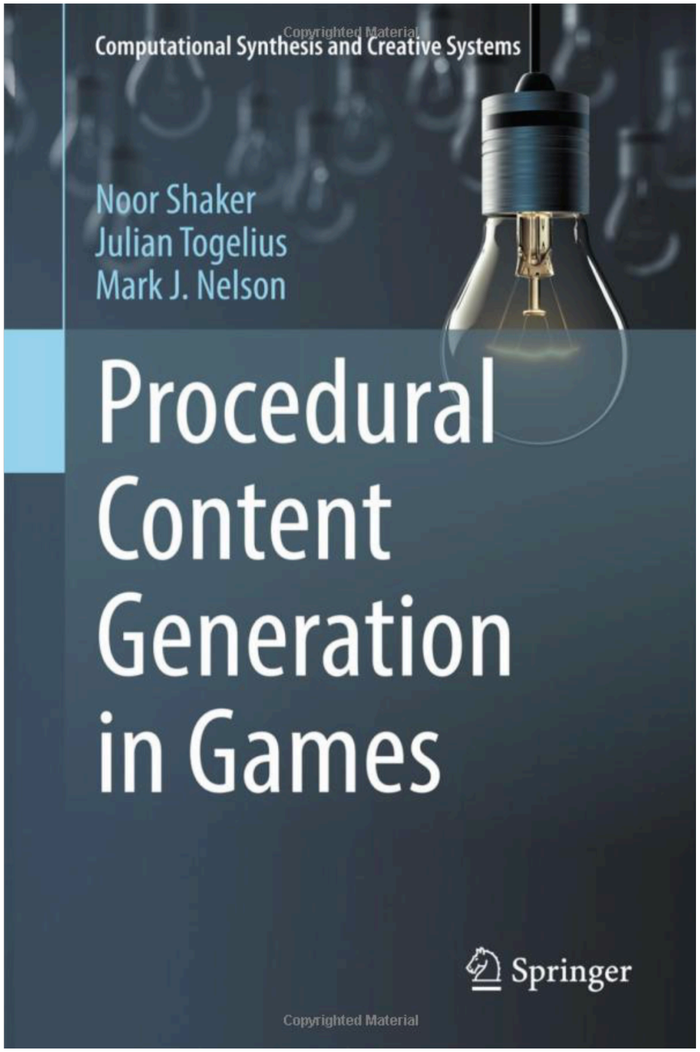
Exhaustive and Semi-Exhaustive Procedural Content Generation

Nathan R. Sturtevant, University of Alberta
Matheus Jun Ota, University of Campinas

AIIDE
November 15, 2018

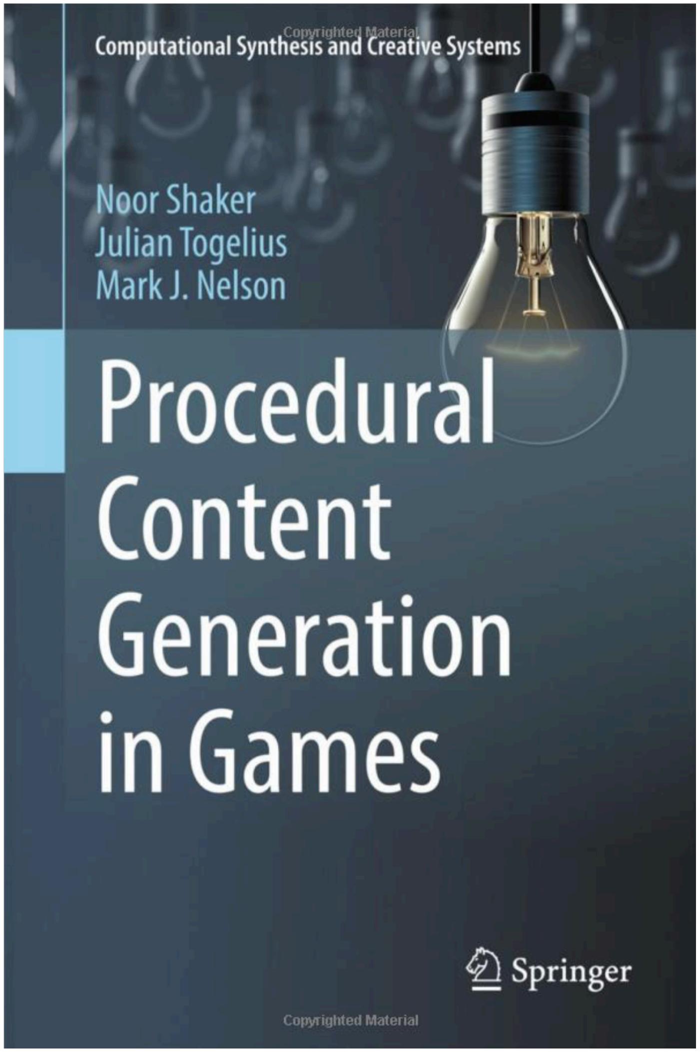
UNIVERSITY OF ALBERTA

PCG Taxonomy



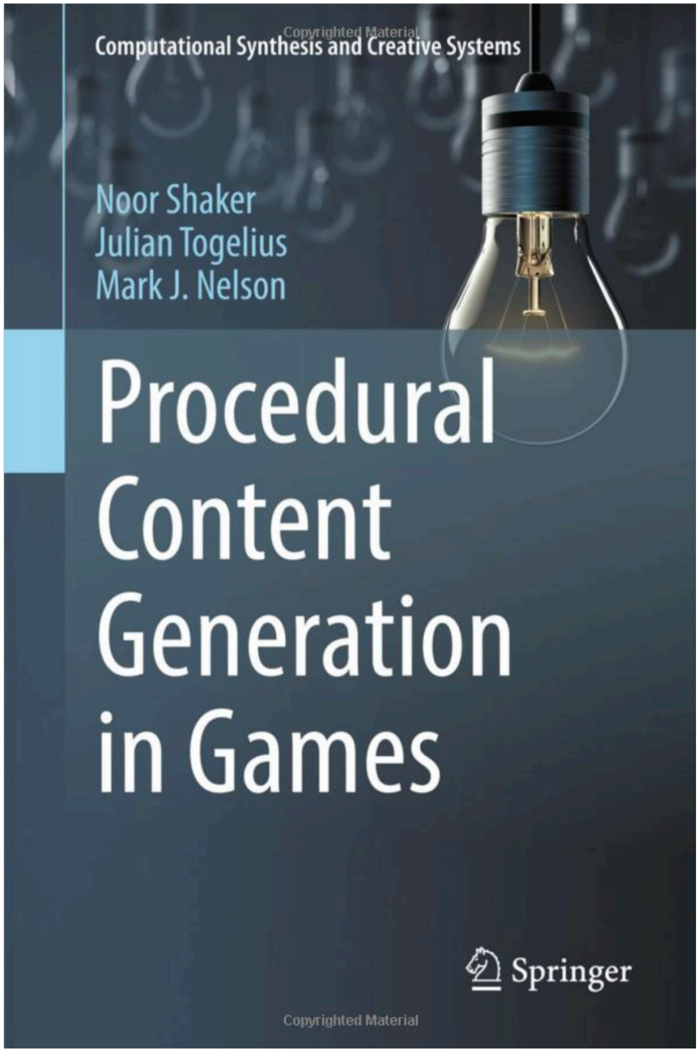
PCG Taxonomy

- Constructive, grammars, etc.



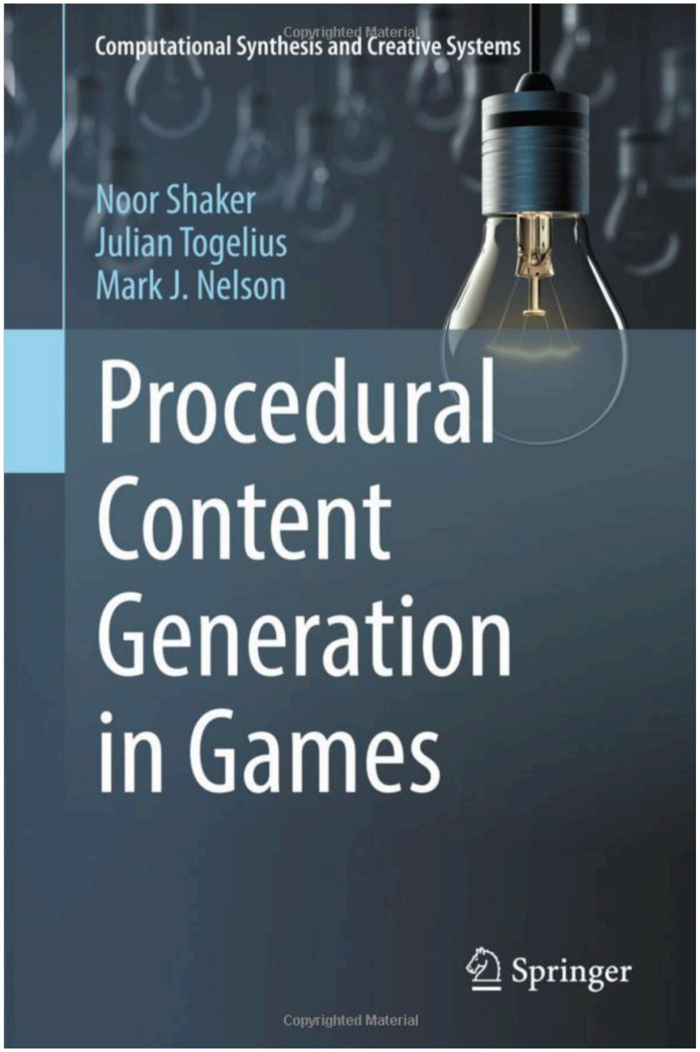
PCG Taxonomy

- Constructive, grammars, etc.
- Search-Based PCG



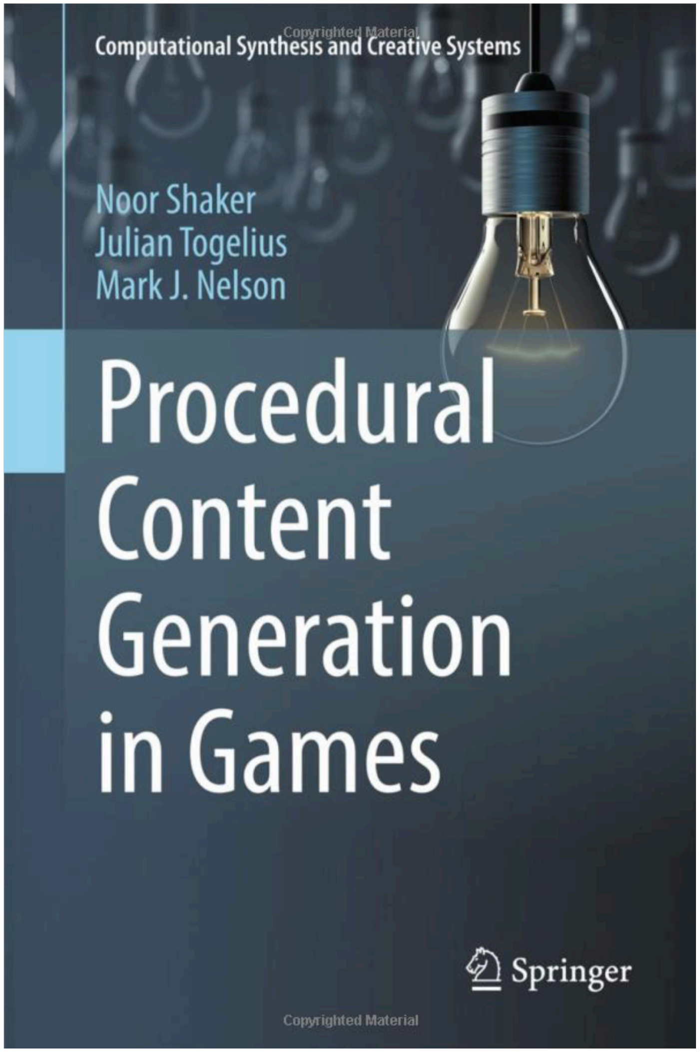
PCG Taxonomy

- Constructive, grammars, etc.
- Search-Based PCG
  - Evolutionary algorithms



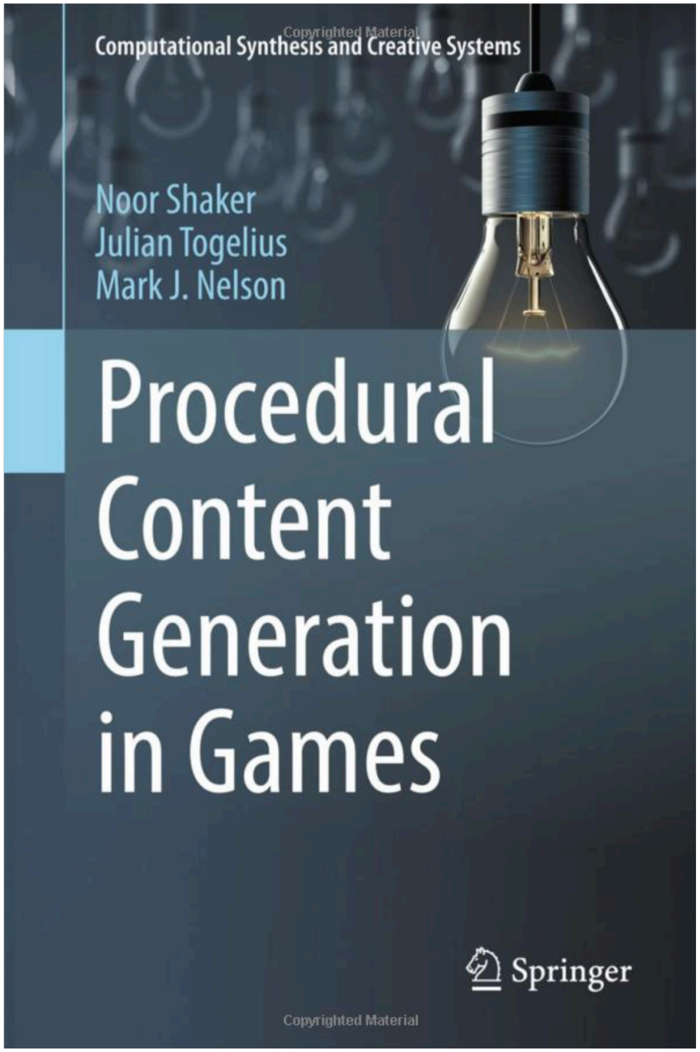
PCG Taxonomy

- Constructive, grammars, etc.
- Search-Based PCG
  - Evolutionary algorithms
  - Other approaches



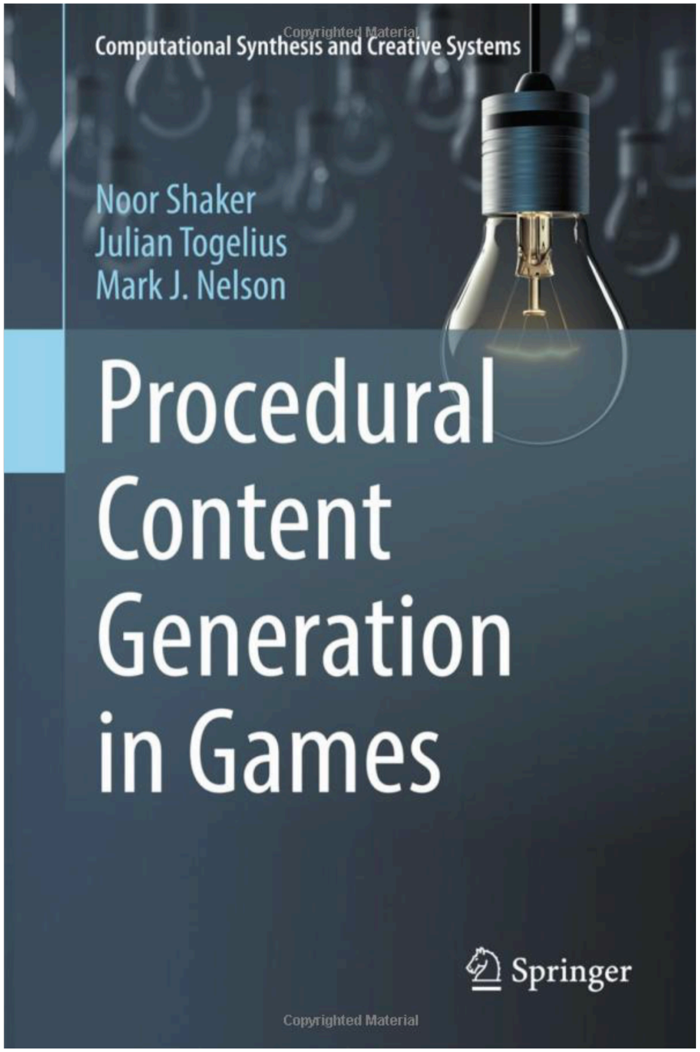
PCG Taxonomy

- Constructive, grammars, etc.
- Search-Based PCG
  - Evolutionary algorithms
  - Other approaches
    - Exhaustive search



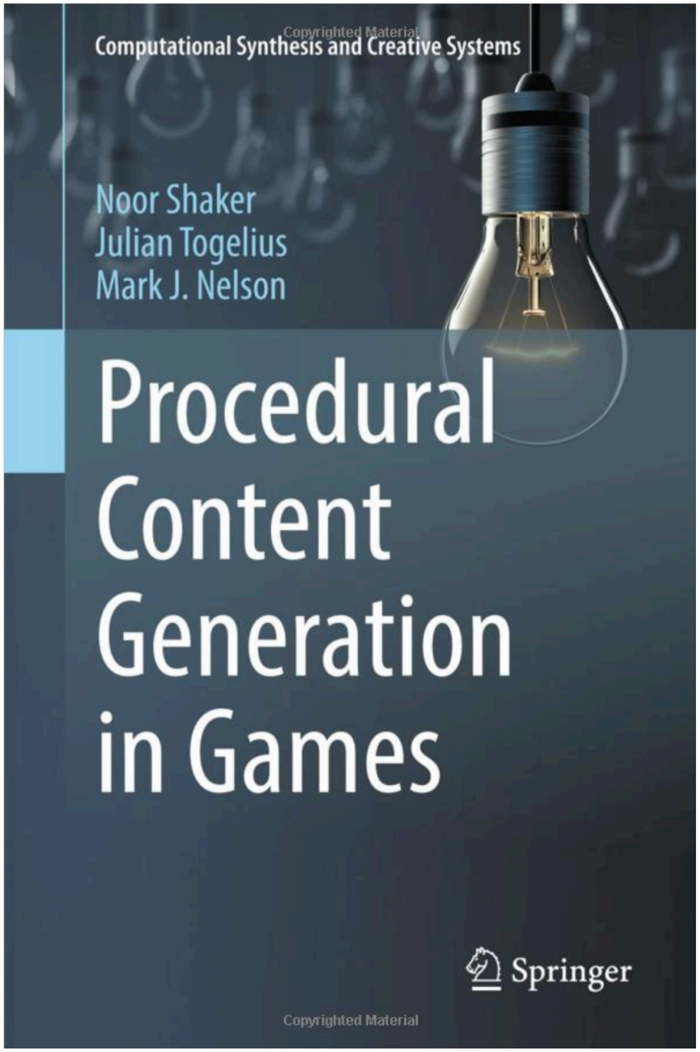
PCG Taxonomy

- Constructive, grammars, etc.
- Search-Based PCG
  - Evolutionary algorithms
  - Other approaches
    - Exhaustive search
    - Random search



PCG Taxonomy

- Constructive, grammars, etc.
- Search-Based PCG
  - Evolutionary algorithms
  - Other approaches
    - Exhaustive search
    - Random search
    - Solver-based (eg ASP)



Exhaustive PCG

Exhaustive PCG

- Synthesize work from other fields (e.g. mathematics) as reference for EPCG approaches

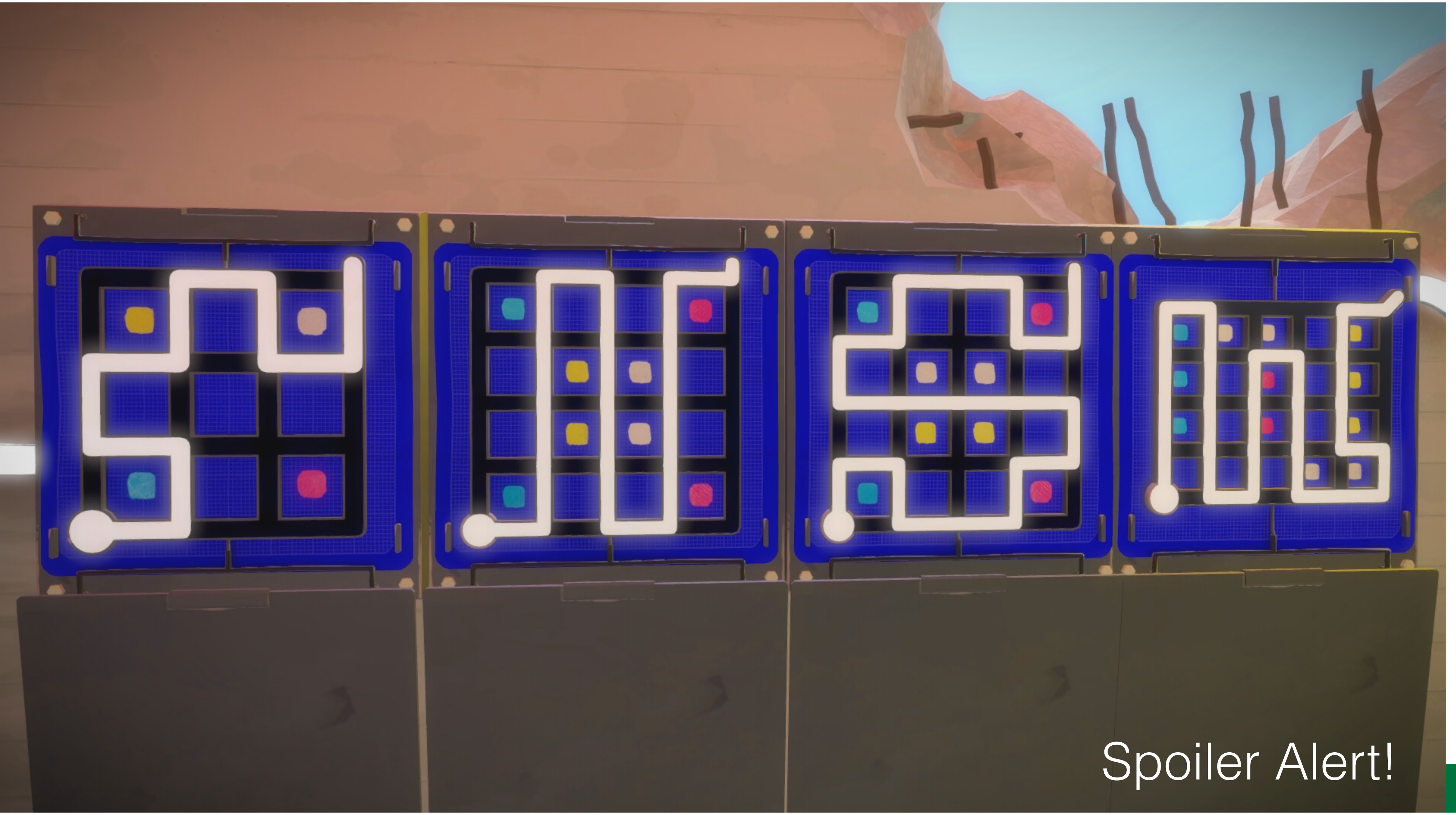
Exhaustive PCG

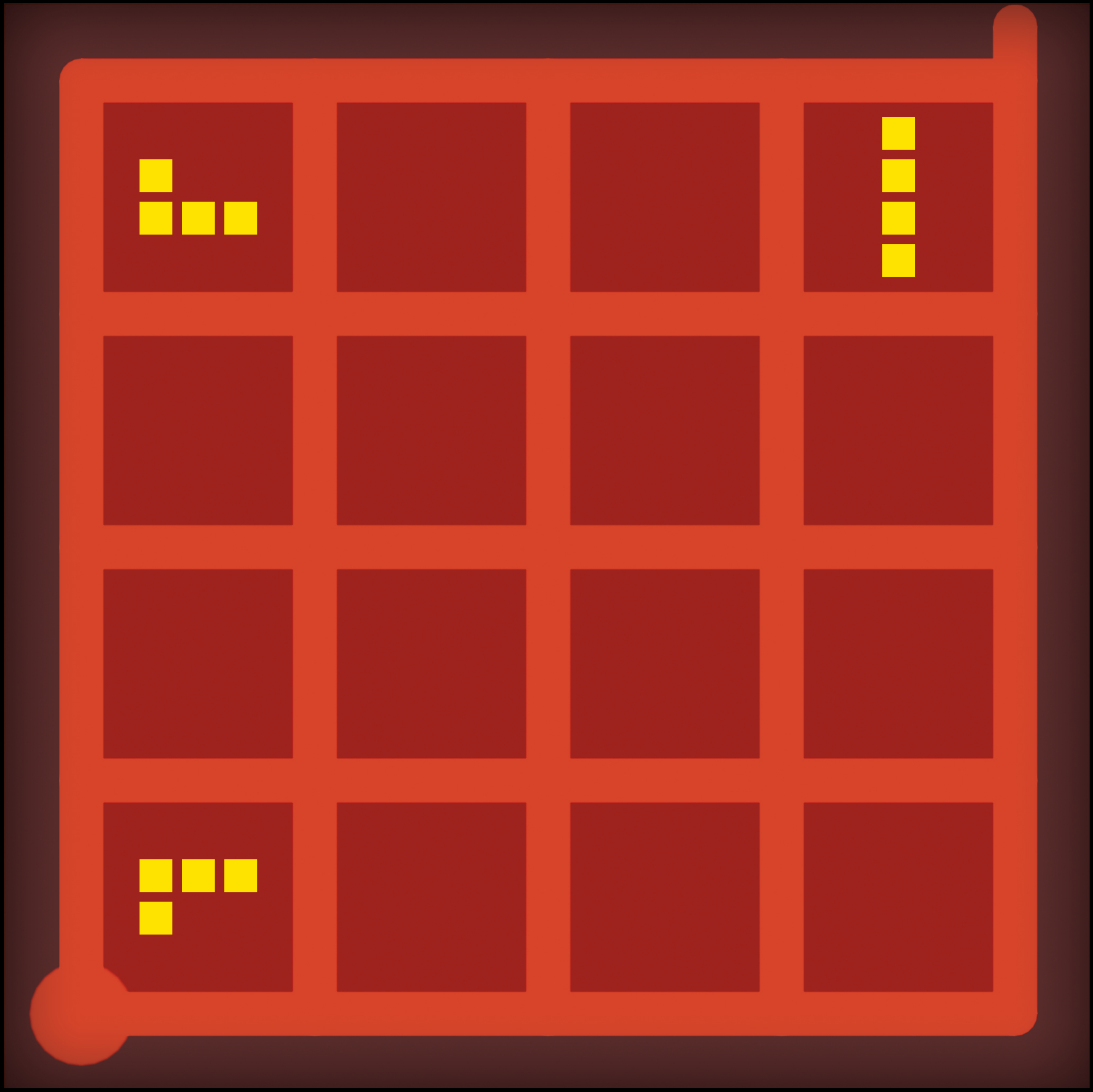
- Synthesize work from other fields (e.g. mathematics) as reference for EPCG approaches
- Give samples of underlying algorithms for EPCG

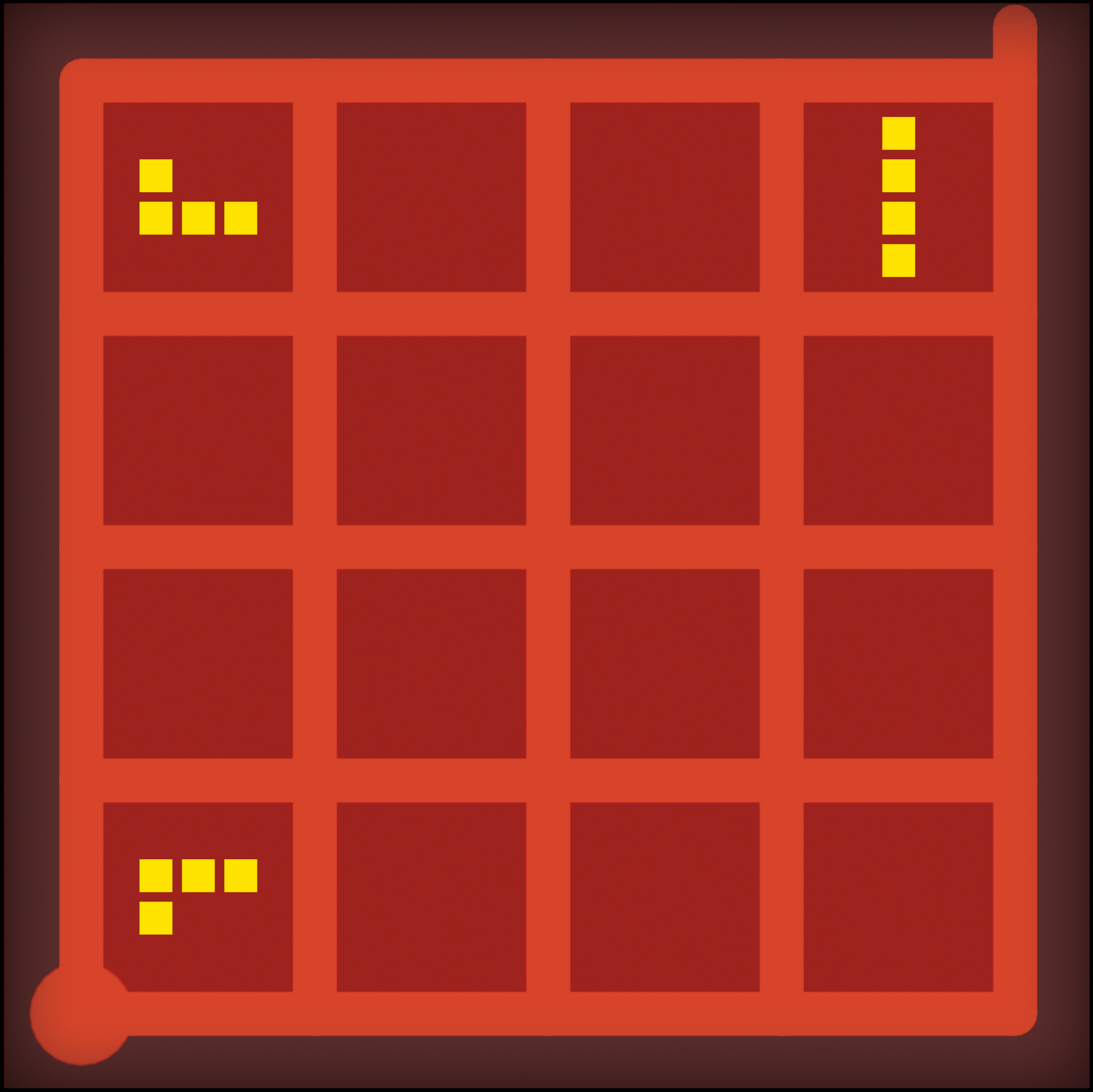
Exhaustive PCG

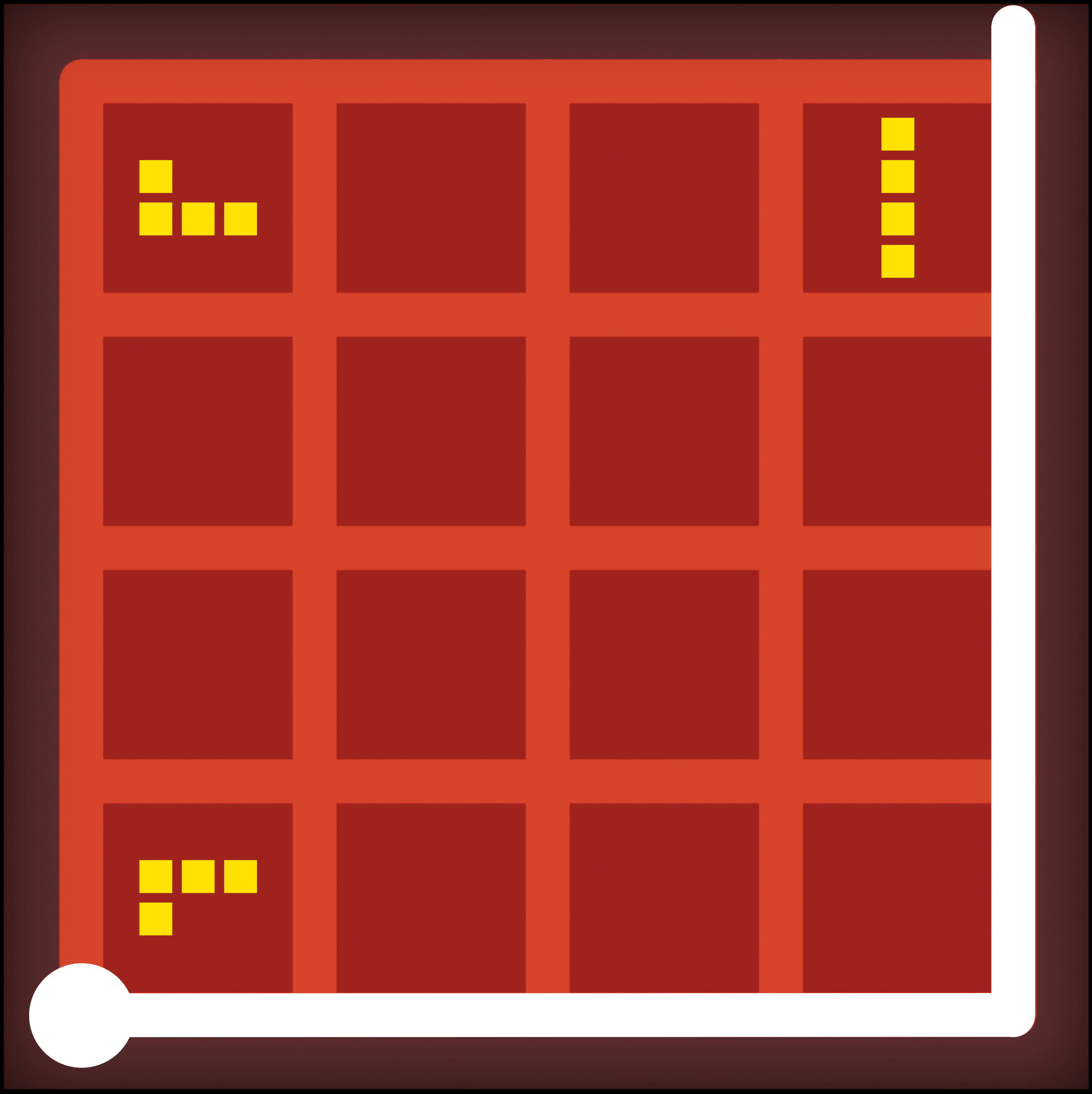
- Synthesize work from other fields (e.g. mathematics) as reference for EPCG approaches
- Give samples of underlying algorithms for EPCG
- Examples of the use of EPCG
  - Mixed-initiative process

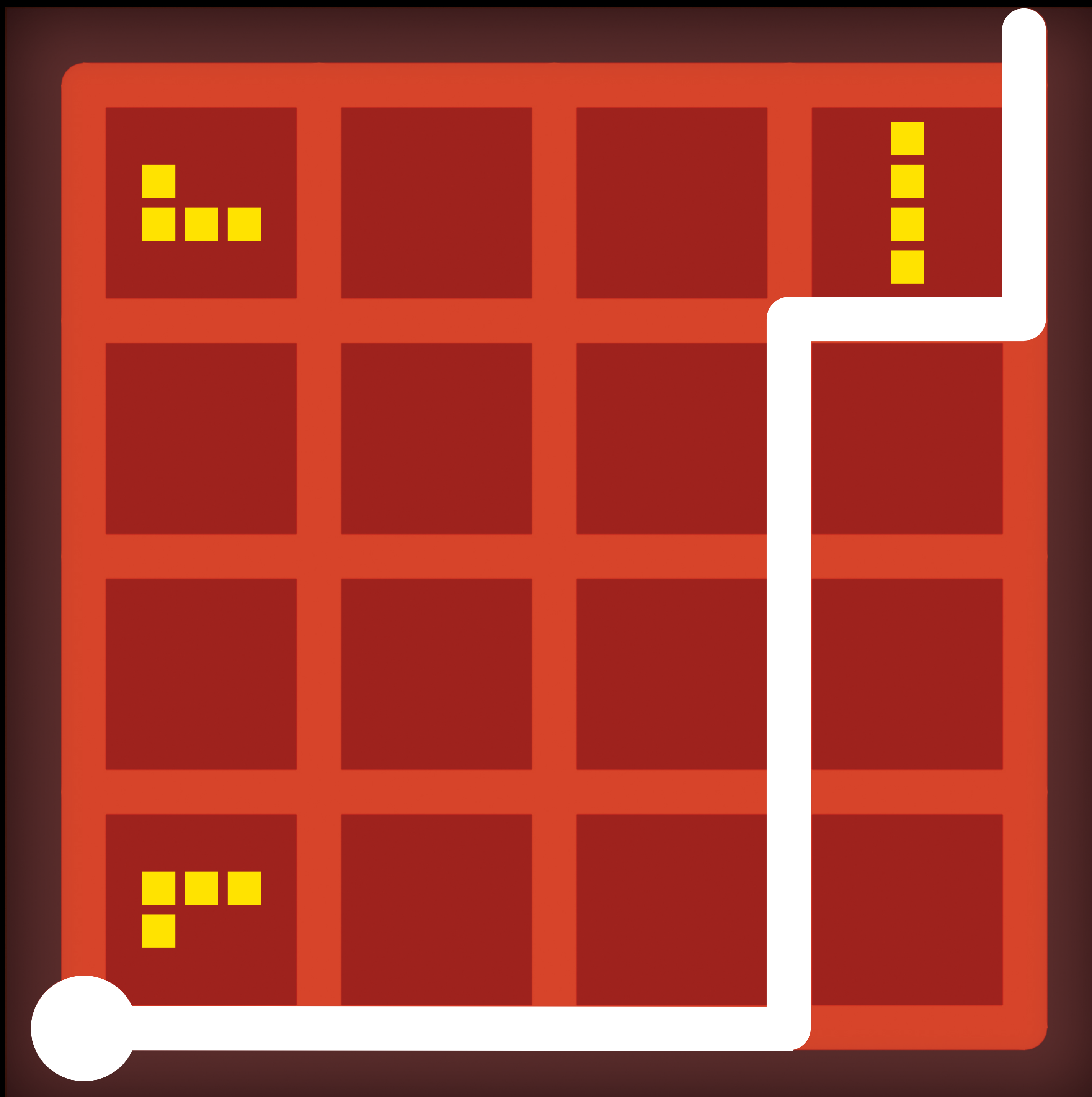
The Witness

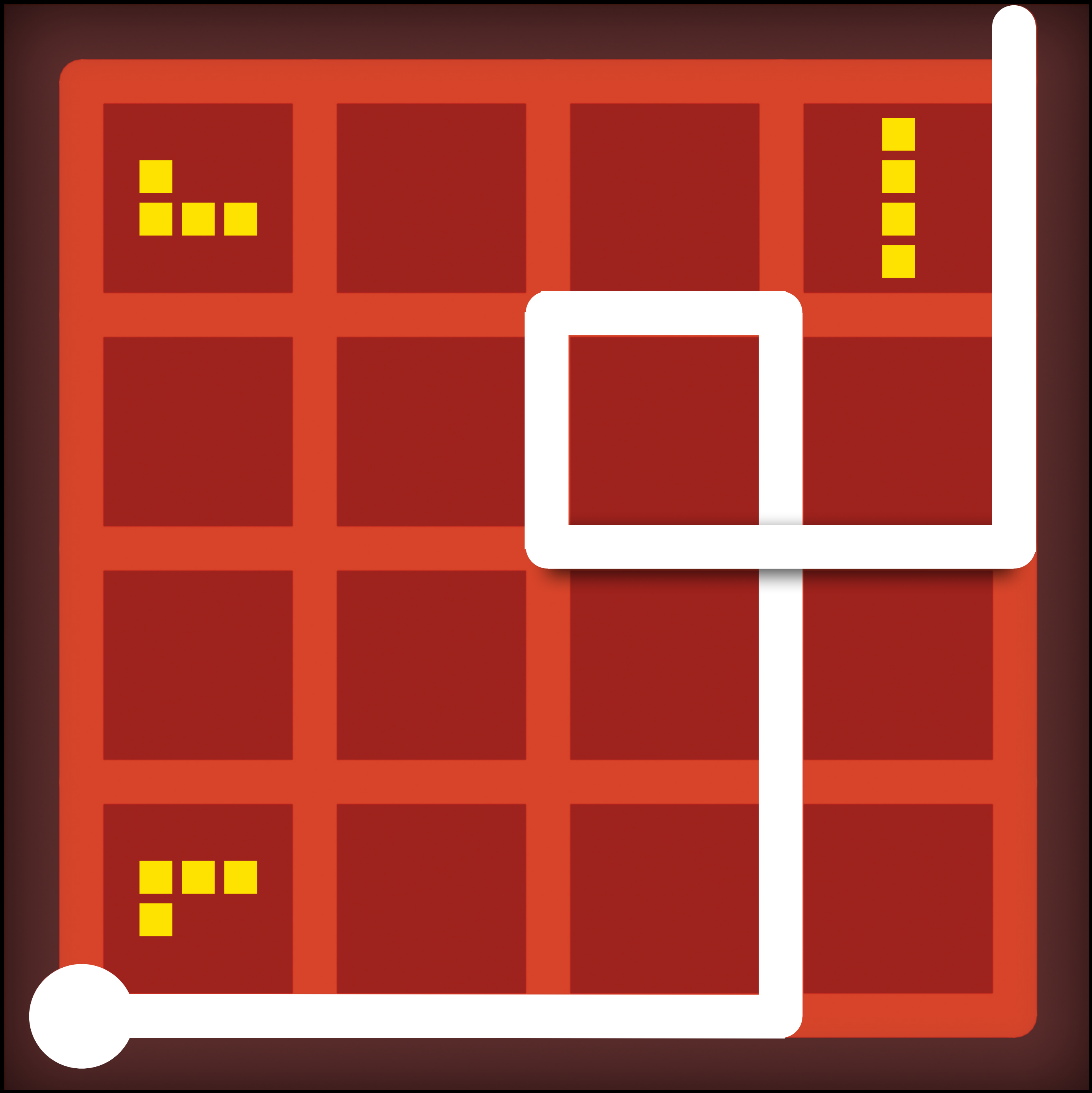




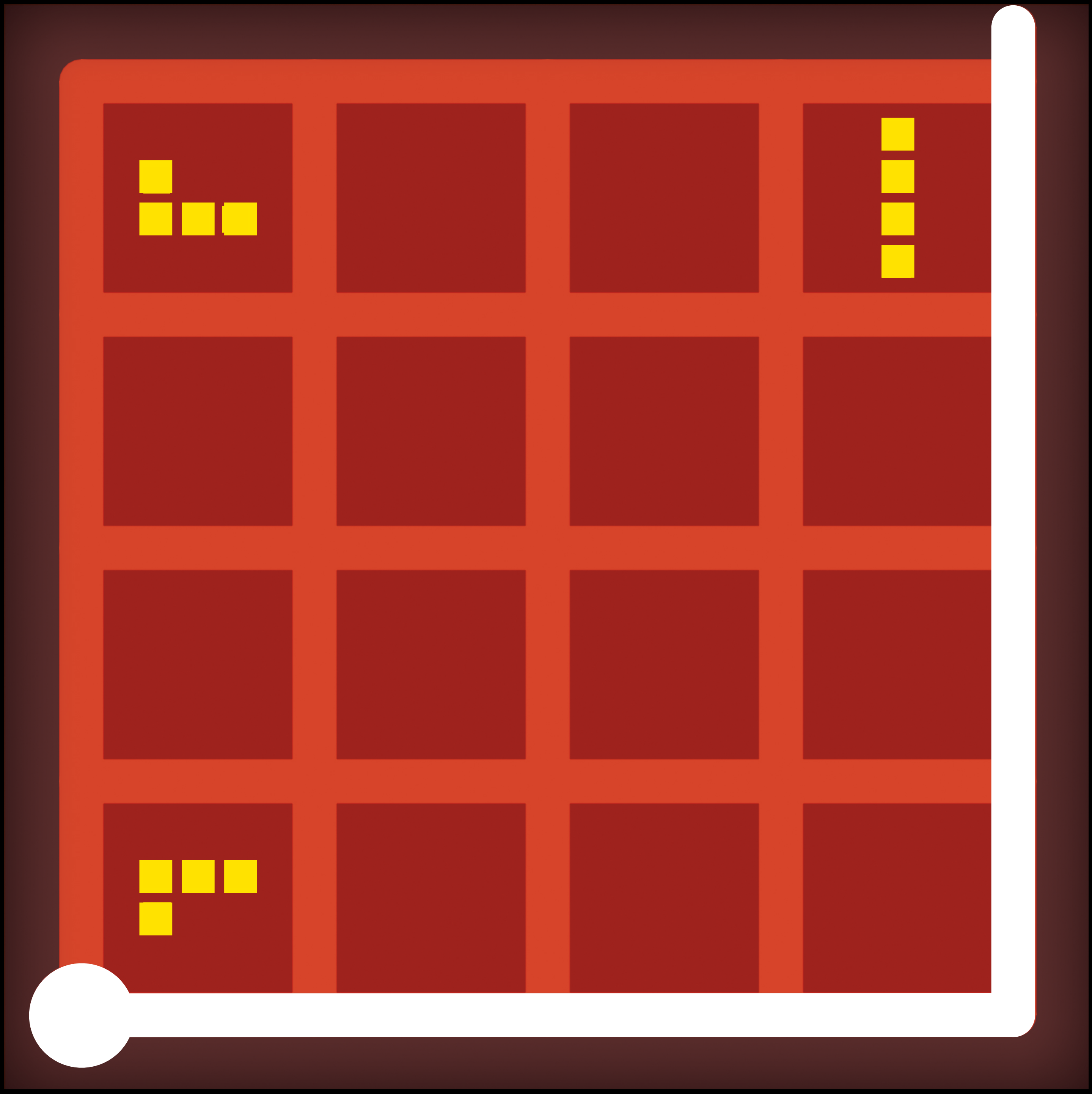


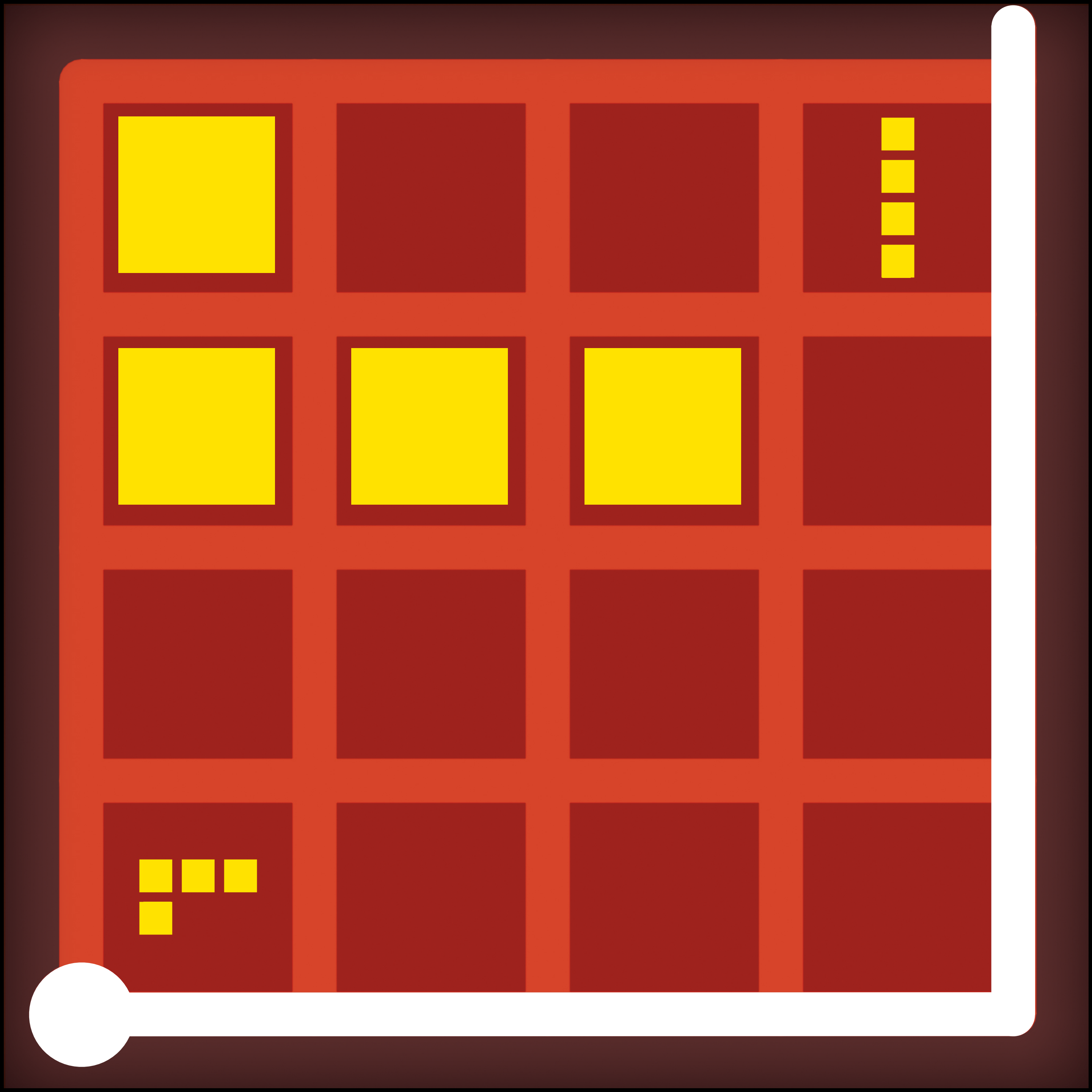


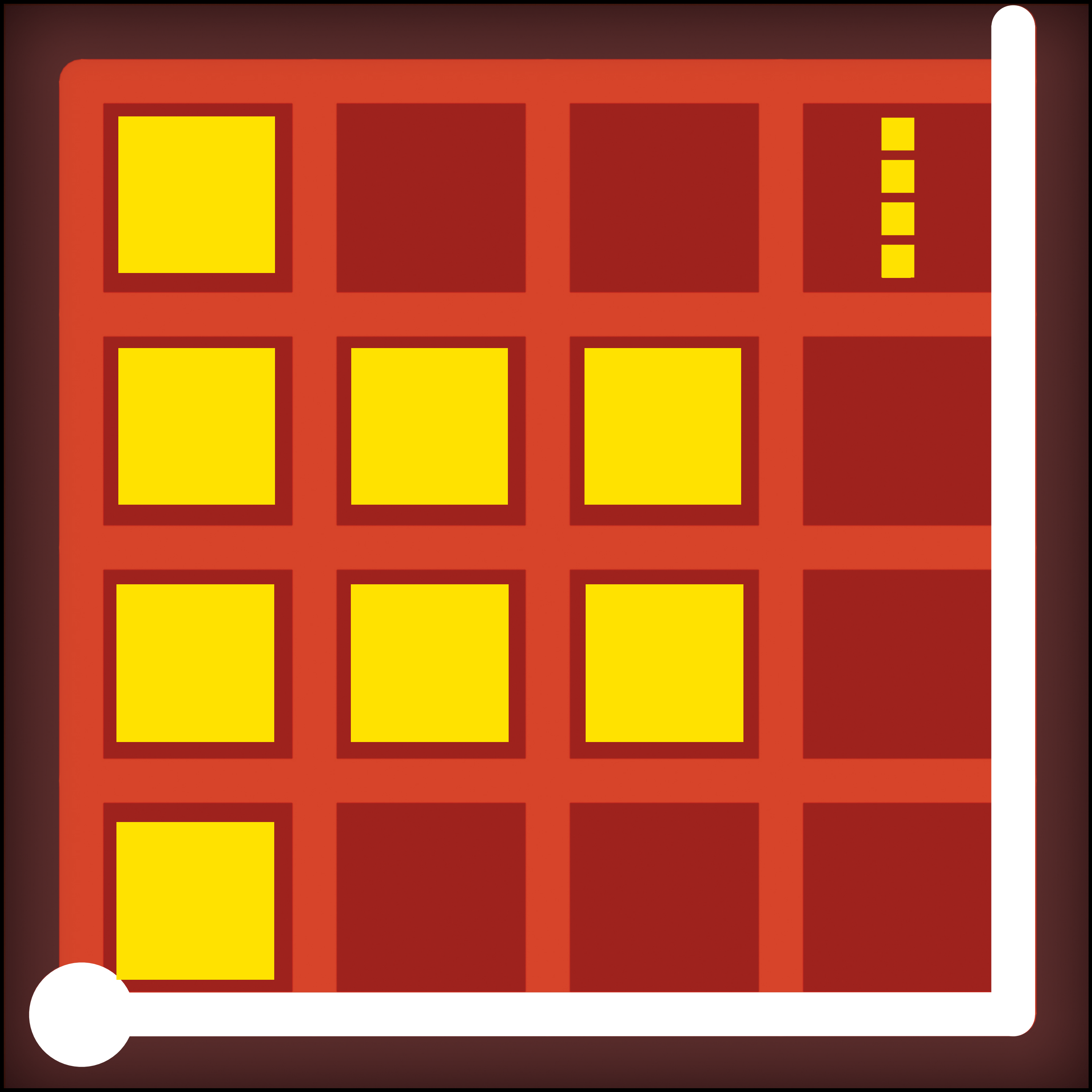


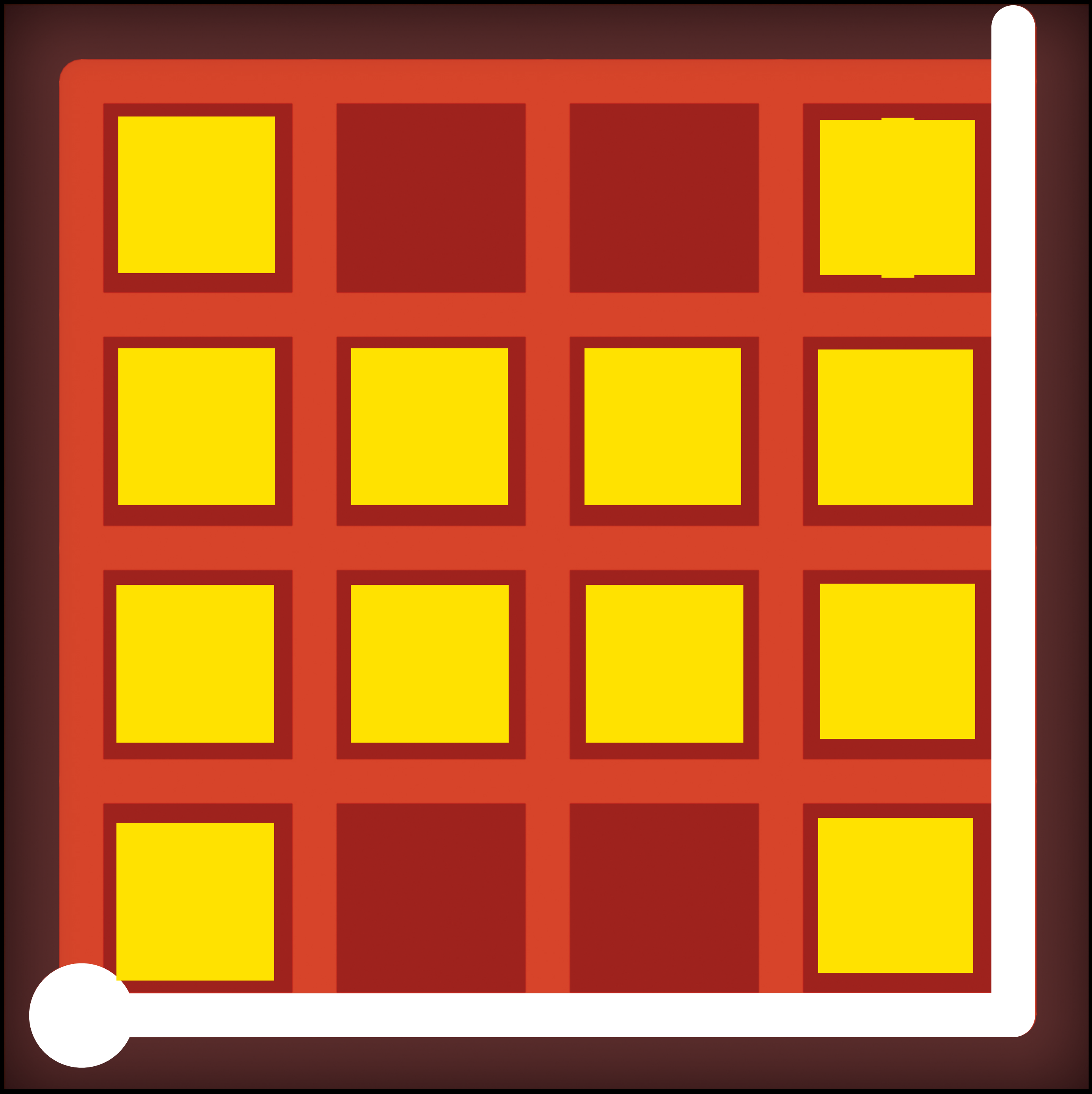


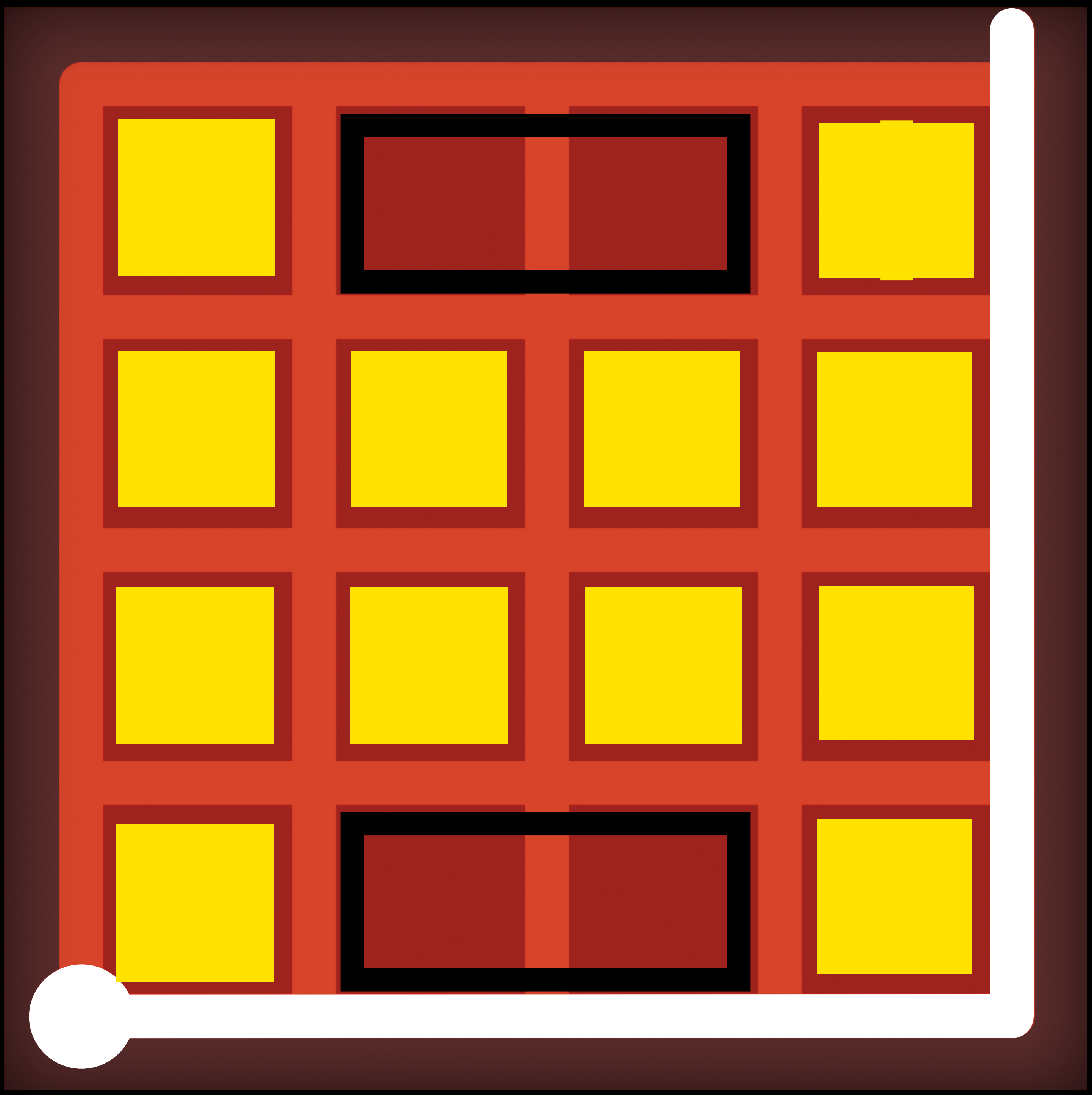

X

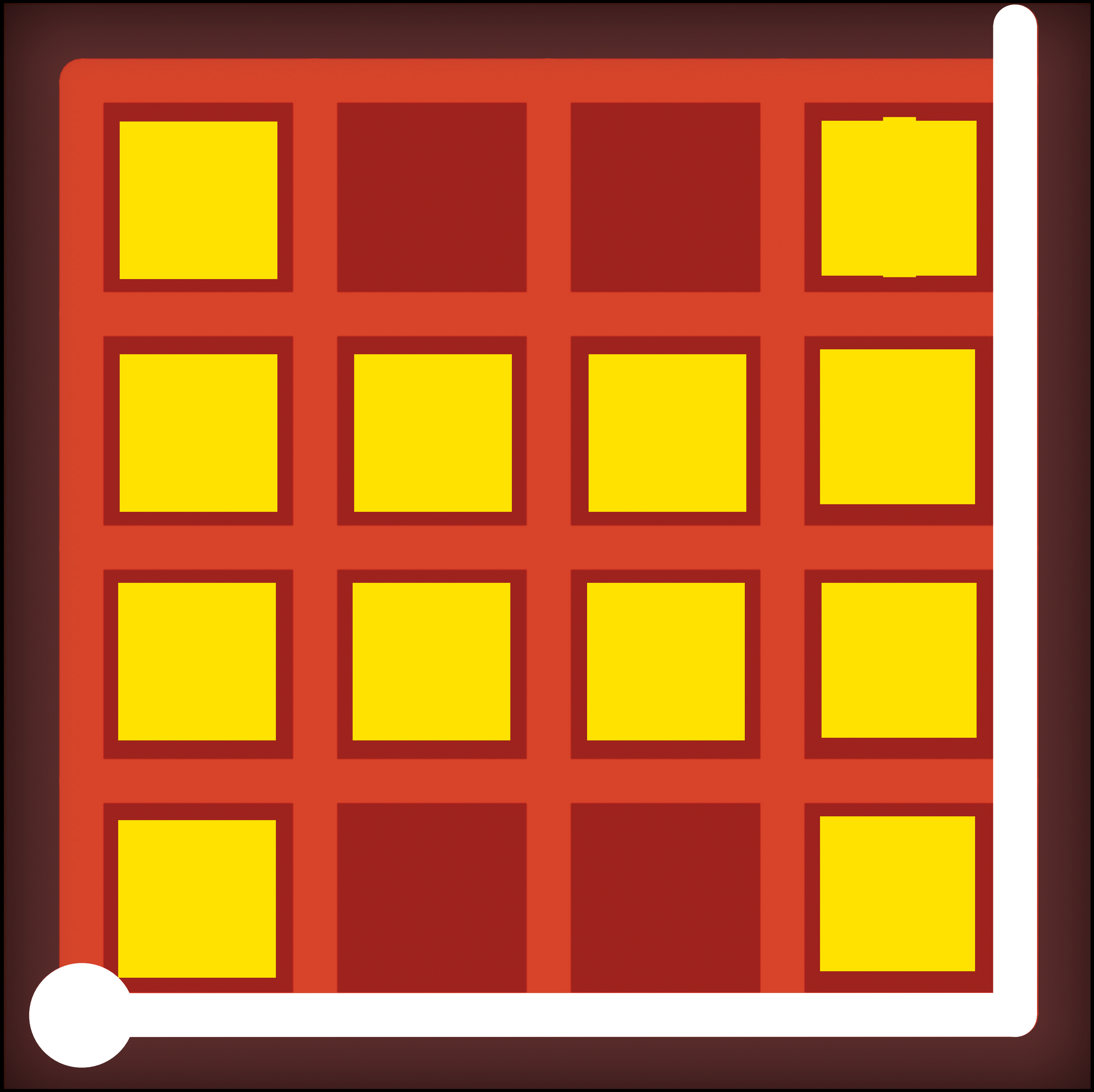


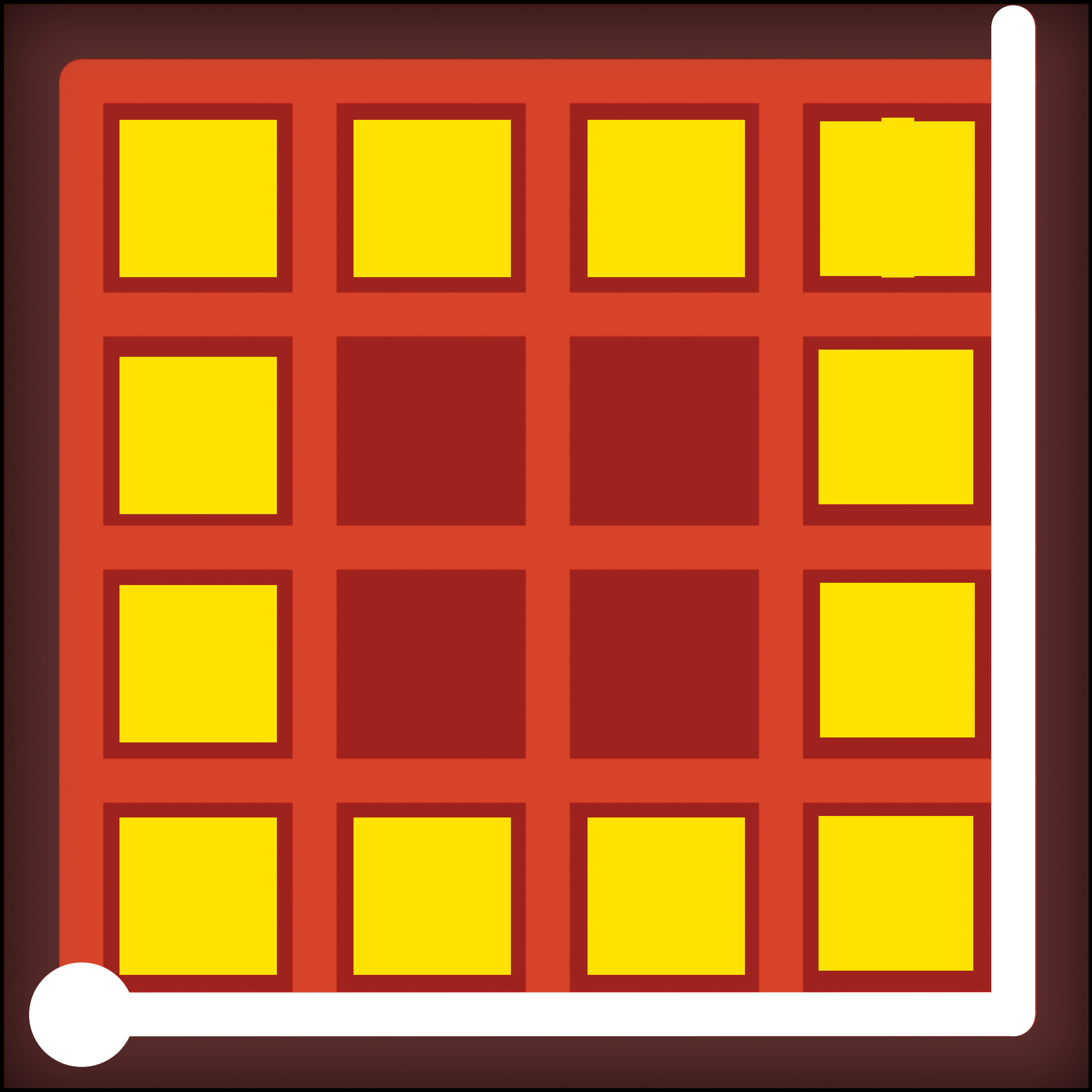


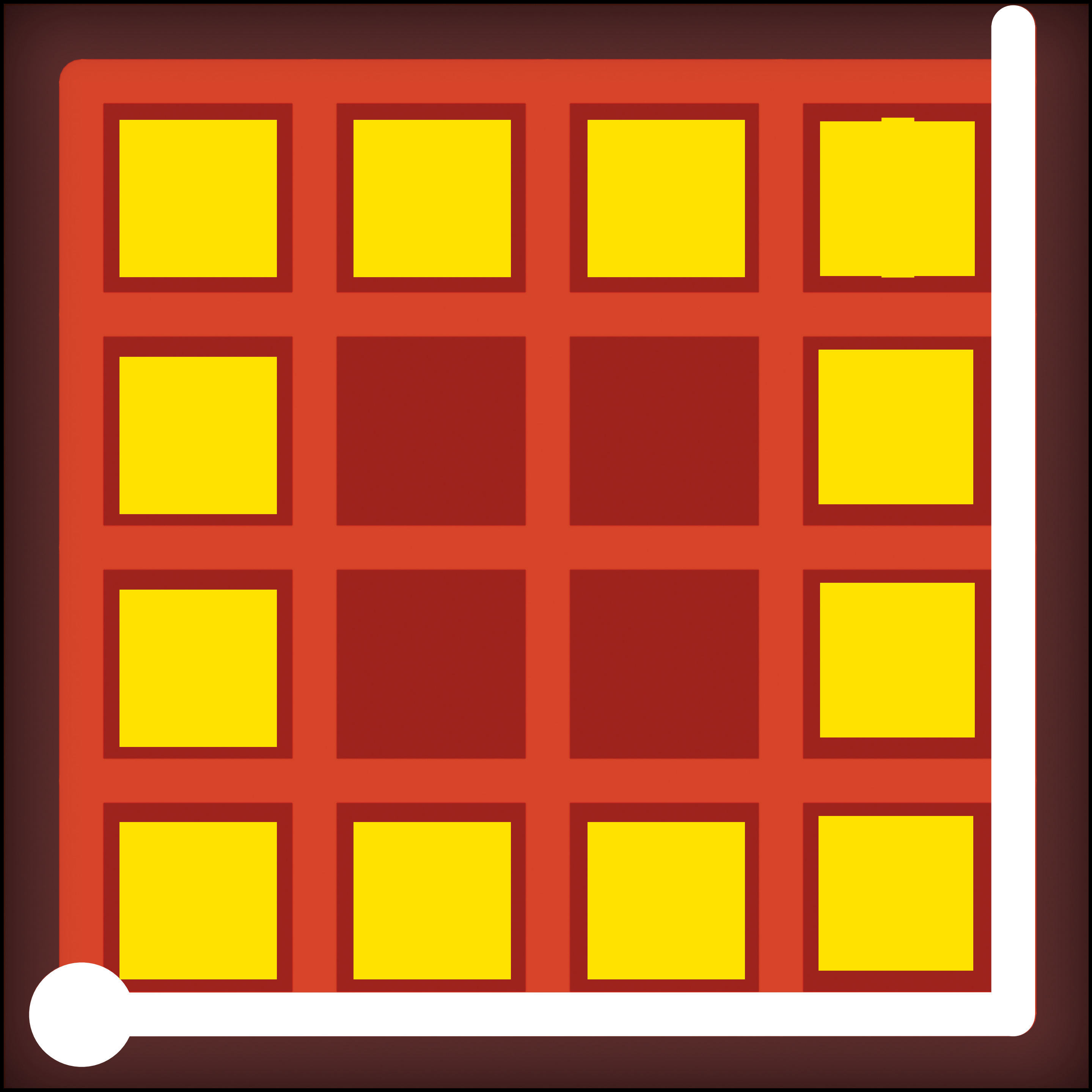


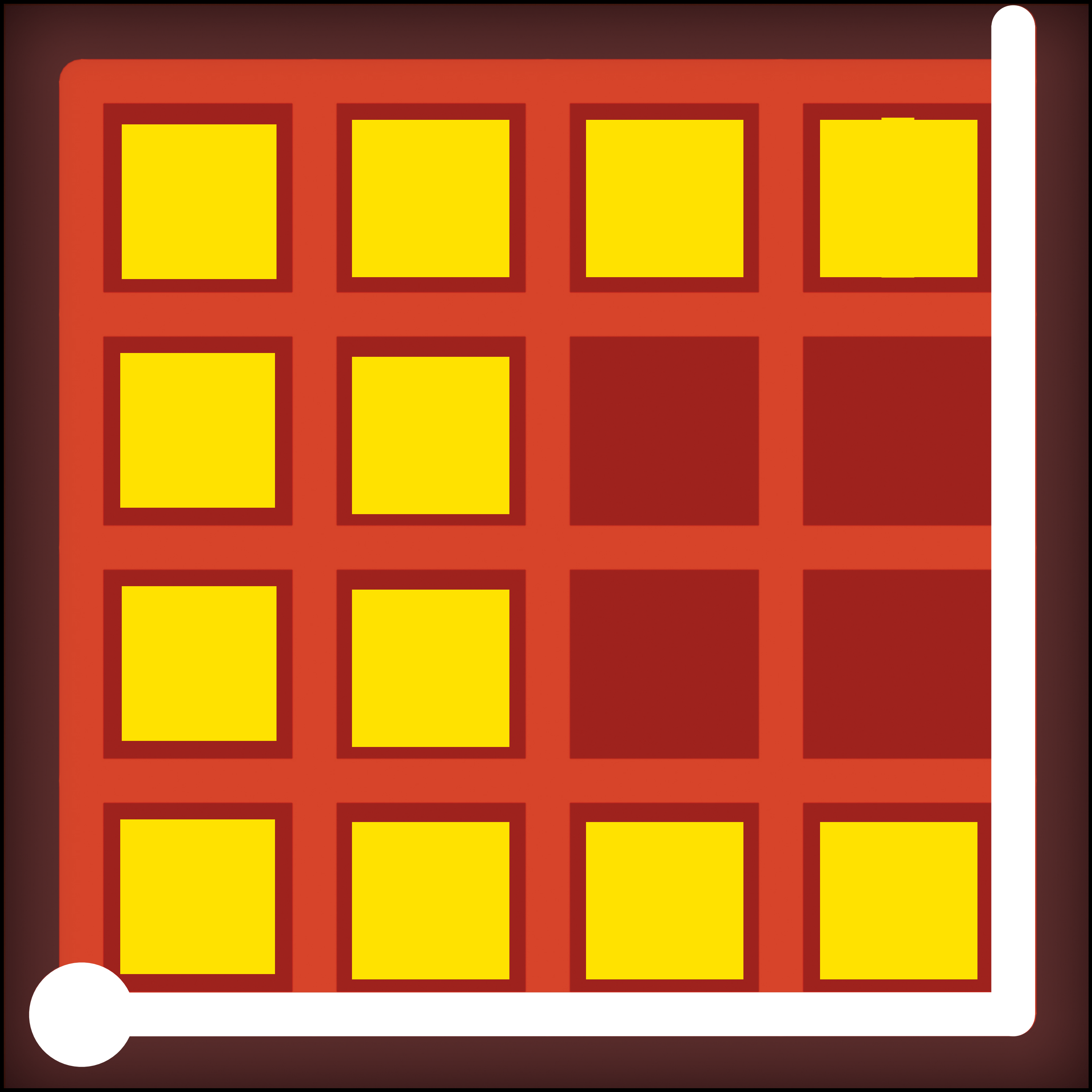


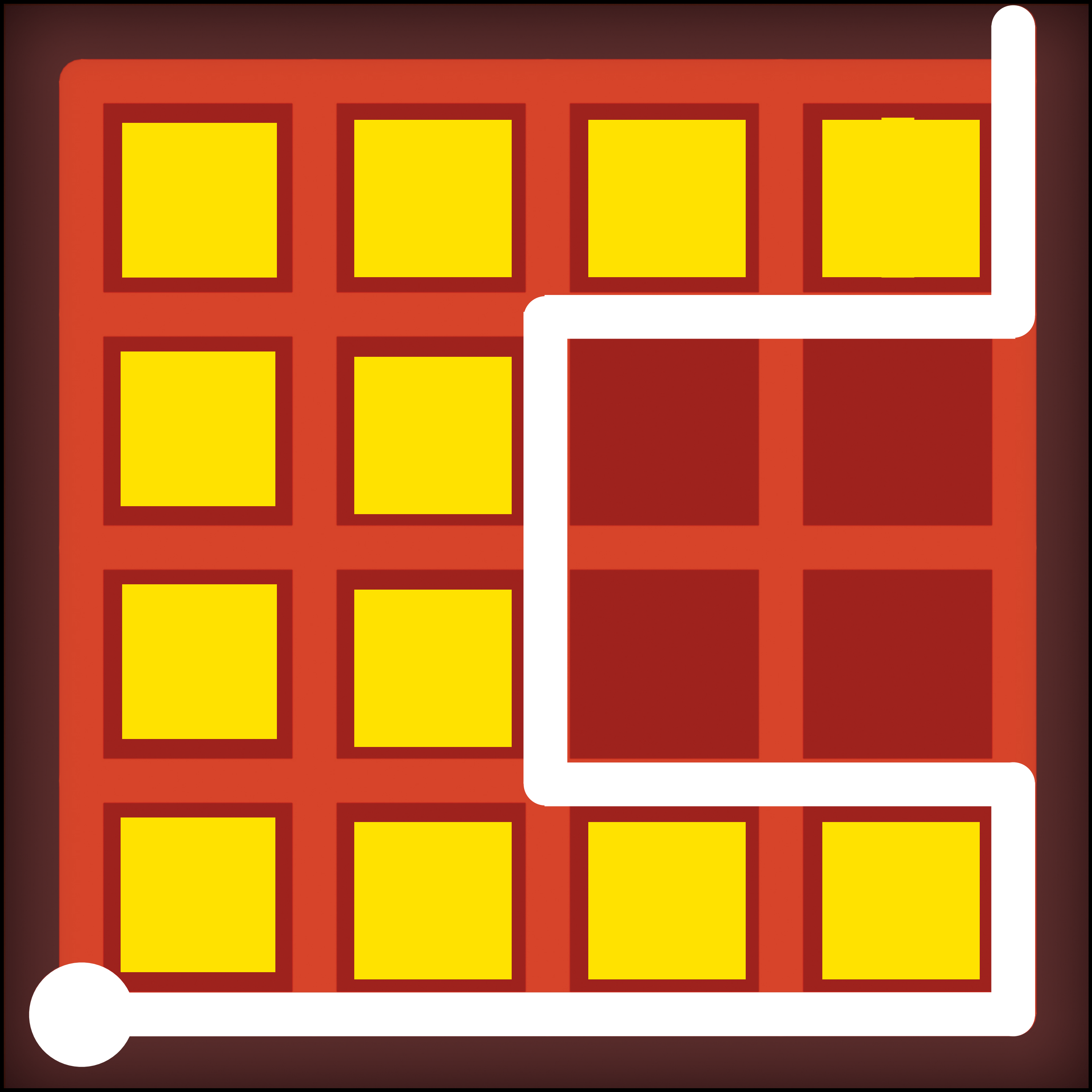






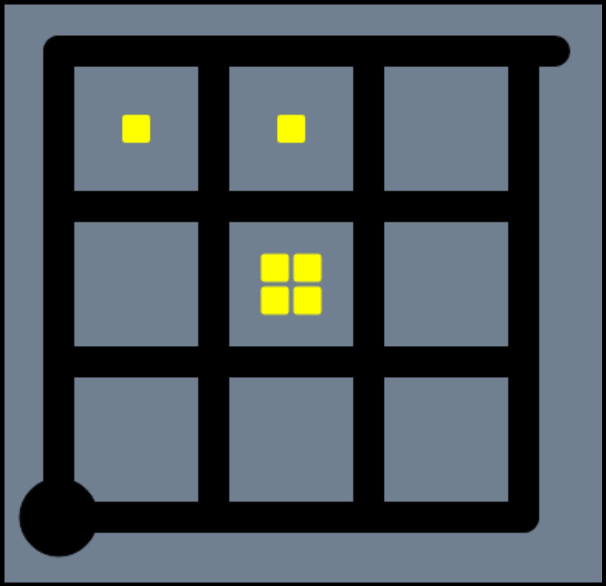


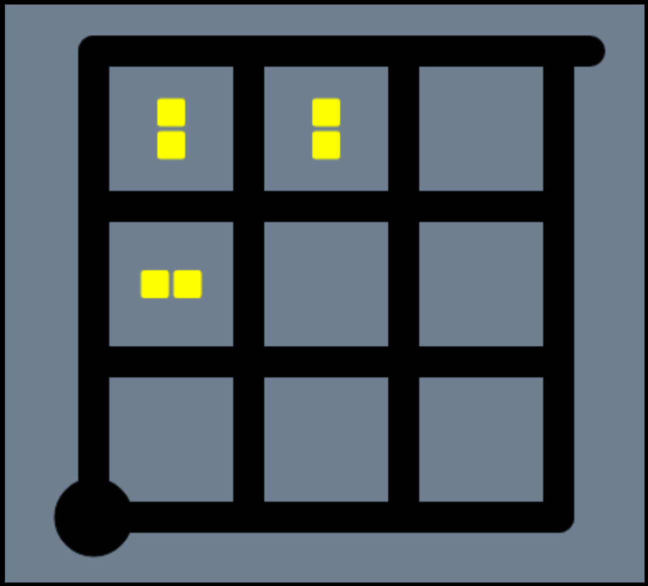


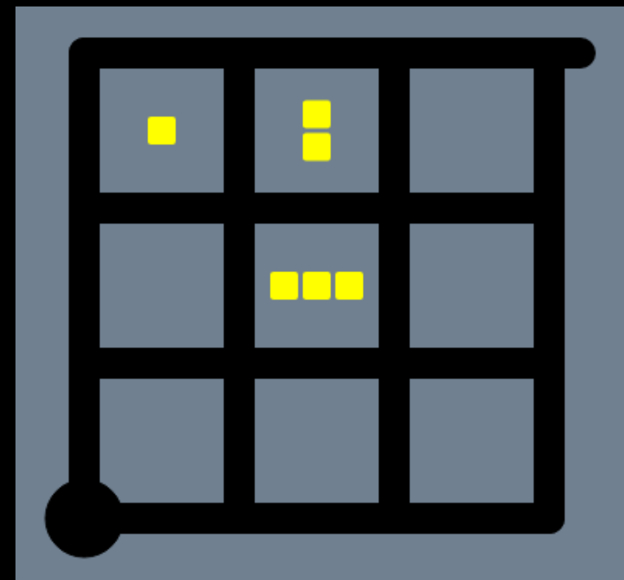


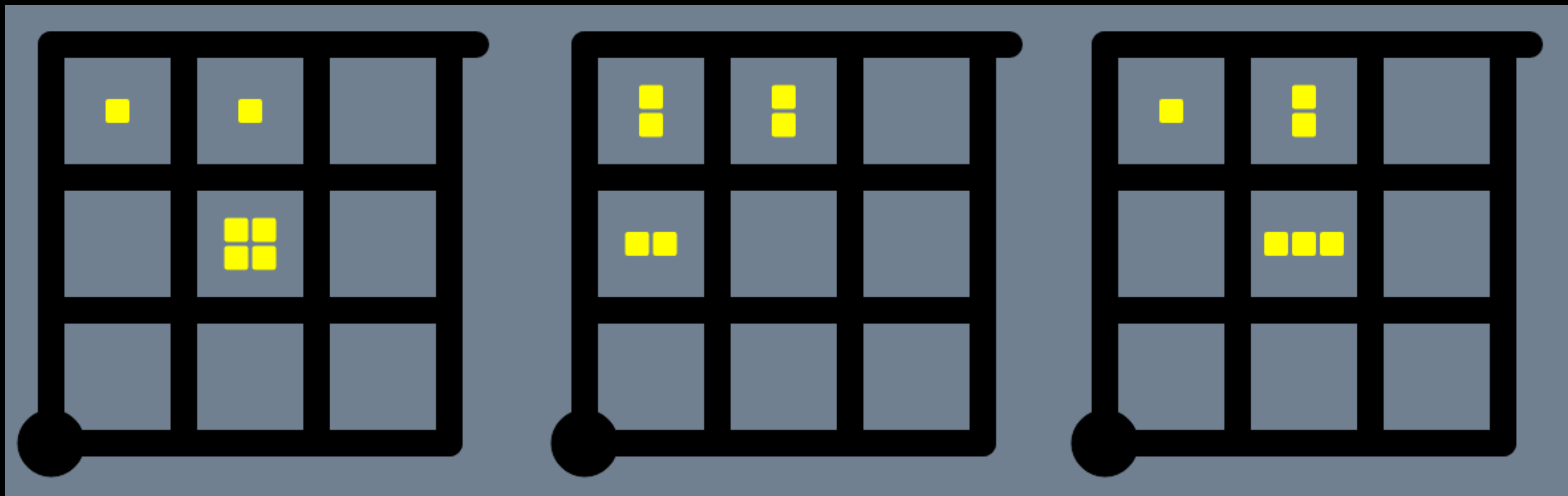
The Design Goal

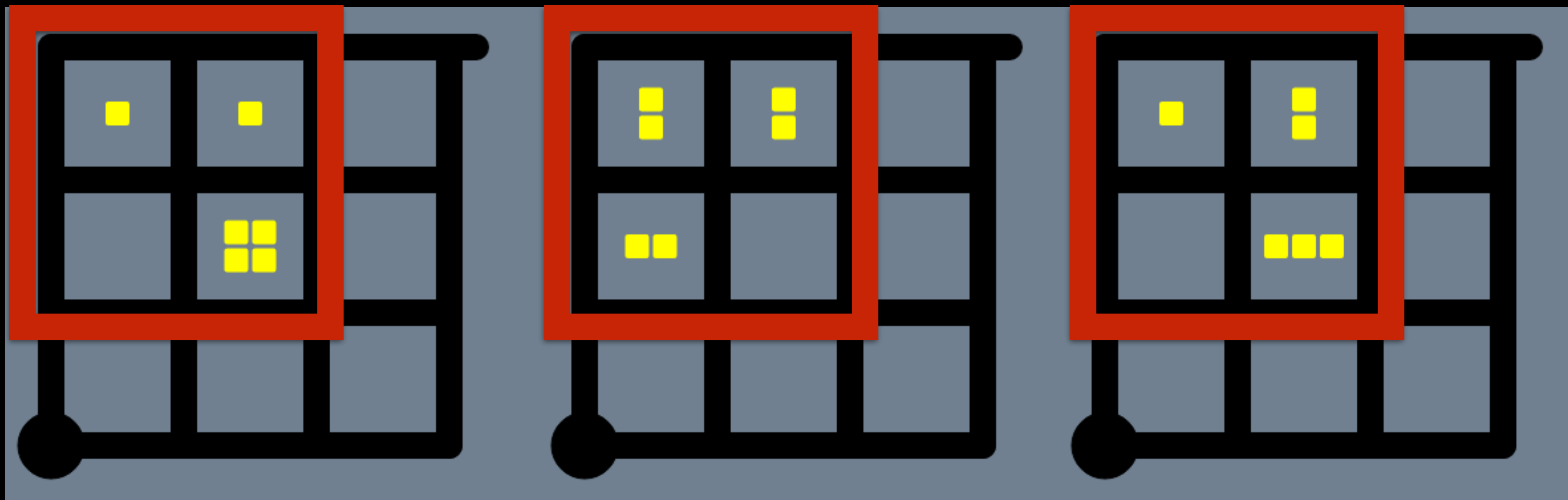
- Solve 3 puzzles simultaneously with the same path
- How do we choose three puzzles?
  - Secret sharing algorithm

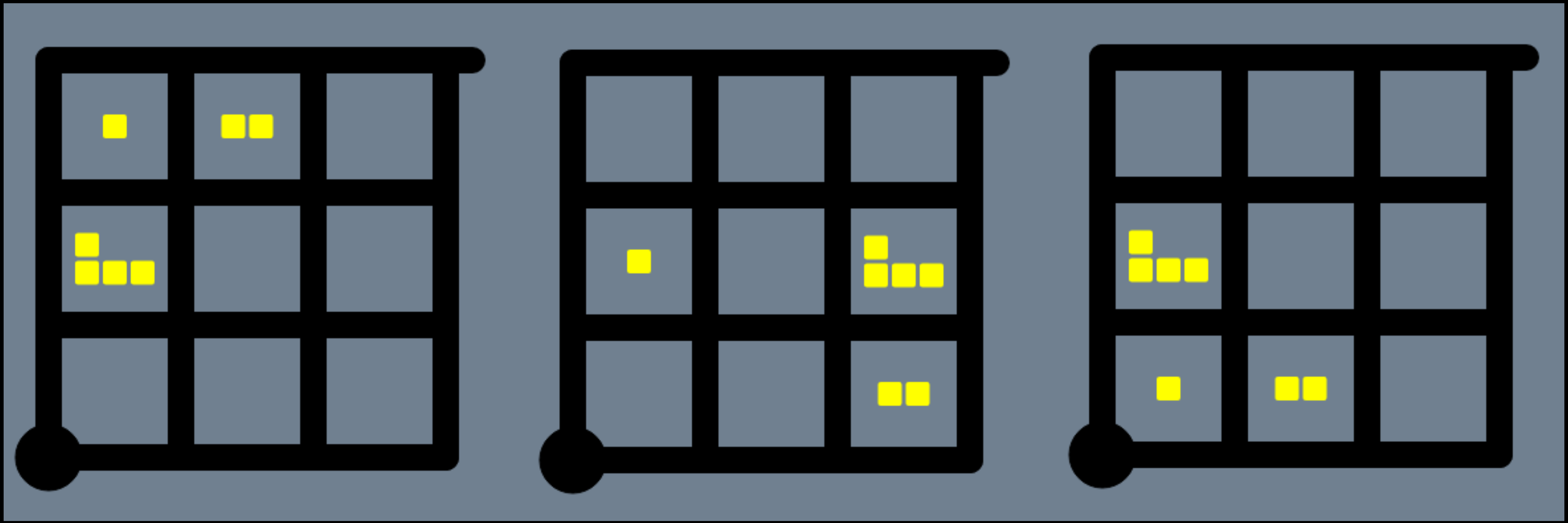


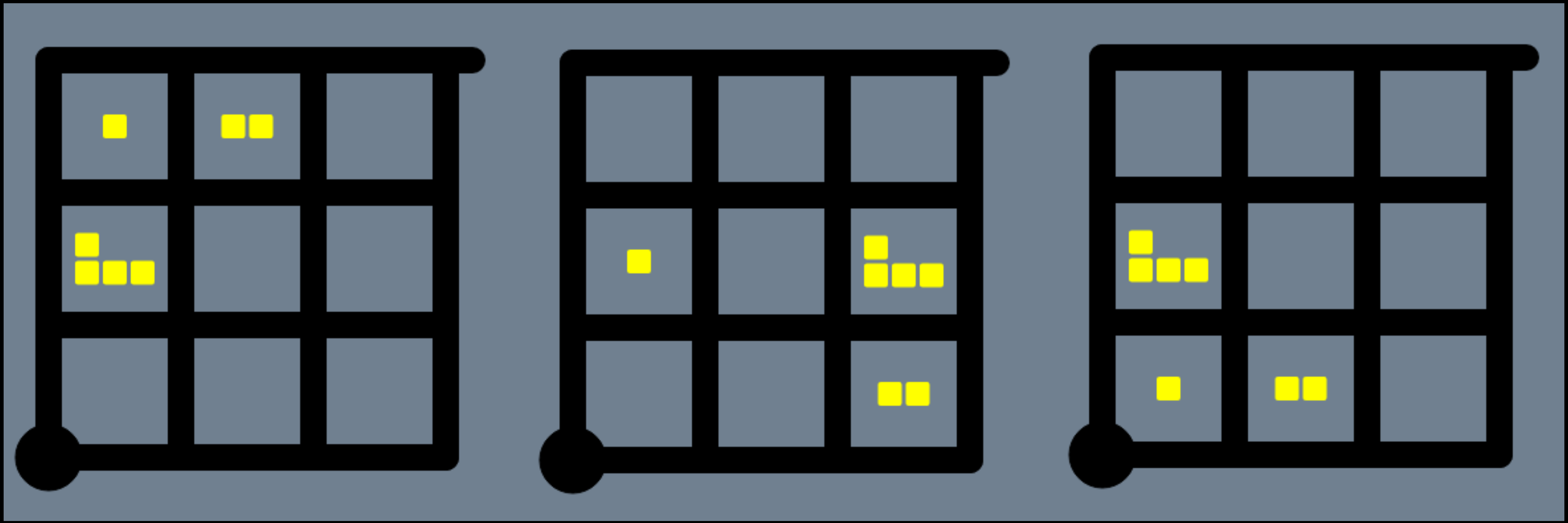












Are you sure this can be solved?

EPCG

EPCG

- **Exhaustive PCG** describes approaches for generating procedural content where all possible content is **methodically generated** and evaluated.

EPCG

- **Exhaustive PCG** describes approaches for generating procedural content where all possible content is **methodically generated** and evaluated.
- Algorithms that are capable of methodically generating all content, but that choose to to skip some content are **semi-exhaustive**.

EPCG

EPCG

- **Evaluator**
  - Evaluates the utility of a given state

EPCG

- **Evaluator**
  - Evaluates the utility of a given state
- **Generator**
  - Enumerates all possible states
    - Combinations
    - Permutations
    - Multi-set
  - Can also be done recursively on variables/values

General Operations

General Operations

- maxRank
  - Comes from computing the total number of configurations

General Operations

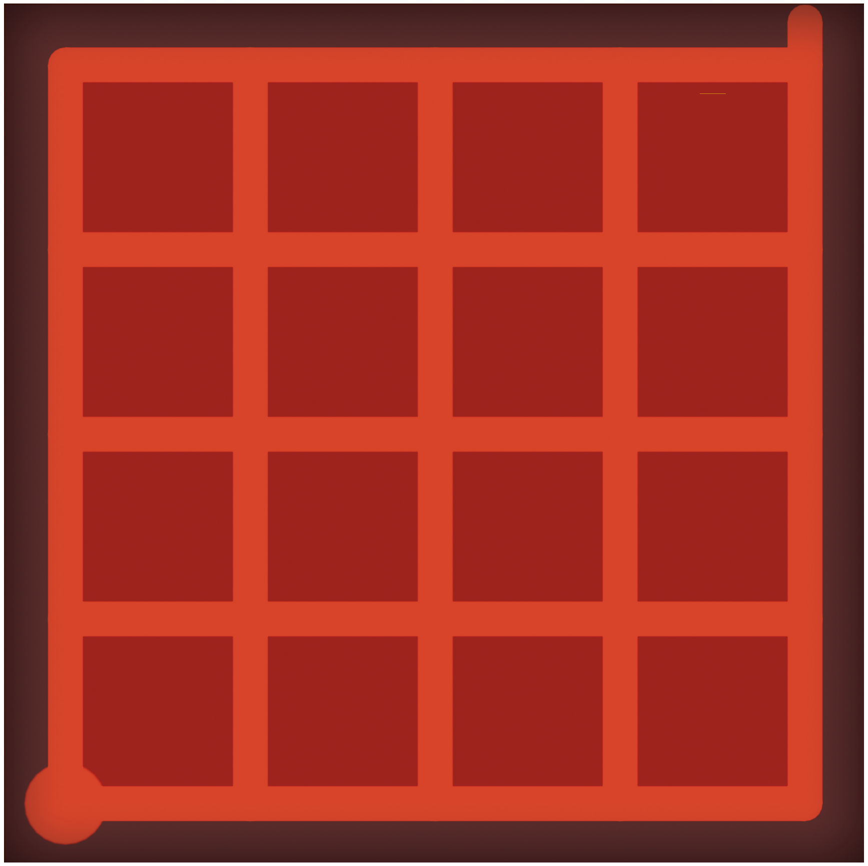
- maxRank
  - Comes from computing the total number of configurations
- hash ← Rank(s)
  - Perfect hash function for a state

General Operations

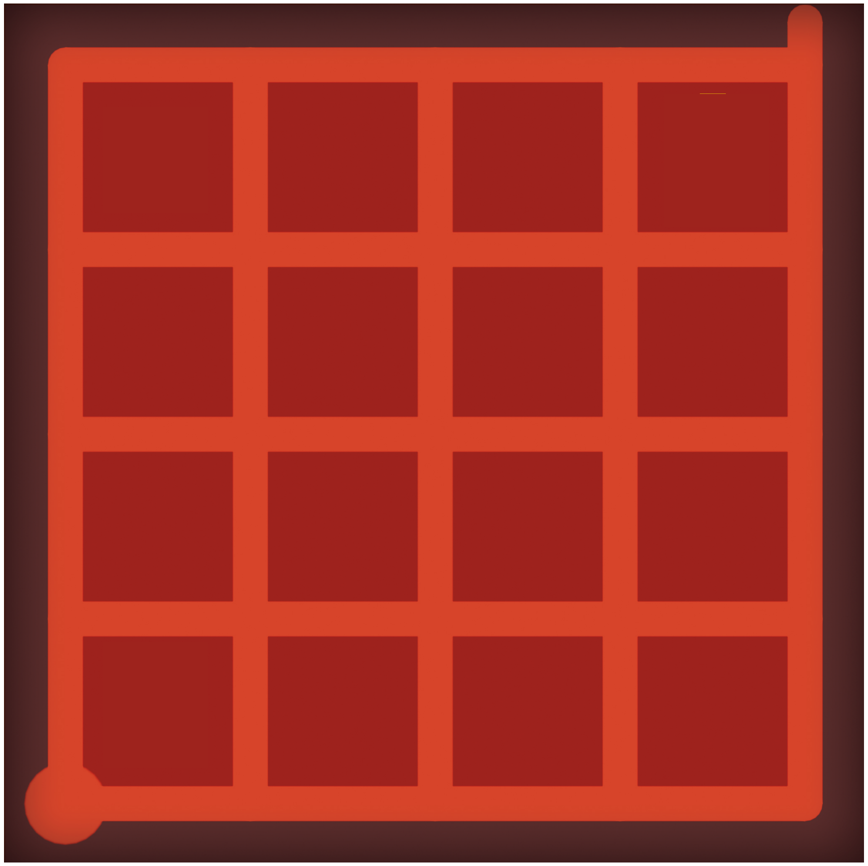
- maxRank
  - Comes from computing the total number of configurations
- hash ← Rank(s)
  - Perfect hash function for a state
- s ← Unrank(hash)
  - Converts a hash back into a state

Example 1

Board



Board

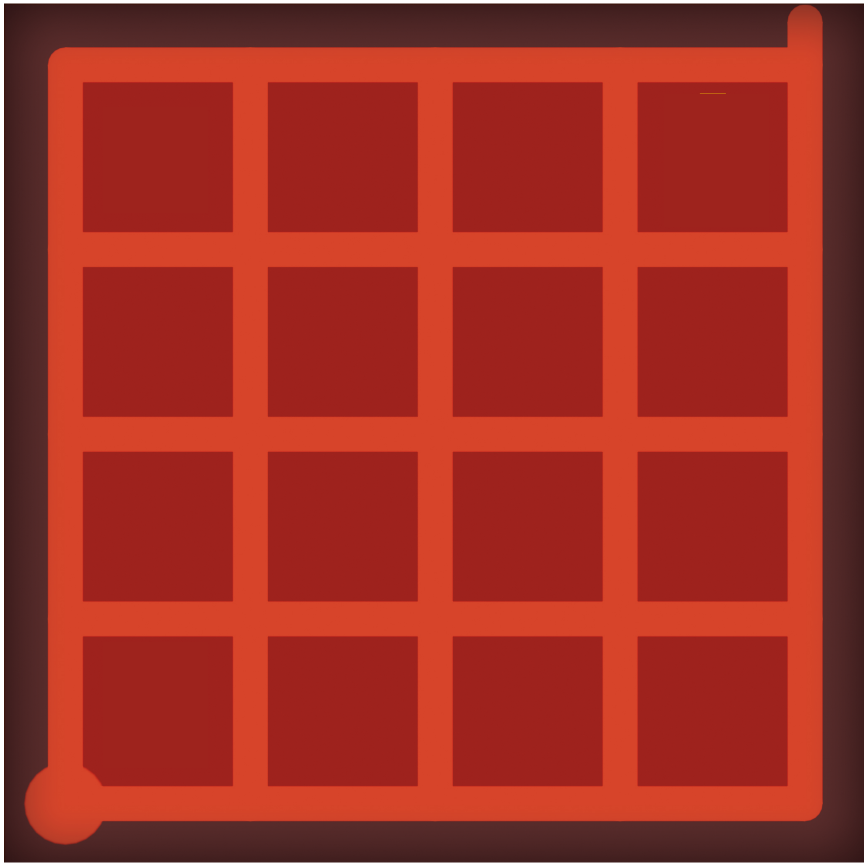


16 locations

3 pieces

11 piece types

Board

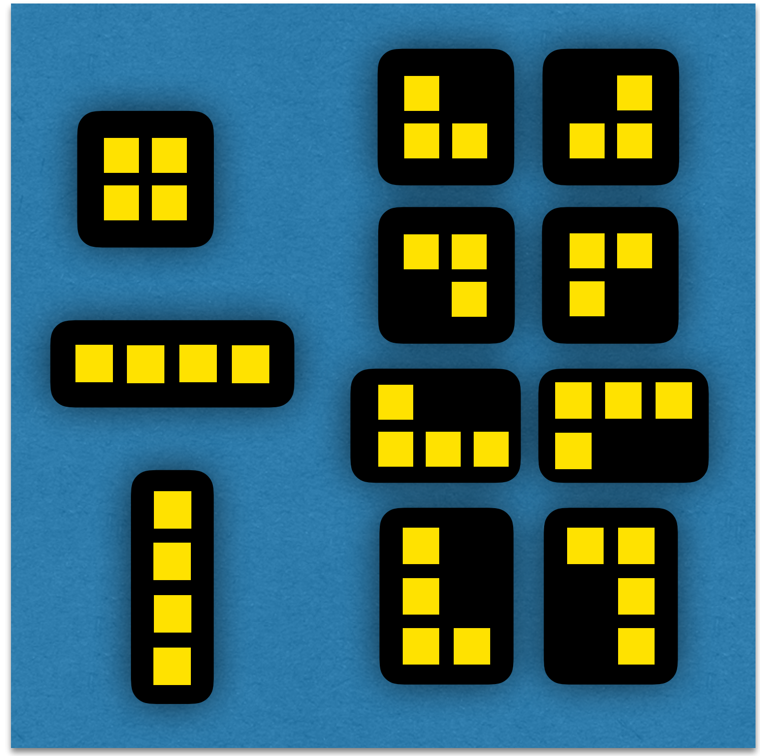


16 locations

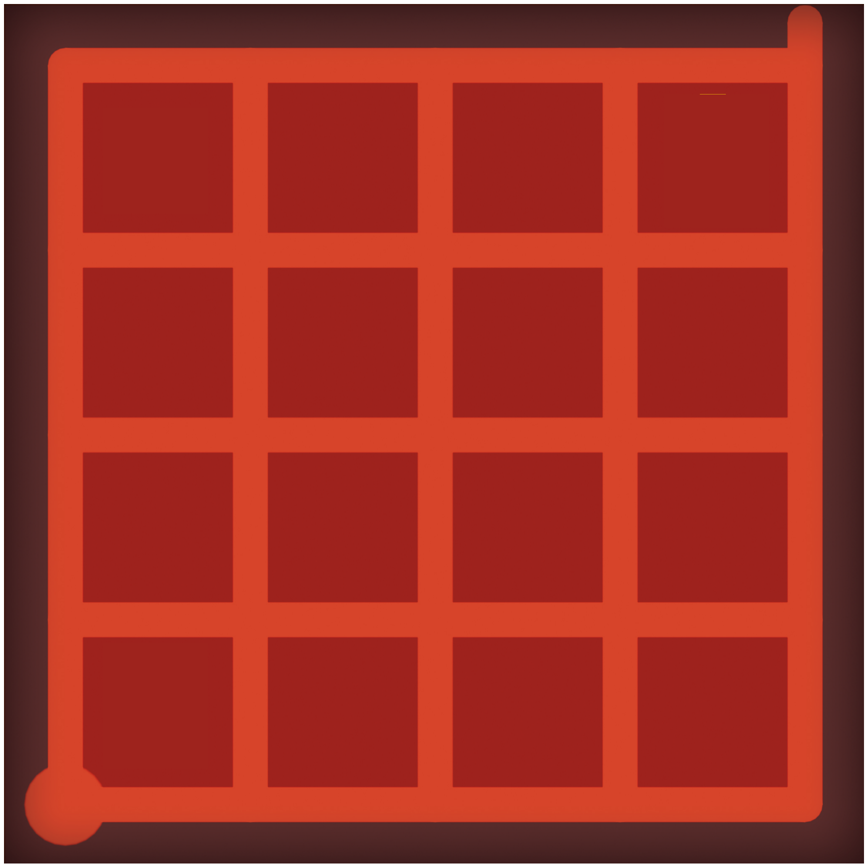
3 pieces

11 piece types

Library

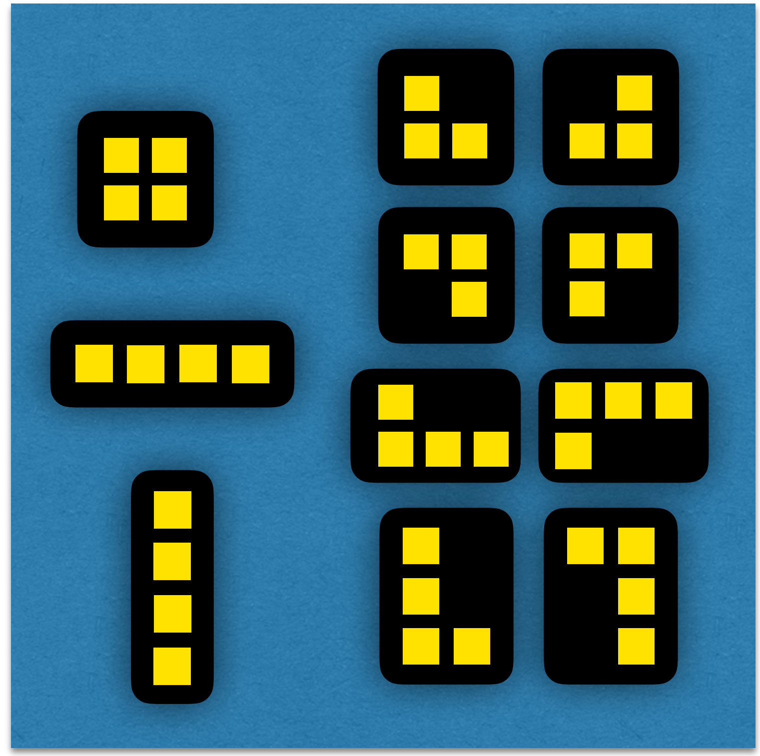


Board



16 locations
3 pieces
11 piece types

Library



$$\binom{16}{3} 11^3 = 745{,}360$$

Exhaustive Approach

Exhaustive Approach

For i = 0 → *maxRank*

Exhaustive Approach

For i = 0 → *maxRank*

s ← Unrank(i)

Exhaustive Approach

For i = 0 → *maxRank*

  s ← Unrank(i)

  localEval ←Eval(s)

Exhaustive Approach

For i = 0 → *maxRank*

s ← Unrank(i)

localEval ←Eval(s)

if (localEval > globalEval)

Exhaustive Approach

For i = 0 → *maxRank*

s ← Unrank(i)

localEval ←Eval(s)

if (localEval > globalEval)

globalEval = localEval

Exhaustive Approach

For i = 0 → *maxRank*

s ← Unrank(i)

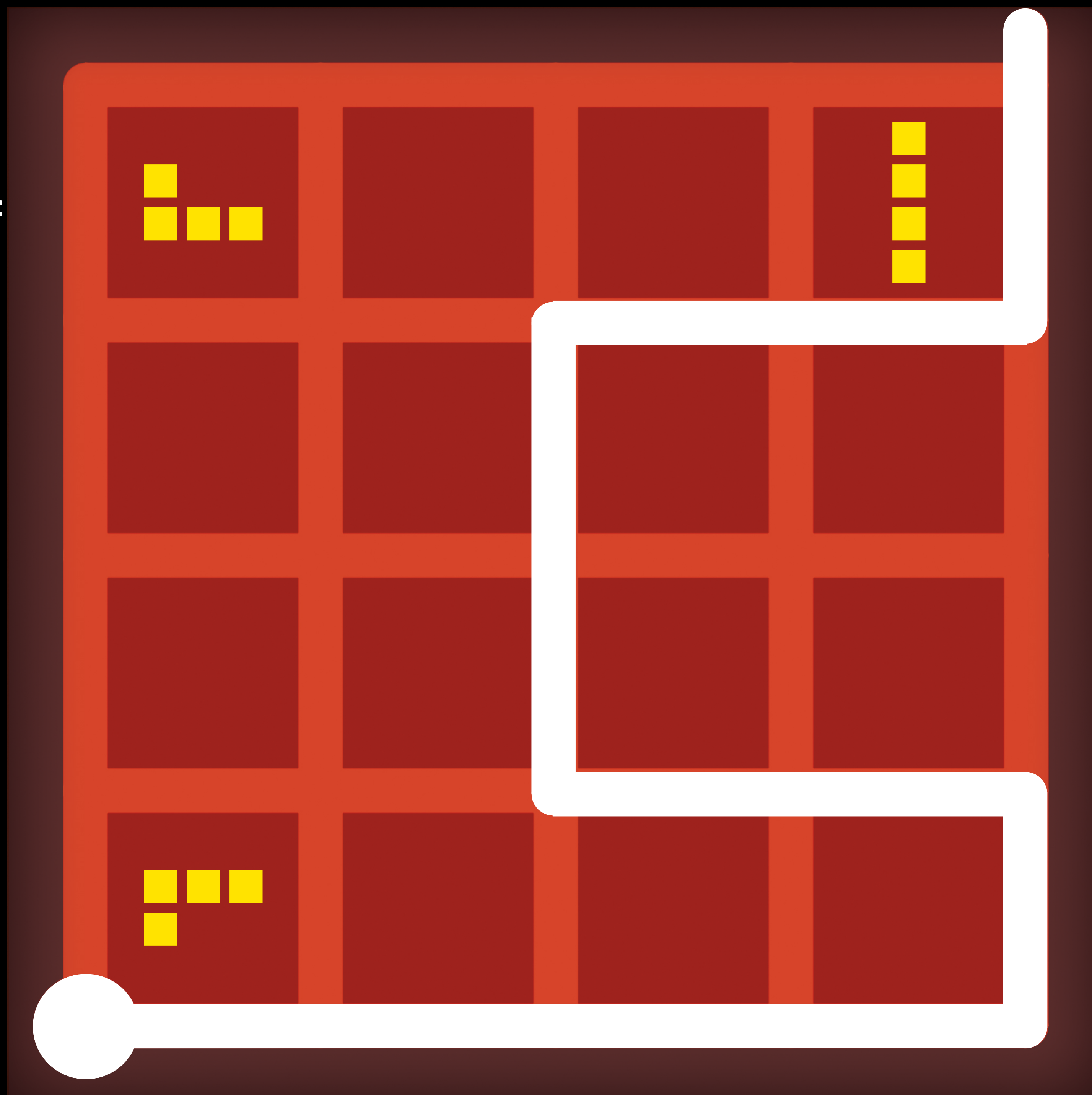
localEval ←Eval(s)

if (localEval > globalEval)

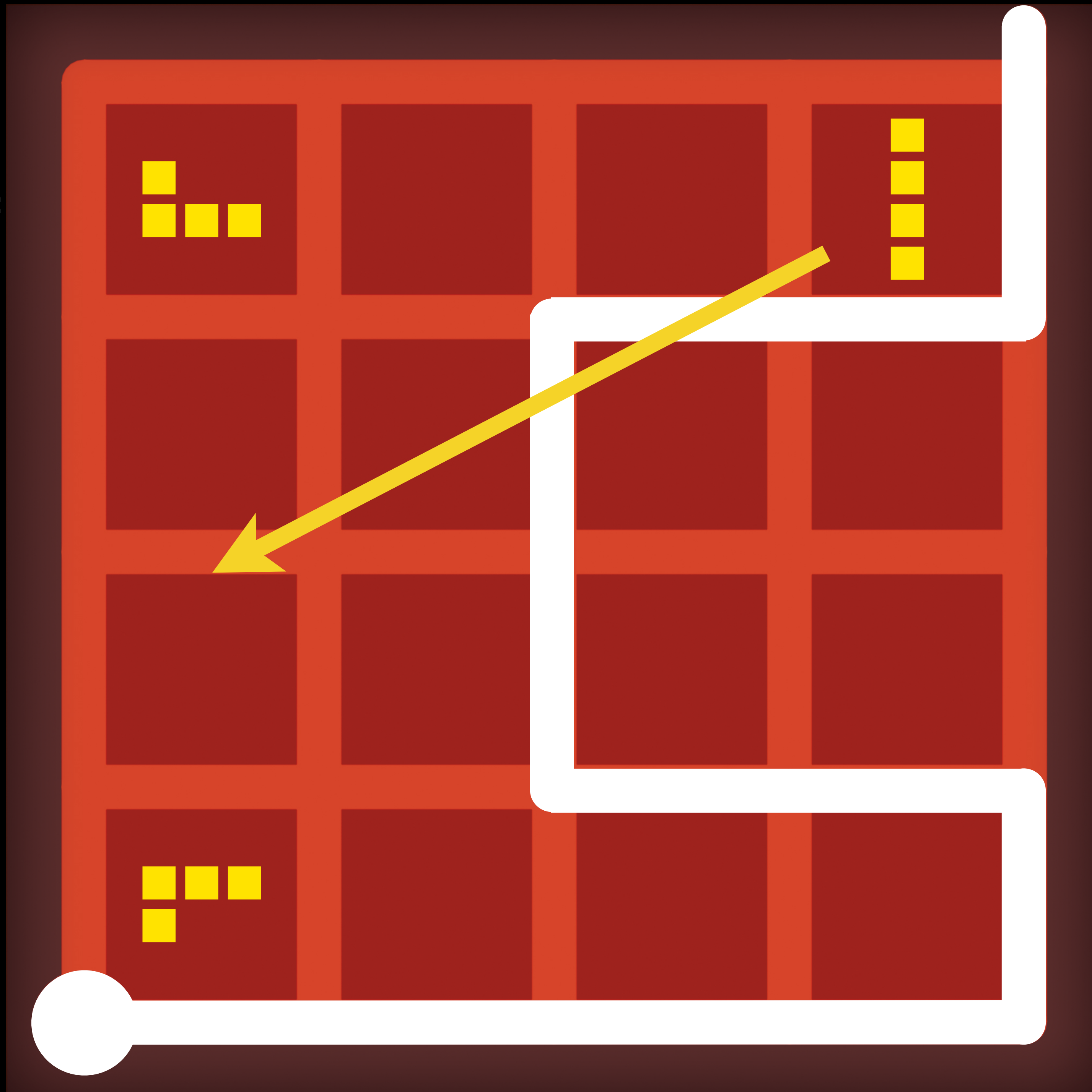
globalEval = localEval

best = i

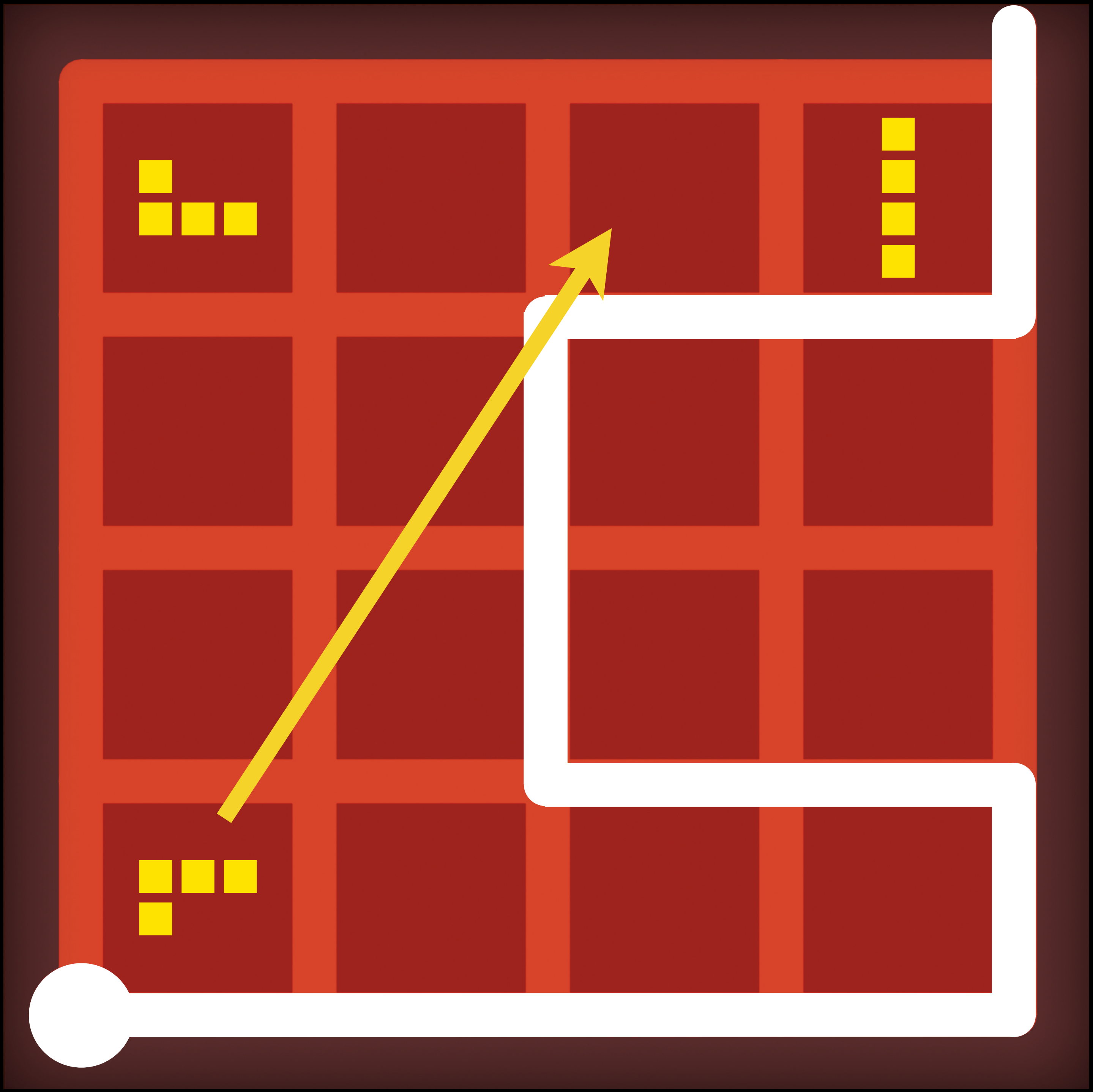
Virtual location of each piece is as far as possible from actual piece



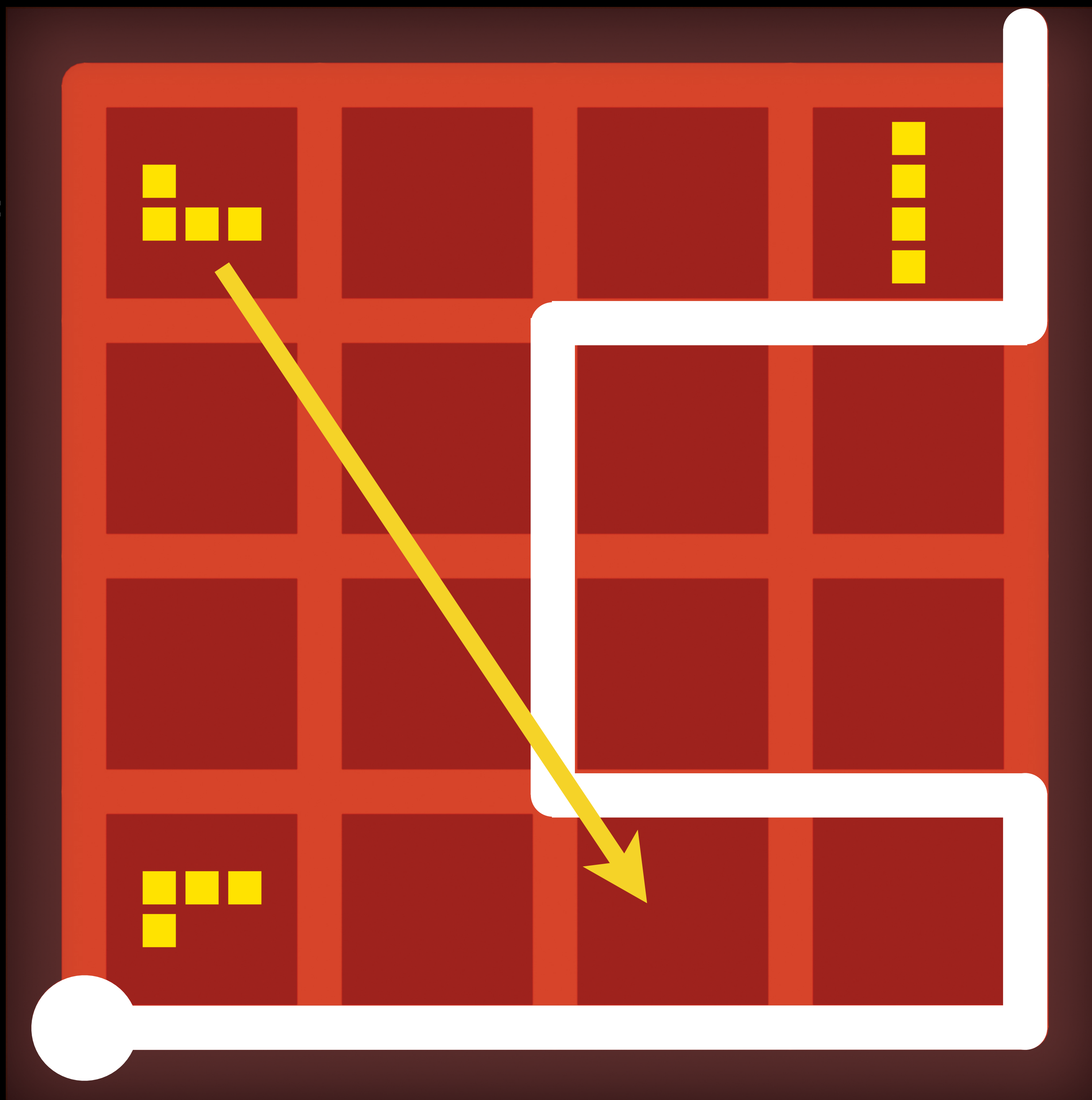
Virtual location of each piece is as far as possible from actual piece



Virtual location of each piece is as far as possible from actual piece

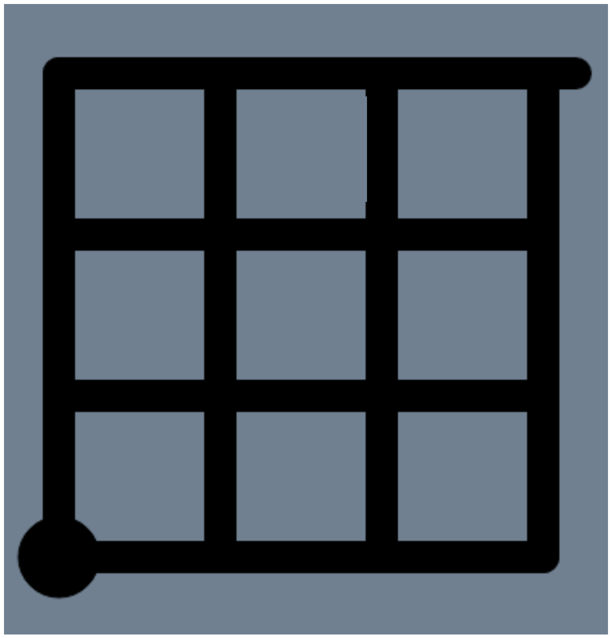


Virtual location of each piece is as far as possible from actual piece

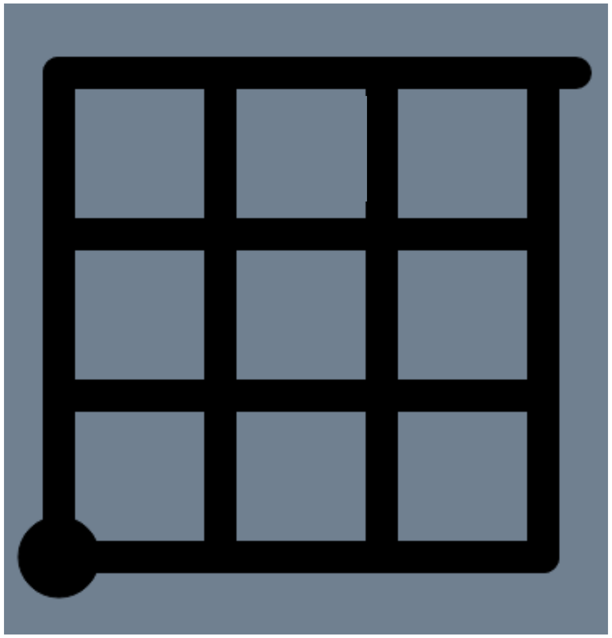


Example 2

Board



Board

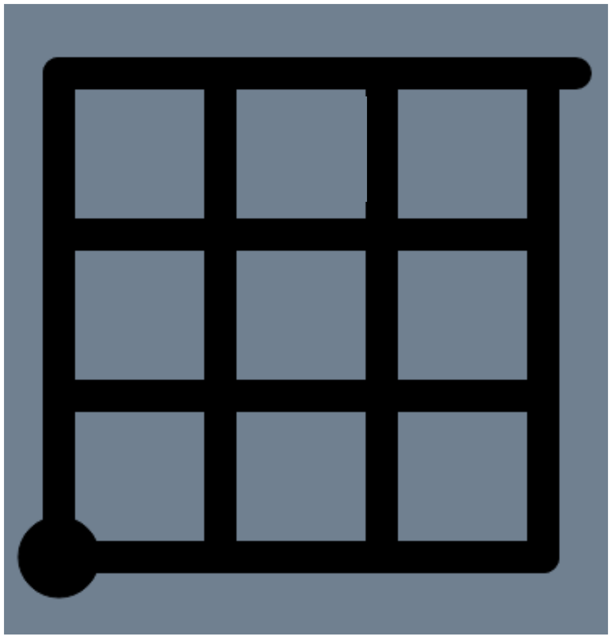


9 locations

3 pieces

12 piece types

Board



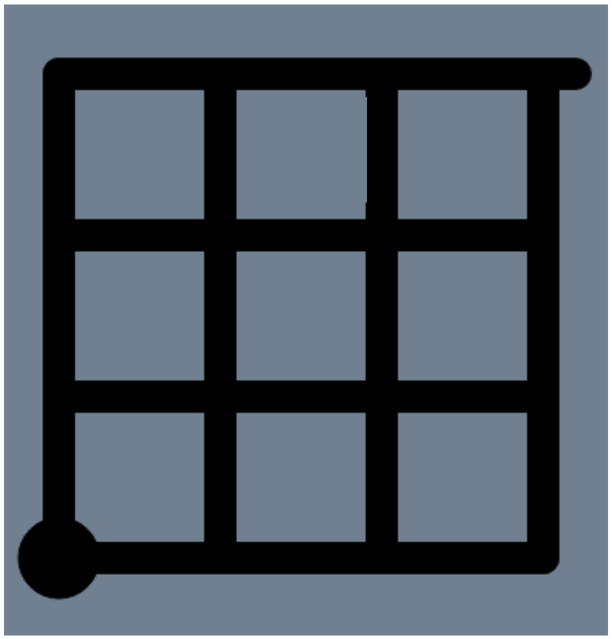
9 locations

3 pieces

12 piece types

$$\binom{9}{3} 12^3 = 145{,}152$$

Board



9 locations

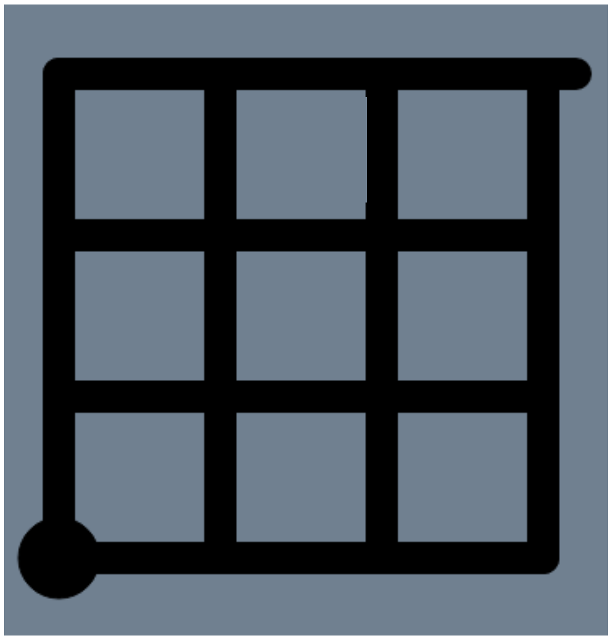
3 pieces

12 piece types

$$\binom{9}{3}12^3 = 145{,}152$$

Triples: 3.06×10^{15}

Board



9 locations
3 pieces
12 piece types

$$\binom{9}{3} 12^3 = 145{,}152$$

Triples: 3.06×10^{15}

Semi-Exhaustive: Branch and Bound
to prune suboptimal solutions

Semi-Exhaustive Approach

Semi-Exhaustive Approach

- Prune **single** boards with too few solutions

Semi-Exhaustive Approach

- Prune **single** boards with too few solutions
- Prune **pairs** of boards with too few solutions

Semi-Exhaustive Approach

- Prune **single** boards with too few solutions
- Prune **pairs** of boards with too few solutions
- Exhaustively enumerate remaining combinations

Semi-Exhaustive Approach

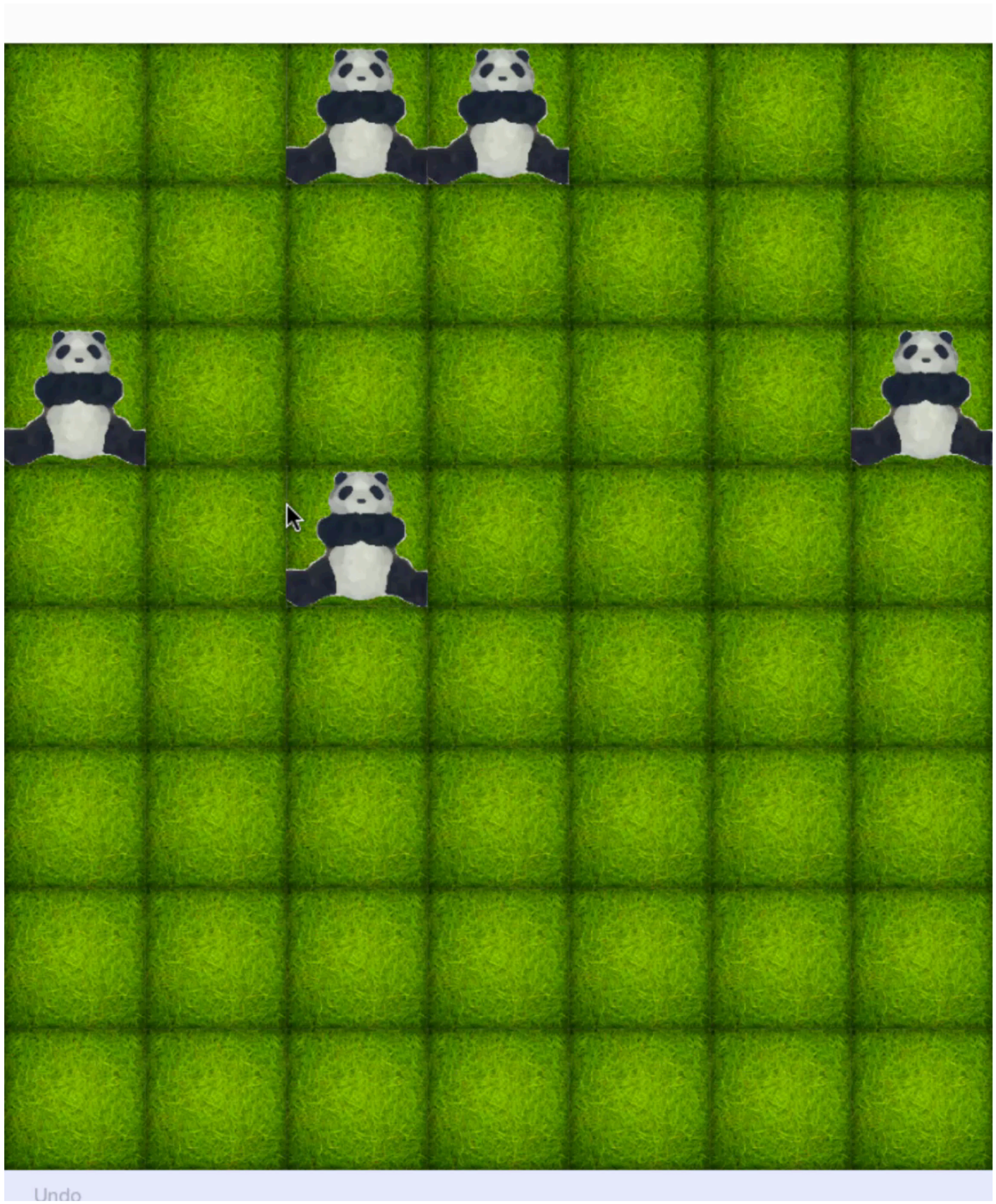
- Prune **single** boards with too few solutions
- Prune **pairs** of boards with too few solutions
- Exhaustively enumerate remaining combinations
  - Continue to prune combinations which are worse then best found so far

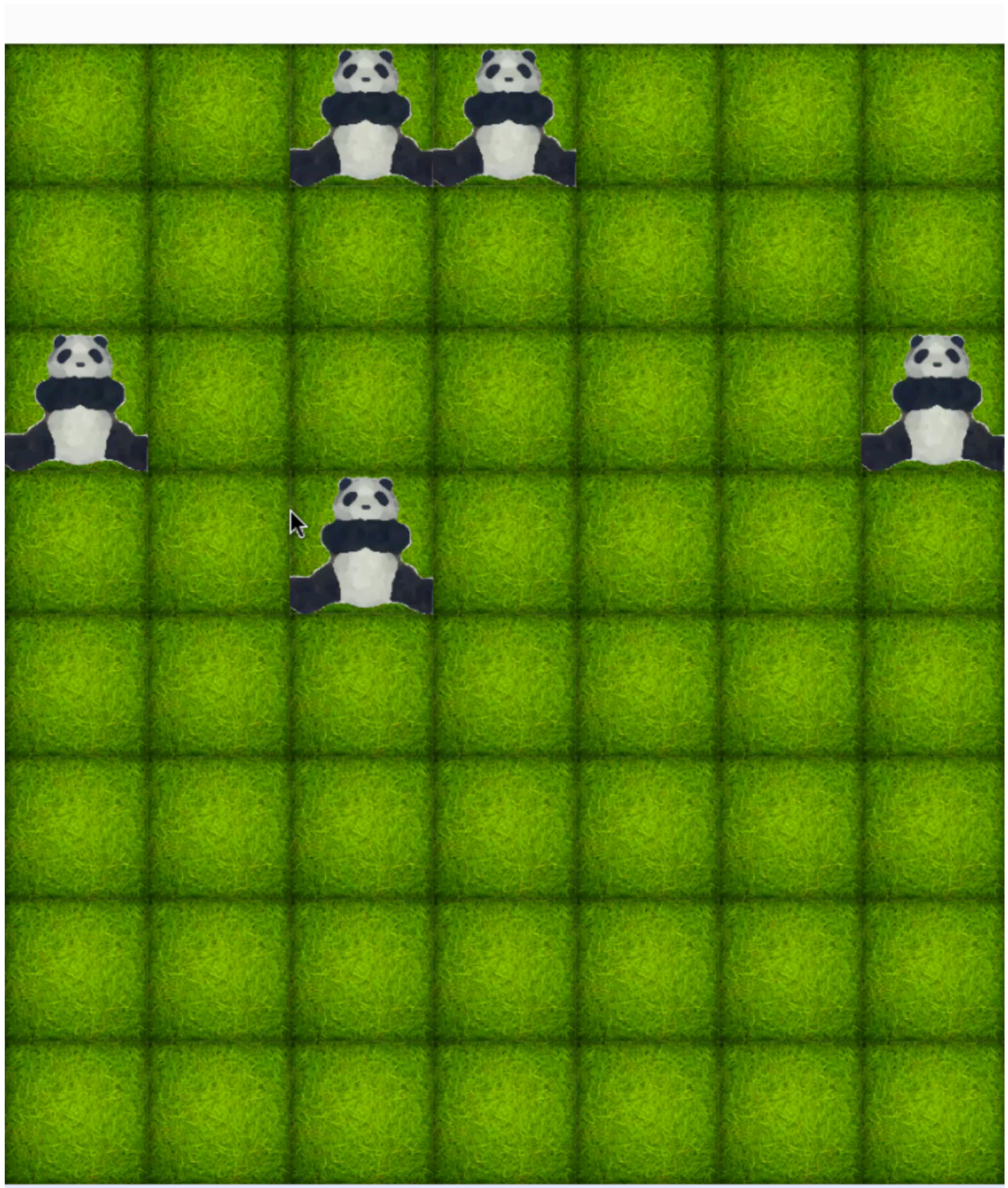
Semi-Exhaustive Approach

- Prune **single** boards with too few solutions
- Prune **pairs** of boards with too few solutions
- Exhaustively enumerate remaining combinations
    - Continue to prune combinations which are worse then best found so far

https://movingai.com/witness.html

Example 3


Undo



Undo

Fling!

- $\binom{56}{10}$ = 35.6 billion boards with 10 pieces
- 15 million boards (0.04%) with 1 solution
- Forward search is expensive
- Not amenable to genetic operations

Retrograde Analysis

- Solve all boards, iteratively increasing the number of pieces on the board
  - 1 piece, 2 pieces, 3 pieces, etc
  - Easy to solve those with *n* pieces by computing from those with *n-1* pieces
  - Avoid re-searching the underlying tree
  - *Requires* the ranking function to look up states in memory

Retrograde Analysis

Retrograde Analysis

- For i = 0 → maxRank

Retrograde Analysis

- For i = 0 → maxRank
  - s ← Unrank(i)

Retrograde Analysis

- For i = 0 → maxRank
  - s ← Unrank(i)
  - for each successor s_i of parent

Retrograde Analysis

- For i = 0 → maxRank
  - s ← Unrank(i)
  - for each successor s_i of parent
    - r ←Rank(s_i)

Retrograde Analysis

- For $i = 0 \rightarrow$ maxRank
  - $s \leftarrow$ Unrank(i)
  - for each successor s_i of parent
    - $r \leftarrow$ Rank(s_i)
    - *Check if solvable/single solution*

Retrograde Analysis

- For i = 0 → maxRank
  - s ← Unrank(i)
  - for each successor s_i of parent
    - r ← Rank(s_i)
    - *Check if solvable/single solution*
  - If *solvable/single solution*

UNIVERSITY OF ALBERTA

Retrograde Analysis

- For i = 0 → maxRank
  - s ← Unrank(i)
  - for each successor s_i of parent
    - r ← Rank(s_i)
    - *Check if solvable/single solution*
  - If *solvable/single solution*
    - mark *i* as single solution / solvable

Then…

Then…

- After efficiently identifying single solution puzzles

Then…

- After efficiently identifying single solution puzzles
- …run EPCG on these puzzles to choose the best

Takeaways

Takeaways

- Many puzzle problems are easy to analyze by computer - even if they are combinatorially large

Takeaways

- Many puzzle problems are easy to analyze by computer - even if they are combinatorially large
- EPCG enables us to ask precise questions about the space of possible puzzles

Takeaways

- Many puzzle problems are easy to analyze by computer - even if they are combinatorially large
- EPCG enables us to ask precise questions about the space of possible puzzles
- See the paper for some of the mathematics behind this analysis

Takeaways

- Many puzzle problems are easy to analyze by computer - even if they are combinatorially large
- EPCG enables us to ask precise questions about the space of possible puzzles
- See the paper for some of the mathematics behind this analysis
- Sample code on www.movingai.com