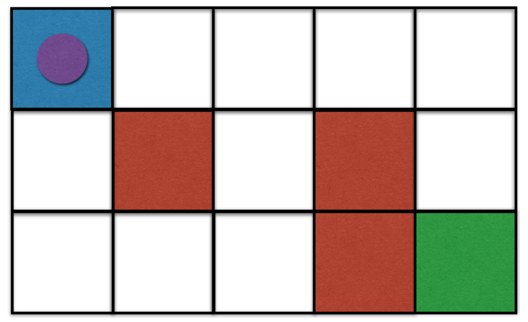

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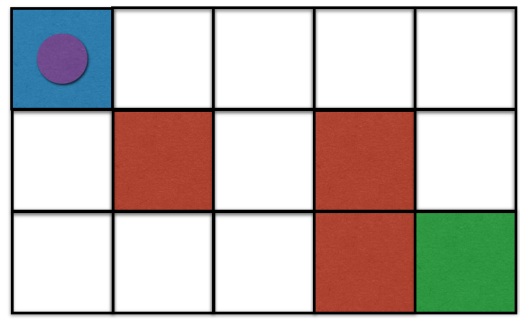

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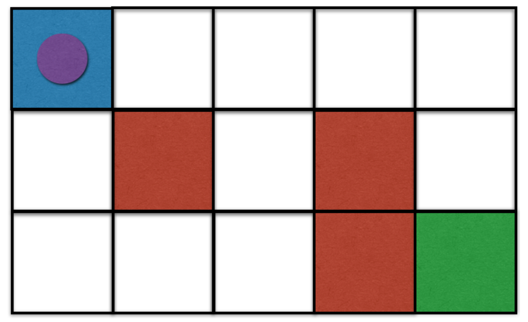

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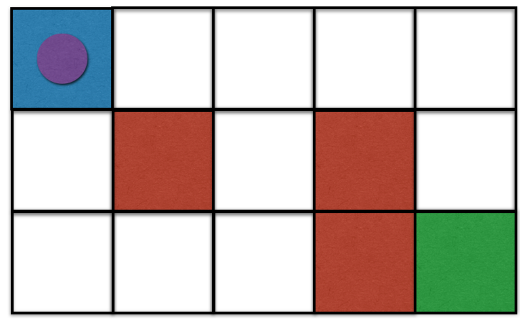

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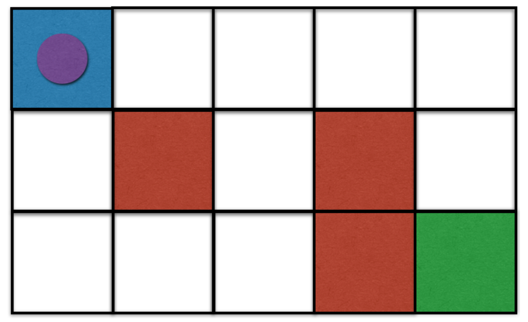

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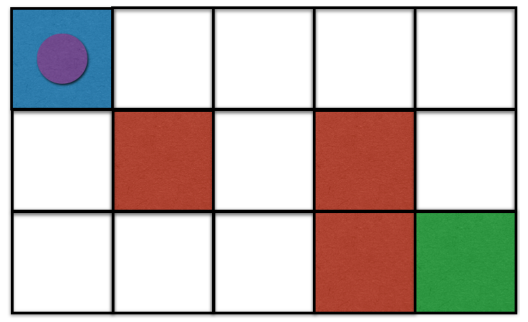

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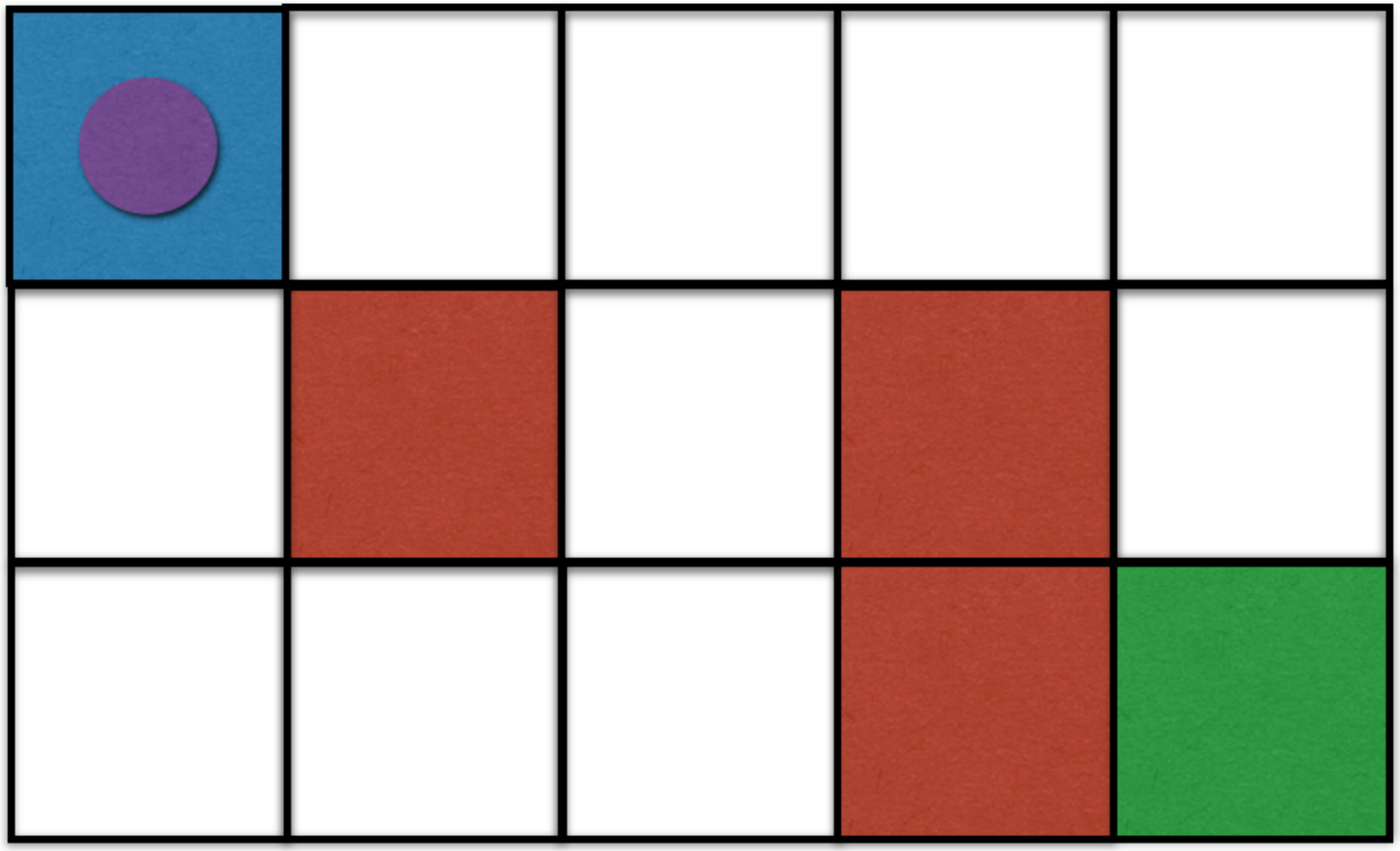

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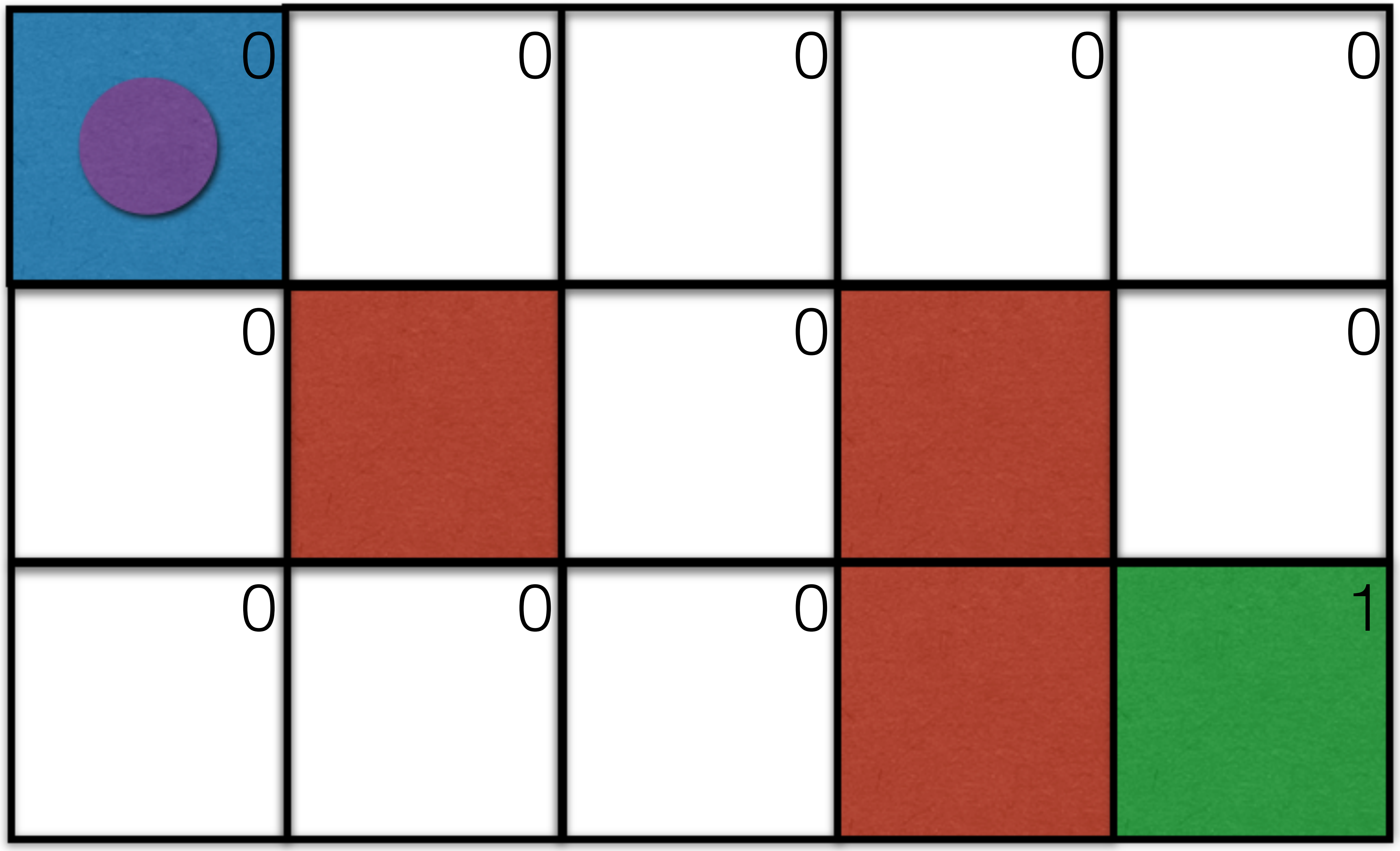

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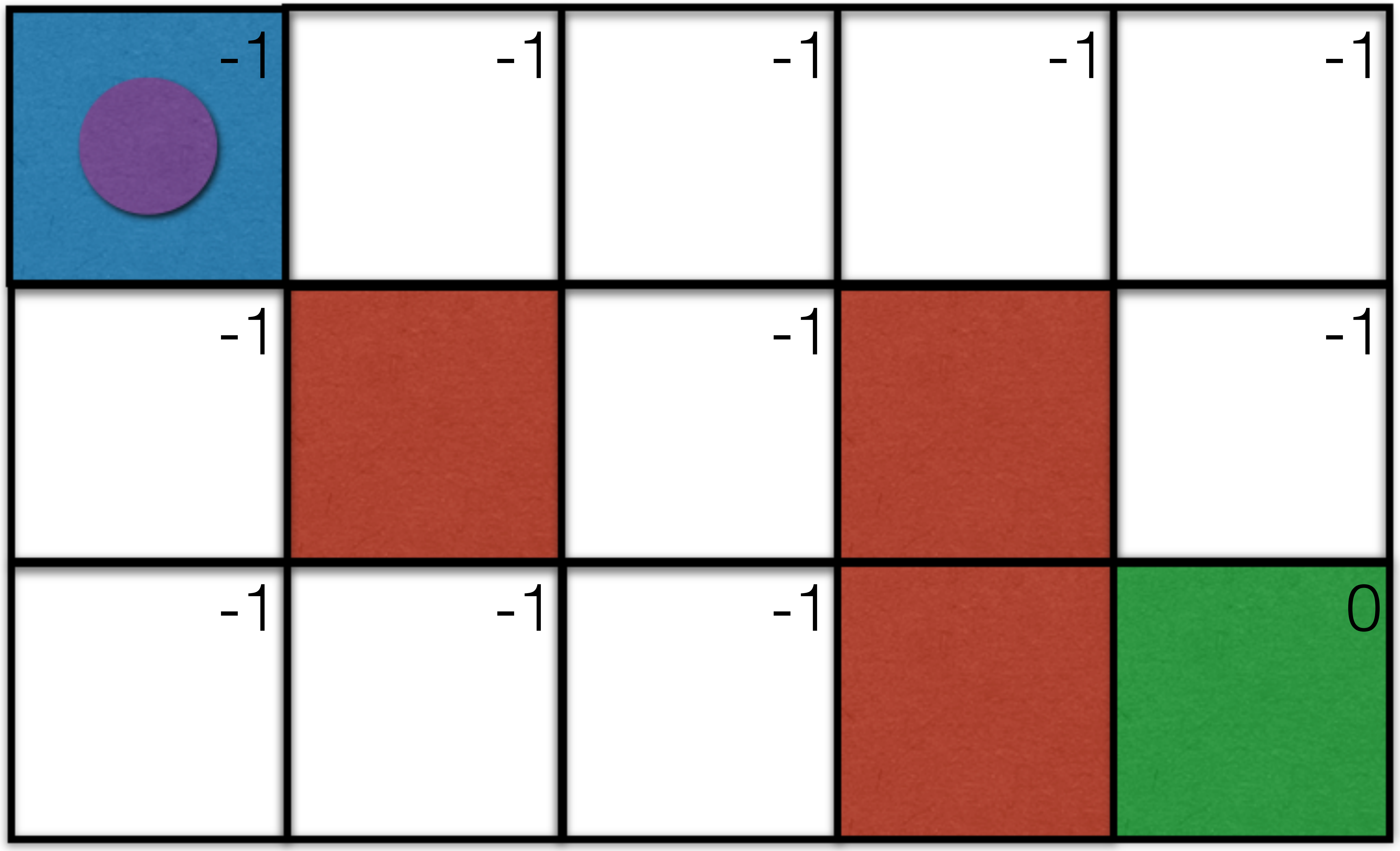

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```
def V(s):
    reward = R(s)
    if is_goal(s):
        return reward
    return reward +
        sum([P(s, pi(s), n_s) * V(n_s) for n_s in states])
```

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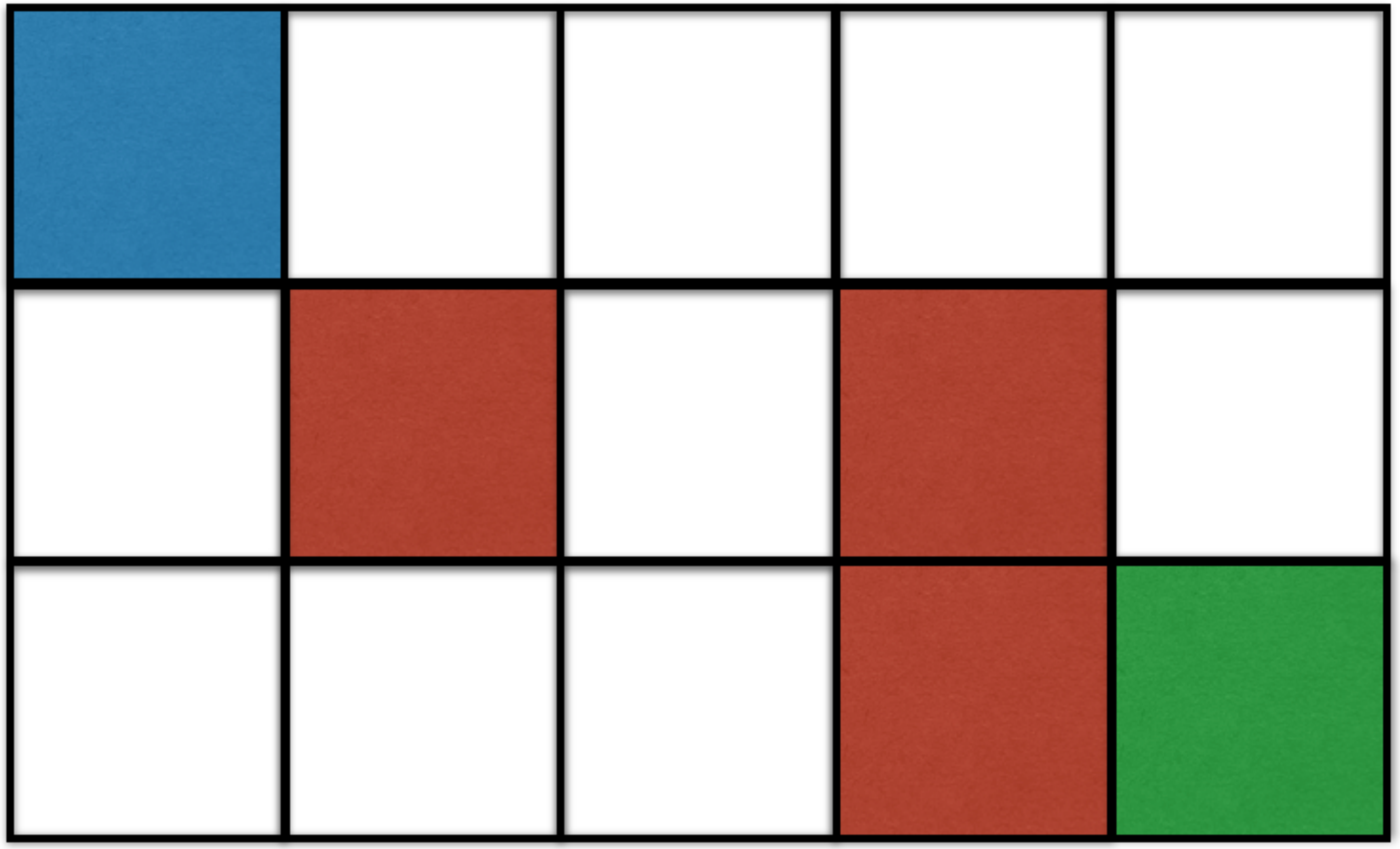

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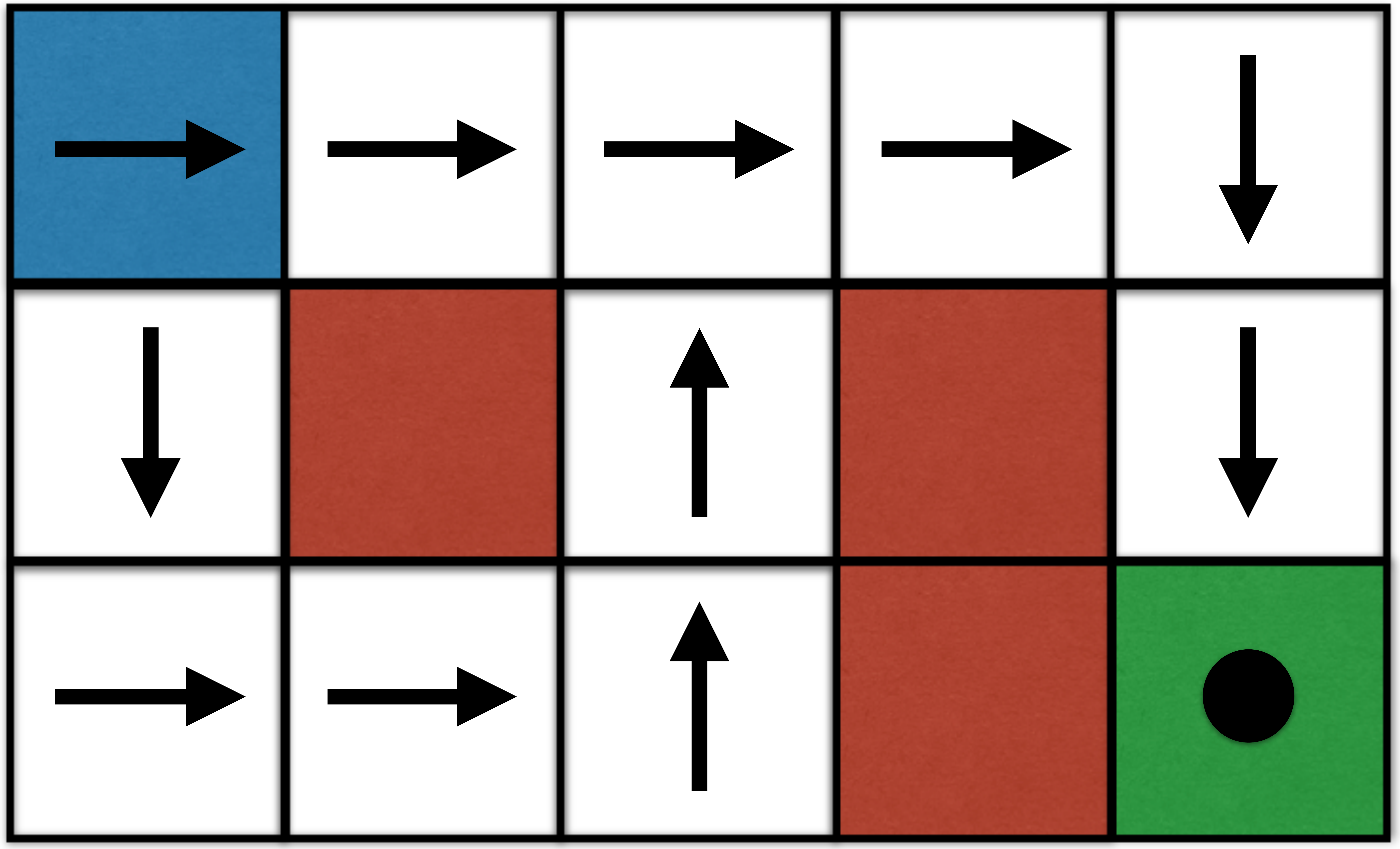

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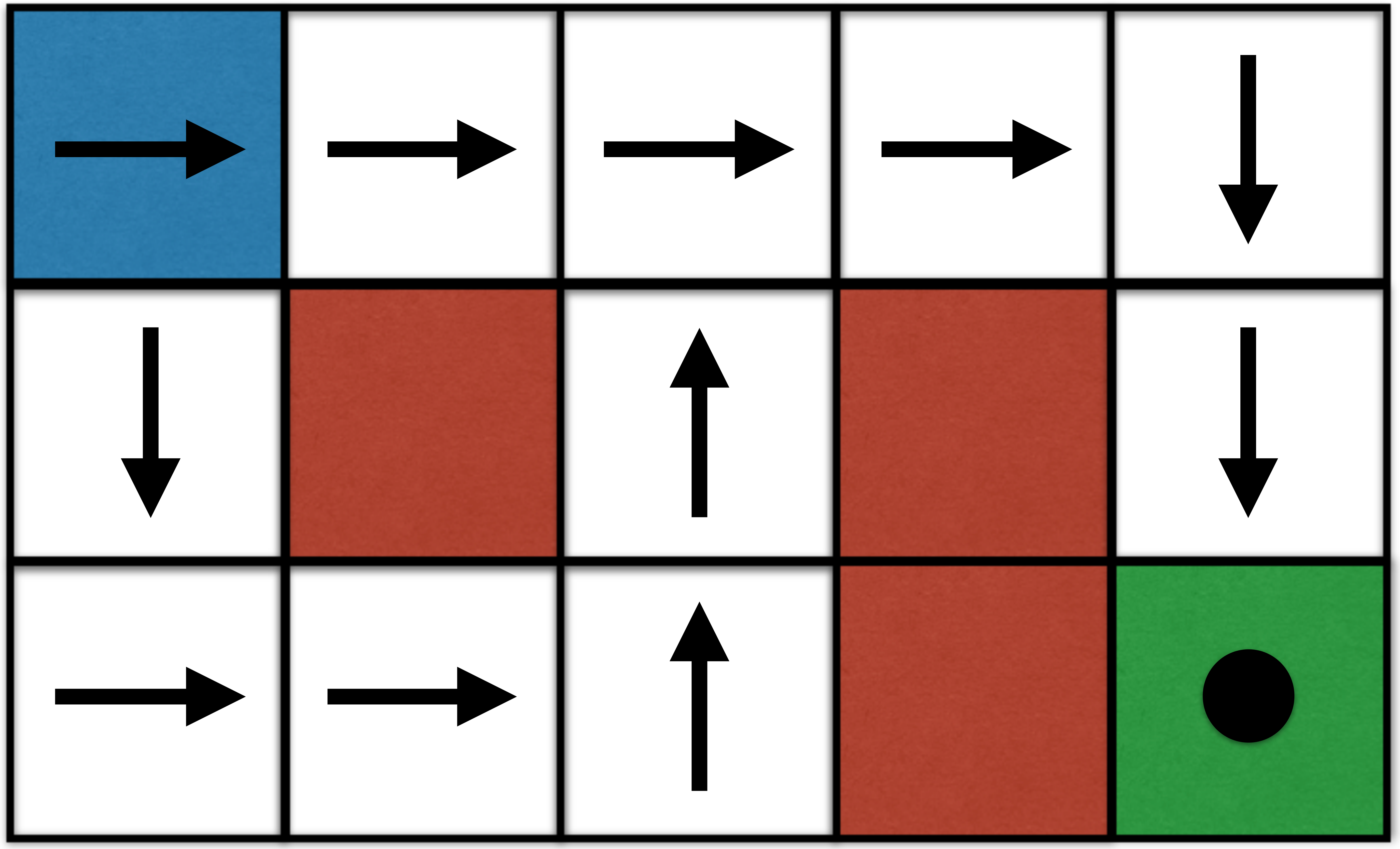

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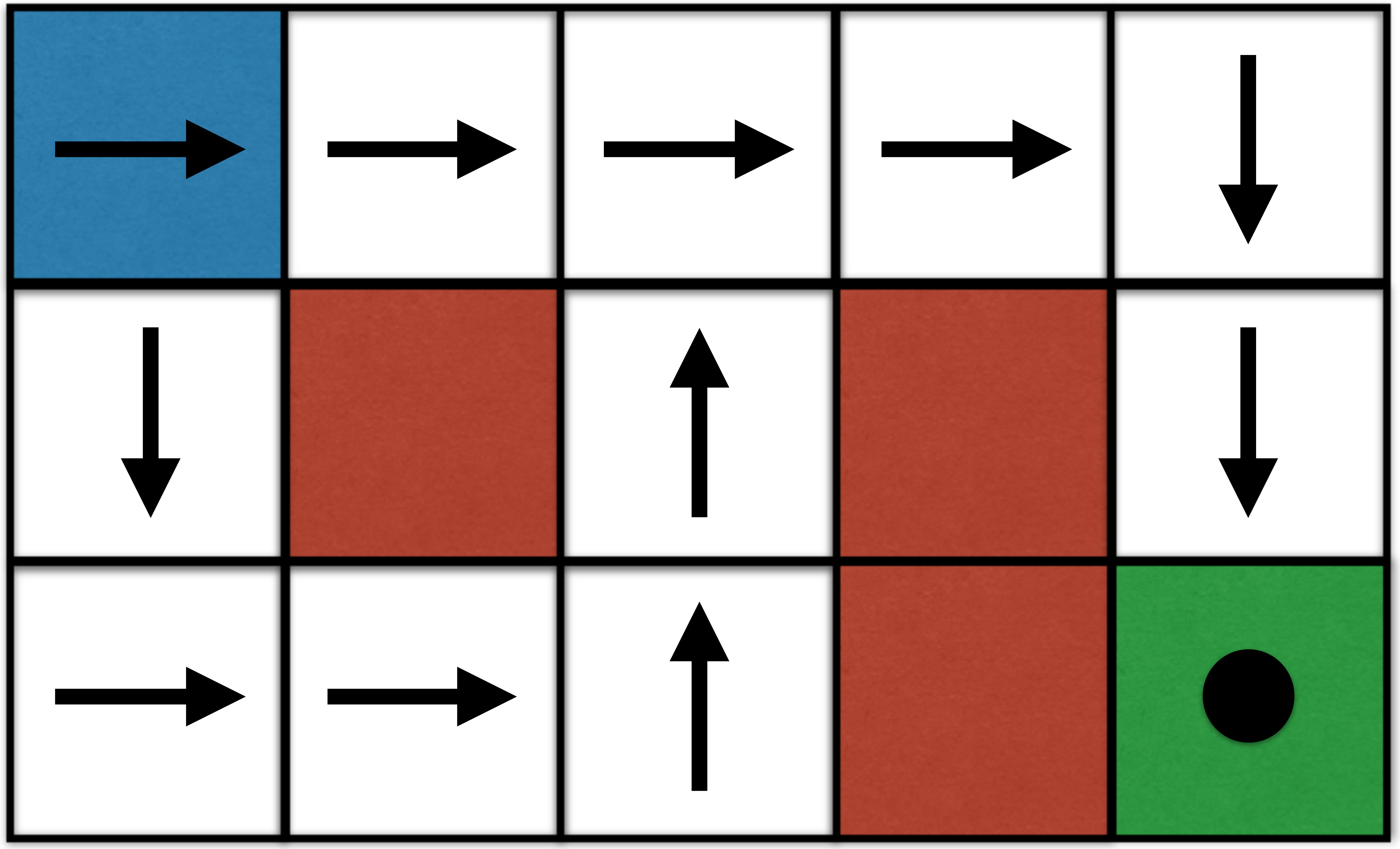

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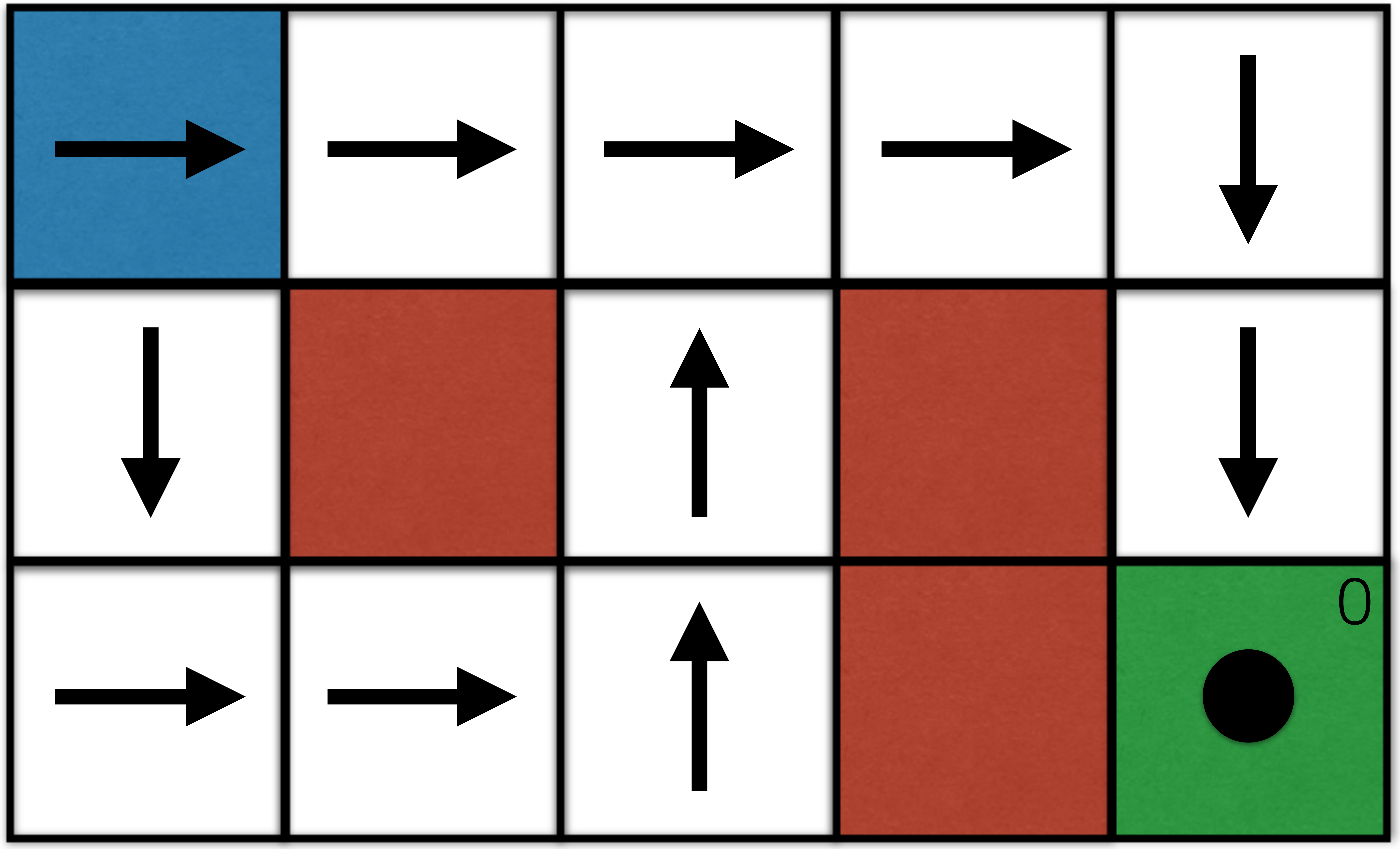

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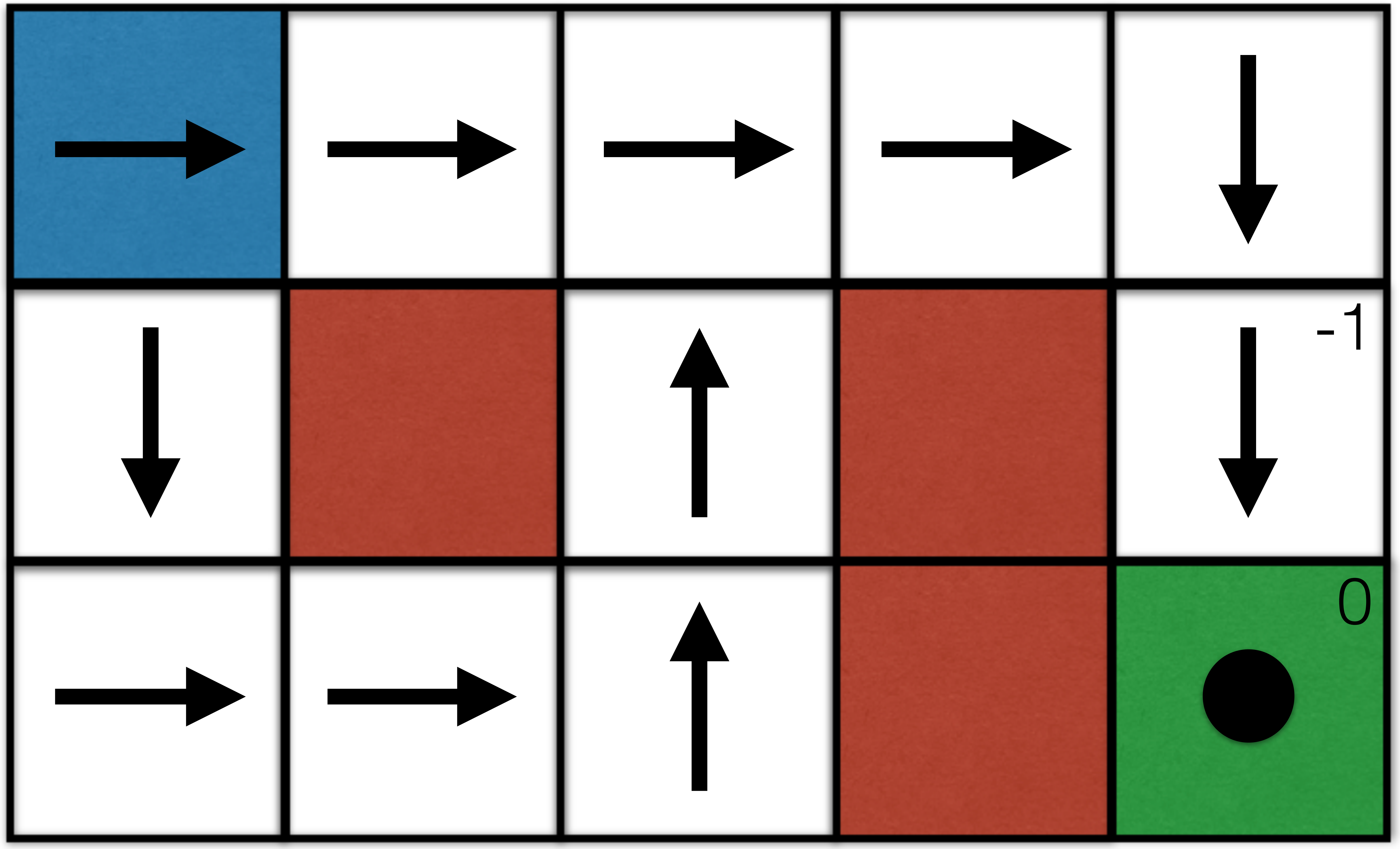

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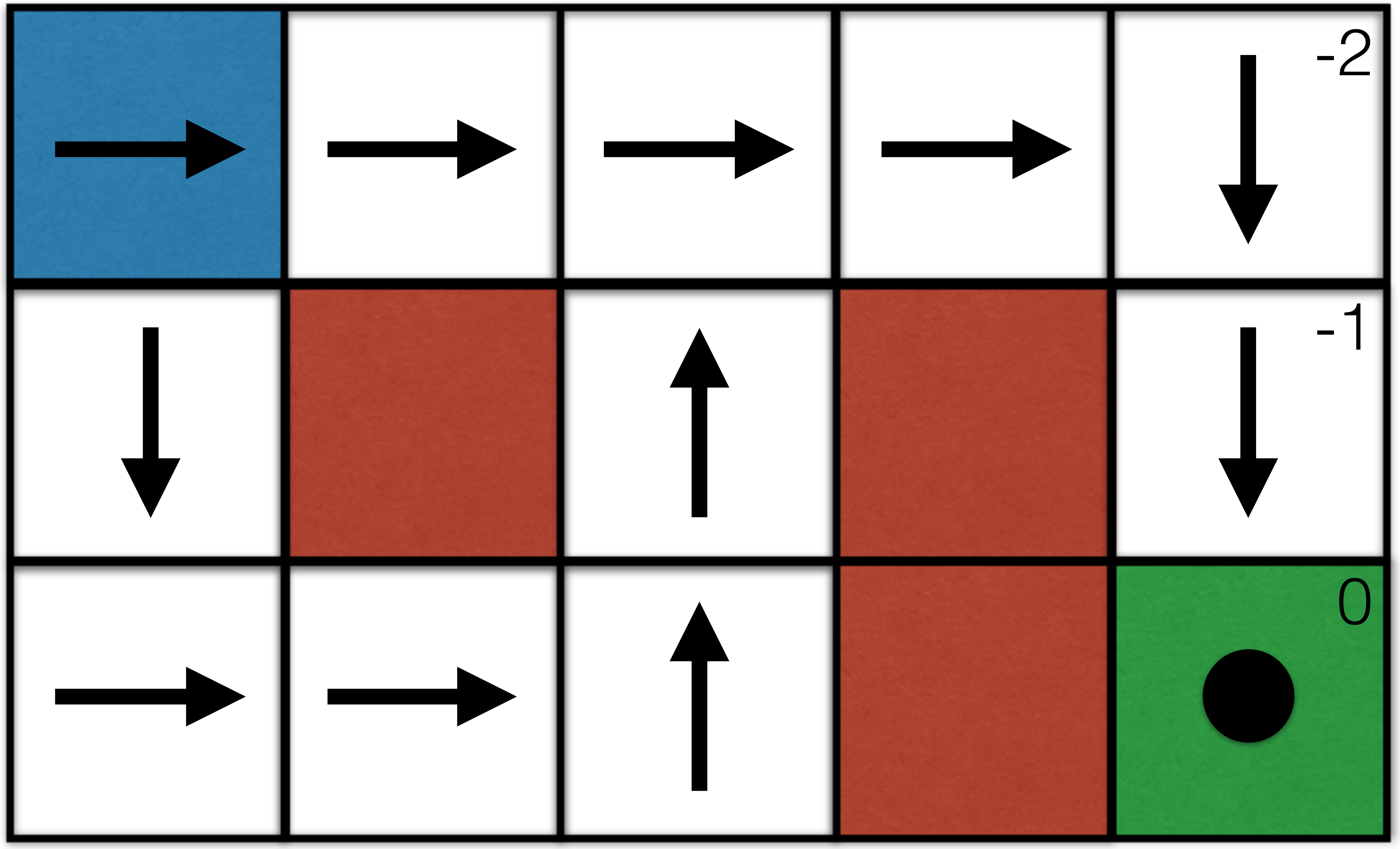

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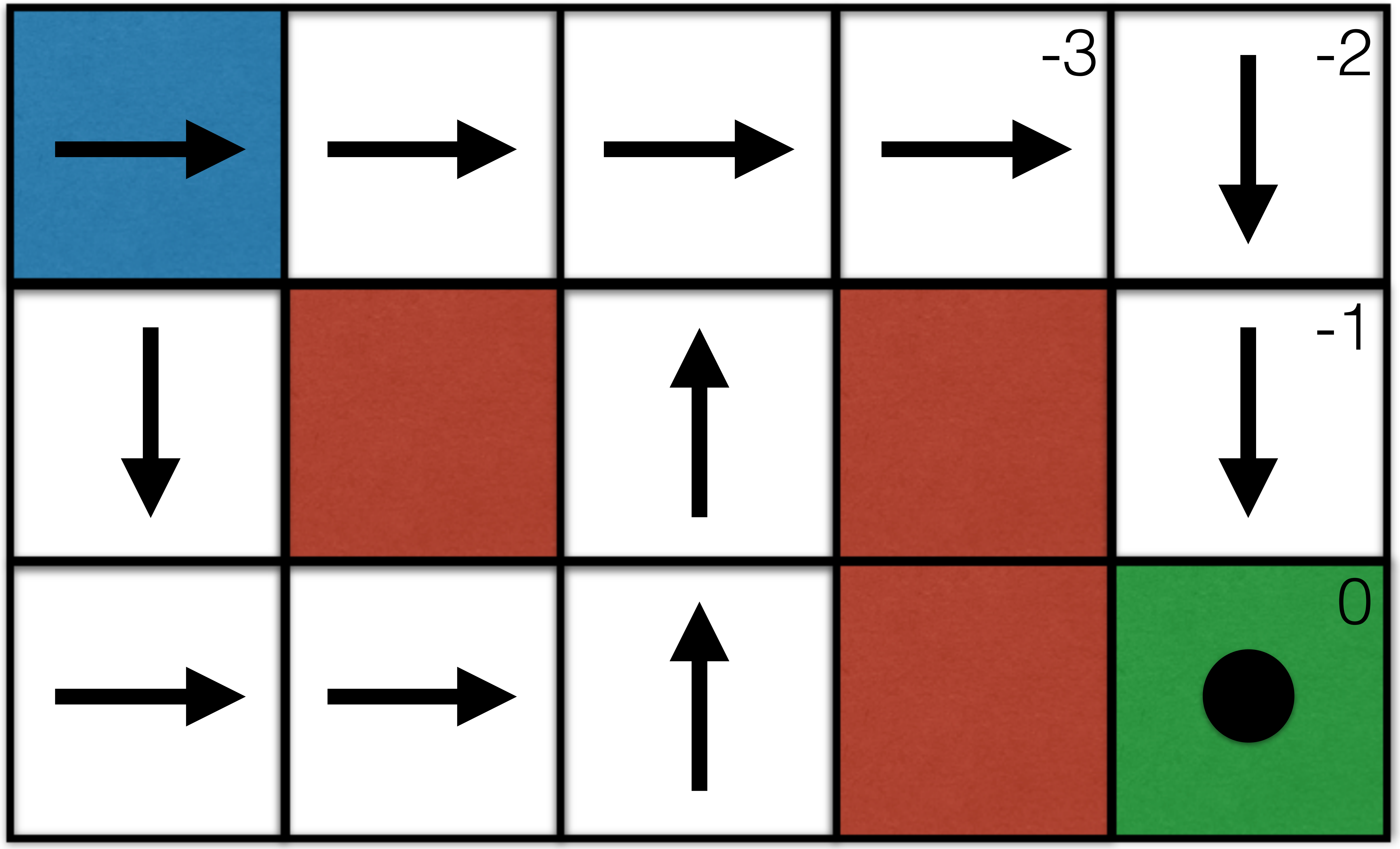

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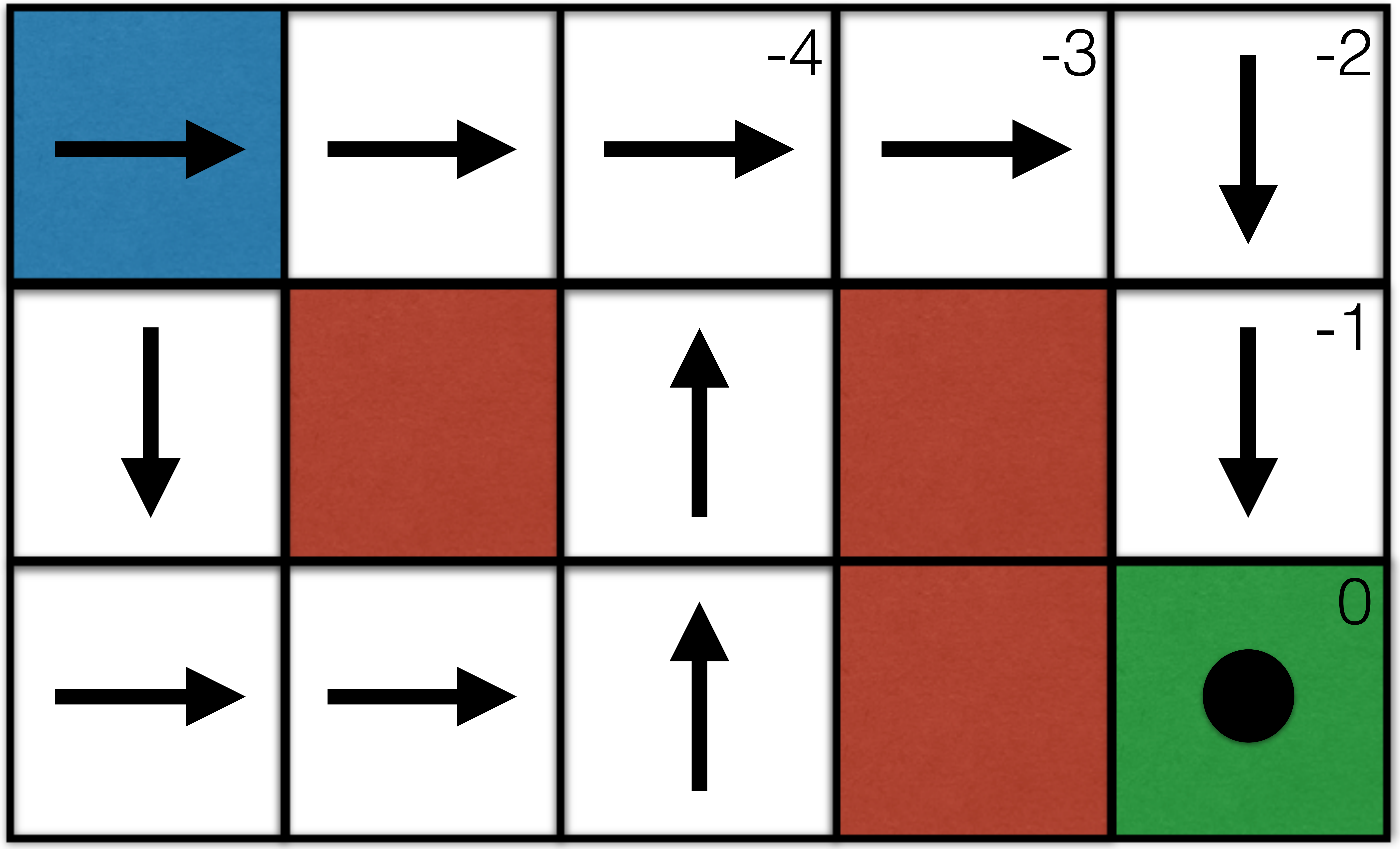

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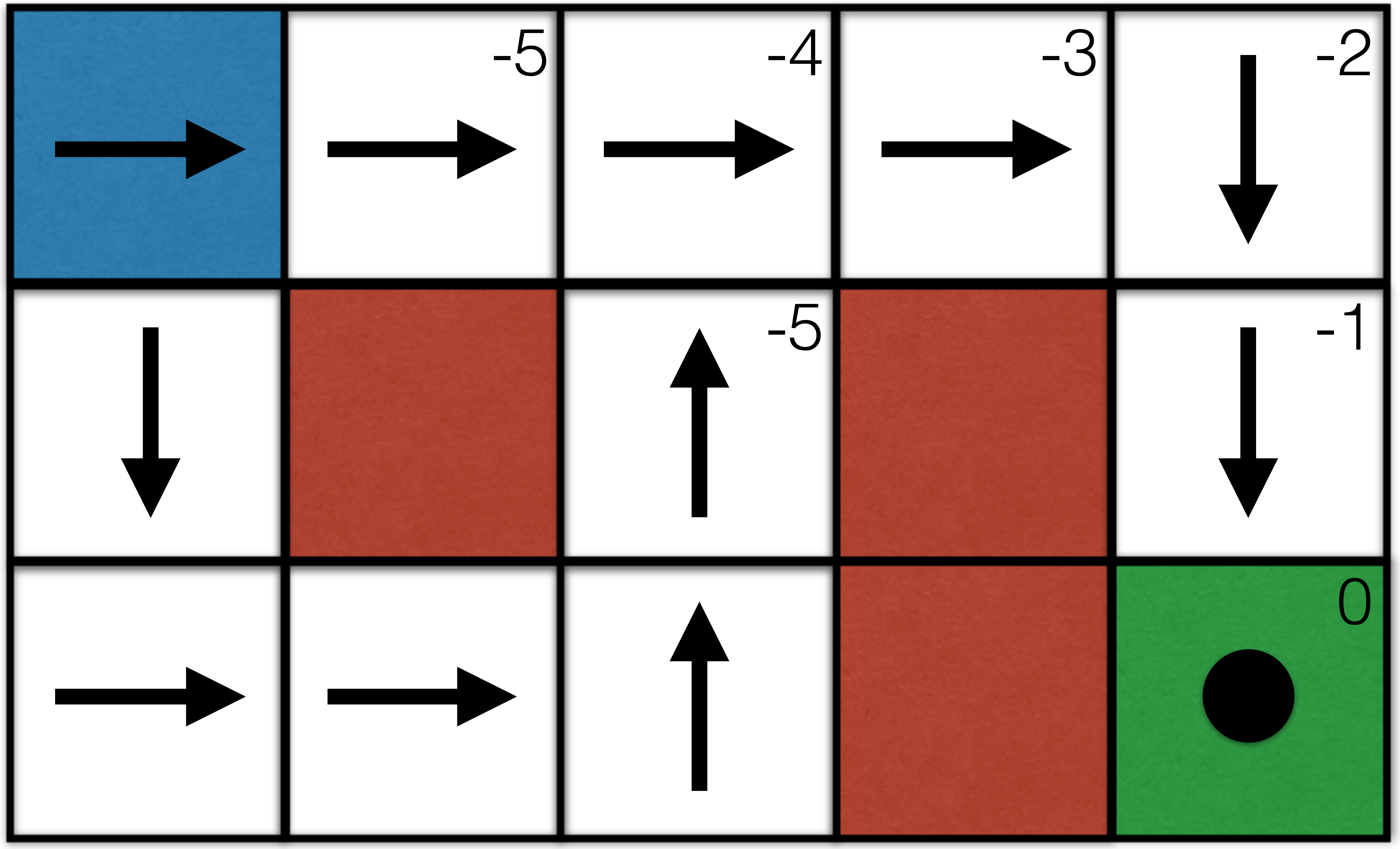

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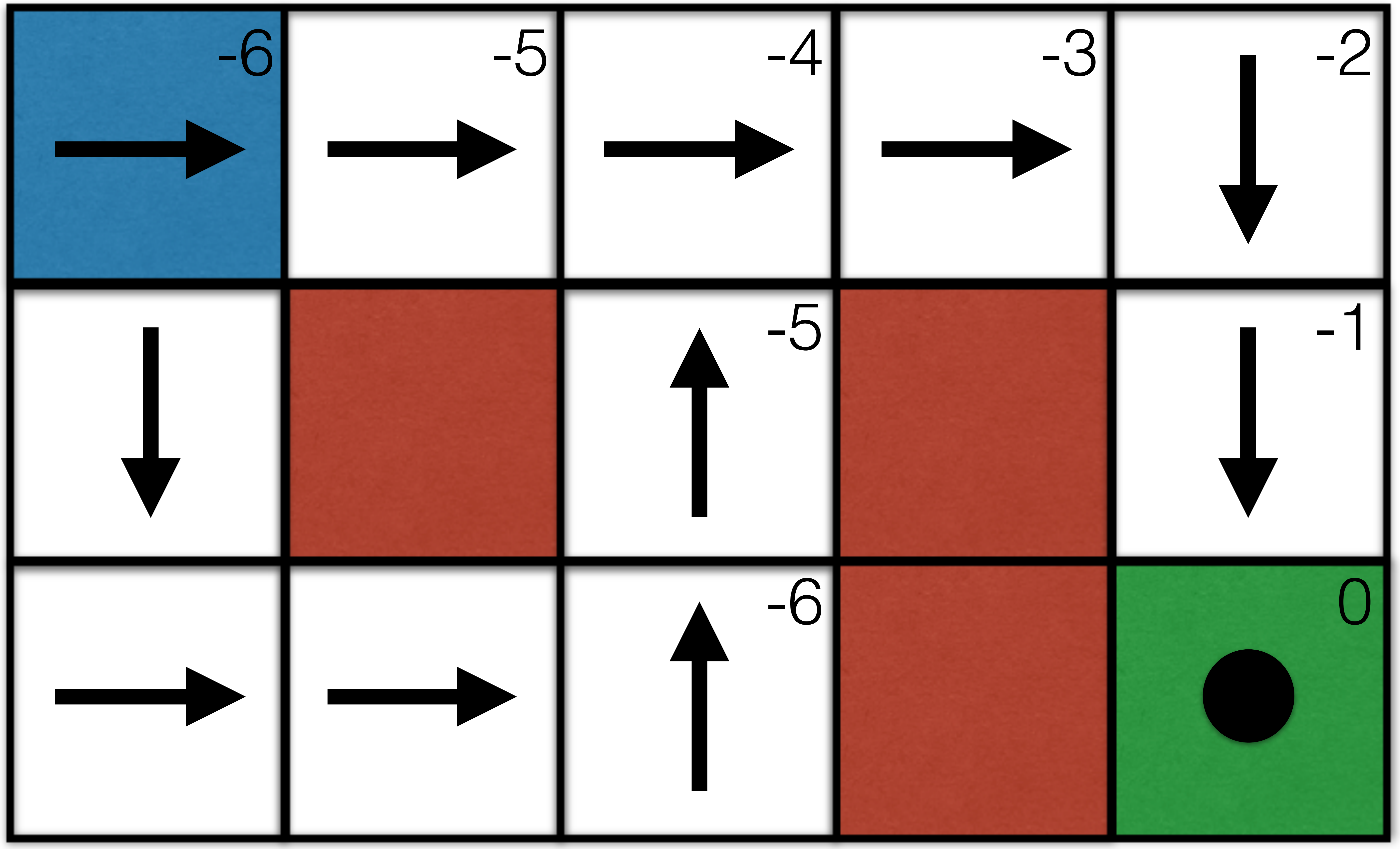

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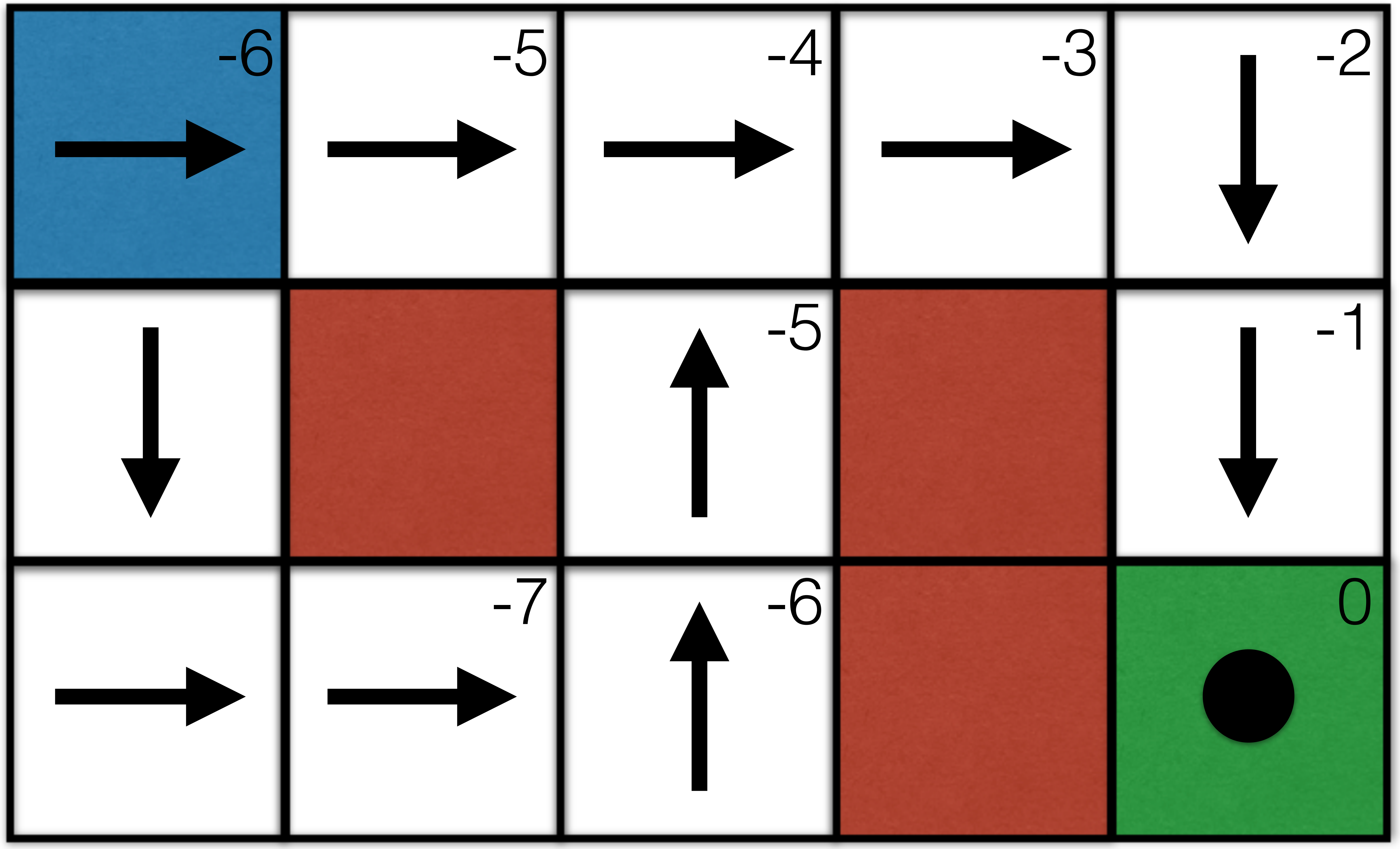

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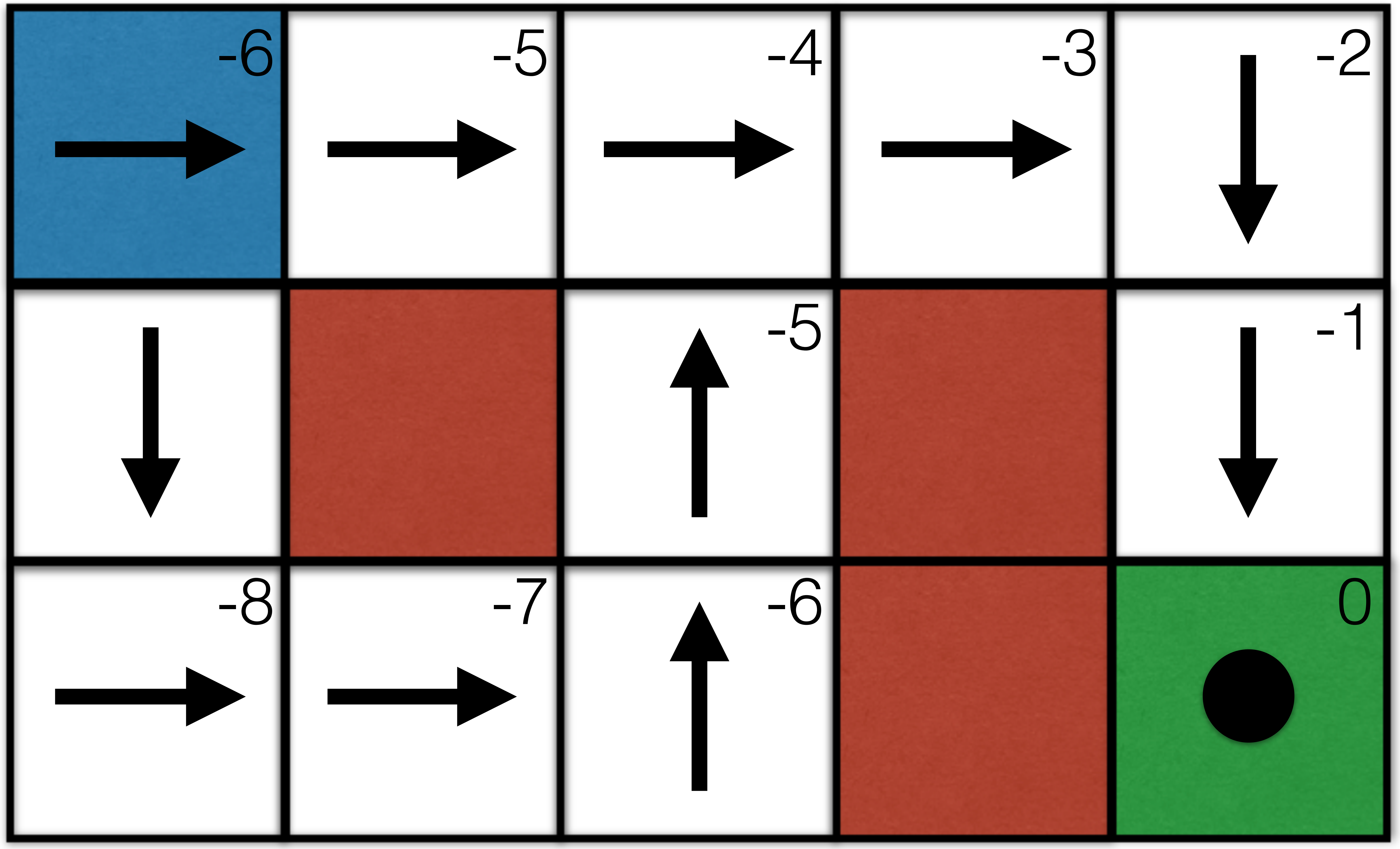

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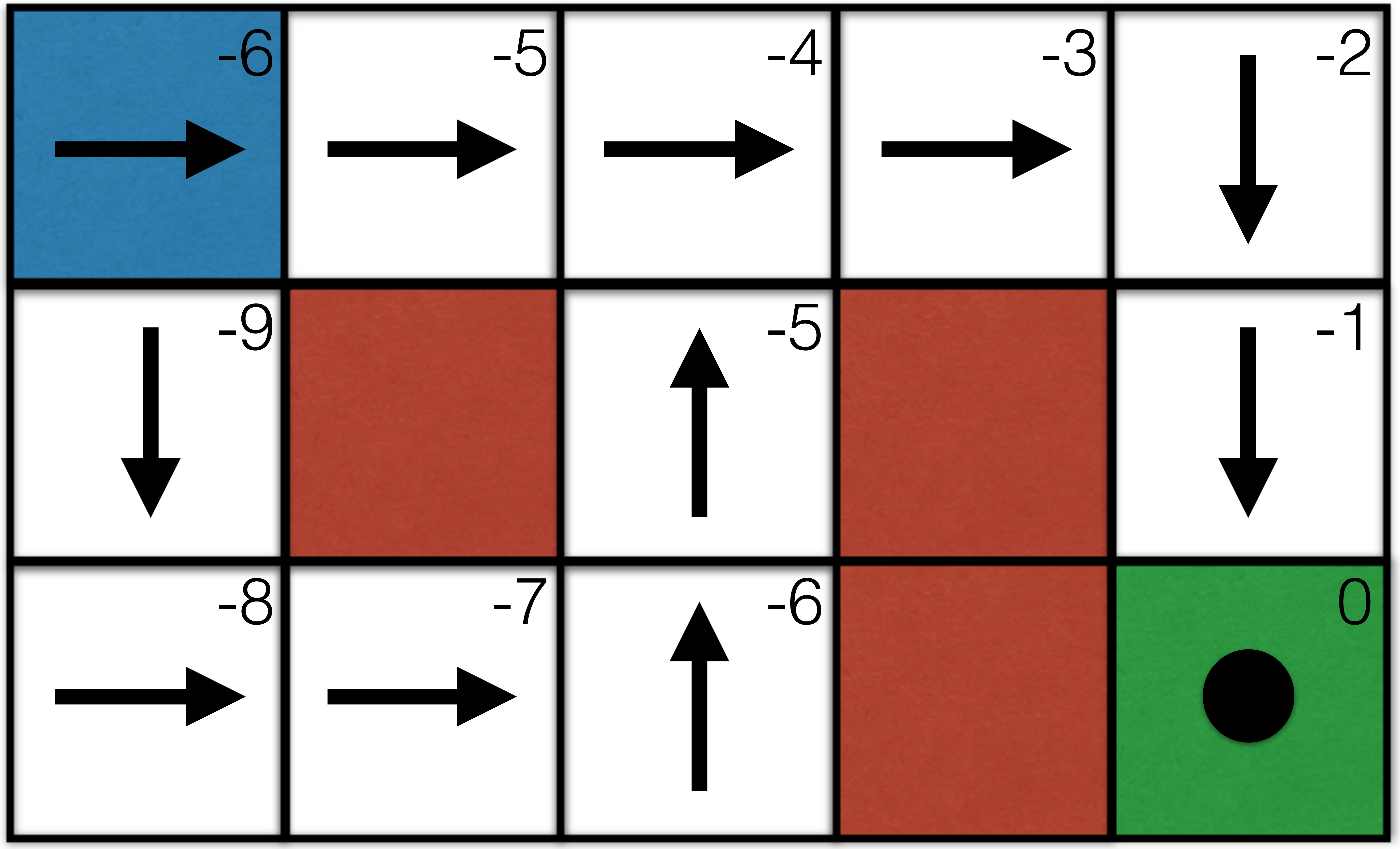

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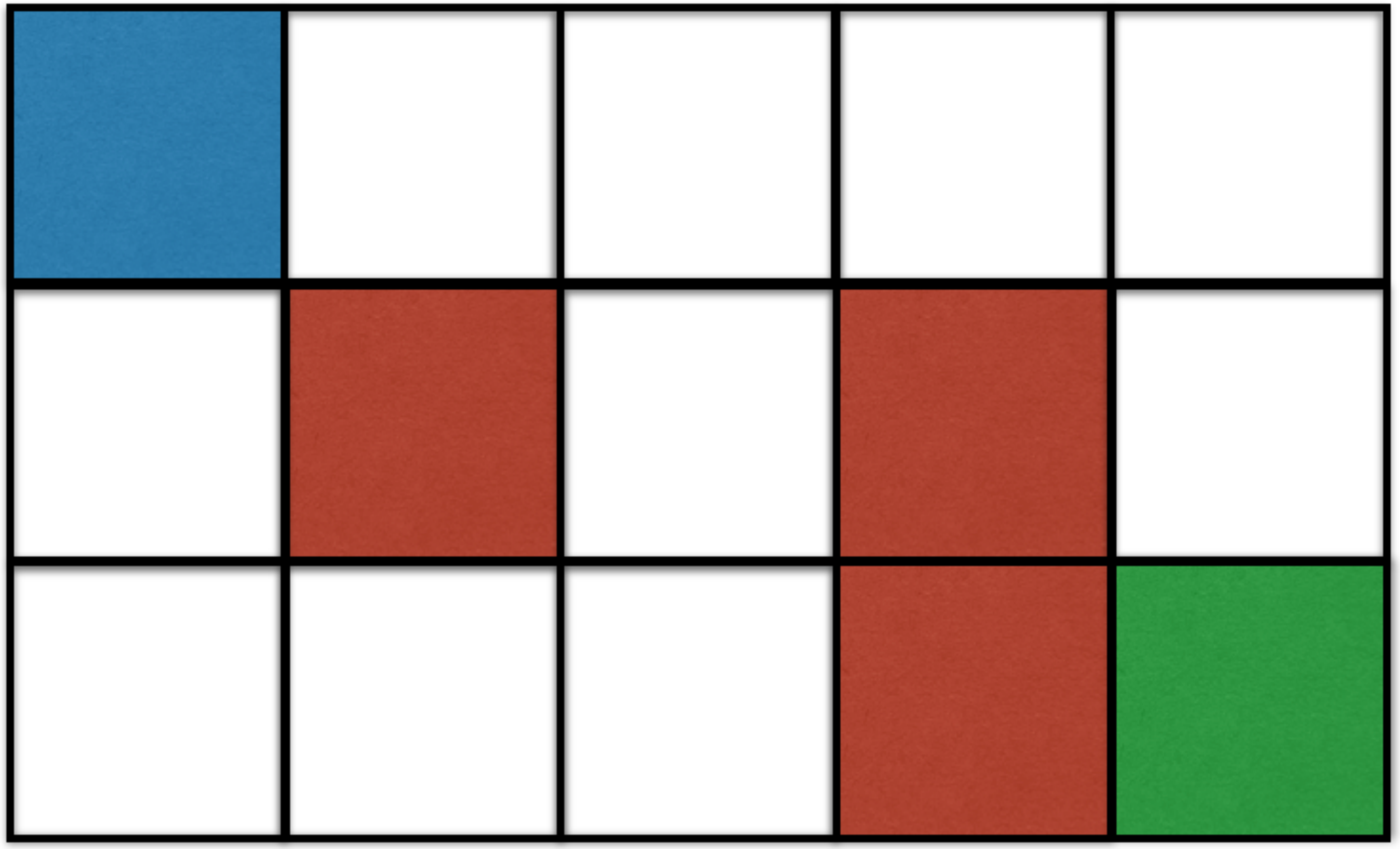

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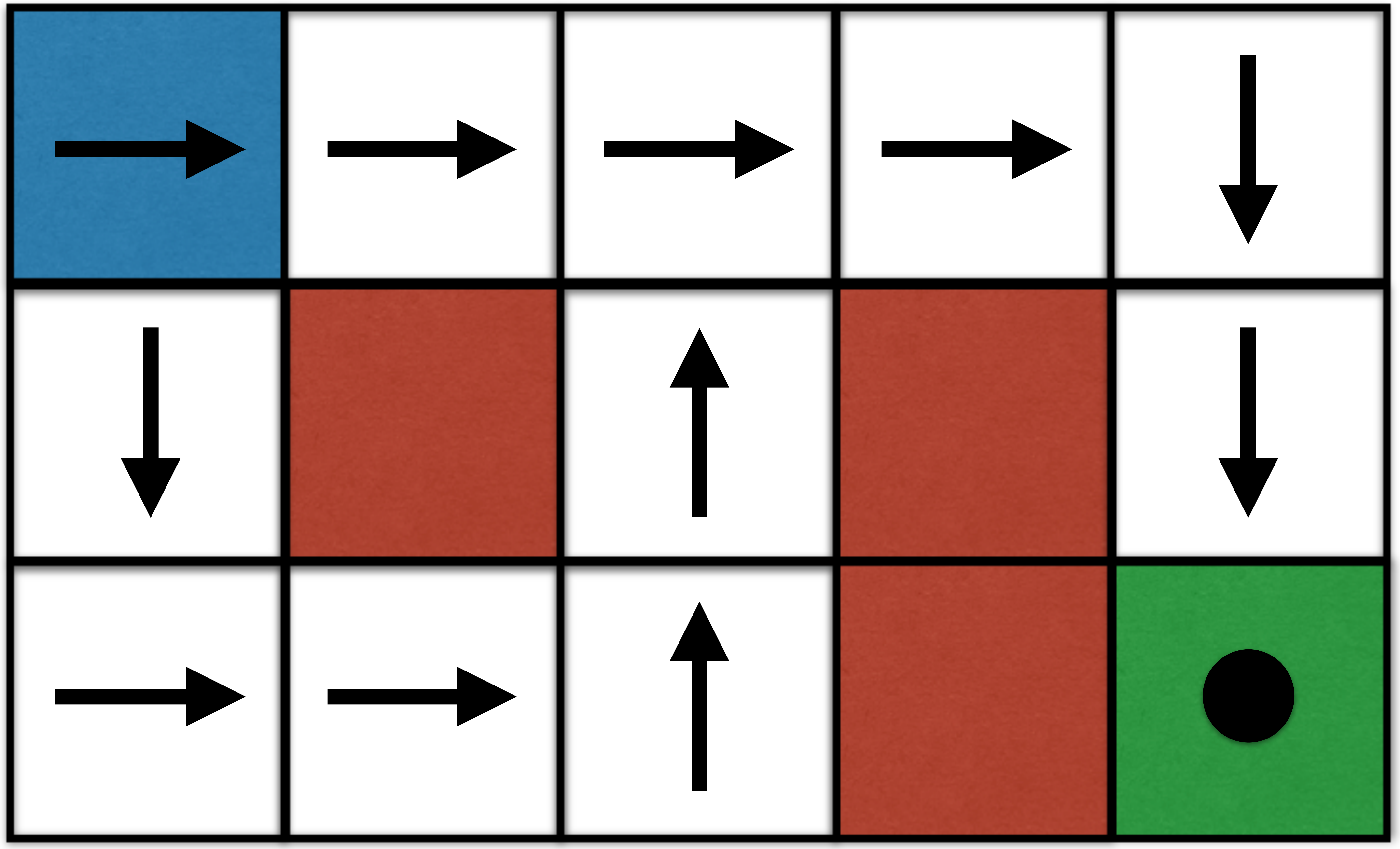

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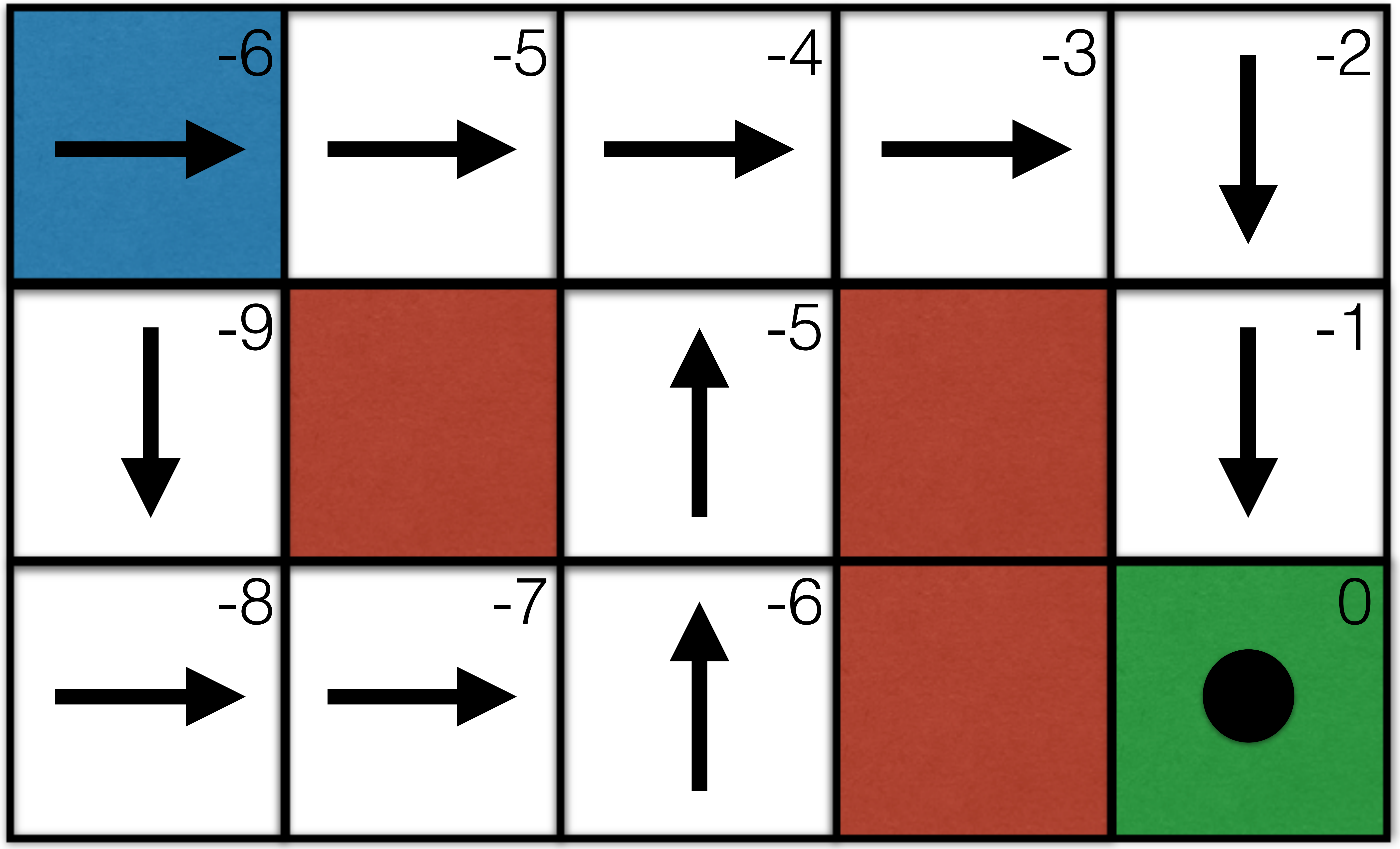

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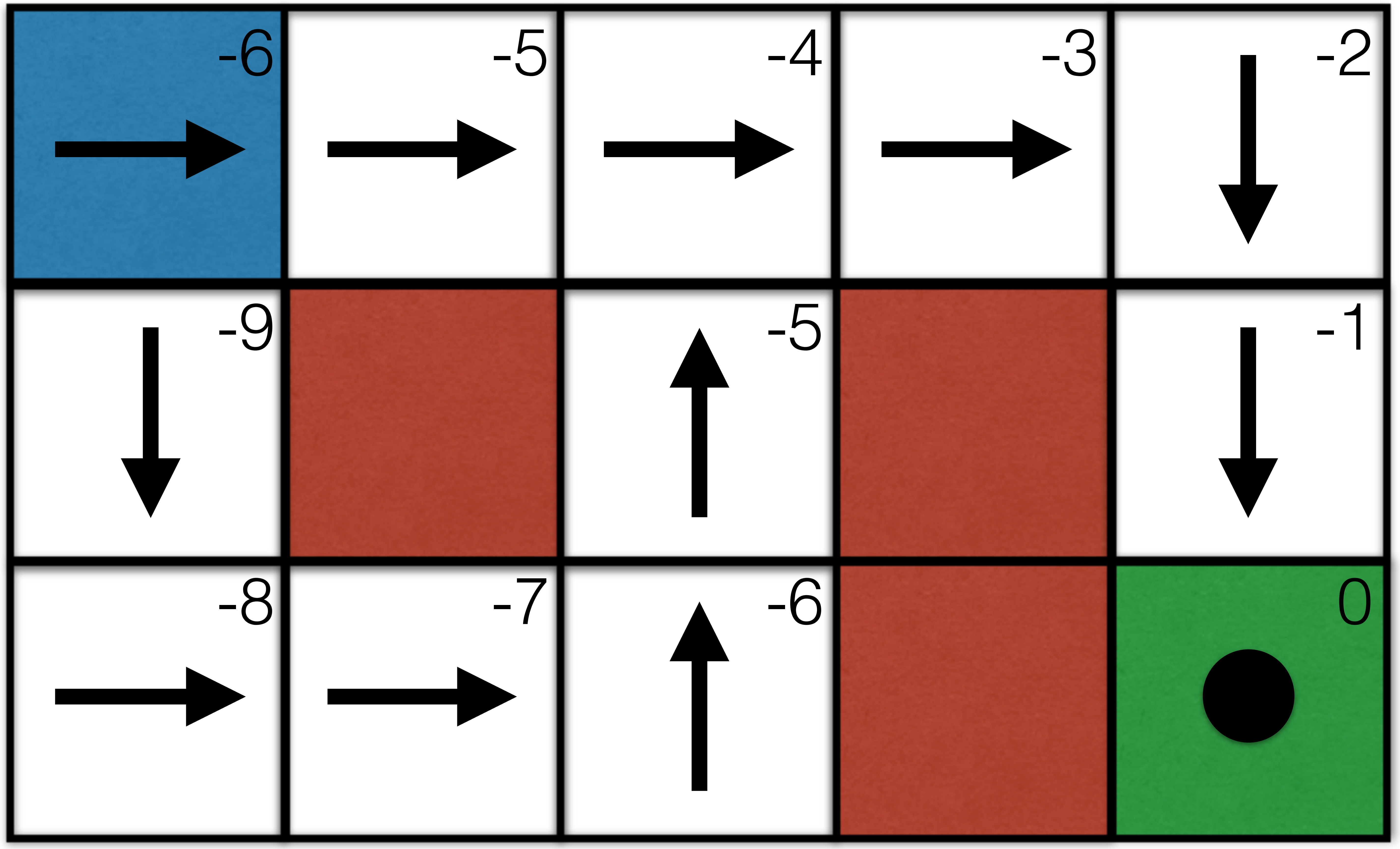

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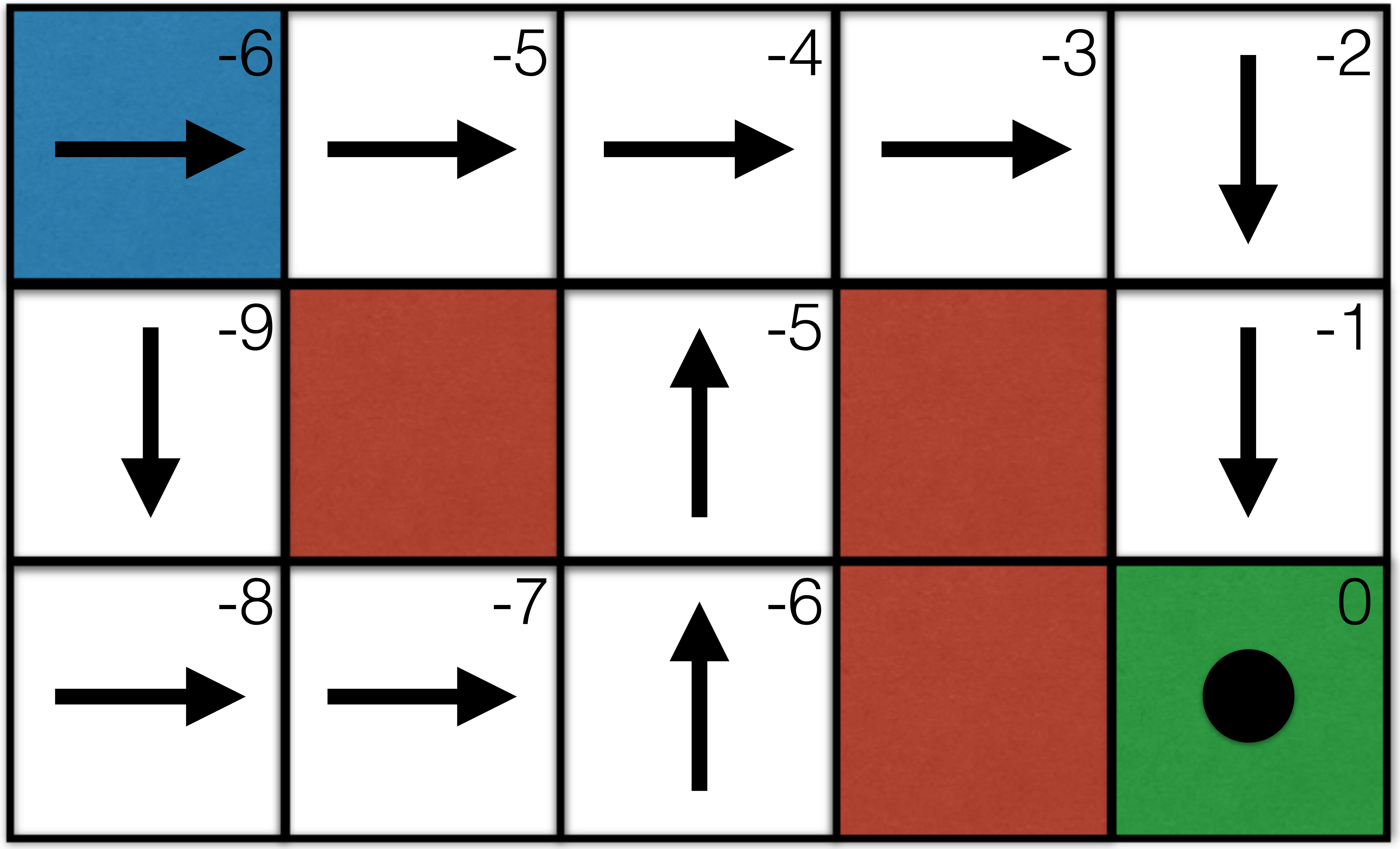

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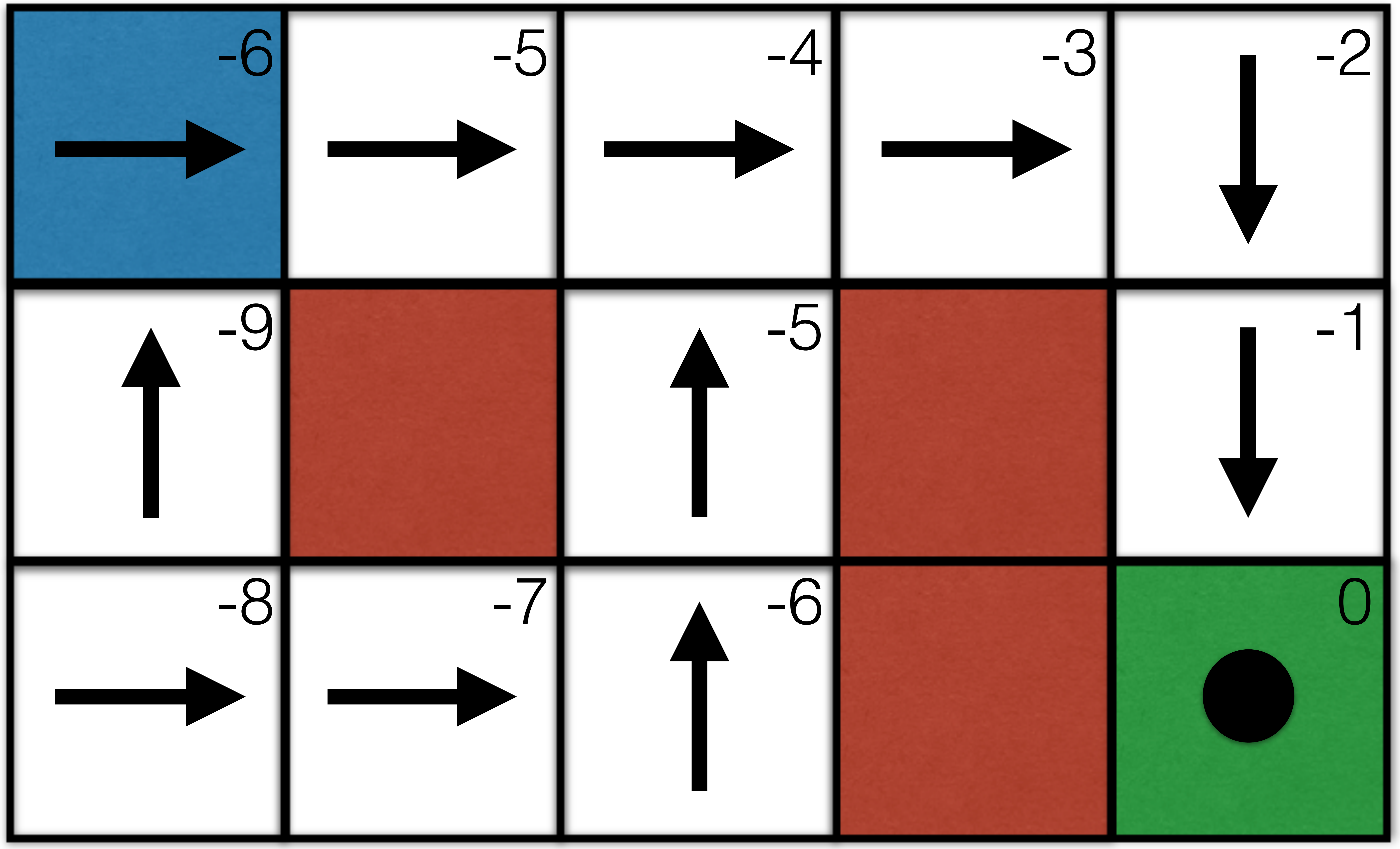

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