

Solving Problems with Critical Variables

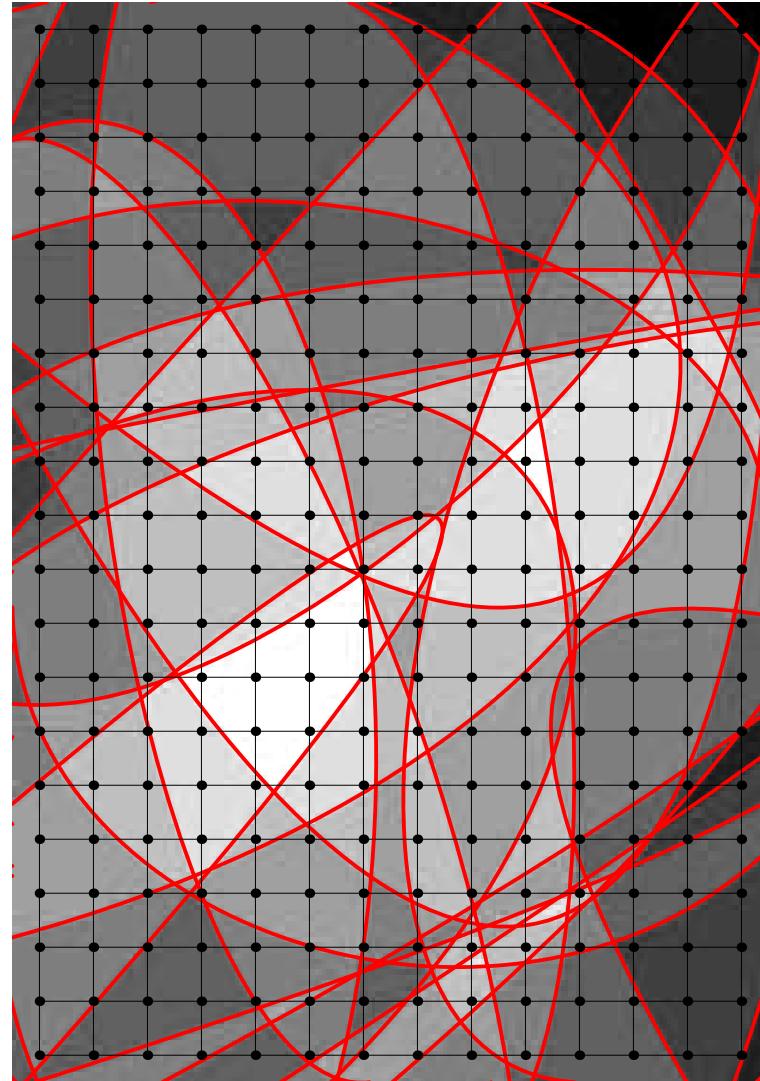
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Electronics and Computer Science
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based on last year's GECCO paper

Outline

1. **Critical Variable Problems**
2. Solving Critical Variable Problems
3. A Toy Example
4. Real Optimisation Problems
5. Max-Sat



Critical Variable Problems

- We consider a *special* class of problems—the critical variable problems—with the following properties
- The problem is represented by a string of variables divided into two groups

C**B****C****E****A****A****E****A****A****A****A****C****B****D****A****B****B****B****A****D****E****A****E****B****C****D****B****A**

- ★ a small set of **critical variables**
- ★ all other variable are **normal variables**
- The position of the critical variables are unknown

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Normal and Critical Variables

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- If the critical variables are fixed then it is easy to optimise the normal variables, e.g. by a hill-climber
- The optimal values for the normal variables will depend on the critical variables
- The critical variables are (at least approximately) uncoupled
- Because the normal variables depend on the critical variables we cannot hill-climb to optimise the critical variables

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Landscape of Critical Variable Problems

- Every configuration of the critical variables is associated with a local optima (found by performing hill-climbing on the normal variables)
- The local minima can be some distance apart since changing a critical variable might require many normal variables to be changed
- The more good critical variables the better the local optima (since the critical variables are *not* strongly coupled)

Landscape of Critical Variable Problems

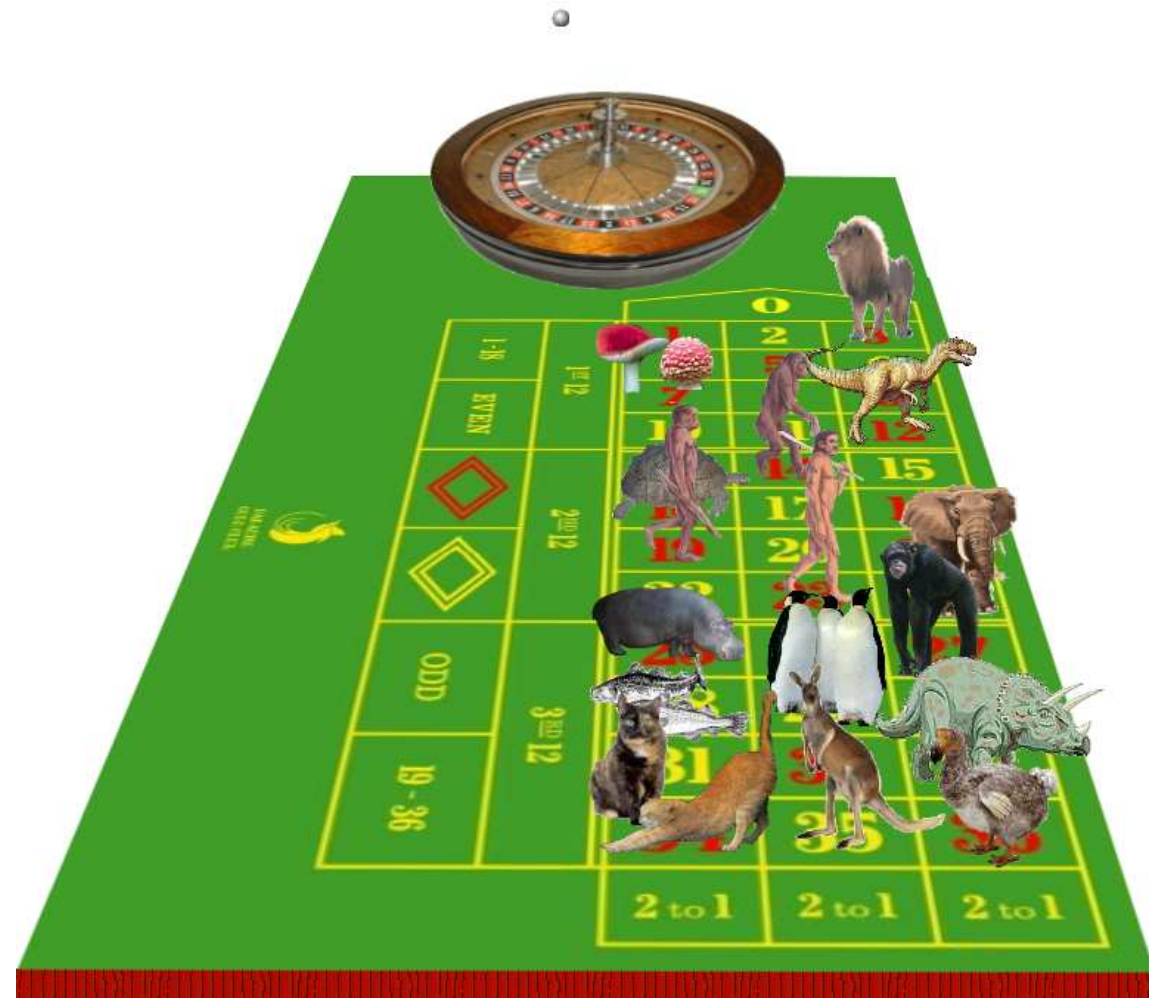
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The Challenge of Critical Variable Problems

- We have a problem with a very large number of local optima
- We don't know which variables are the critical variables
- The probability of guessing which variables are critical variables is vanishingly small—we are looking for a small number of variables hidden in a crowd of normal variables
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Solving Critical Variable Problems

- We can solve Critical Variable Problems using two levels of search
 - ★ use a hill-climber to optimise the normal variables
 - ★ use crossover to optimise the critical variables
- We need to optimise the normal variables to evaluate the fitness of the critical variables

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A Hybrid GA Solver

- This leads to a hybrid GA algorithm:
 1. generate a random population
 2. perform hill-climbing on each member of the population
 3. **for** $t = 1$ **to** T
 - (a) select the fitter members of the population
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What's Happening

- Hill-climbing optimises the normal variables which allows us to evaluate the fitness of the critical variables
- Selection increases the proportion of good critical variables
- Crossover mixes up the critical variables thus allowing exploration of the space of critical variables
- Crossover will mess up the normal variables so that they will need to be re-optimised at each step

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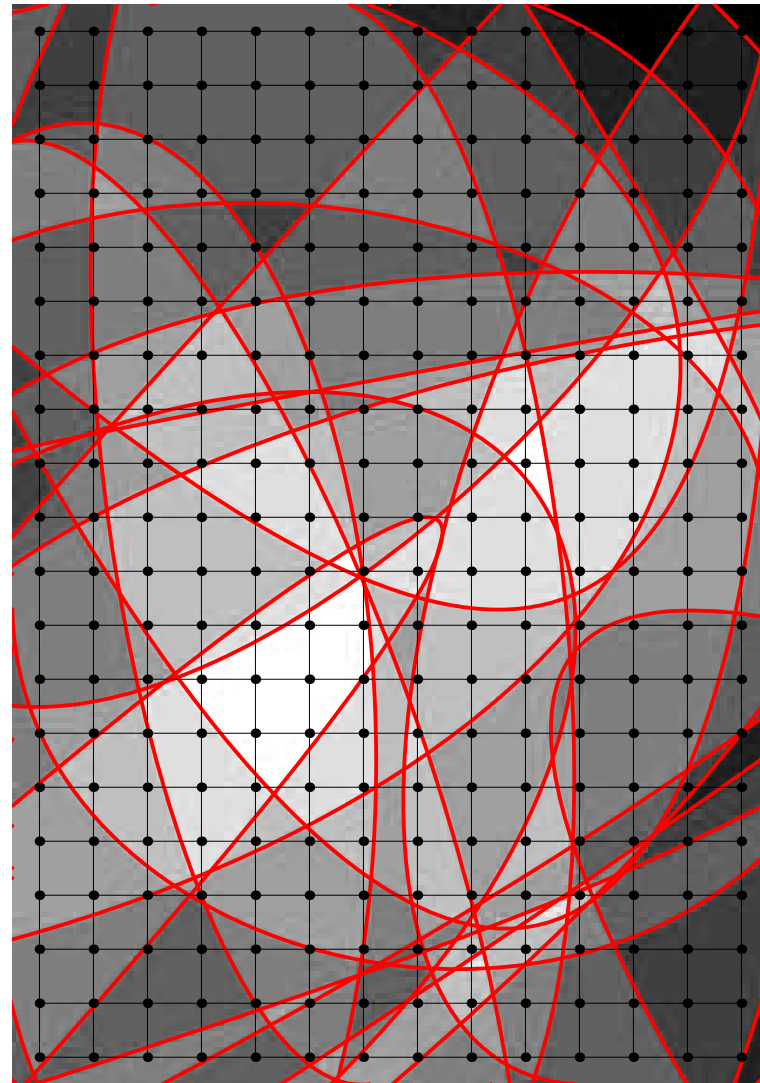
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Simple Example

- We consider binary strings with variables $X_i \in \{-1, 1\}$
- Fitness made up of two parts:

$$F = F_{\text{critical}} + F_{\text{normal}}$$

- ★ A contribution depending only on the critical variables

$$F_{\text{critical}} = \sum_{i \in \text{critical}} X_i$$

- ★ The normal variables contribute in blocks

$$F_{\text{normal}} = \sum_{i \in \text{critical}} F_i^{\text{block}}, \quad F_i^{\text{block}} = X_i \sum_{j \in \text{block}(i)} X_{j_i}$$

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Fitness Landscape

Binary String

1	-1	1	1	1	-1	-1	1	-1	1	-1	1	-1	1	1	1	1	1	-1	1	-1	-1	-1	1
---	----	---	---	---	----	----	---	----	---	----	---	----	---	---	---	---	---	----	---	----	----	----	---

F
-2

Fitness Landscape

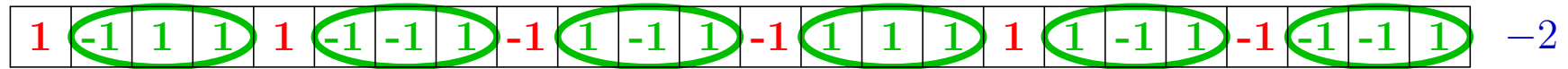
Critical Variables

1	-1	1	1	1	-1	-1	1	-1	1	-1	1	1	1	1	1	-1	1	-1	-1	1
---	----	---	---	---	----	----	---	----	---	----	---	---	---	---	---	----	---	----	----	---

F
 -2

Fitness Landscape

Normal Variables

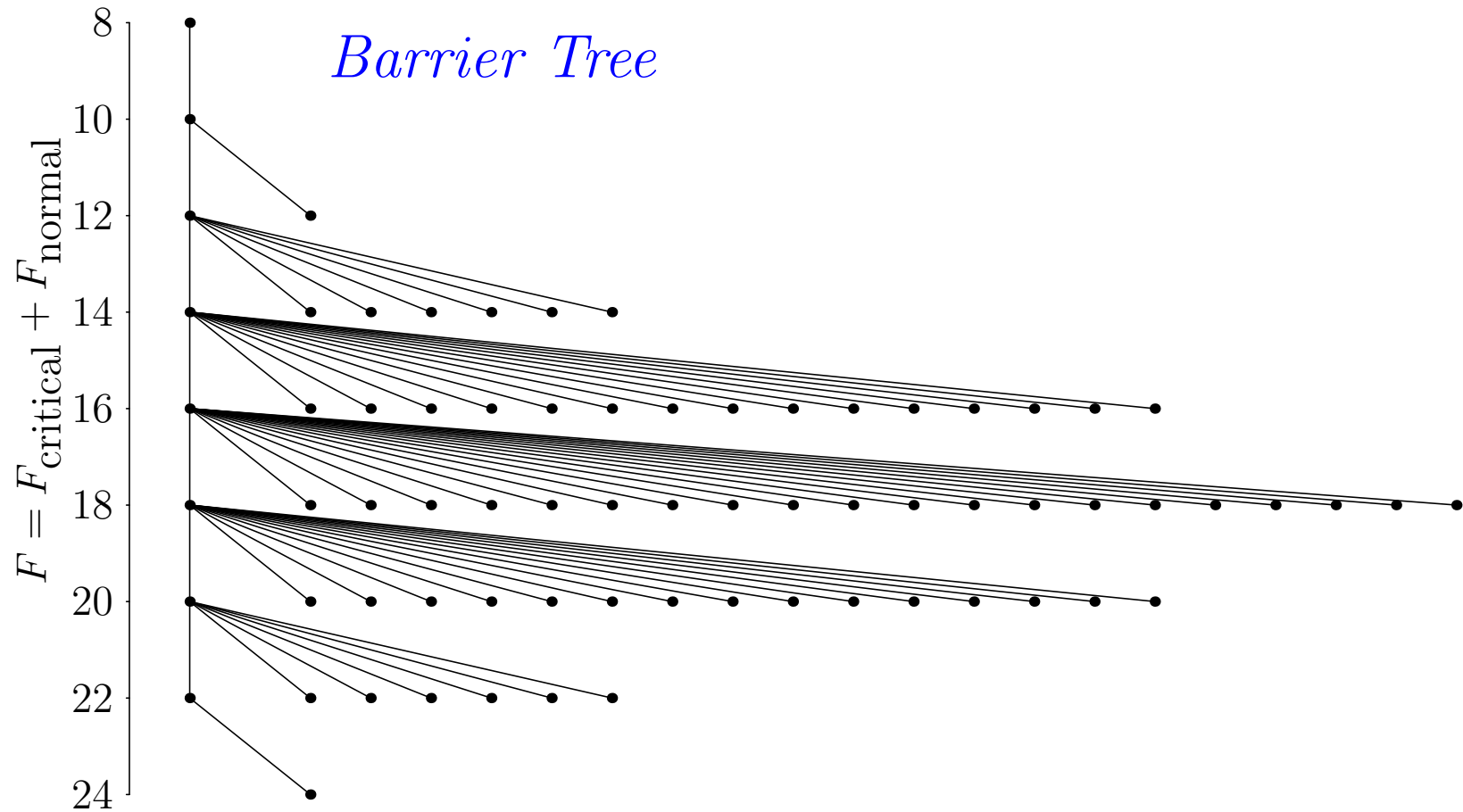


Fitness Landscape

Binary String

1	-1	1	1	1	-1	-1	1	-1	1	-1	1	-1	1	1	1	1	1	-1	1	-1	-1	-1	1
---	----	---	---	---	----	----	---	----	---	----	---	----	---	---	---	---	---	----	---	----	----	----	---

F
-2

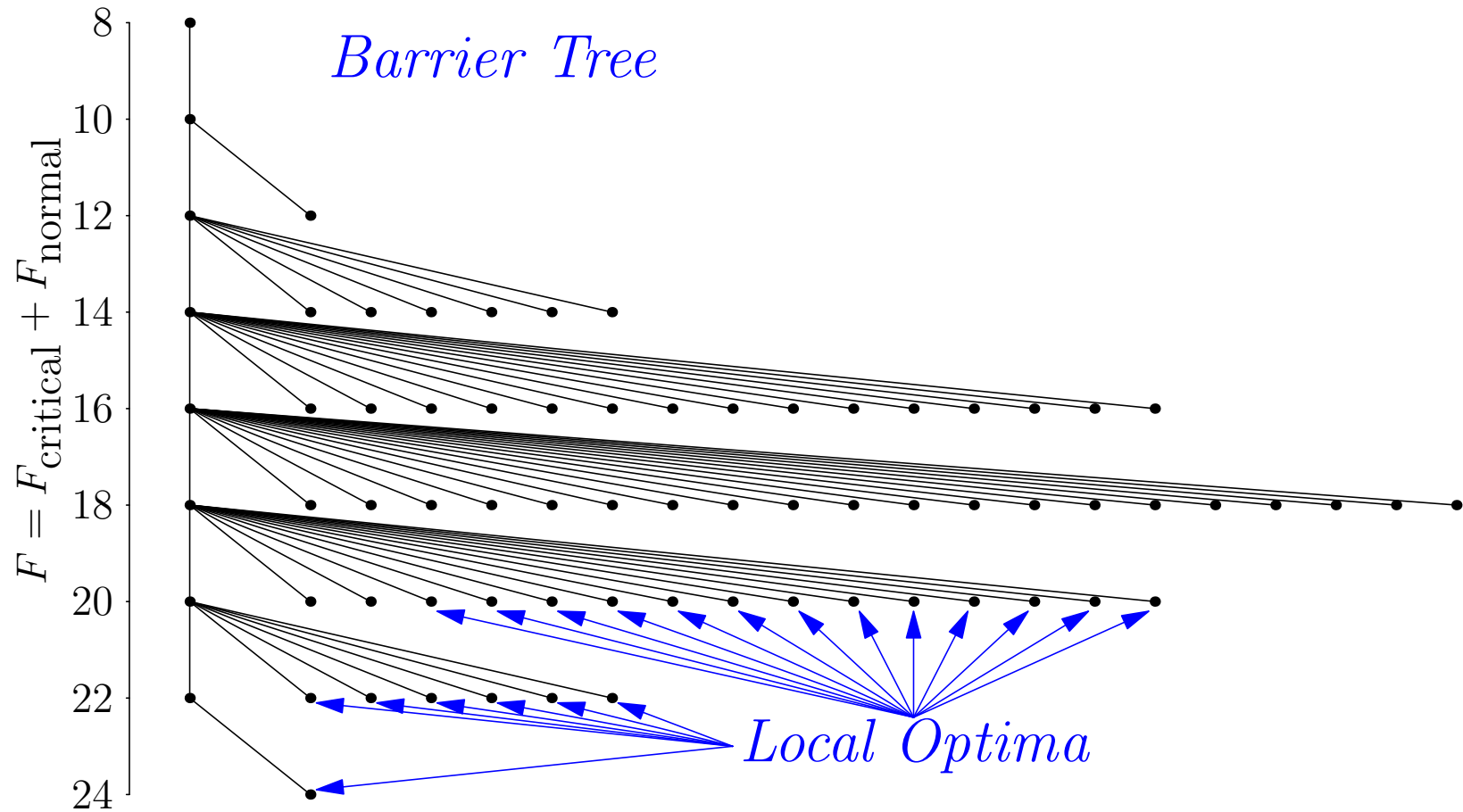


Fitness Landscape

Binary String

1	-1	1	1	1	-1	-1	1	-1	1	-1	1	-1	1	1	1	1	1	-1	1	-1	-1	-1	1
---	----	---	---	---	----	----	---	----	---	----	---	----	---	---	---	---	---	----	---	----	----	----	---

F
-2

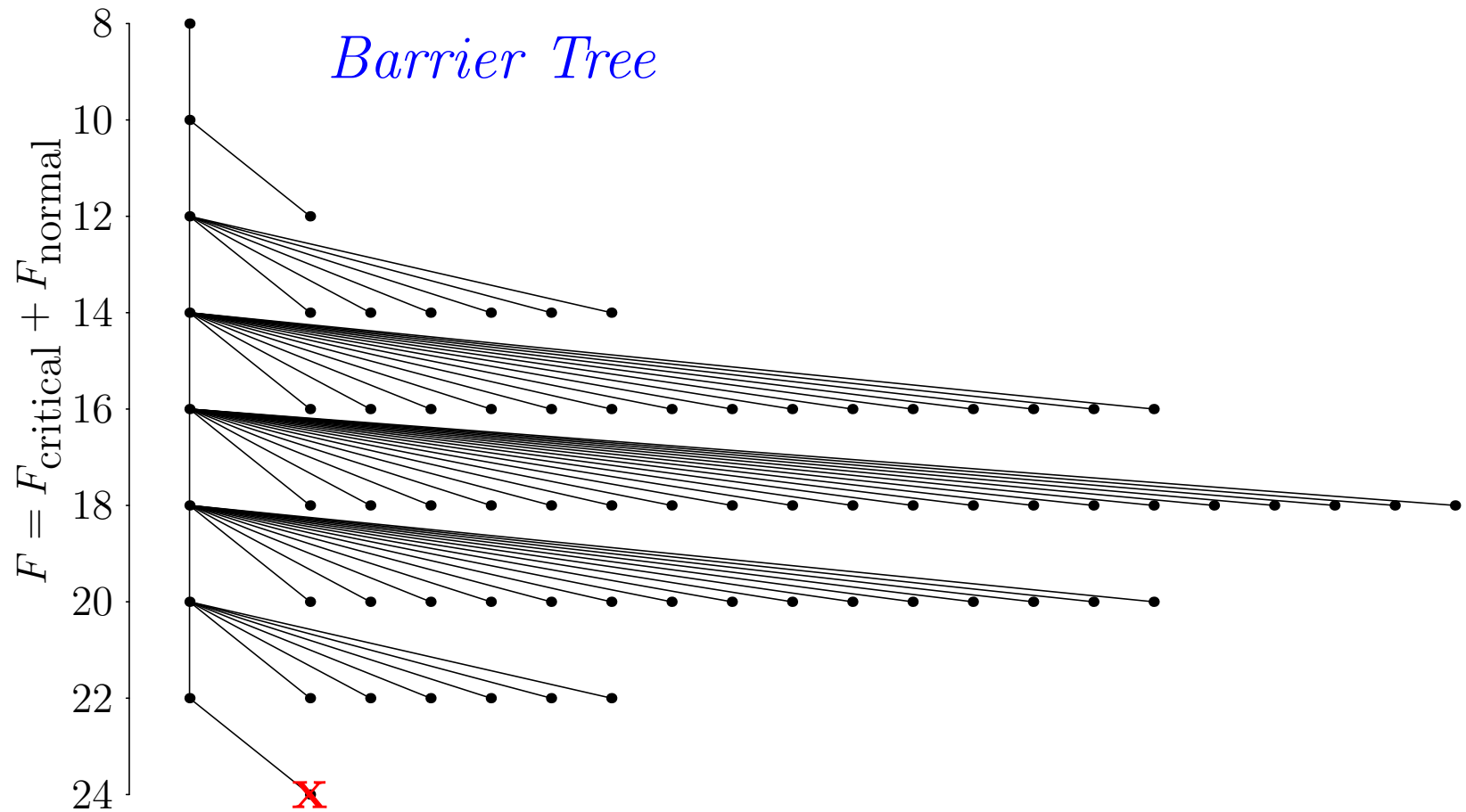


Fitness Landscape

Binary String

1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---

F
24

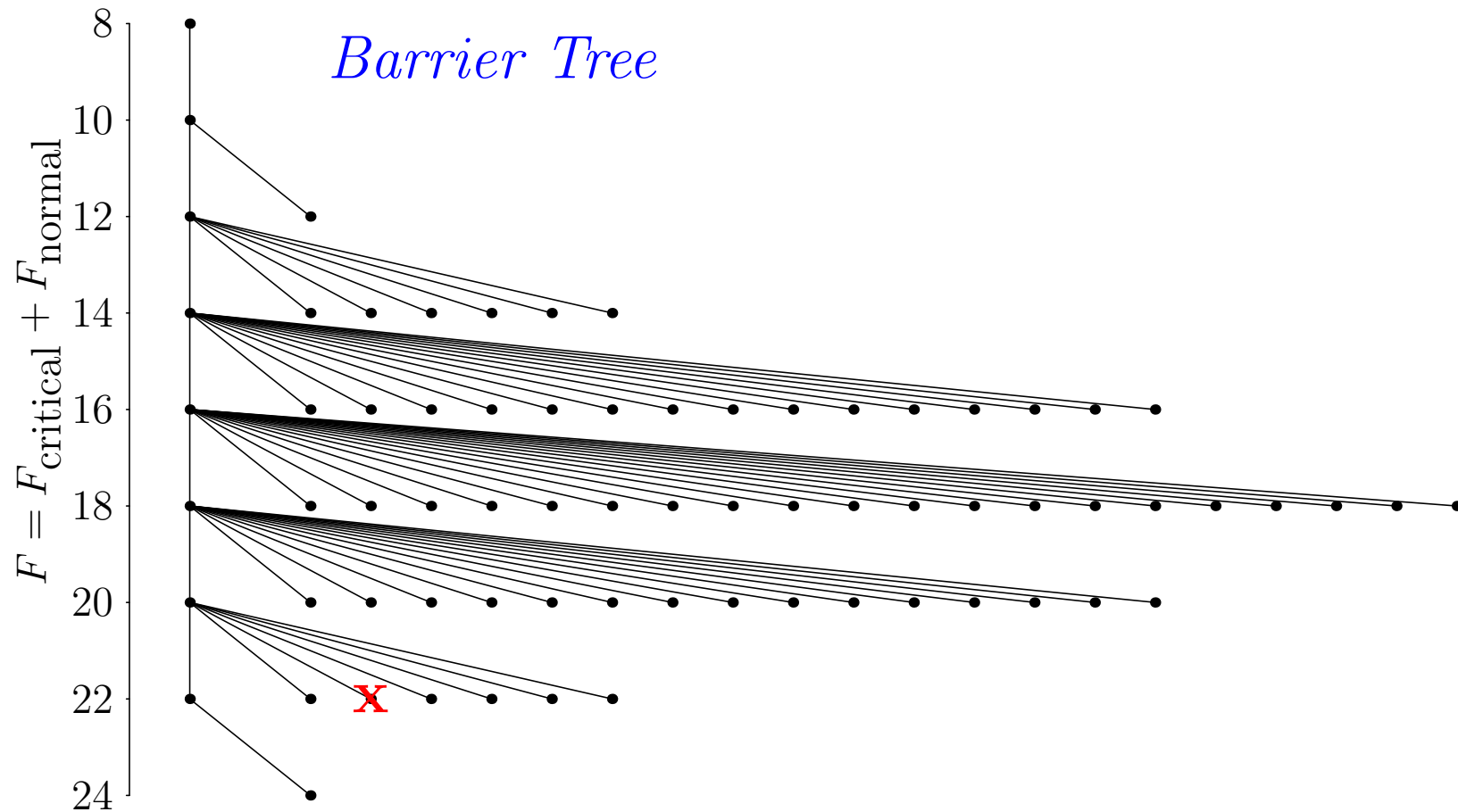


Fitness Landscape

Binary String

1	1	1	1	-1	-1	-1	-1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
---	---	---	---	----	----	----	----	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---

F
22

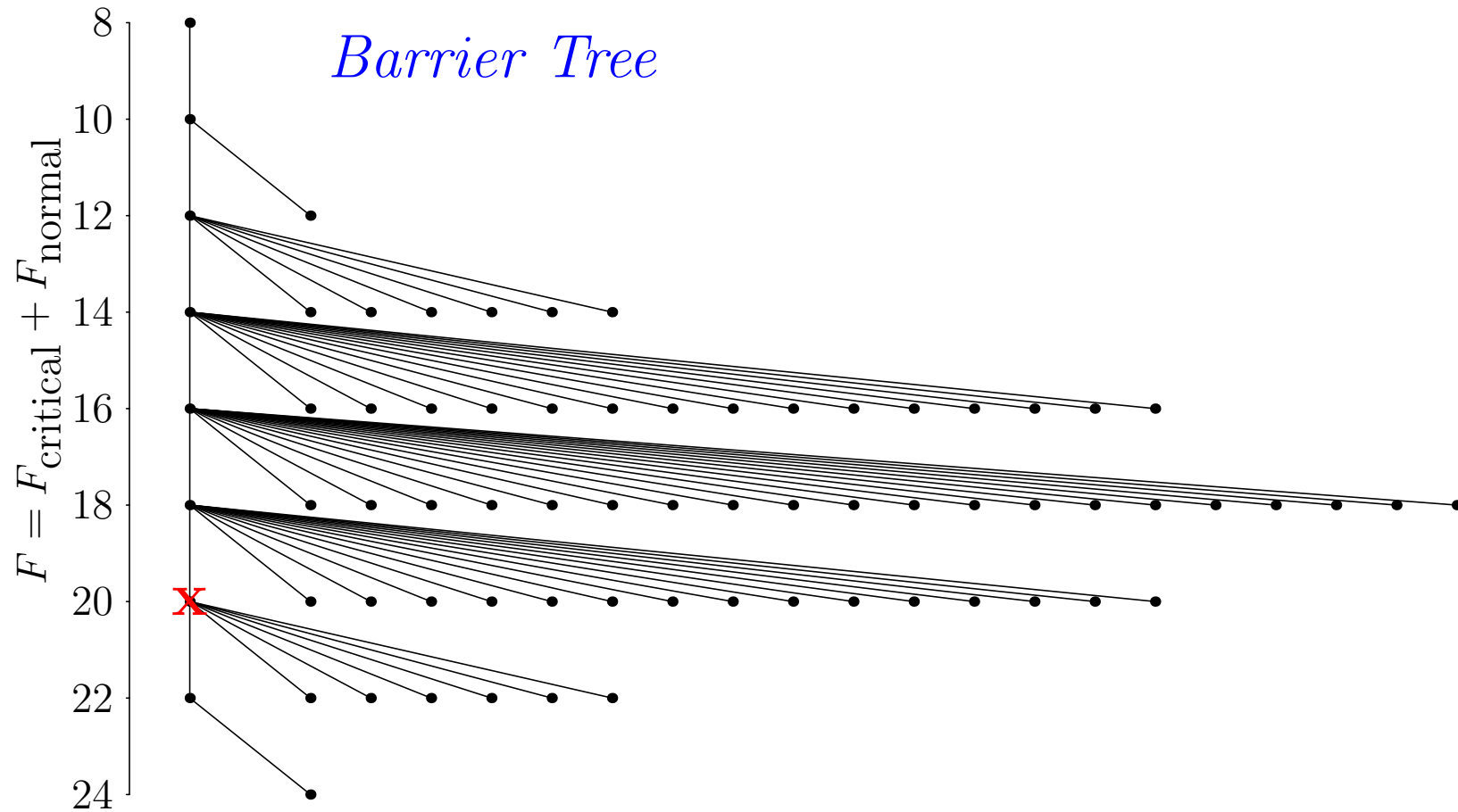


Fitness Landscape

Binary String

1	1	1	1	1	1	-1	-1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
---	---	---	---	---	---	----	----	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---

F
20

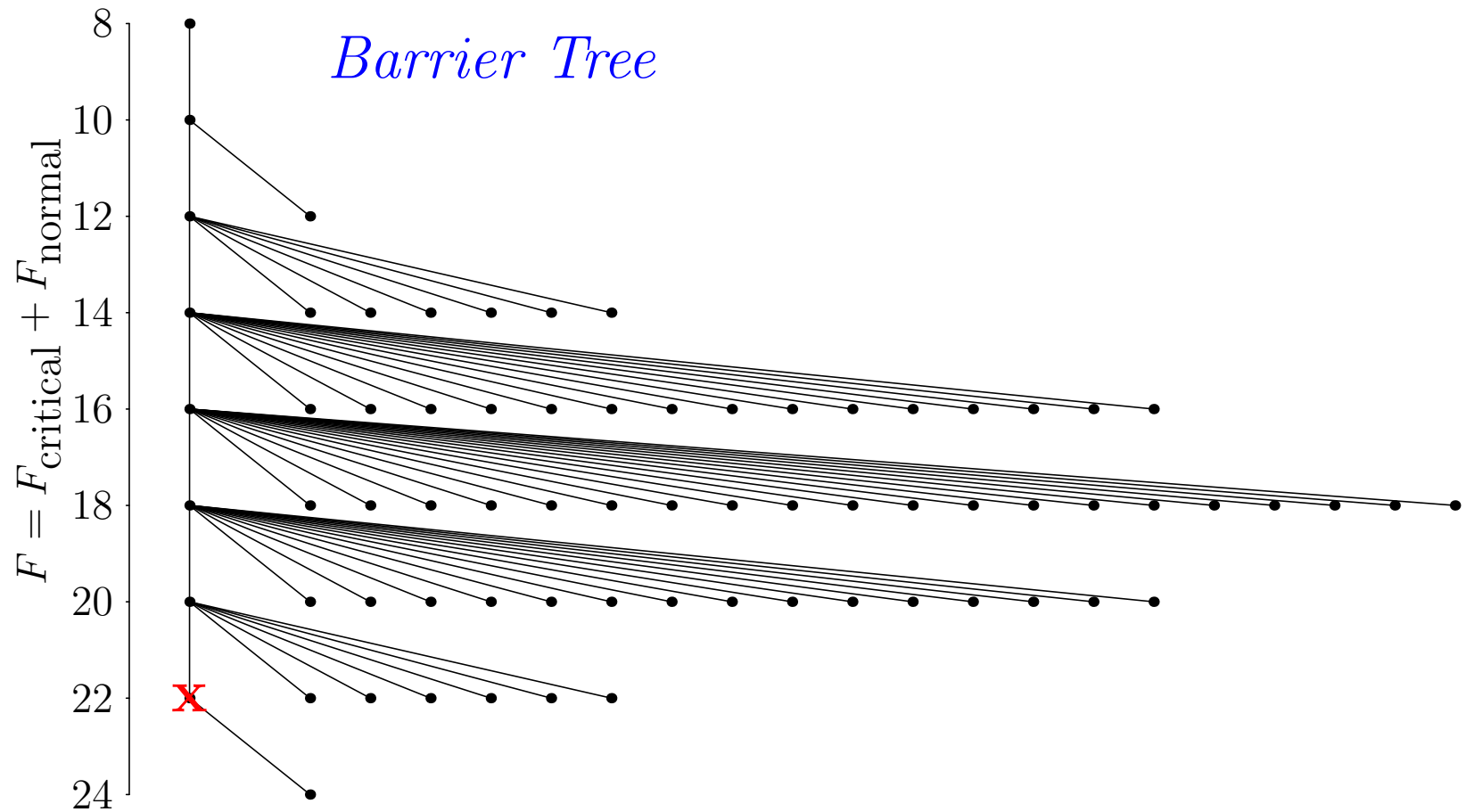


Fitness Landscape

Binary String

1	1	1	1	1	1	1	-1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
---	---	---	---	---	---	---	----	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---

F
22

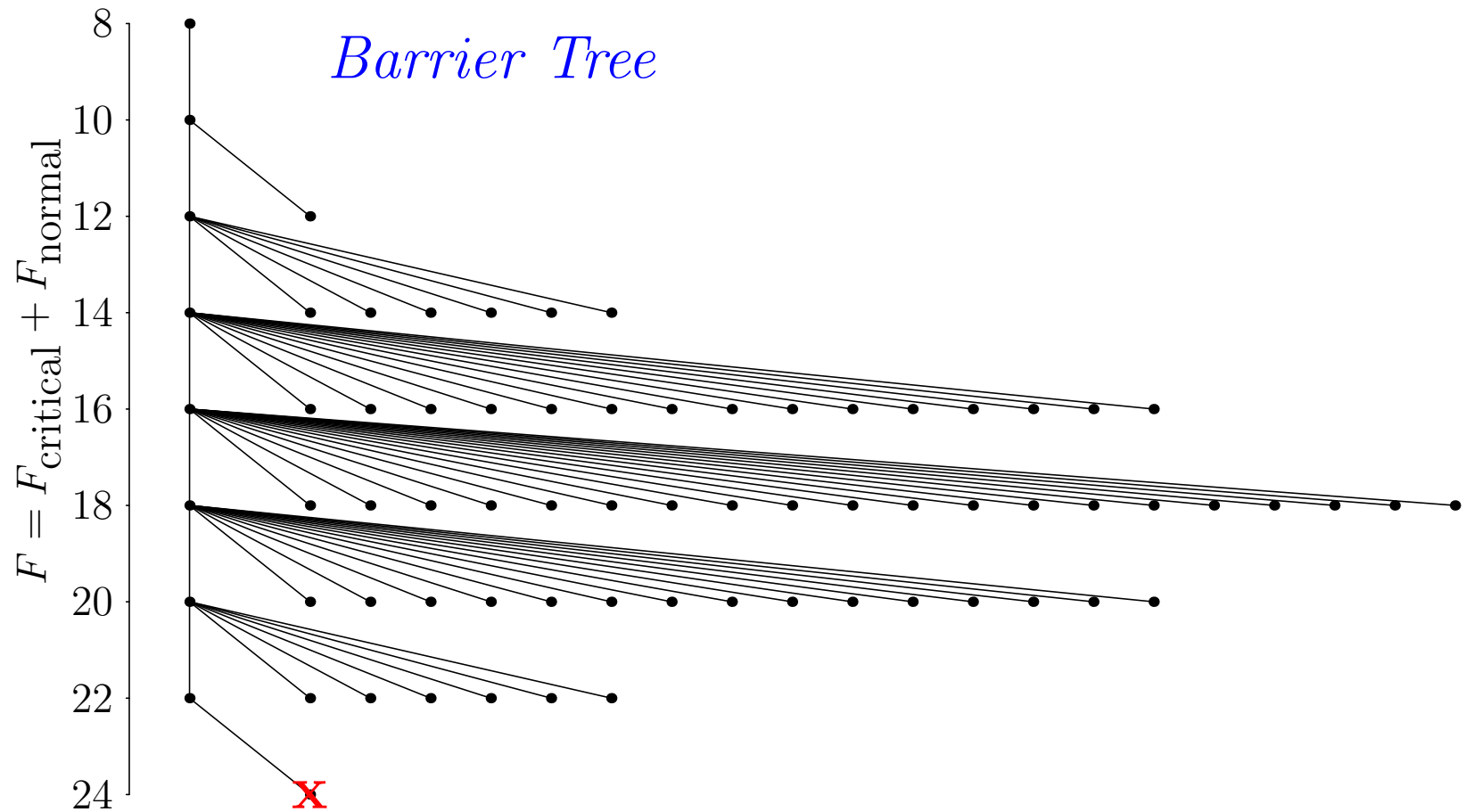


Fitness Landscape

Binary String

1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---

F
24



Simulation of GA

Initial Population

-1-1-1-1 1 1-1-1 1 1-1-1-1-1-1 1 1 1 1 1 1-1	0
-1-1 1 1-1-1-1-1-1 1-1-1 1-1-1-1 1-1-1 1 1 1 1	4
1 1-1-1 1-1-1 1-1-1-1-1-1-1-1-1 1-1 1-1 1 1 1-1	2
1-1-1 1 1 1-1-1 1 1 1-1 1-1-1-1 1-1-1 1-1 1-1	-2
1-1-1-1 1 1 1-1 1 1 1 1-1 1 1 1 1 1 1-1-1 1 1	2
1-1 1-1 1-1-1 1 1 1 1 1 1-1-1 1-1 1 1 1-1-1-1 1 1	0
-1-1-1 1 1-1 1 1 1-1 1 1-1 1 1-1 1 1-1 1-1-1 1 1	-2
1-1-1-1-1-1 1 1-1-1-1-1-1 1-1-1-1-1 1-1-1 1 1-1	-4
-1 1 1 1-1 1 1 1-1-1-1-1-1 1-1-1-1-1 1-1 1 1-1 1	-4
1-1-1-1-1-1 1 1 1-1-1-1-1 1 1 1-1-1-1-1-1-1 1	-8

Simulation of GA

Population after 1 hill-climbing step

-1	-1	-1	-1	1	1	-1	-1	1	1	-1	-1	-1	-1	-1	1	1	1	1	1	1	1	2	
-1	-1	1	1	-1	-1	-1	-1	-1	1	-1	-1	1	-1	1	-1	-1	1	-1	-1	1	1	1	4
1	1	-1	-1	1	-1	-1	1	-1	-1	1	-1	-1	-1	-1	1	-1	1	-1	1	1	1	-1	2
1	-1	-1	1	1	1	1	-1	-1	1	1	1	-1	1	-1	-1	-1	1	-1	-1	1	-1	-1	-2
1	-1	-1	-1	1	1	1	-1	1	1	1	1	-1	1	1	1	1	1	1	1	-1	-1	1	2
1	-1	1	-1	1	-1	-1	1	1	1	1	-1	-1	1	-1	1	1	1	1	-1	-1	-1	1	0
-1	-1	-1	1	1	1	1	1	1	1	1	1	-1	-1	1	1	1	-1	1	-1	1	-1	1	0
1	-1	-1	-1	-1	-1	-1	1	1	-1	-1	-1	-1	-1	-1	-1	-1	1	-1	-1	1	1	-1	-4
-1	1	1	1	-1	1	1	1	1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	1	1	-1	1	-2
1	-1	-1	-1	-1	-1	-1	1	1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-4

Simulation of GA

Population after 50 hill-climbing steps

-1-1-1-1111111111-1-1-1-1111111111	20
1-111-1-1-1-1-1-1-1-11111-1-1-1-11111	16
111111-11-1-1-1-1-1-1-111111111111	18
1111111111-1-1-1-1-1-1-1-1-111111	20
11111111111111111111-1-1-1-1	22
1111111111-1-1-1-111111111111	22
-1-1-1-11111111111111-1-1-1-1-1-1-1	18
11111-111-1-1-1-1-1-1-1-1-1-1-1-1-1-1	14
-1-1-1-11111-1-1-1-1-1-1-1-1-1-11111	16
-1-1-1-11111-1-1-1-11111-1-1-1-1-1-1	16

Simulation of GA

Population after selection

-1	-1	-1	-1	1	1	1	1	1	1	1	1	-1	-1	-1	-1	1	1	1	1	1	1	1	20	
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	-1	-1	-1	-1	22
1	1	1	1	1	1	-1	1	-1	-1	-1	-1	-1	-1	-1	1	1	1	1	1	1	1	1	1	18
1	1	1	1	1	1	1	1	1	1	1	1	-1	-1	-1	-1	-1	-1	-1	1	1	1	1	1	20
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	-1	-1	-1	-1	22
1	1	1	1	1	1	1	1	1	1	1	1	-1	-1	-1	-1	1	1	1	1	1	1	1	1	22
-1	-1	-1	-1	1	1	1	1	1	1	1	1	1	1	1	1	-1	-1	-1	-1	-1	-1	-1	-1	18
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	-1	-1	-1	-1	22
1	1	1	1	1	1	1	1	1	1	1	1	-1	-1	-1	-1	1	1	1	1	1	1	1	1	22
1	1	1	1	1	1	1	1	1	1	1	1	-1	-1	-1	-1	1	1	1	1	1	1	1	1	22

Simulation of GA

Population after uniform crossover

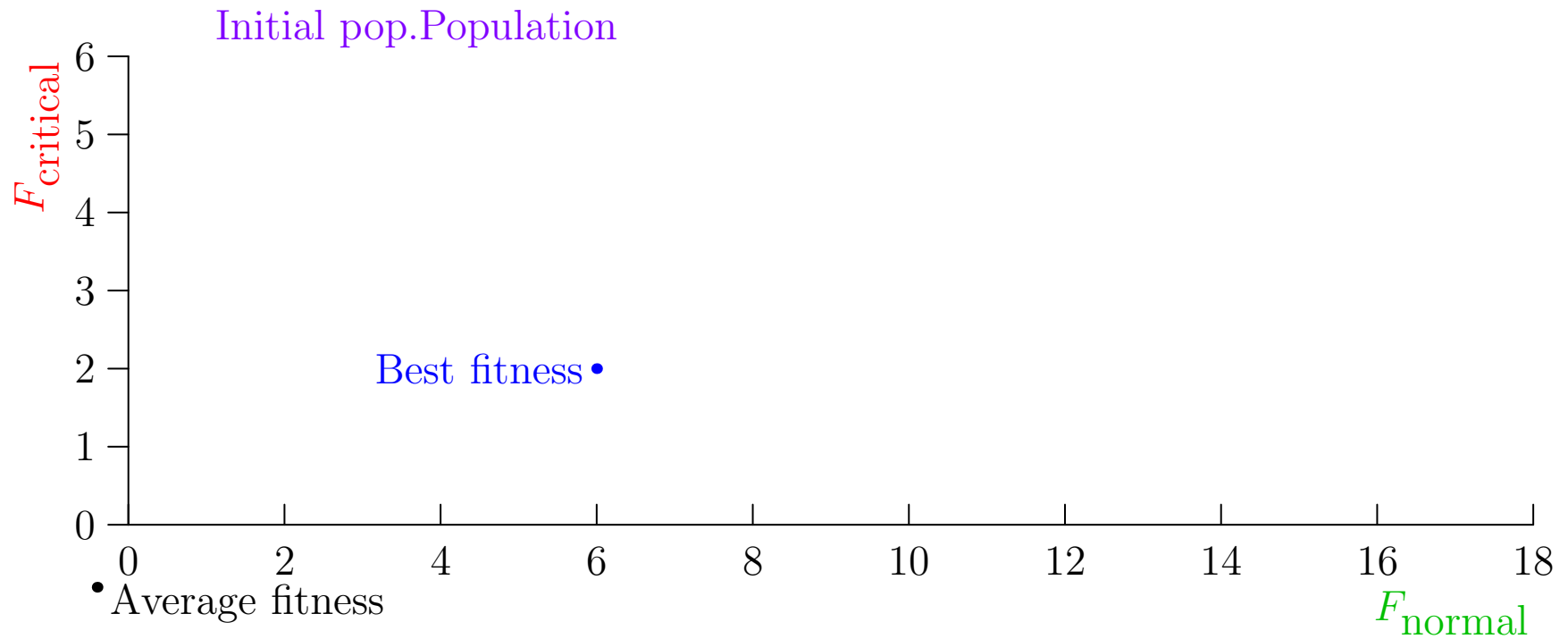
-1	1	1	-1	1	1	1	1	1	1	1	1	1	-1	-1	1	1	1	1	-1	1	1	-1	8	
1	-1	-1	1	1	1	1	1	1	1	1	1	-1	1	1	-1	1	1	1	1	1	-1	-1	1	10
1	1	1	1	1	1	1	1	-1	1	1	1	-1	-1	1	1	1	1	1	-1	1	1	1	2	
1	1	1	1	1	1	1	1	1	1	1	1	-1	-1	-1	-1	1	-1	-1	-1	1	1	1	1	16
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	-1	1	1	1	1	1	-1	1	-1	18
1	1	1	1	1	1	1	1	1	1	1	1	-1	-1	-1	-1	-1	1	1	1	1	1	1	1	14
1	1	-1	1	1	1	1	1	1	1	1	1	-1	1	-1	1	1	-1	-1	1	-1	-1	1	1	6
1	1	1	1	1	1	-1	1	1	-1	-1	-1	1	1	-1	-1	1	1	1	1	1	-1	-1	-1	6
1	1	1	1	1	1	1	1	1	1	1	1	-1	-1	-1	1	1	1	1	-1	1	-1	1	14	
-1	-1	1	-1	1	1	1	1	1	1	1	1	1	-1	1	-1	-1	-1	1	1	-1	1	1	-1	6

Simulation of GA

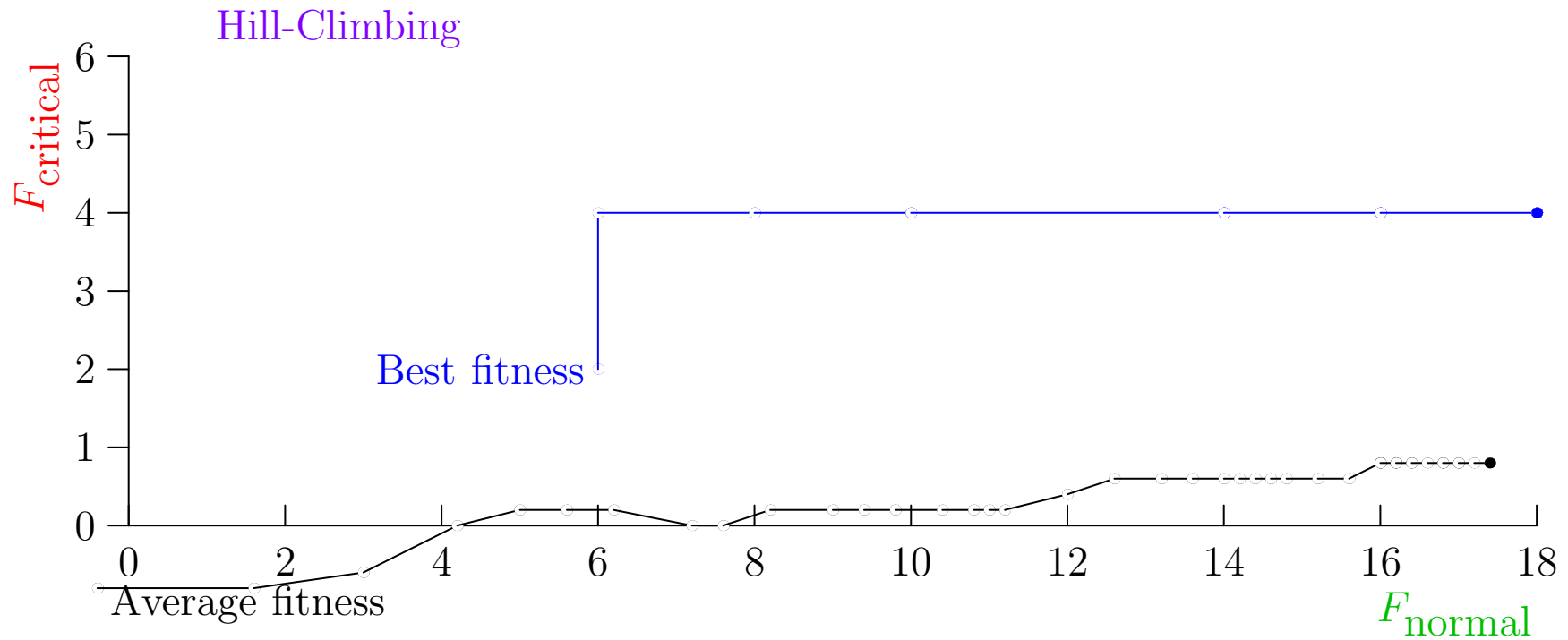
Population after 50 hill-climbing steps

1	1	1	-1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	-1	-1	-1	-1	20
1	1	1	1	1	1	1	1	1	1	1	1	-1	-1	-1	-1	1	1	1	1	1	1	1	22
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	-1	-1	-1	-1	22
1	1	1	1	1	1	1	1	1	1	1	1	-1	-1	-1	-1	1	1	1	1	1	1	1	22
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	24
1	1	1	1	1	1	1	1	1	1	1	1	-1	-1	-1	-1	1	1	1	1	1	1	1	22
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	24
1	1	1	1	1	1	1	1	1	1	1	1	1	-1	1	1	1	1	1	1	1	1	1	22
1	1	1	1	1	1	1	1	1	1	1	1	-1	-1	-1	-1	1	1	1	1	1	1	1	22
-1	-1	1	-1	1	1	1	1	1	1	1	1	1	-1	1	1	1	1	1	1	1	1	1	18

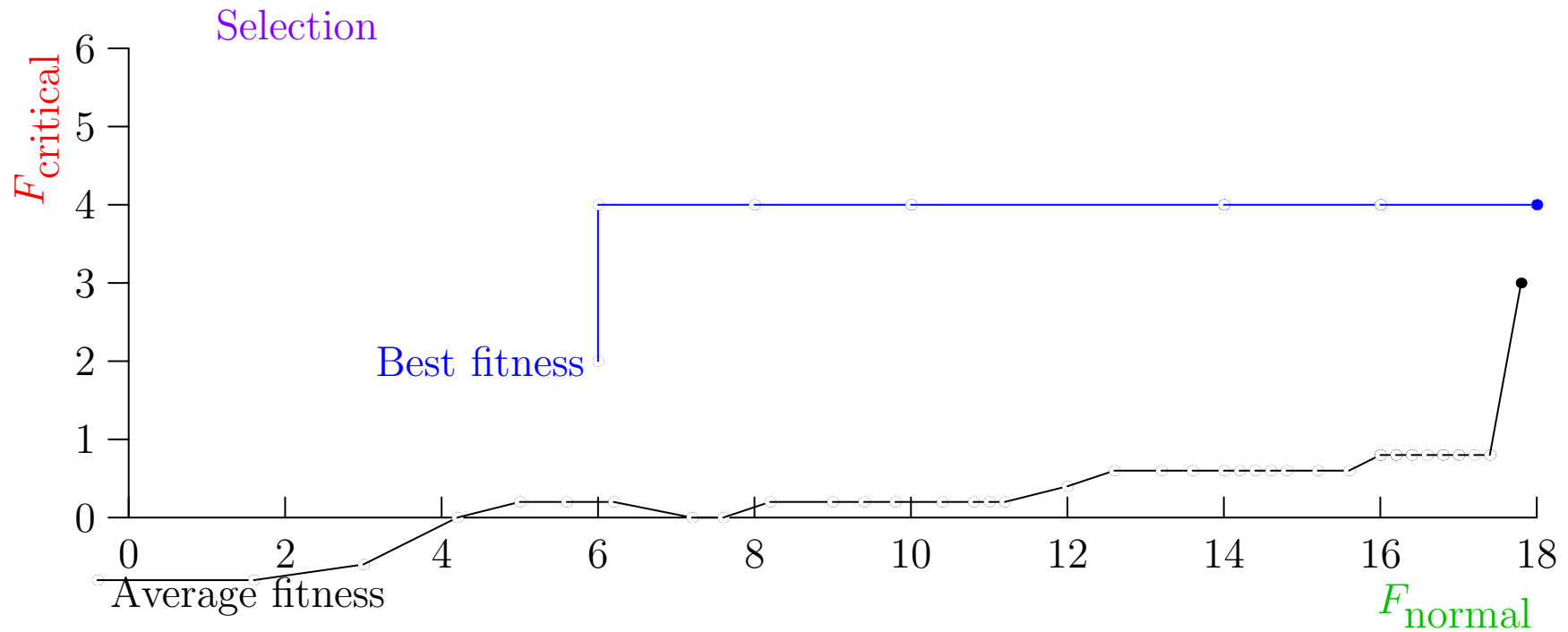
Evolution of Fitness



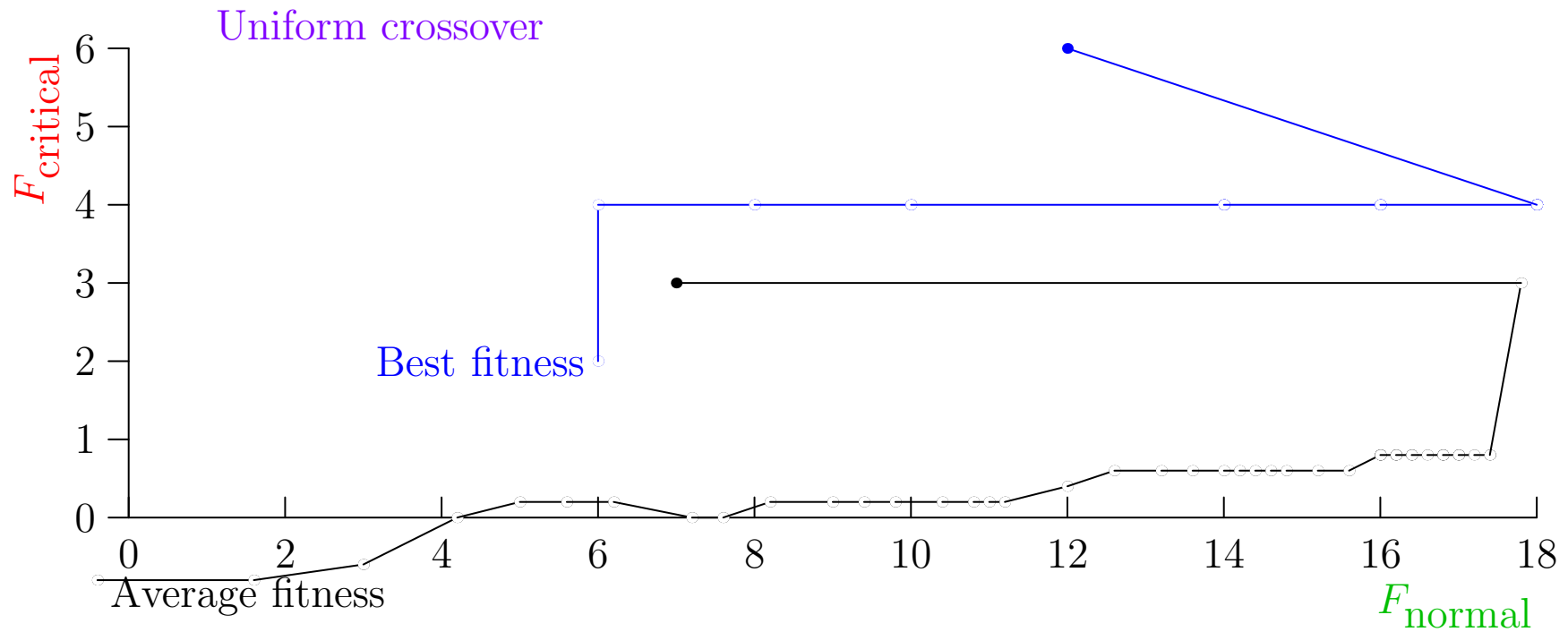
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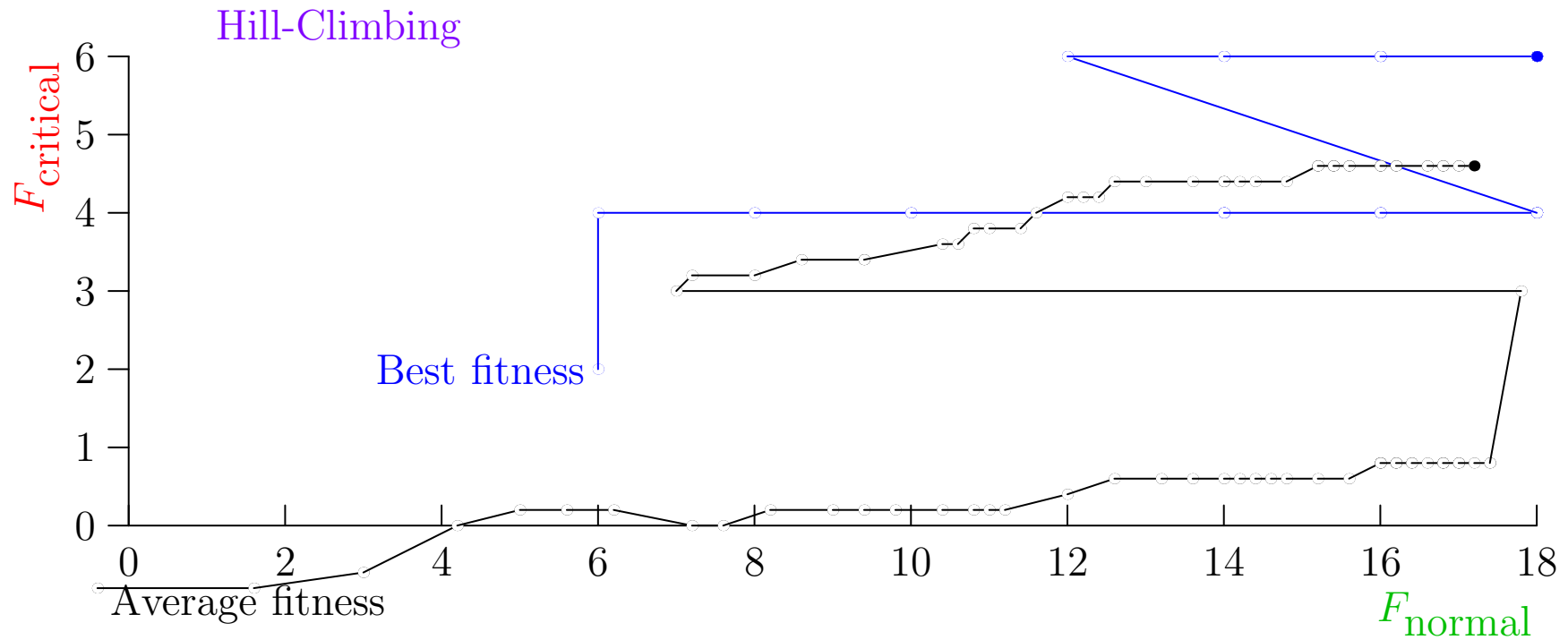
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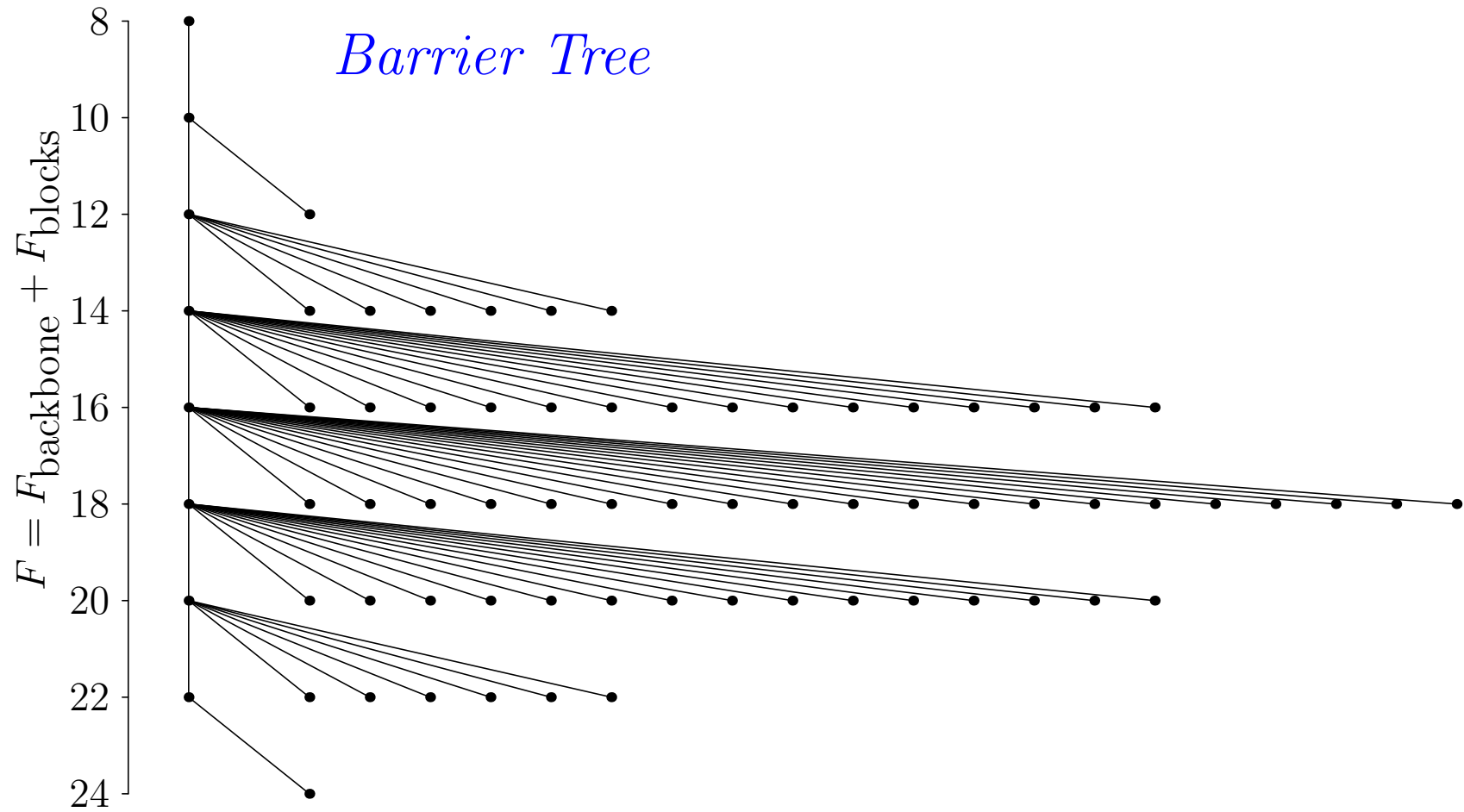


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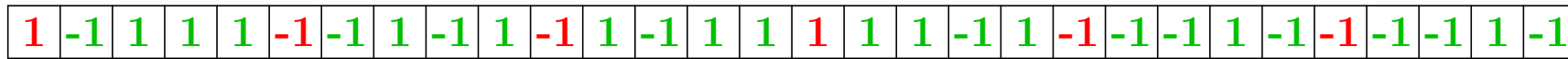
Making the Problem Harder

Binary String

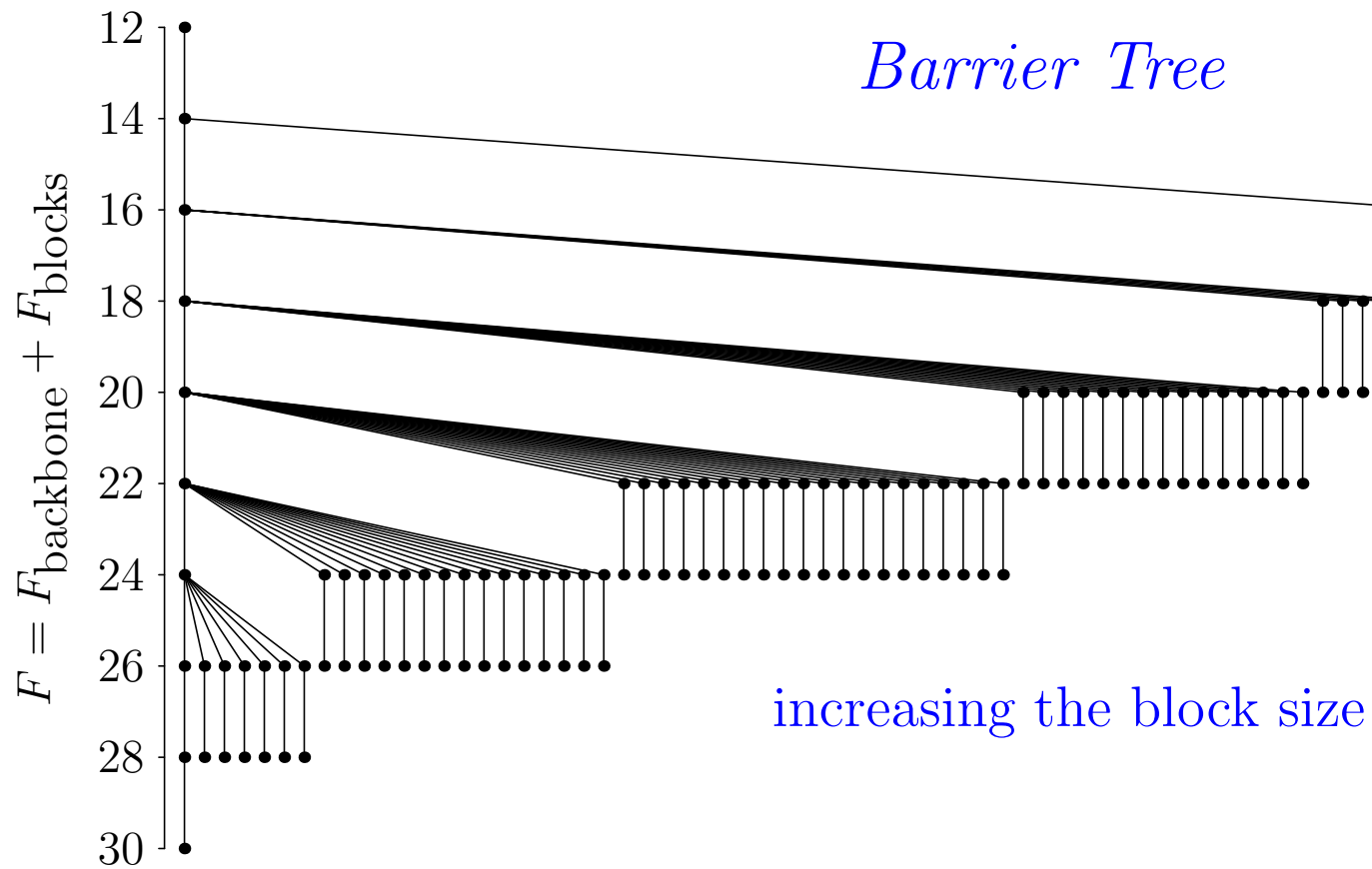


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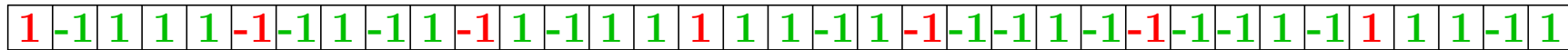


F
4



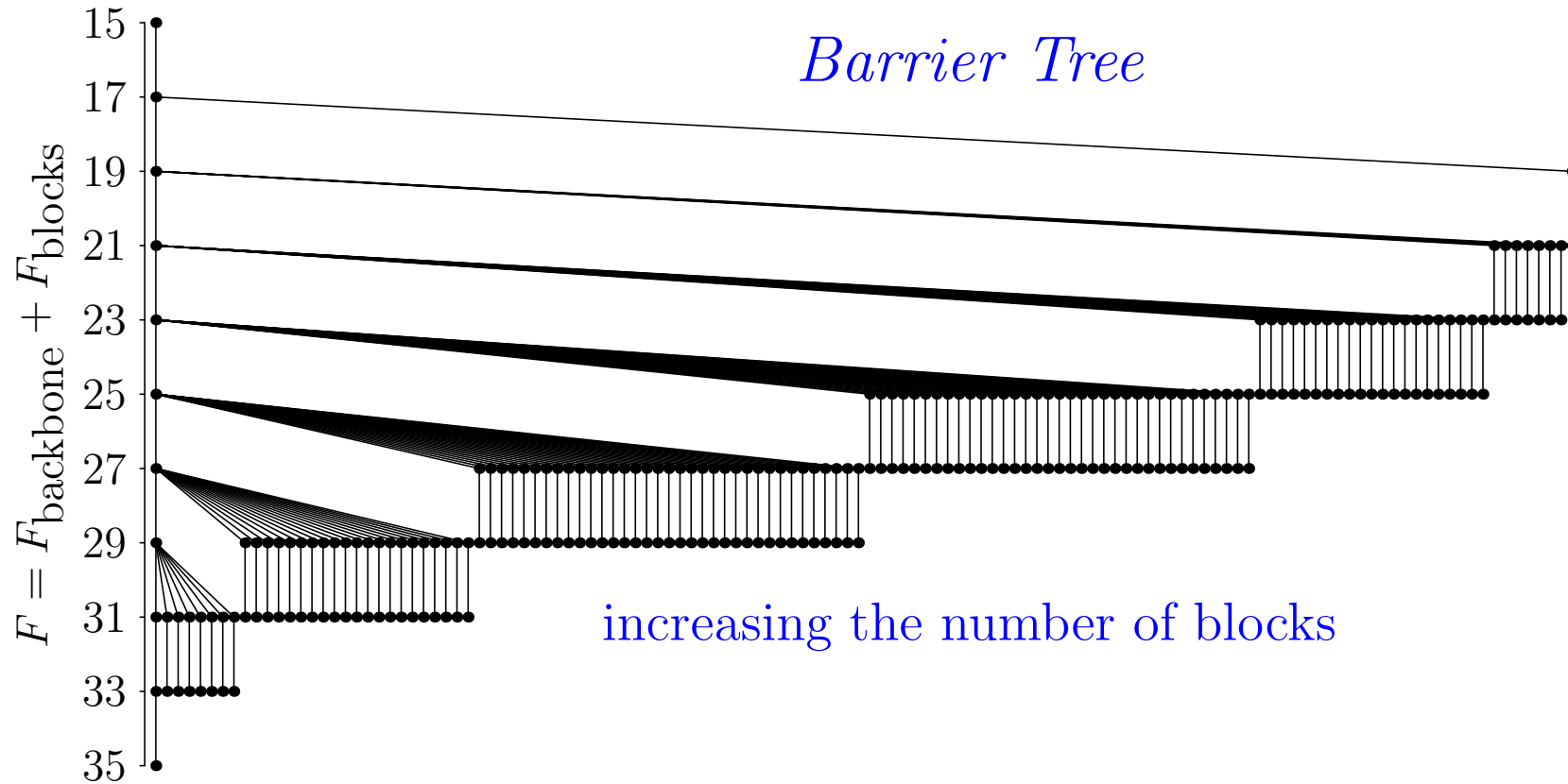
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F
7

Barrier Tree



Provably Efficient?

- A challenge for algorithm complexity people

Can you set this up so that a hybrid GA is provably polynomial while a hill-climber is exponential?

- Hybrid GA appears to be equivalent to solving ones-max using uniform crossover
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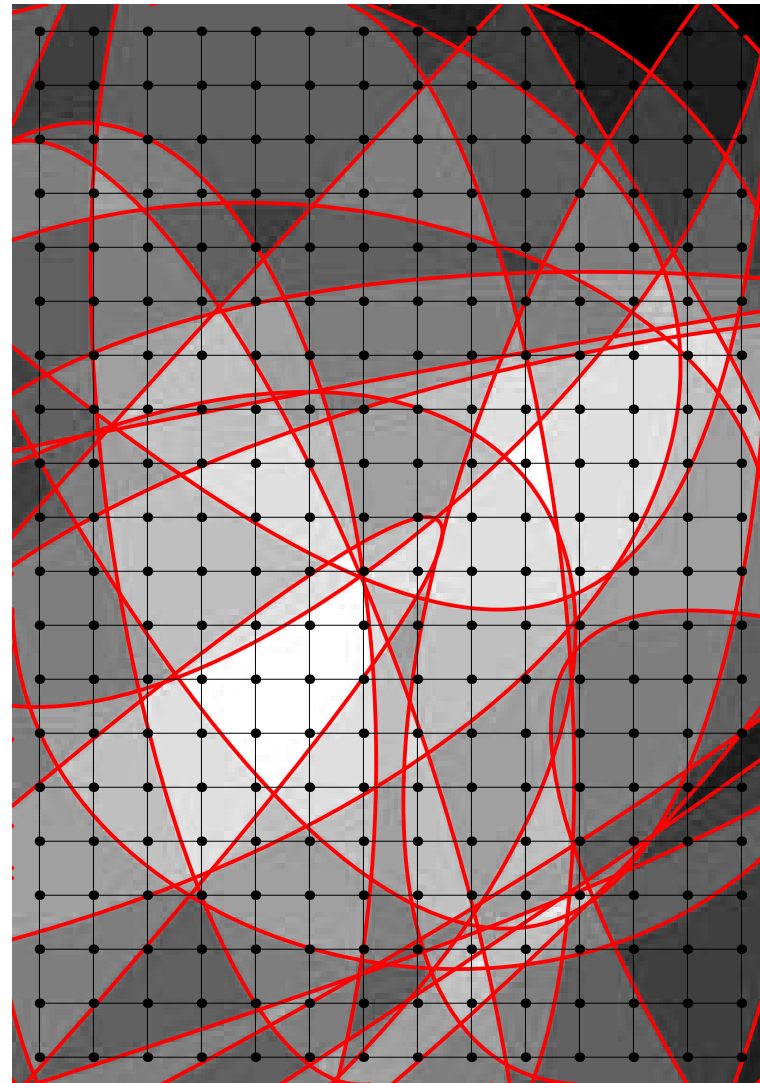
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Outline

1. Critical Variable Problems
2. Solving Critical Variable Problems
3. A Toy Example
4. **Real Optimisation Problems**
5. Max-Sat



Common Observation

- A very common observation is that, for many hard problems, it can take many hours to find a good solution
- If you perturb the solution (e.g. by changing 10% of the variables) you get to a solution with a very poor fitness value
- But, if you then run a hill-climber you return to the same quality of solution in a fraction of a second even though initially it took hours to reach the solution
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- Recently the idea of a backdoor has been put forward
- These exactly match on to the definition of critical variables
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- They have been studied (empirically) in the context of very small SAT problems
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- How can this be?

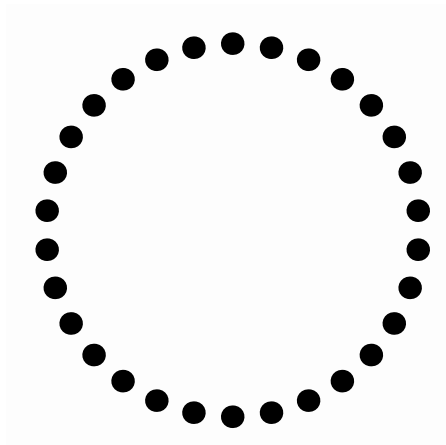
Easy NP-Hard Problems

- Not all instances of NP-hard problems are difficult
- What is the shortest tour of this TSP problem?

- In fact, for some problems (e.g. subset-sum) almost all instances seem to be easy
- Where are the hard problems?

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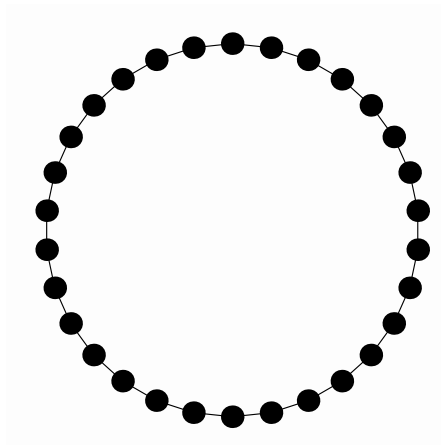
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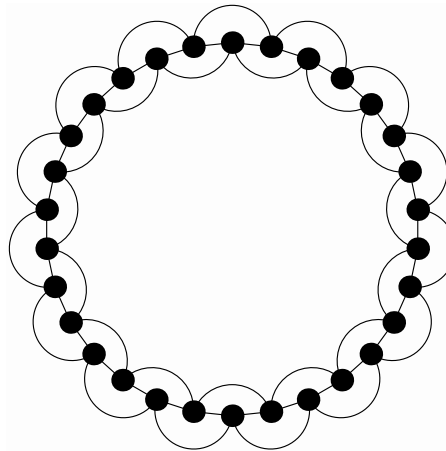
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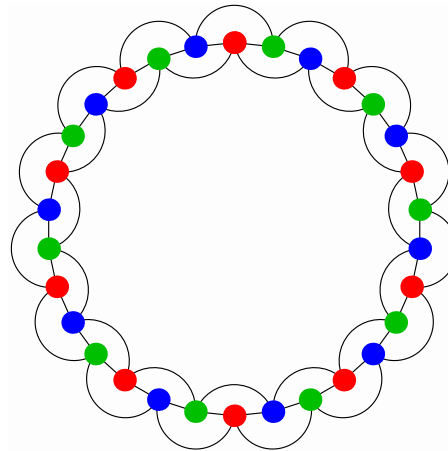
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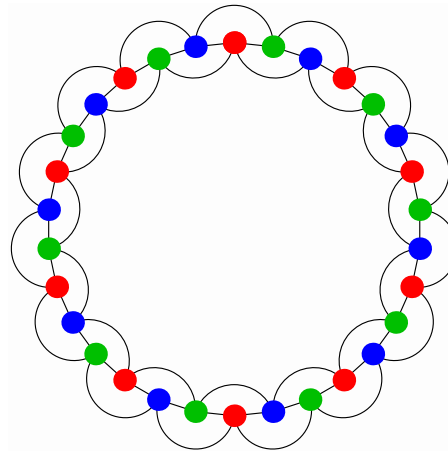
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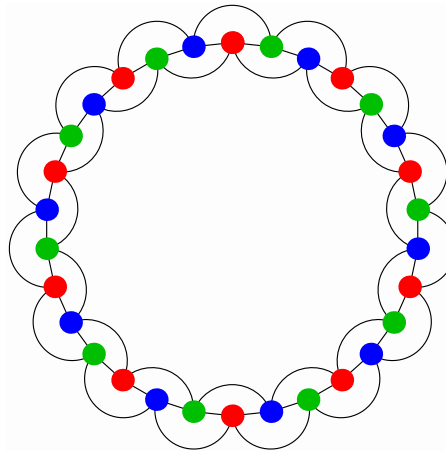
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Phase Transitions

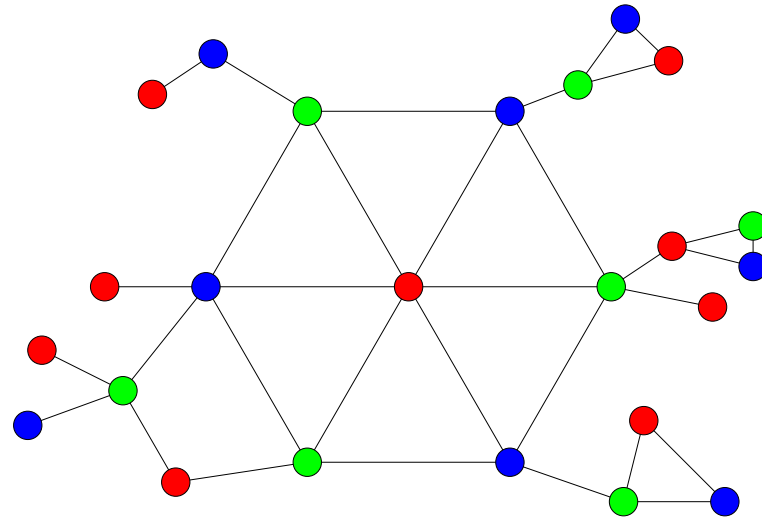
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Example of Phase Transitions

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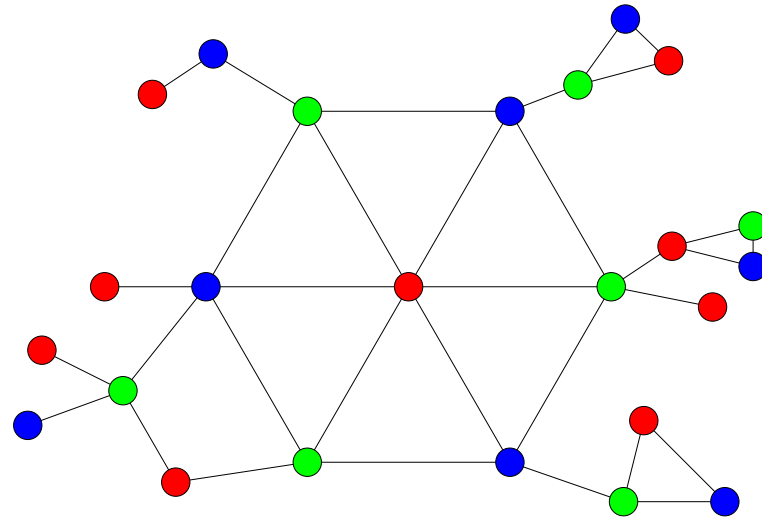


- In SAT (finding an assignment of Boolean values that makes a formula written in CNF true), instances become hard when the ratio of clauses to variables reaches a critical value

$$(X_1 \vee \neg X_2 \vee X_3) \wedge (\neg X_1 \vee X_3 \vee X_4) \wedge (\neg X_2 \vee \neg X_3 \vee \neg X_4)$$

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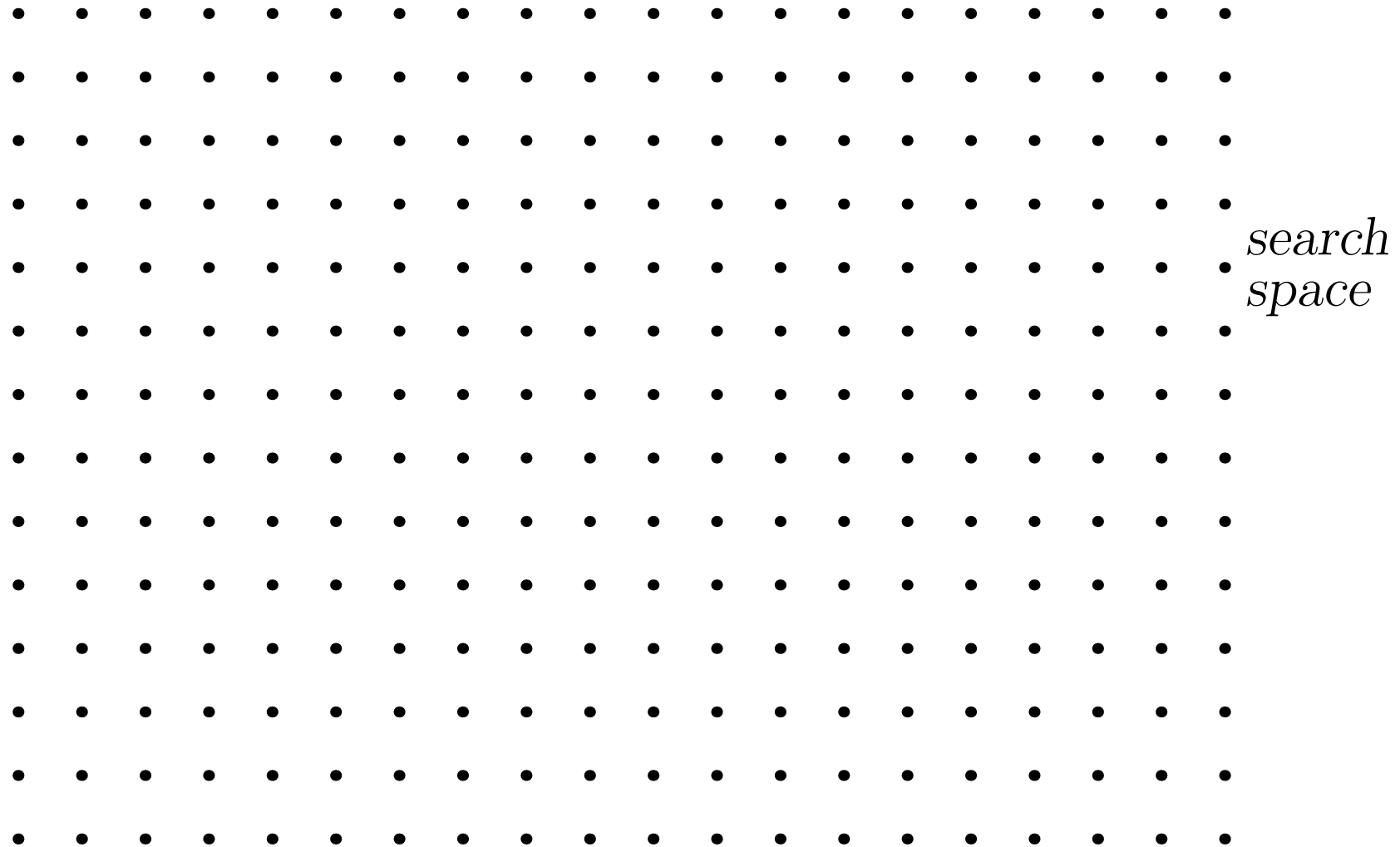
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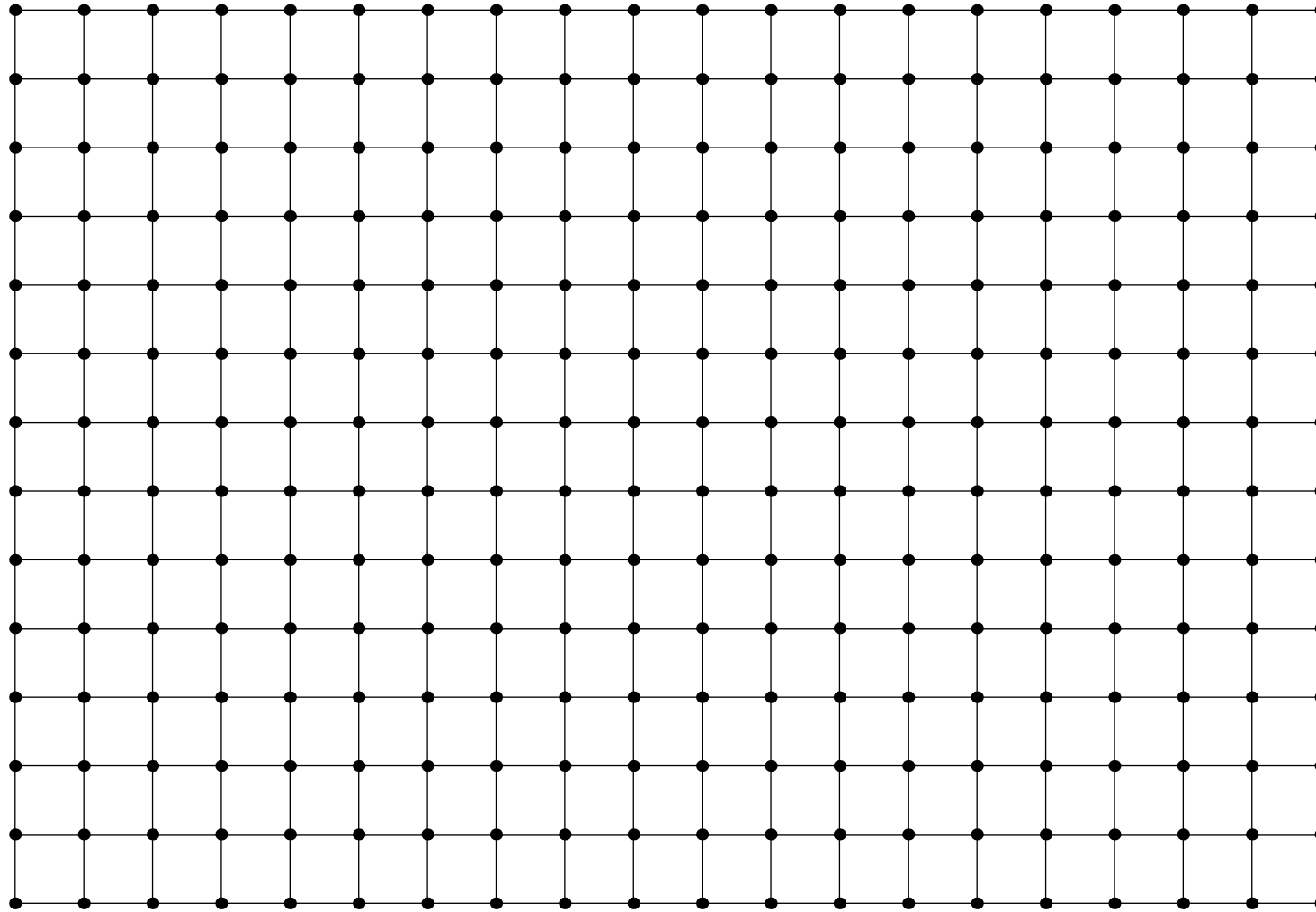
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Schematic of Phase Transition

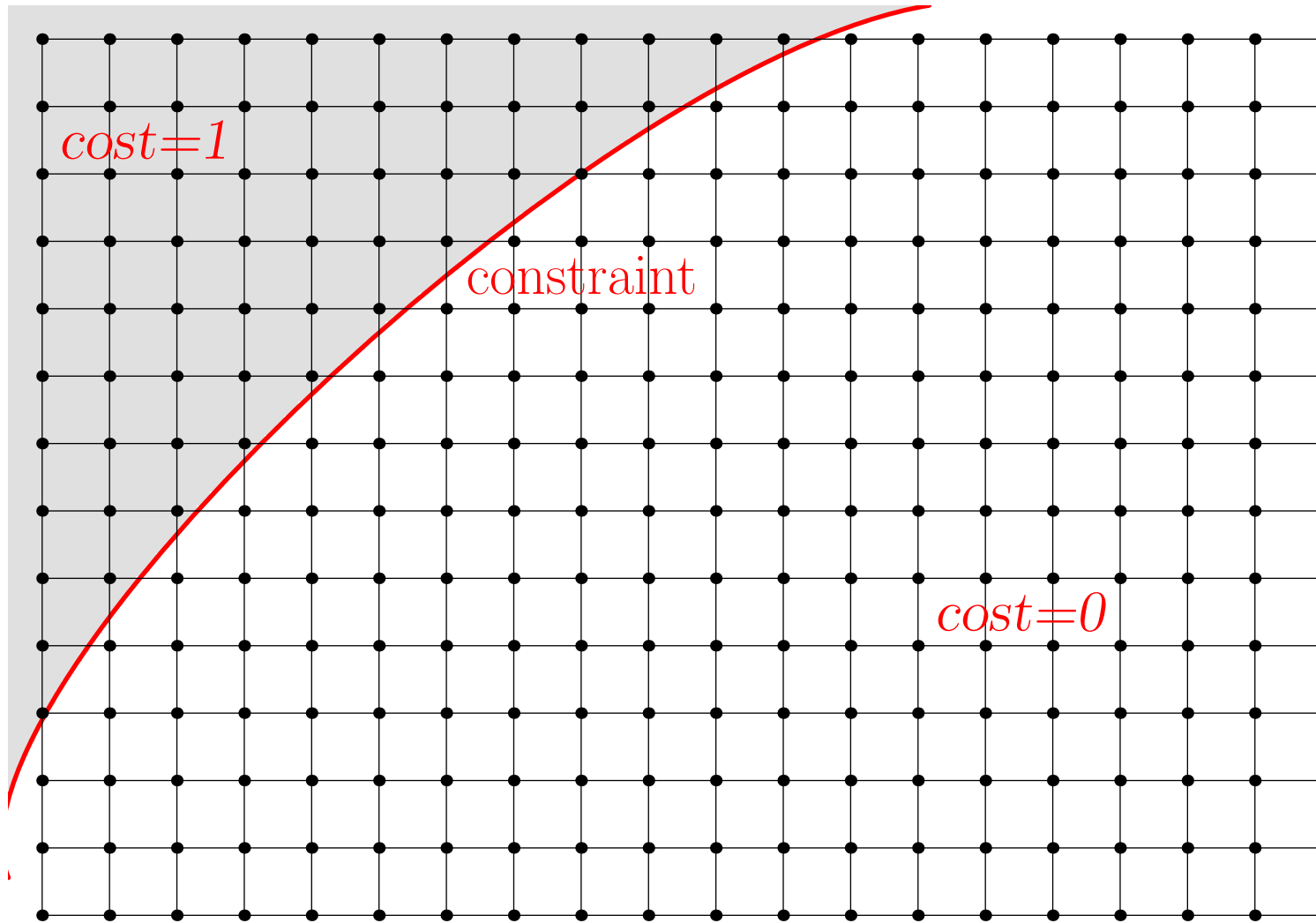


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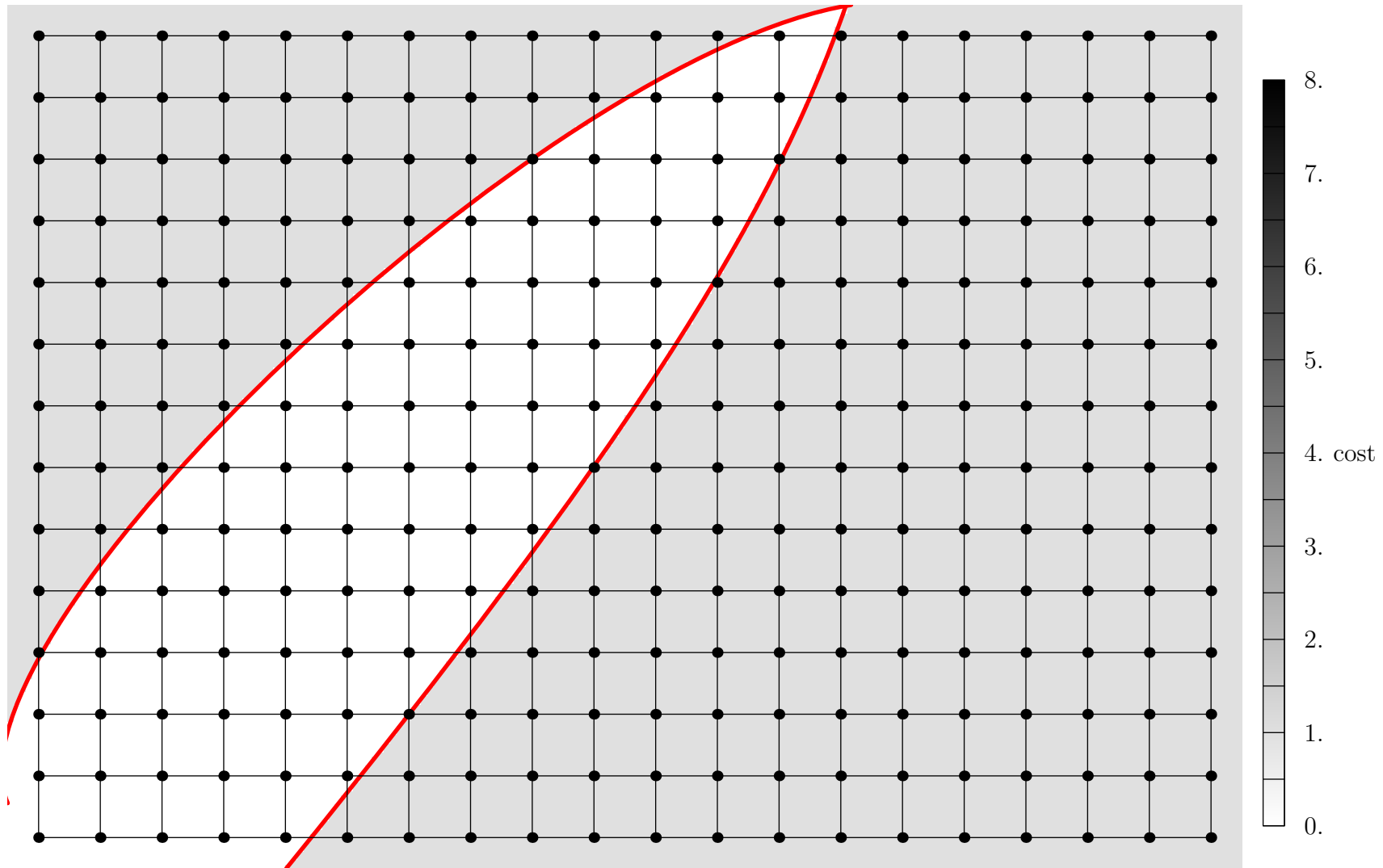


*adjacency
graph*

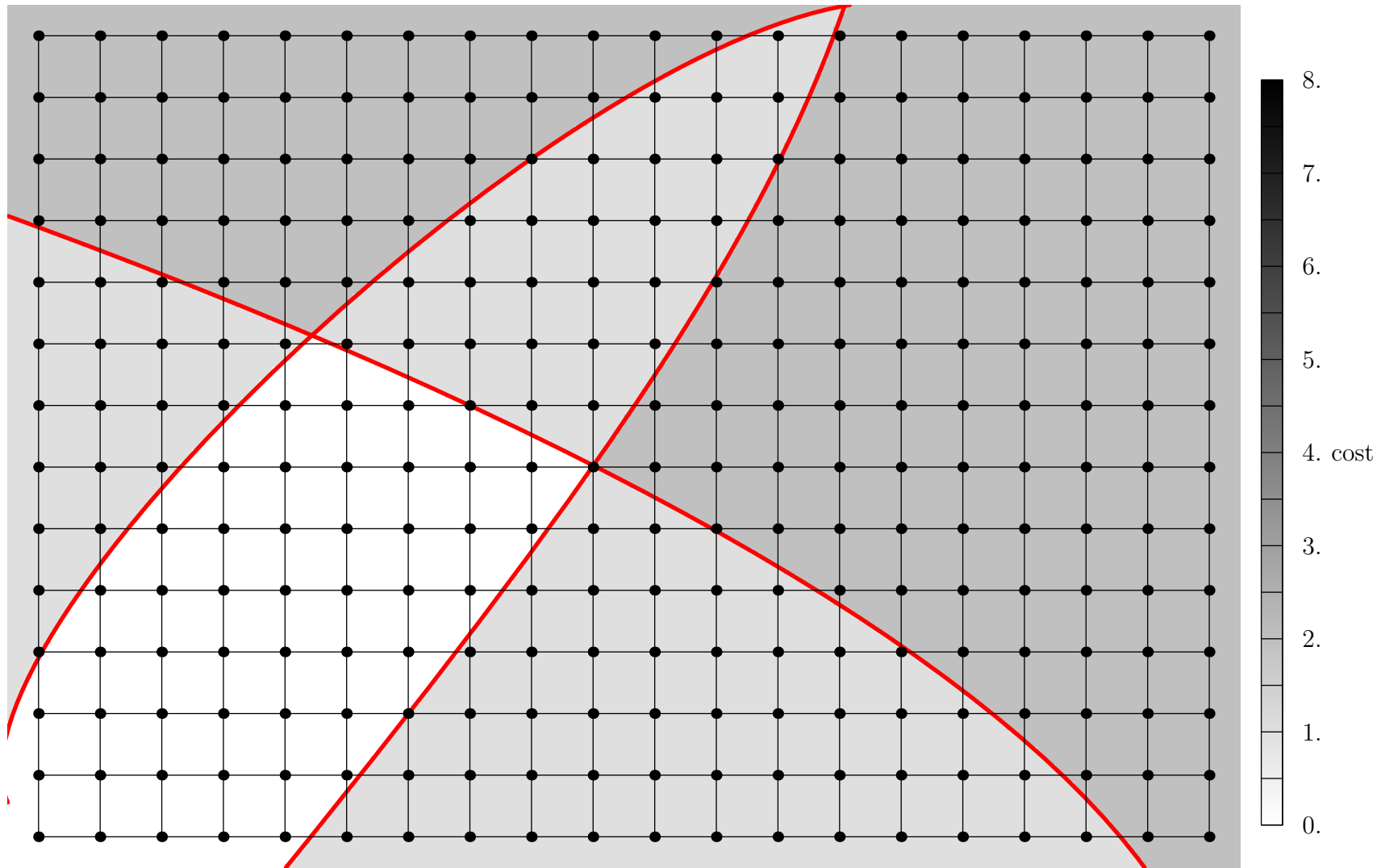
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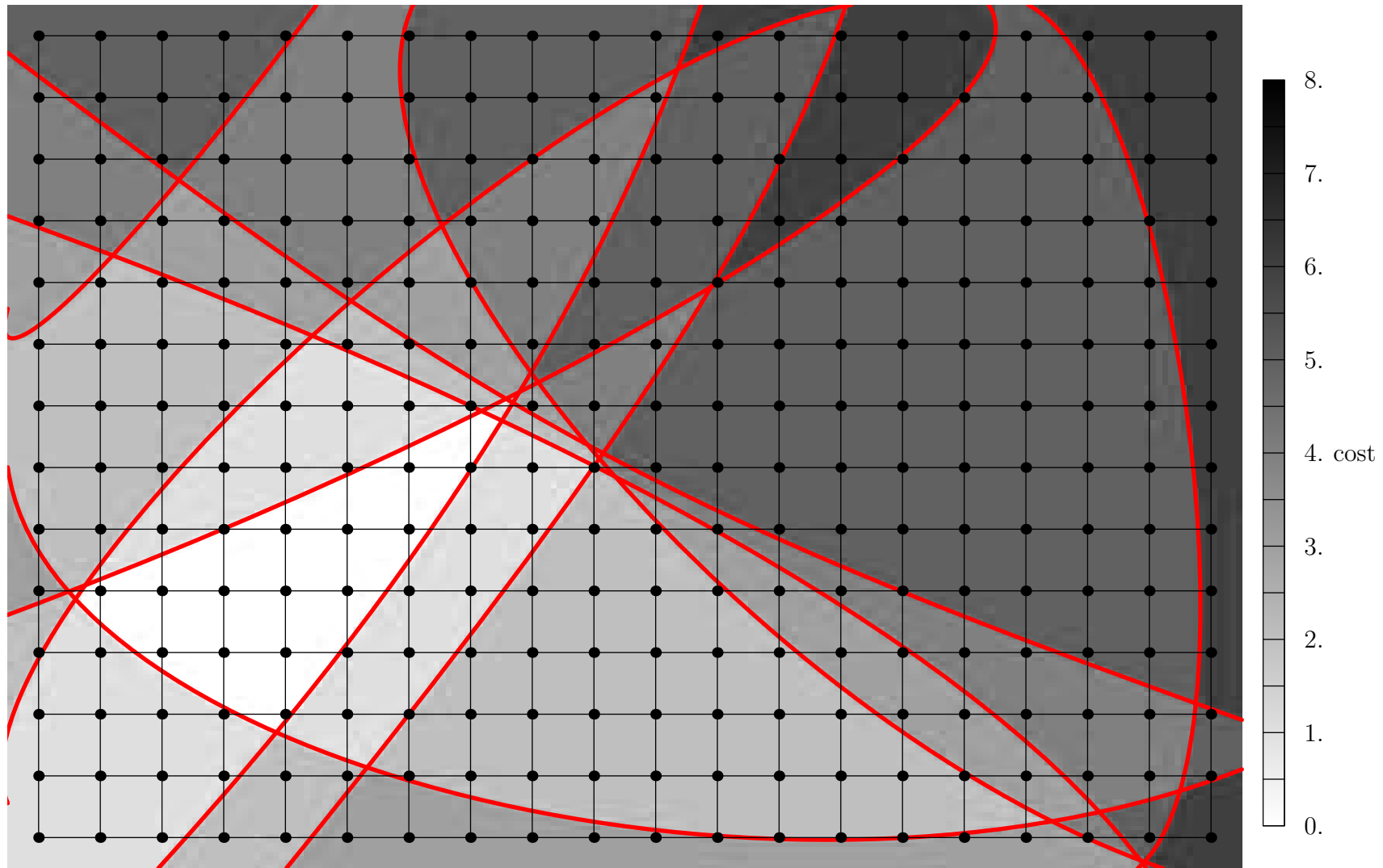
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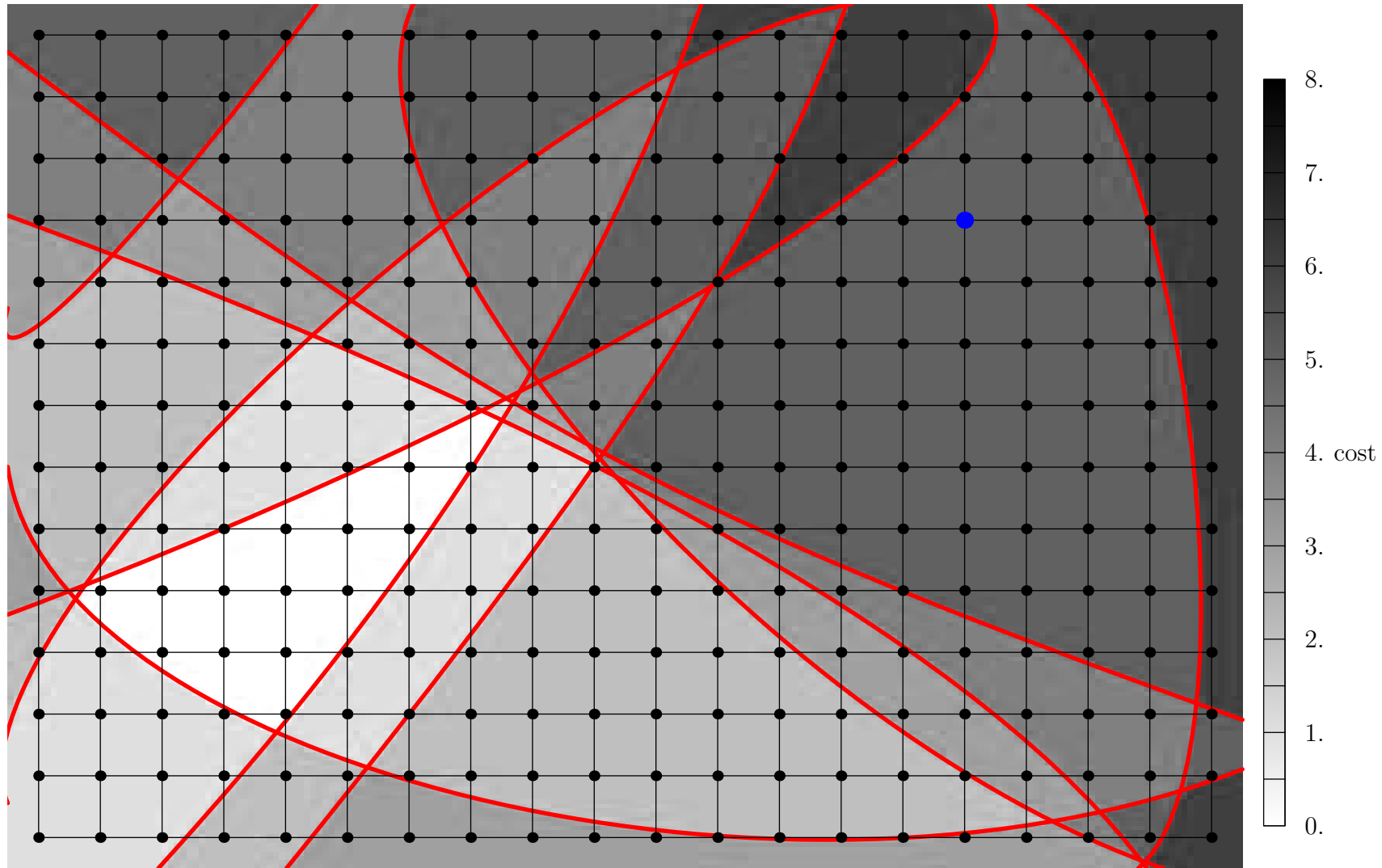
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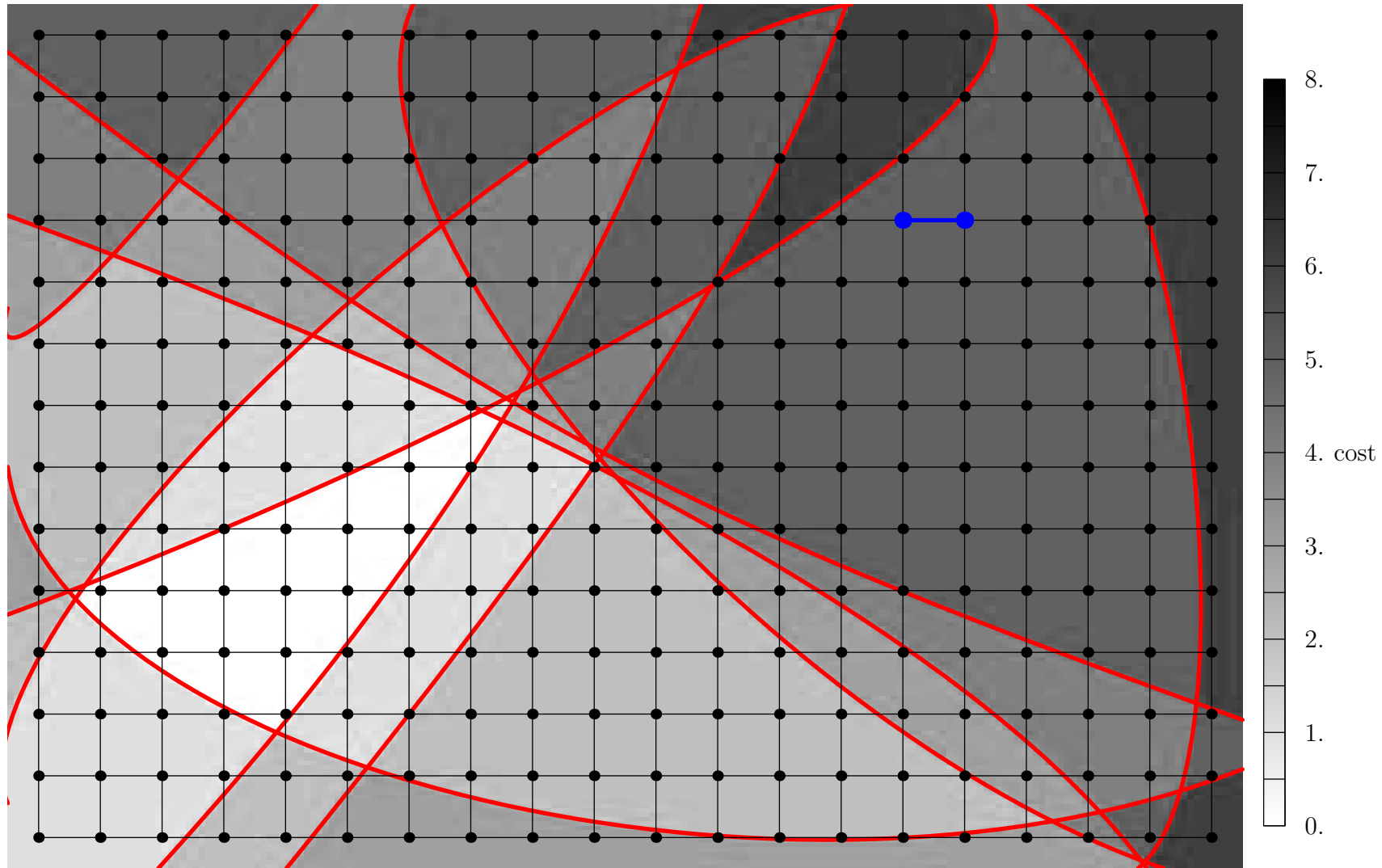
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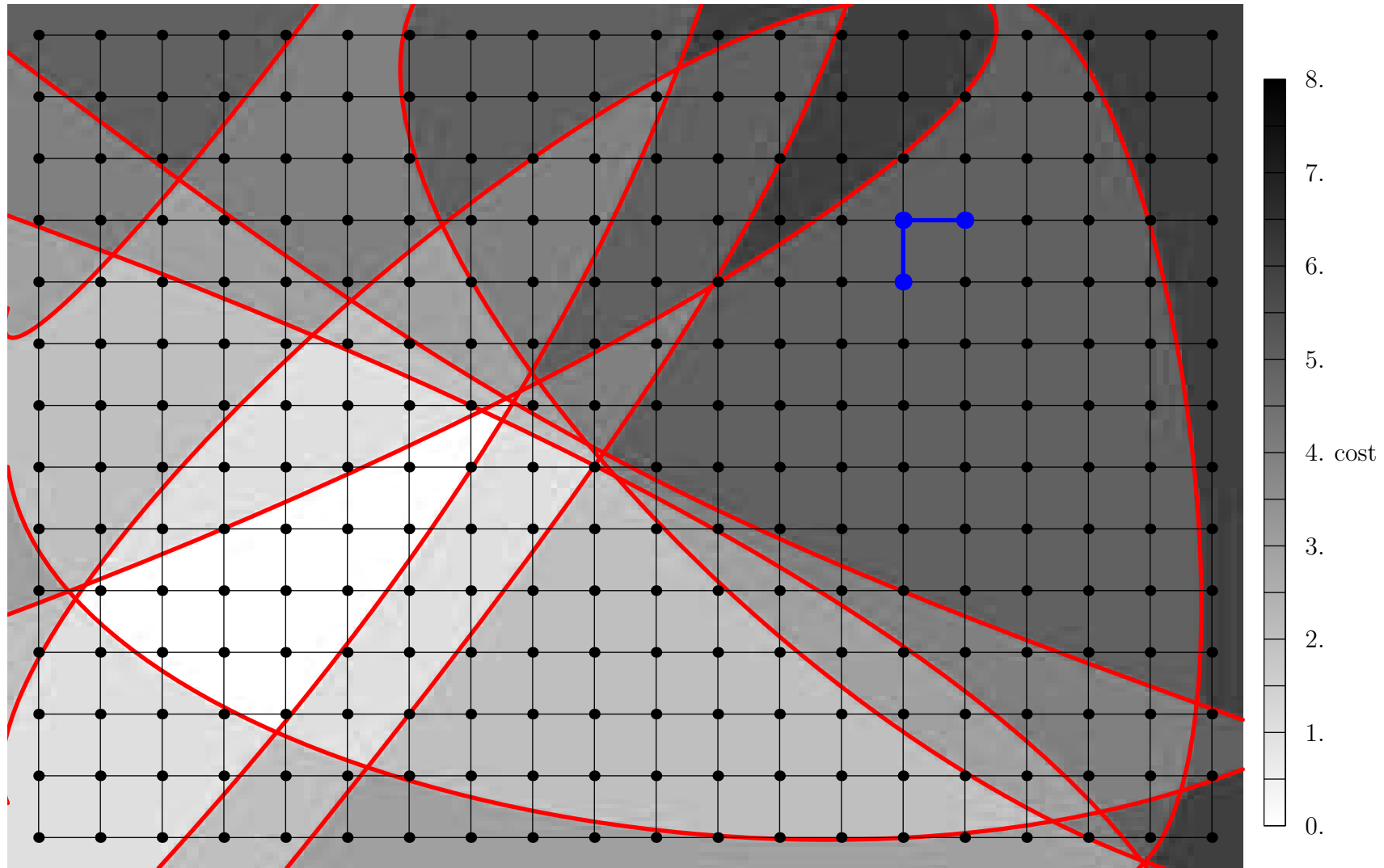
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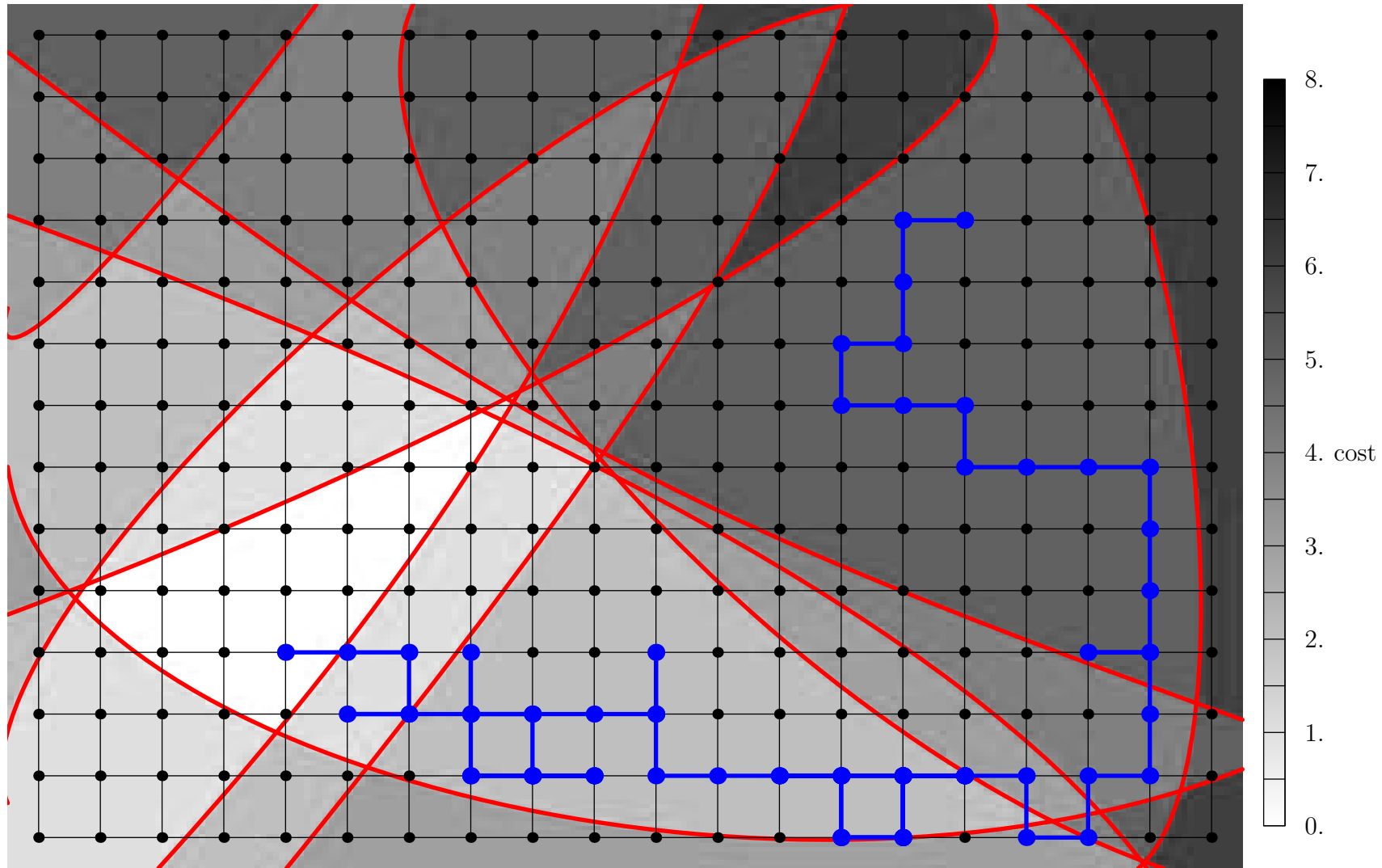
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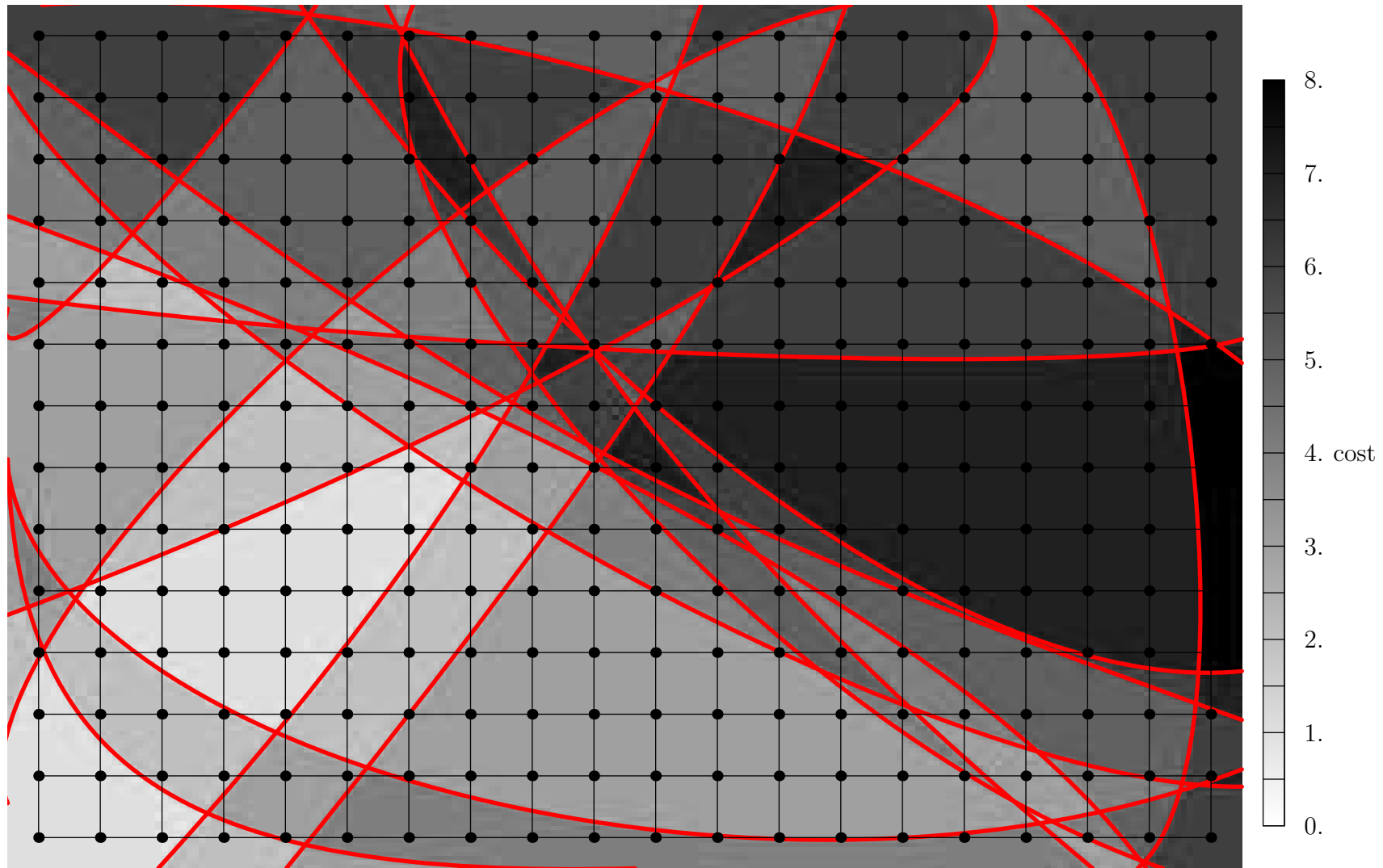
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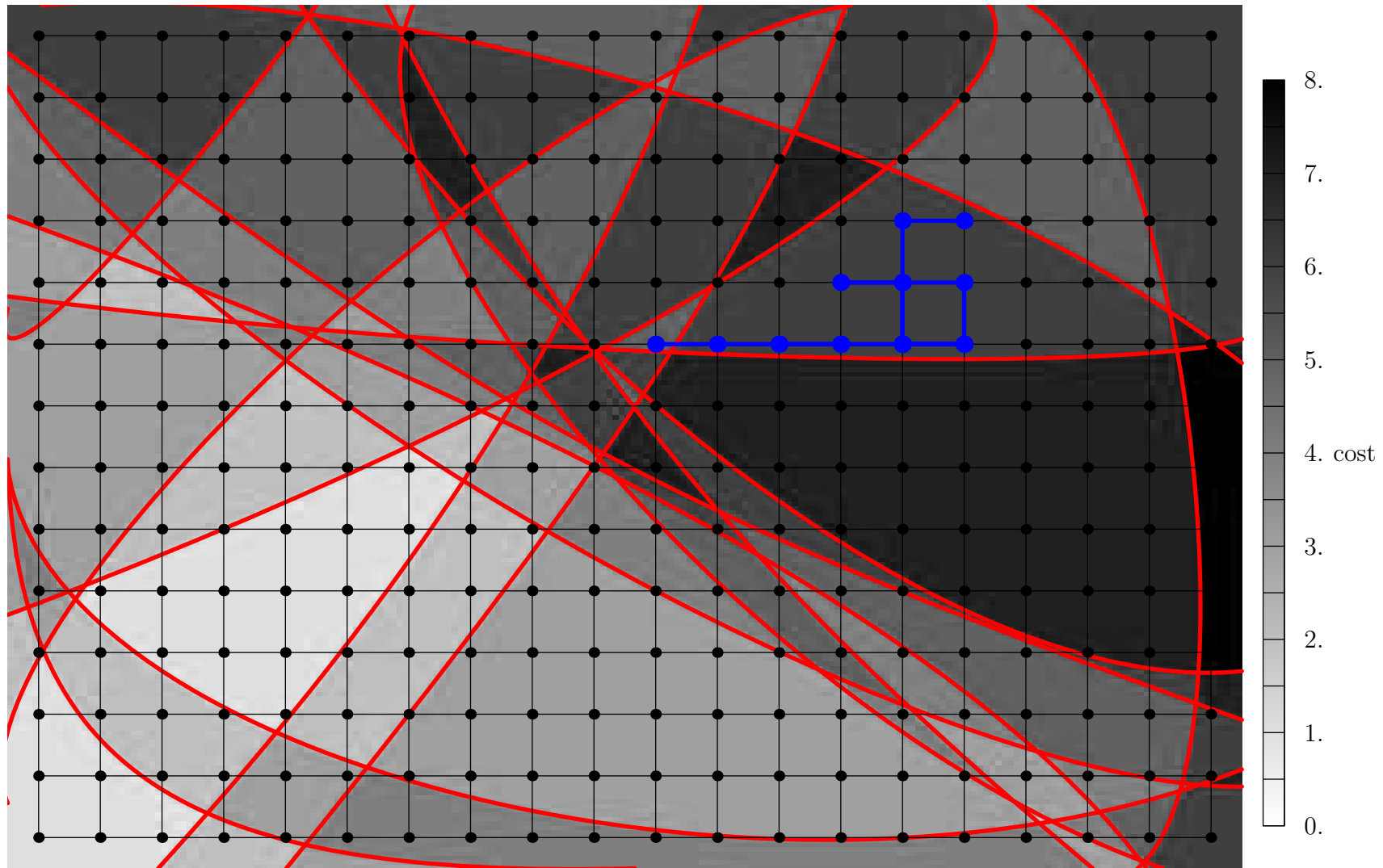
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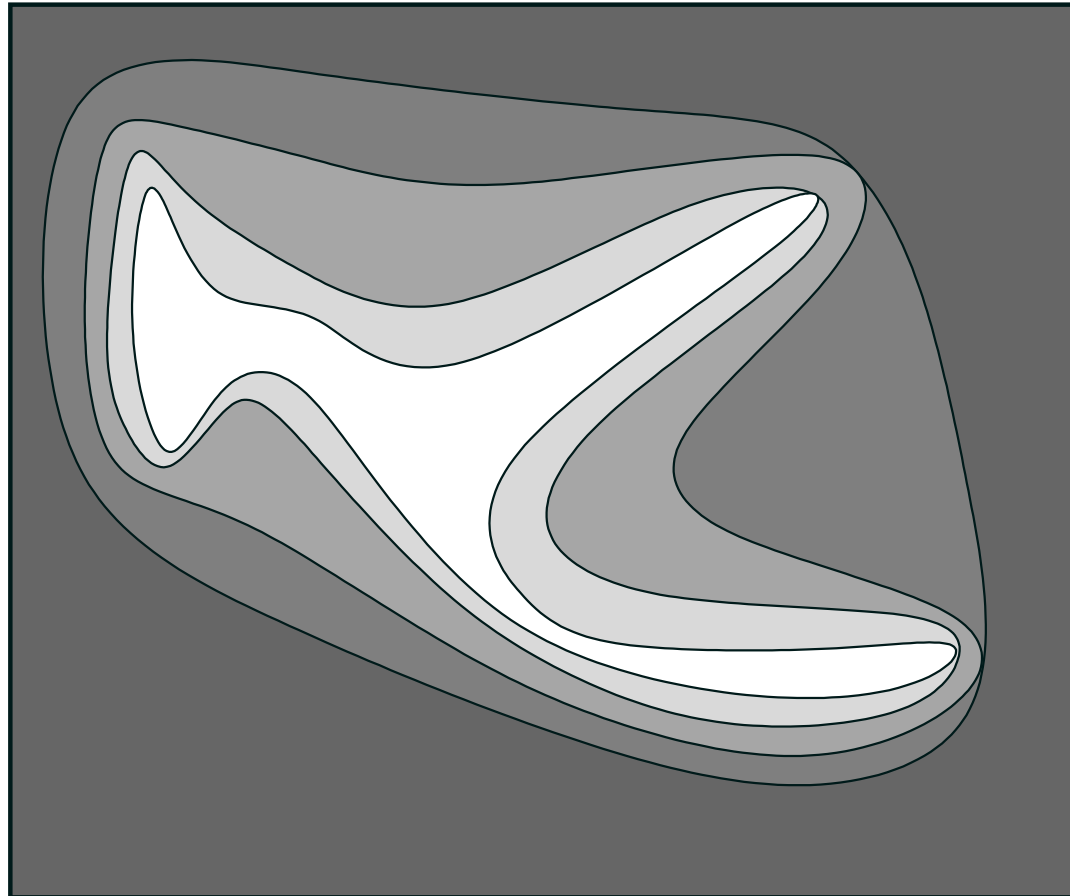


Schematic of Phase Transition



Schematic of Fitness Landscape

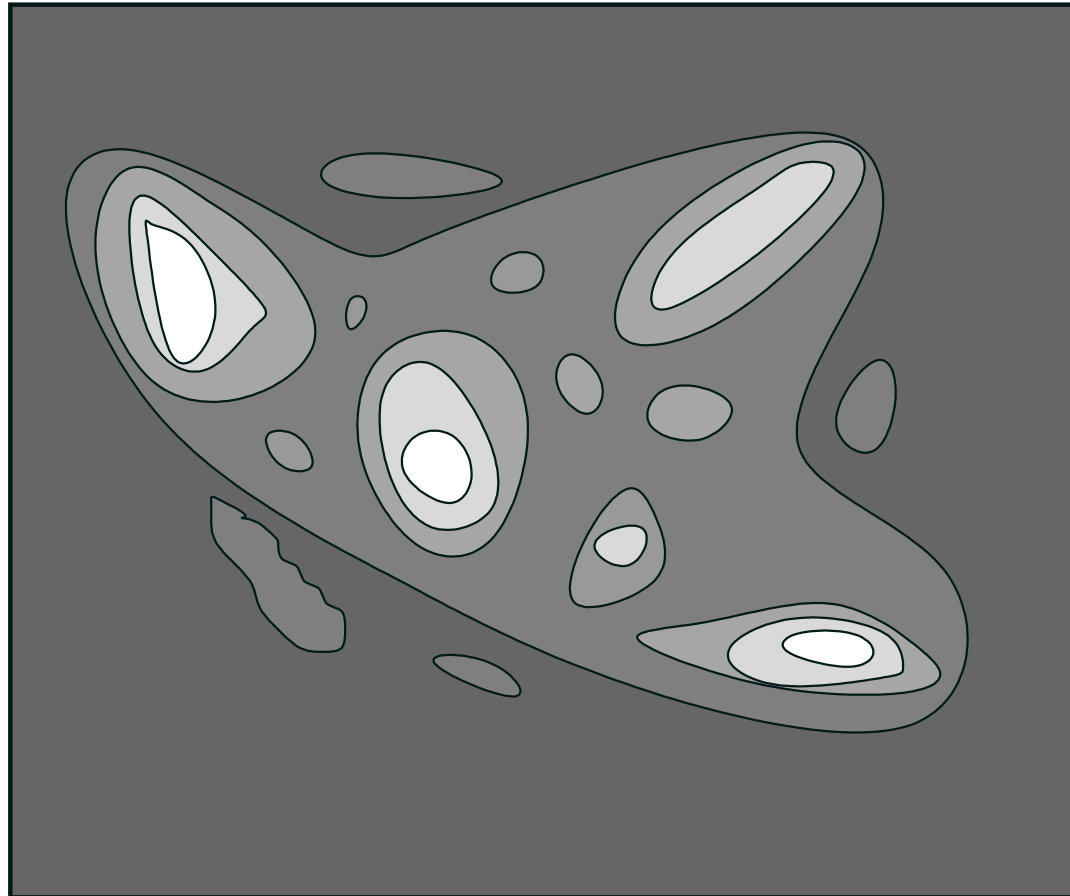
Global optima in white



Easy Phase $\alpha < \alpha_c$

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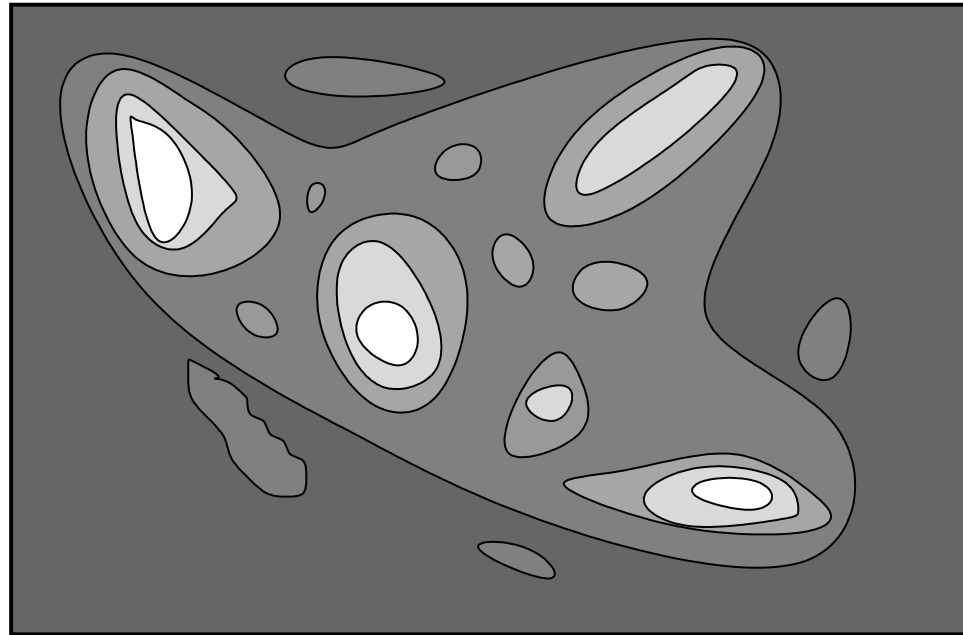
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Hard Phase $\alpha > \alpha_c$

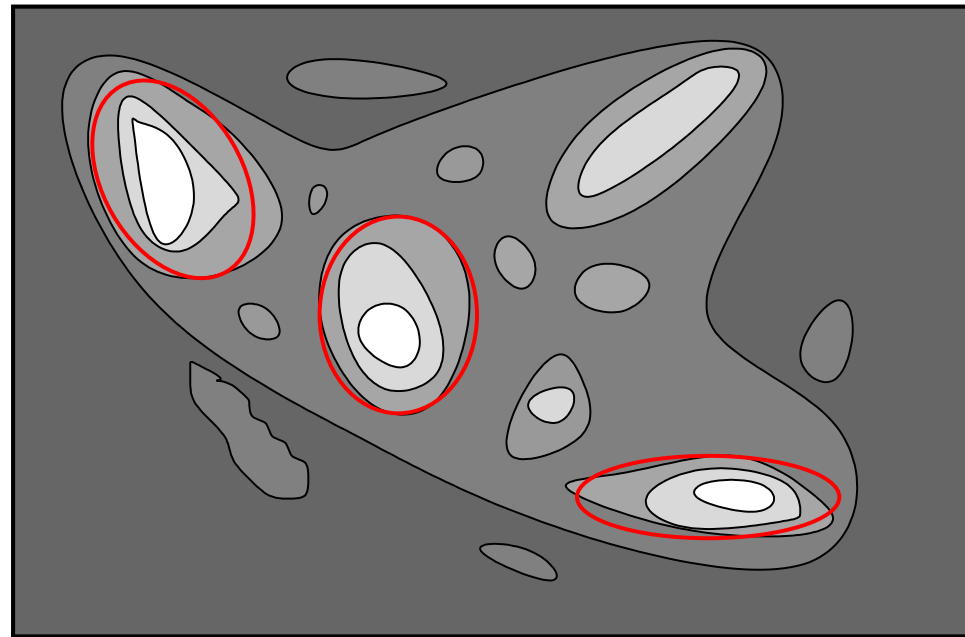
Critical Variables

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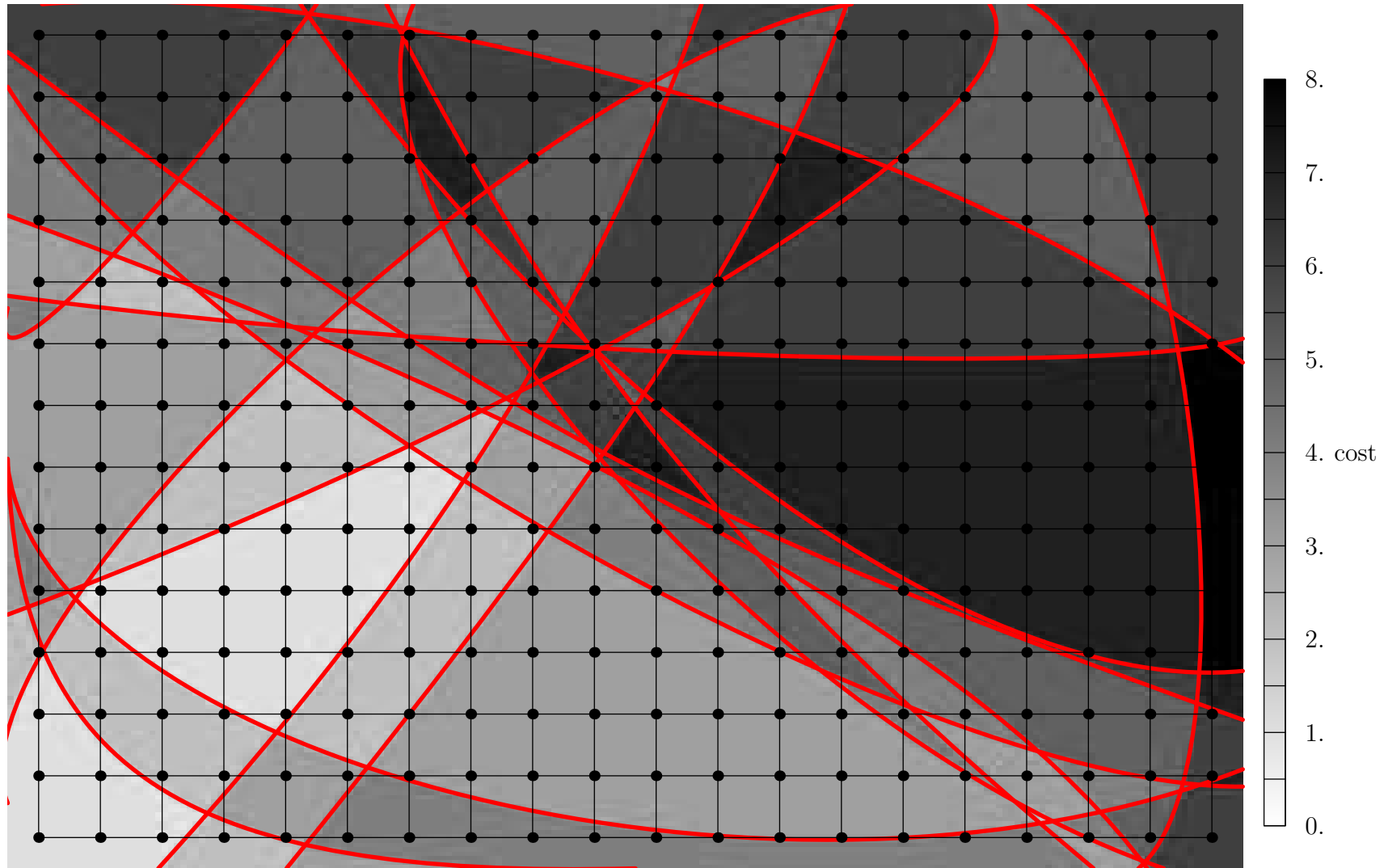


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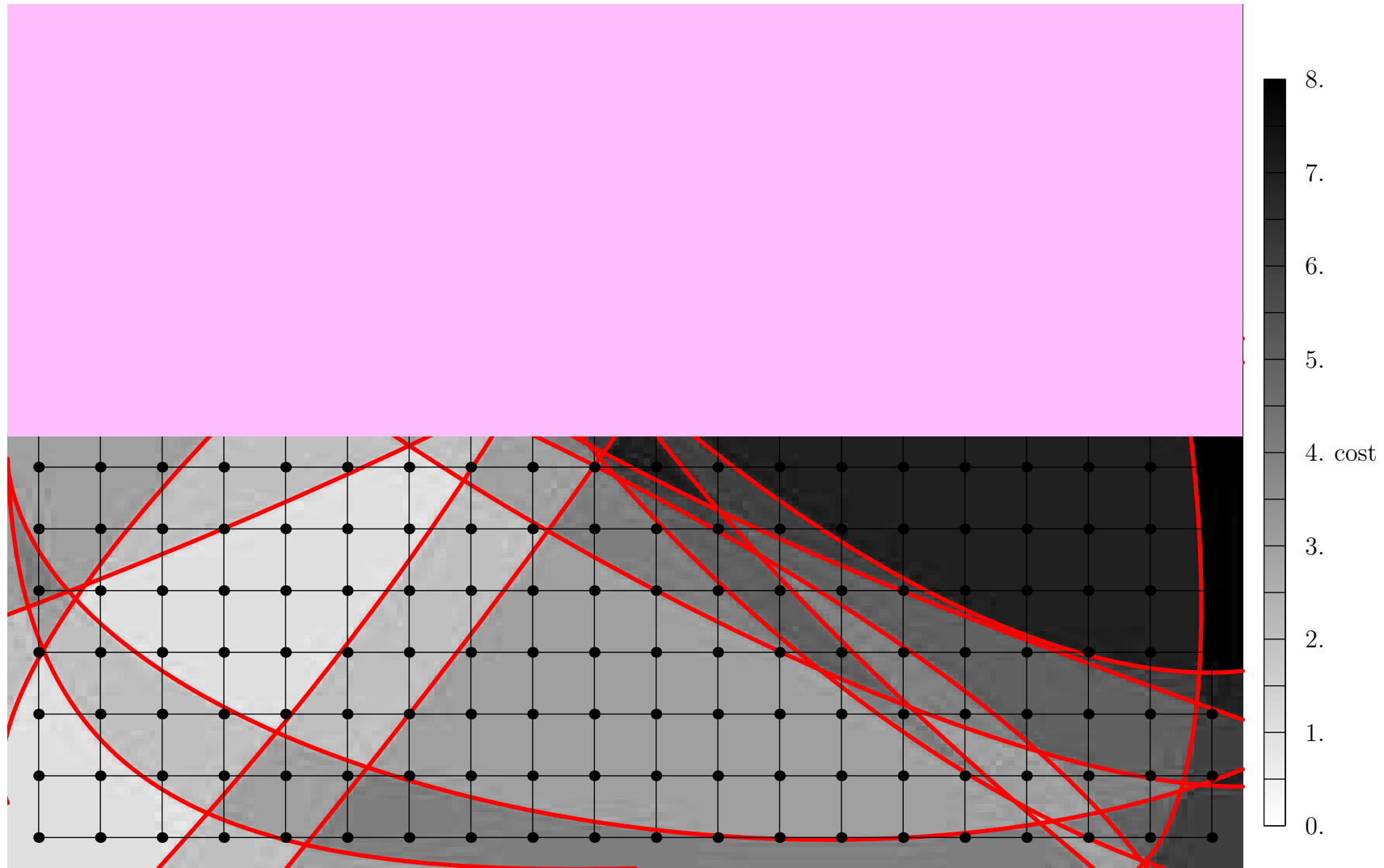
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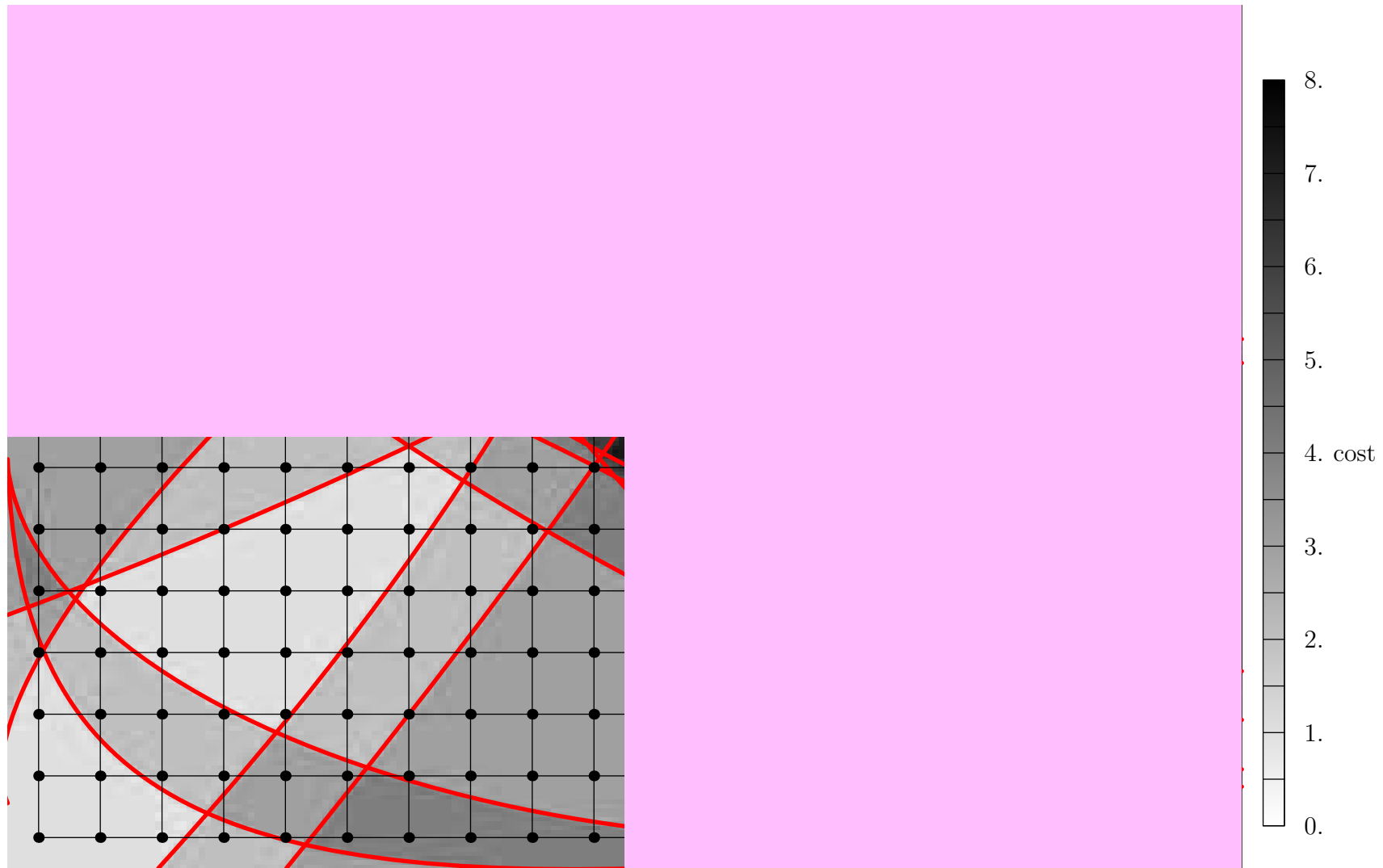
Setting Critical Variables



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Are There Examples of This Strategy Working?

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 - ★ Used a hybrid GA
 - ★ Their method used a fast local search method (taboo search)
 - ★ And a clever crossover
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- The crossover operator seemed to act as an efficient method for finding good critical variables
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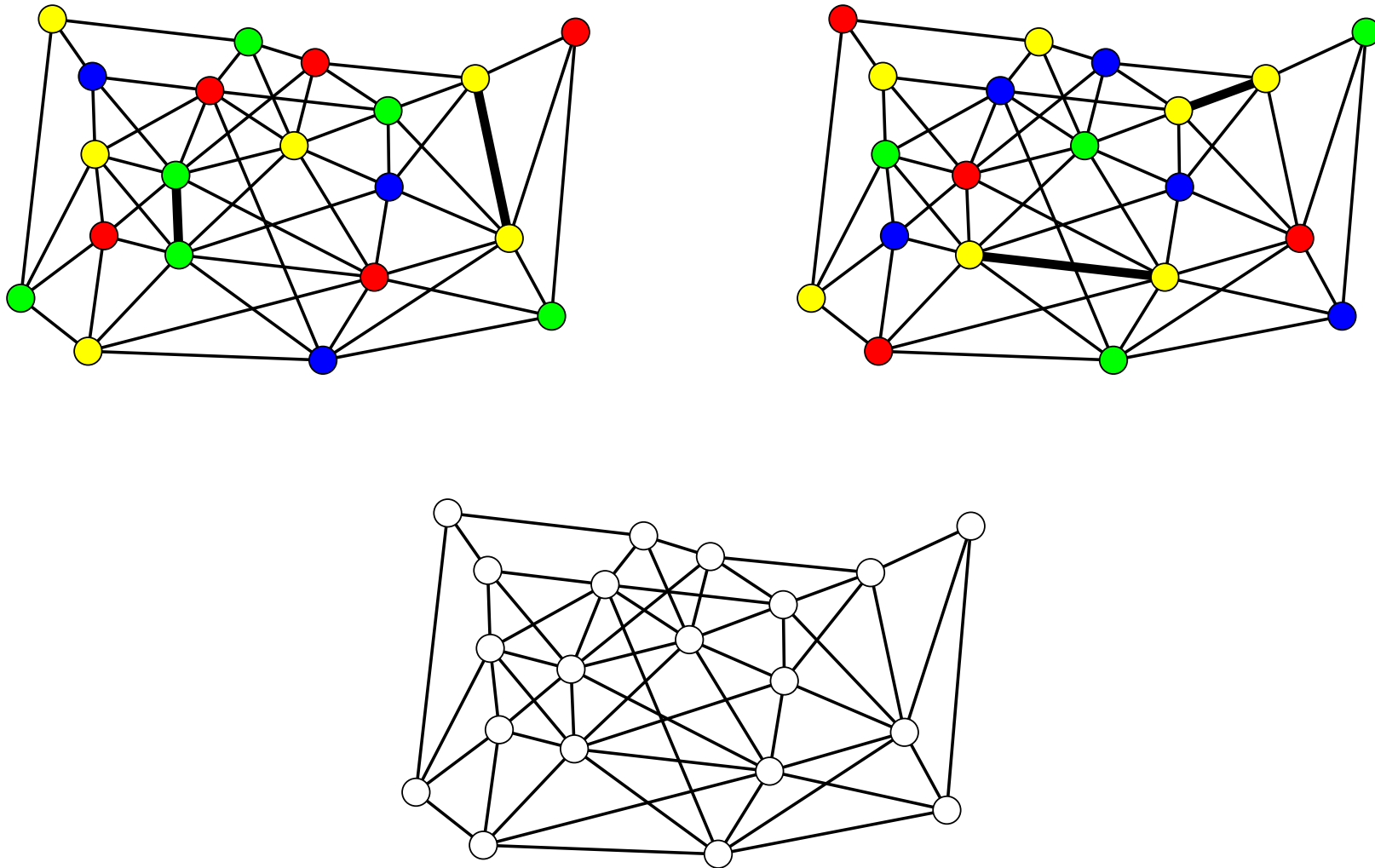
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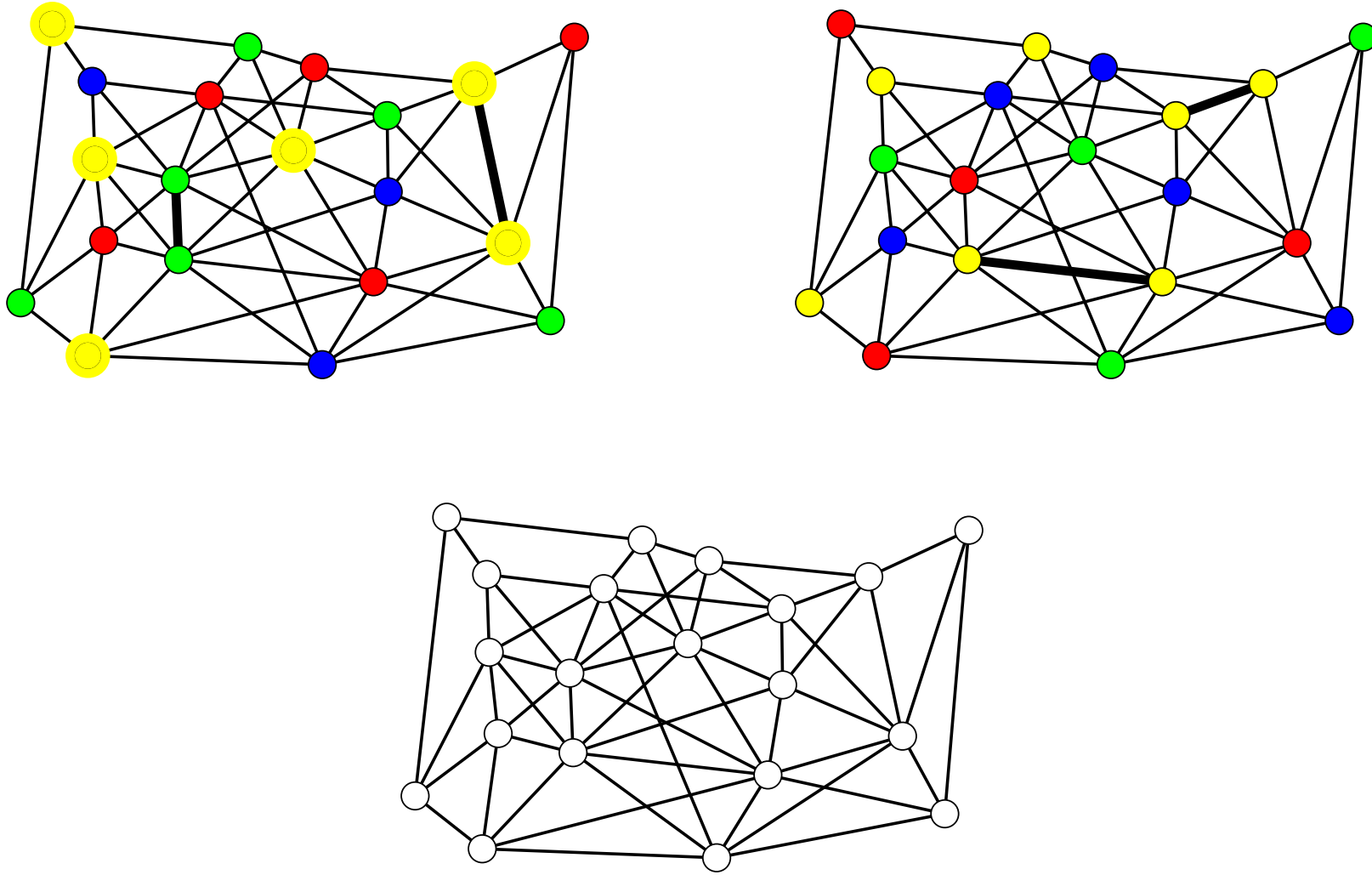
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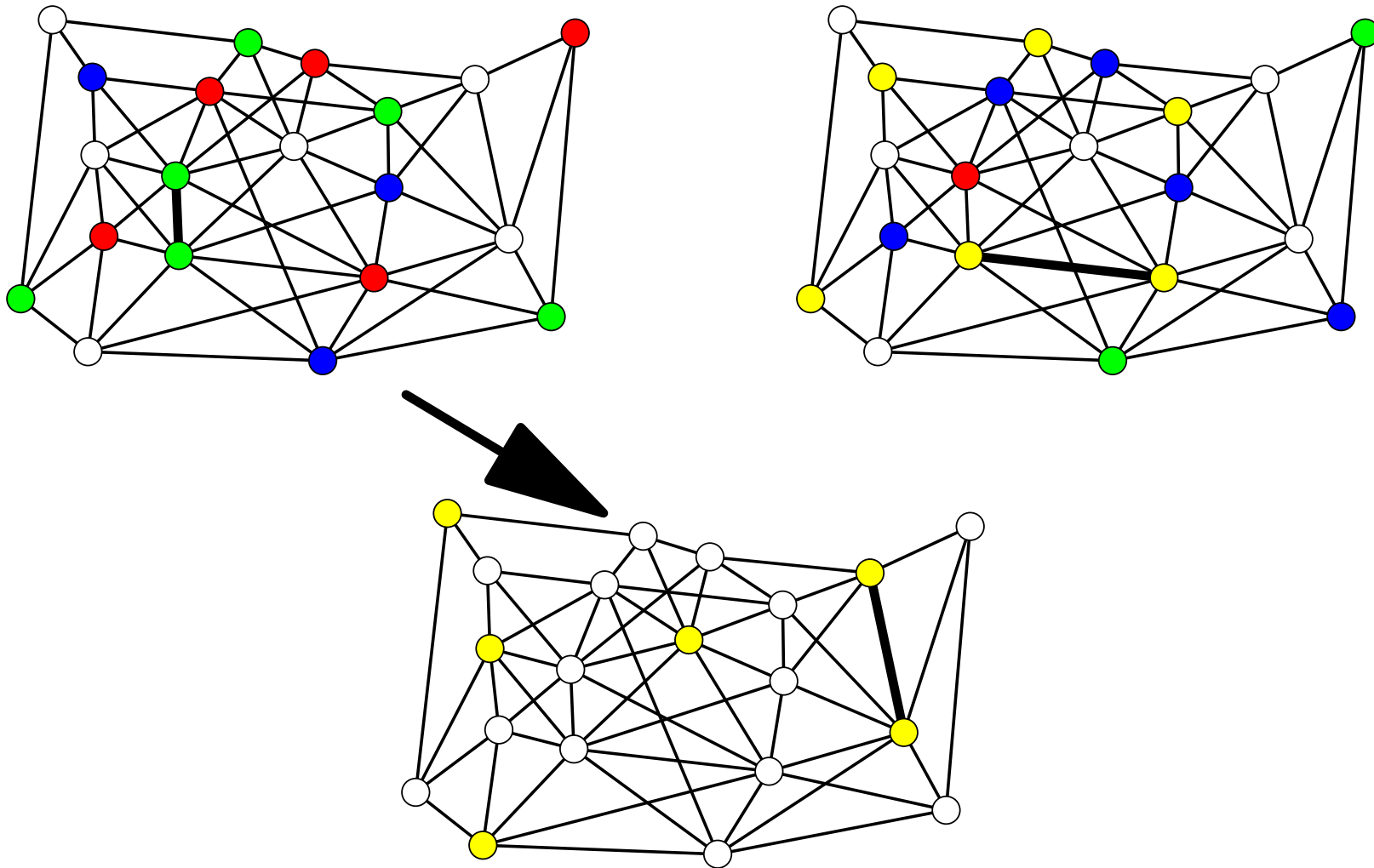
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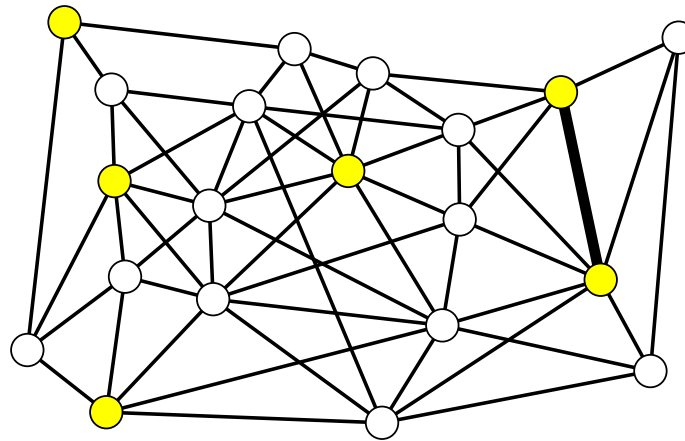
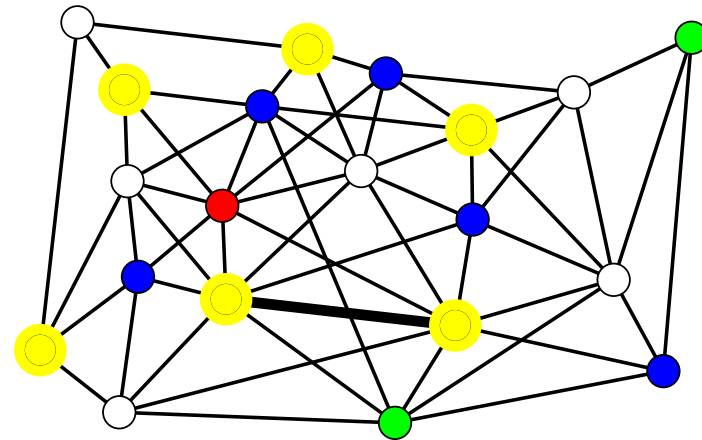
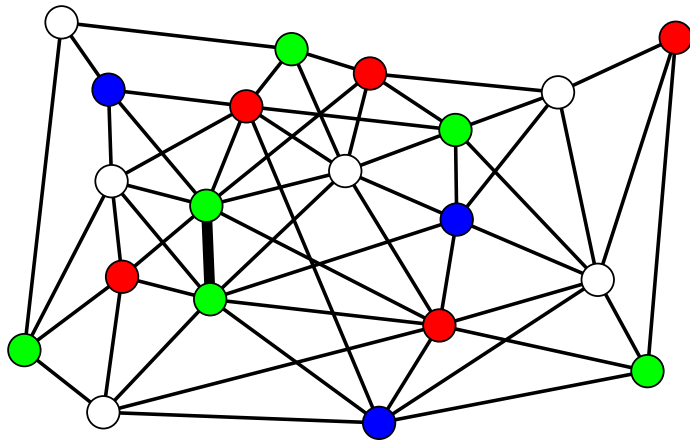
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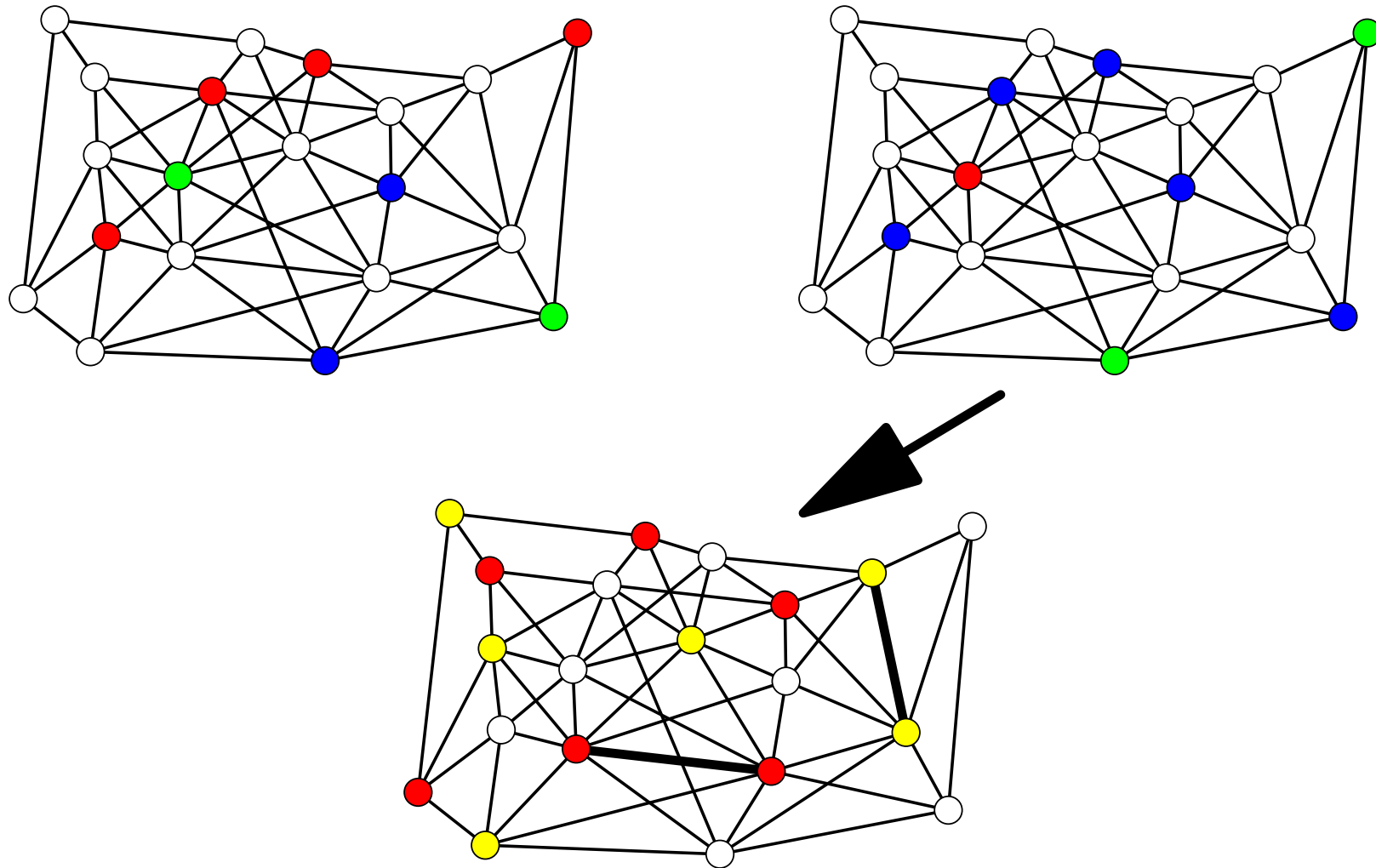
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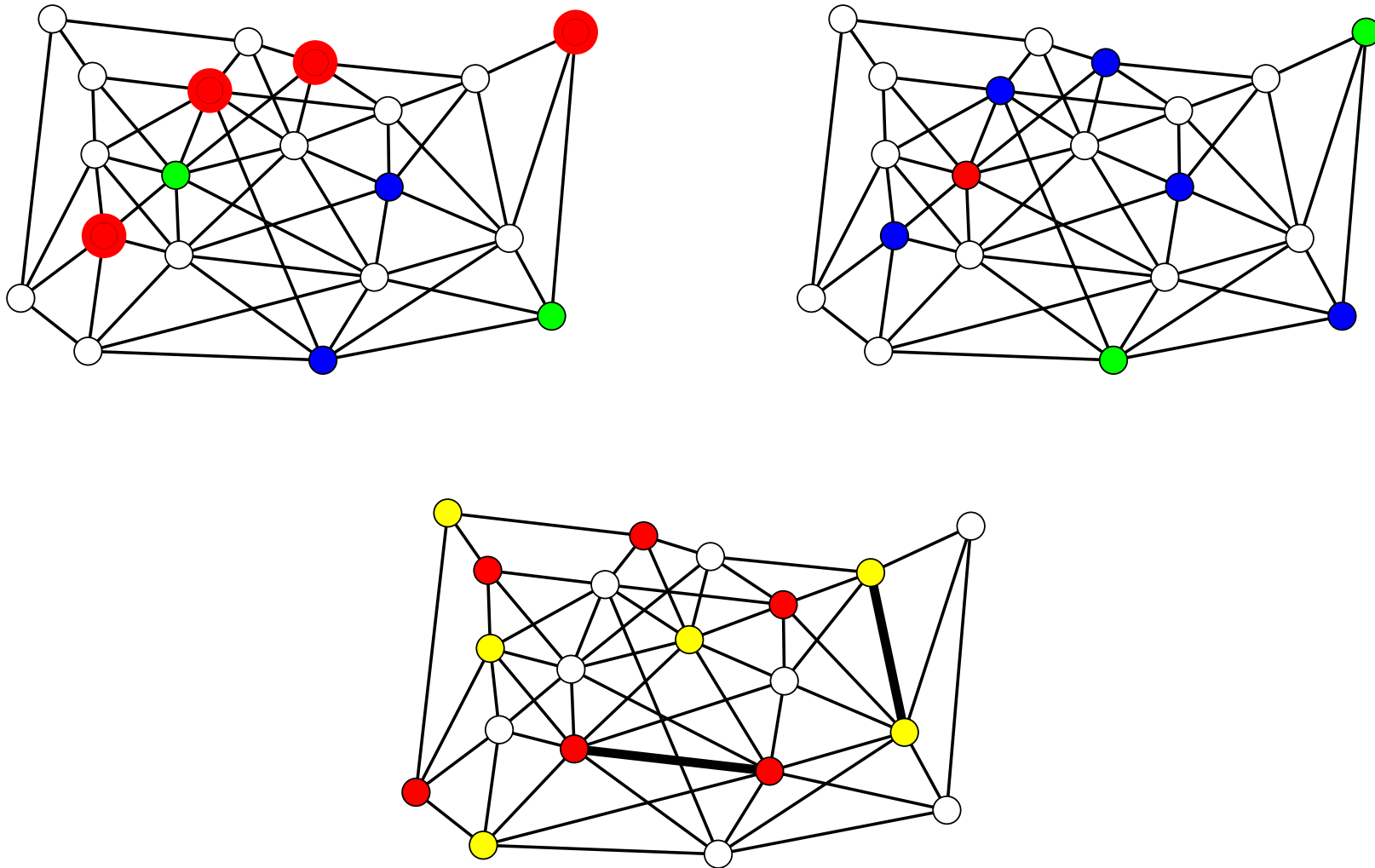
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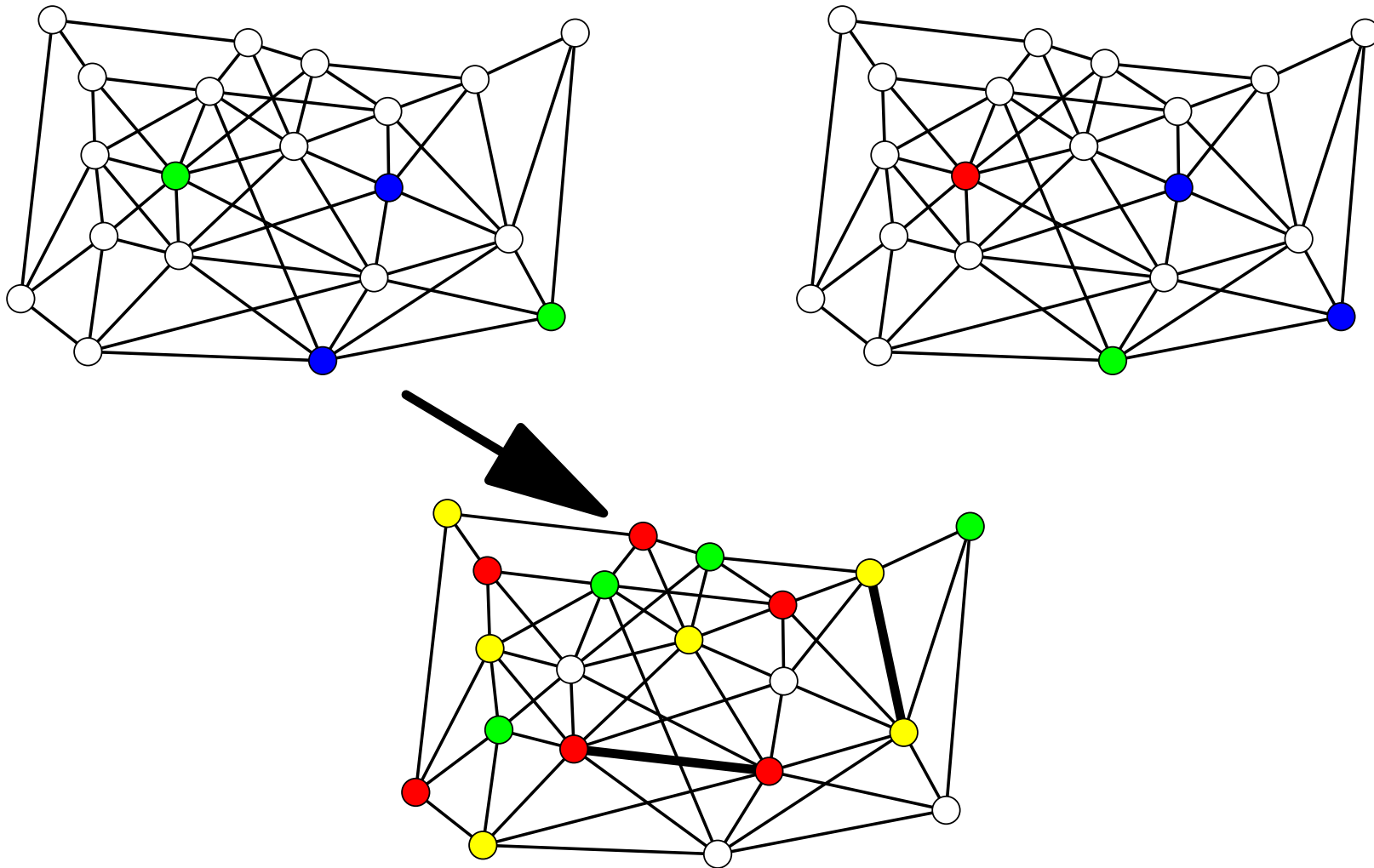
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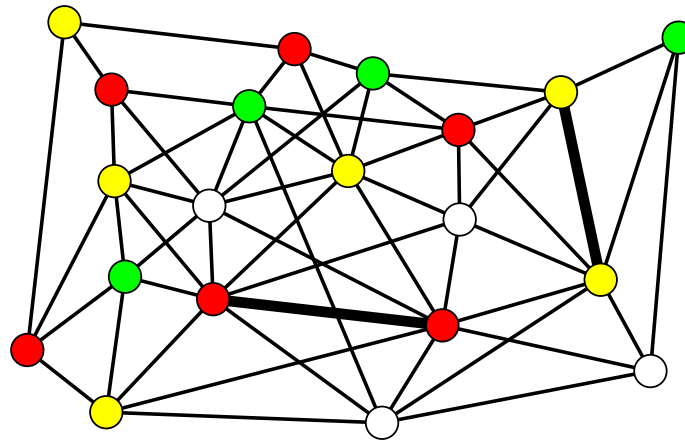
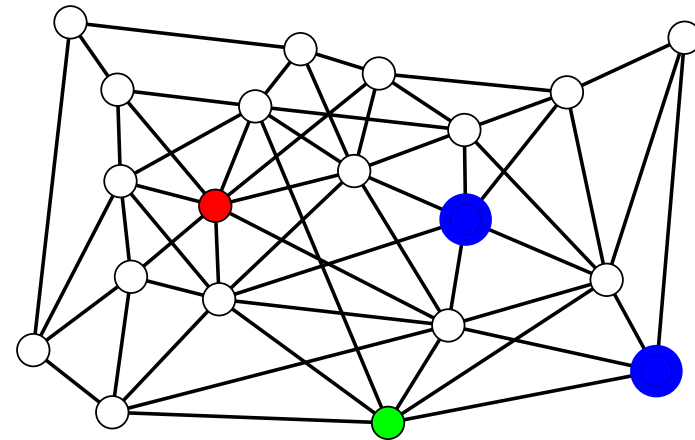
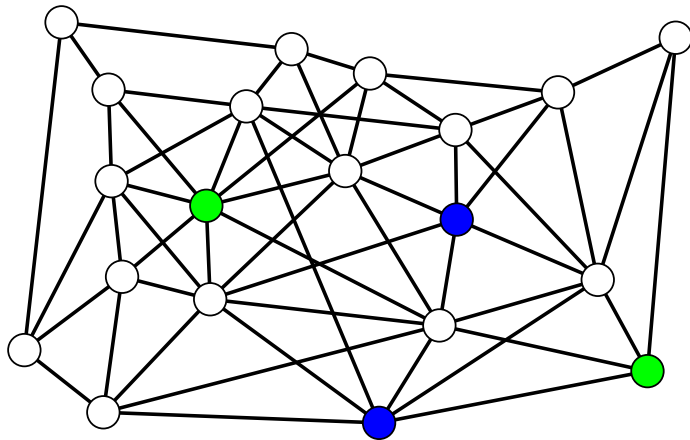
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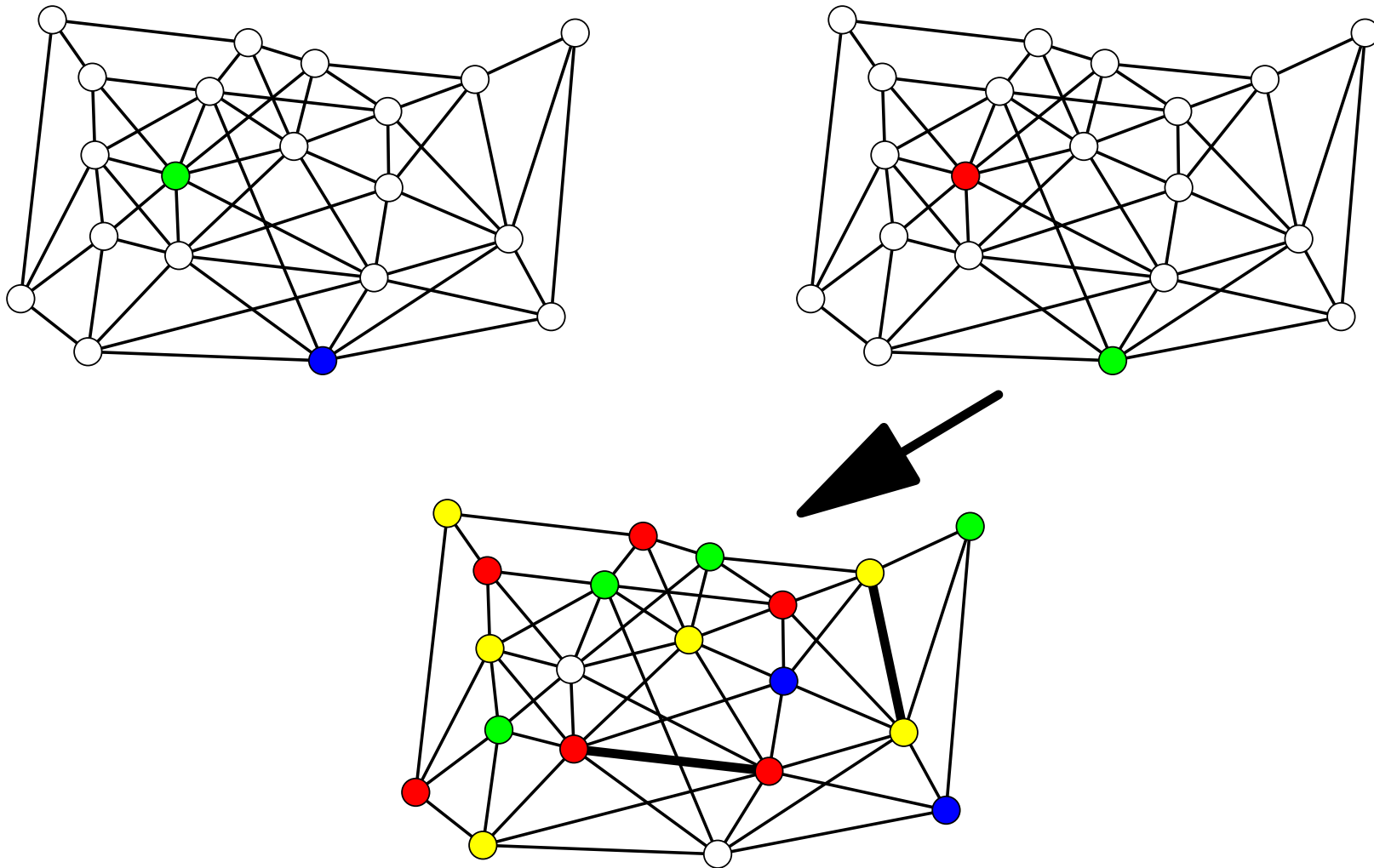
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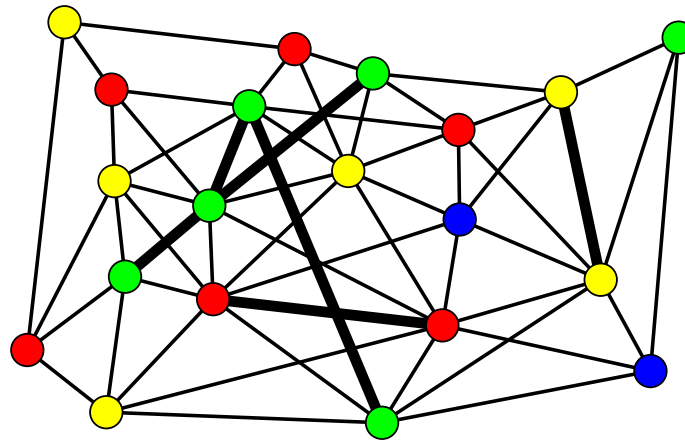
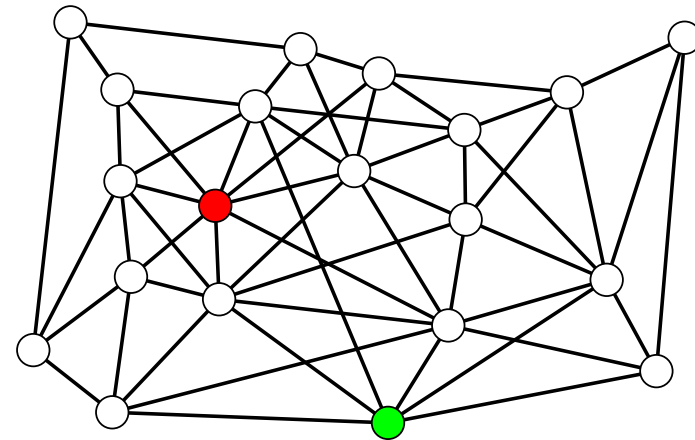
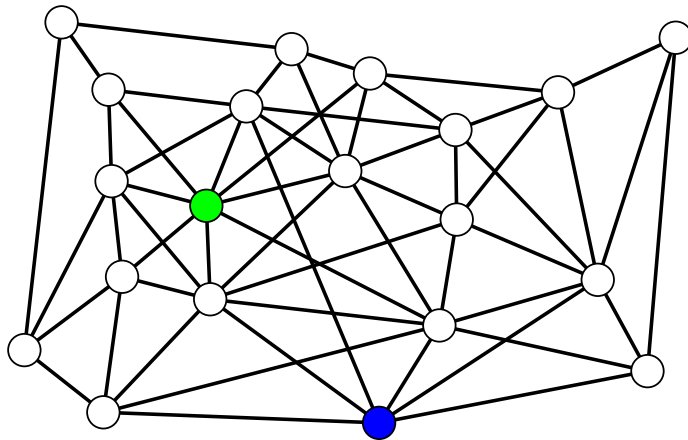
Galinier and Hao Crossover



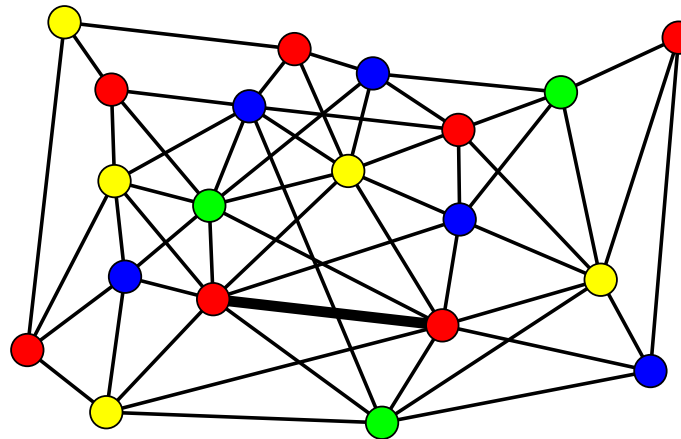
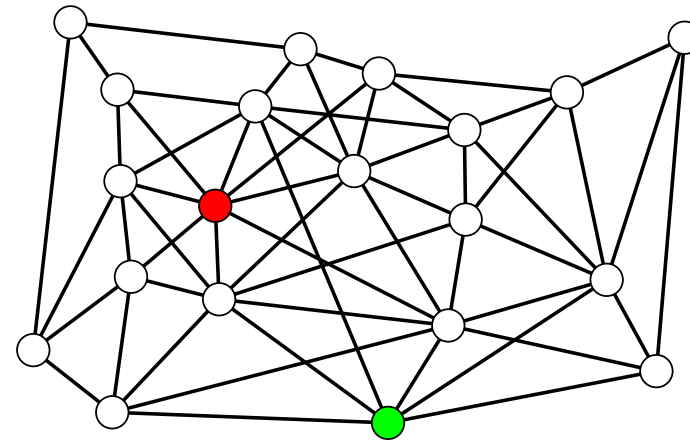
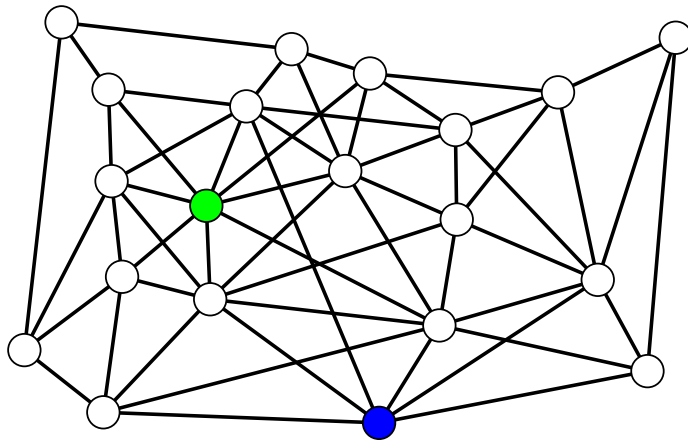
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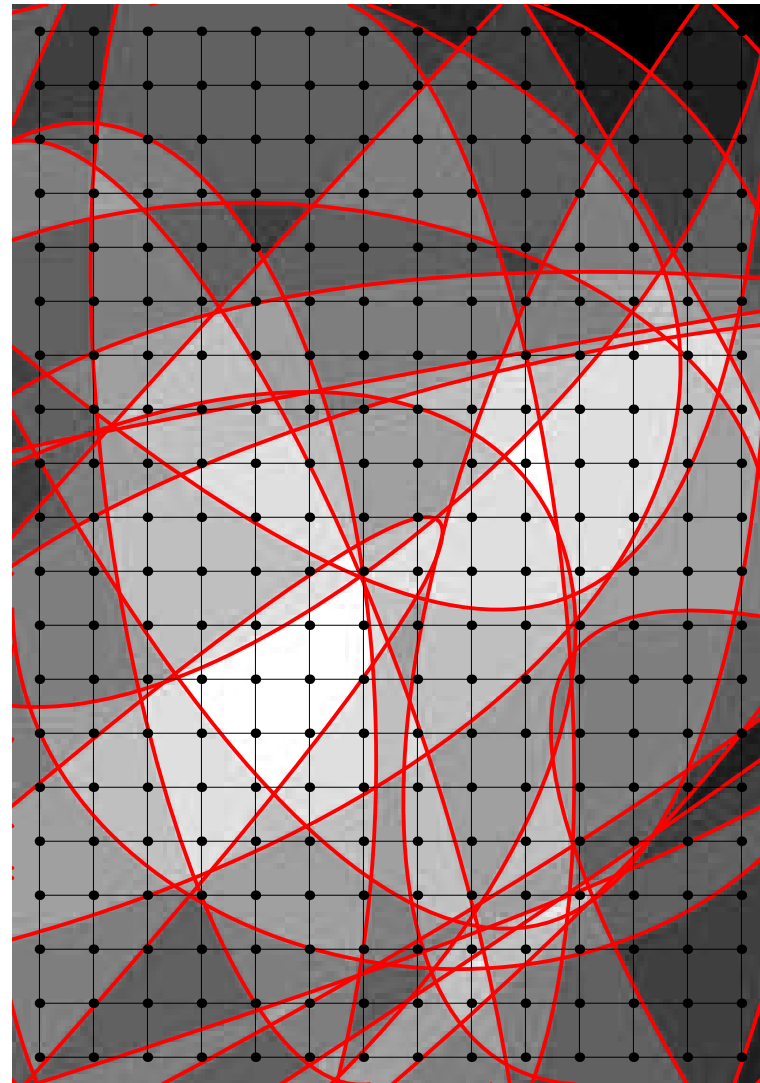
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Outline

1. Critical Variable Problems
2. Solving Critical Variable Problems
3. A Toy Example
4. Real Optimisation Problems
5. **Max-Sat**



Work in Progress

- and finally. . . , some work in progress
- Carried out by a PhD student Mohamed Qasem
- Detailed study of MaxSat

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- Problem of choosing binary variables $X \in \{T, F\}^n$ to satisfy as many clauses as possible
- Clause is a disjunction of literals (variables or their negation), e.g.

$$\neg X_4 \vee X_7 \vee \neg X_{17}$$

- Fitness is number of satisfied clauses
- We consider Max-3-Sat where each clause contains 3 literals
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How Max-Sat Becomes Difficult

- For $\alpha \gg \alpha_c$, the problem becomes hard because of the proliferation of local minima
- The better the local optima the larger the basin of attraction
- As the problem becomes large the number of local optima grows exponentially
- This growth is rather slow so small problems are easy to solve by multiple hill-climbing
- Need to look at instances with several hundred variables before they become hard

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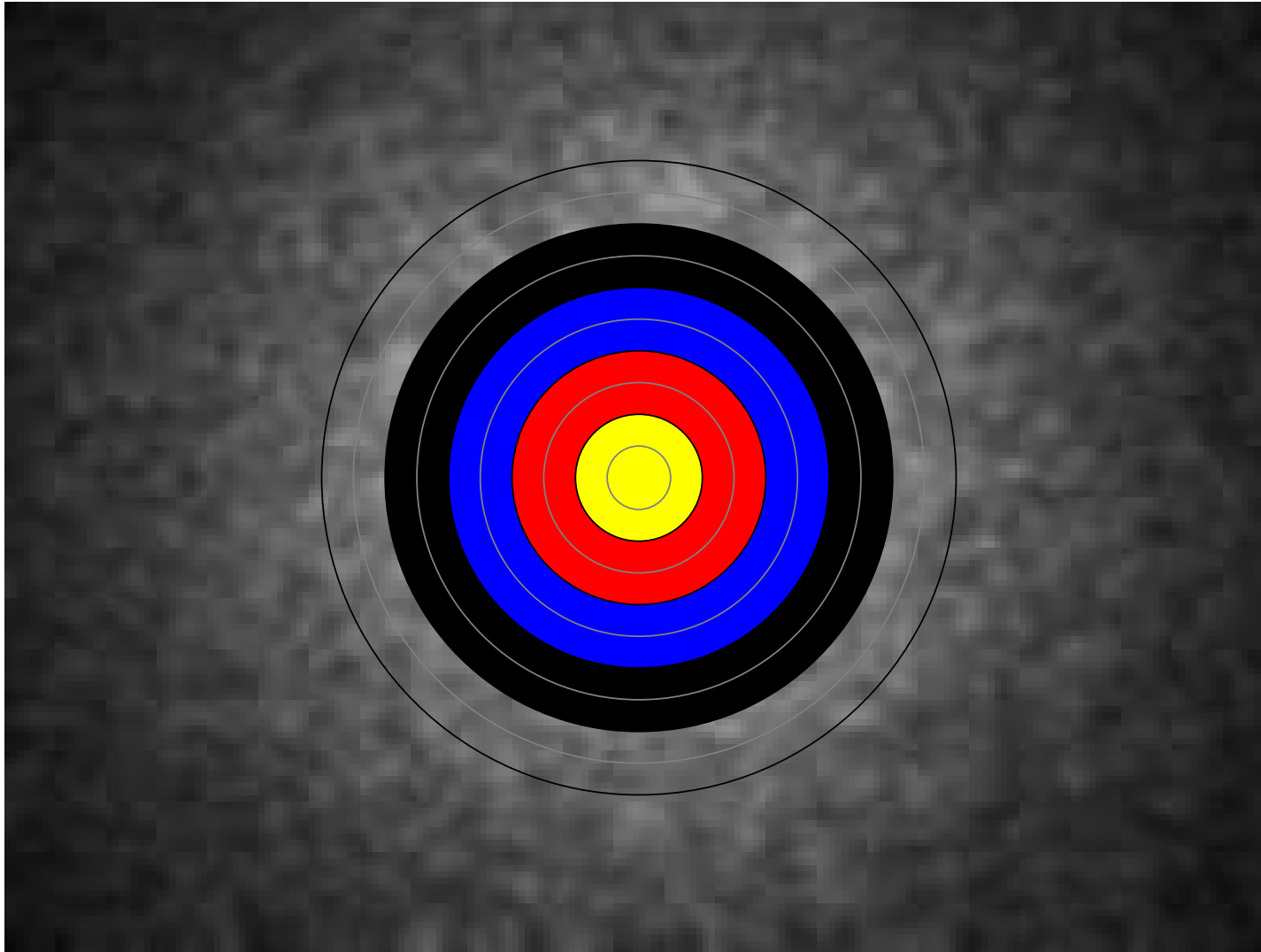
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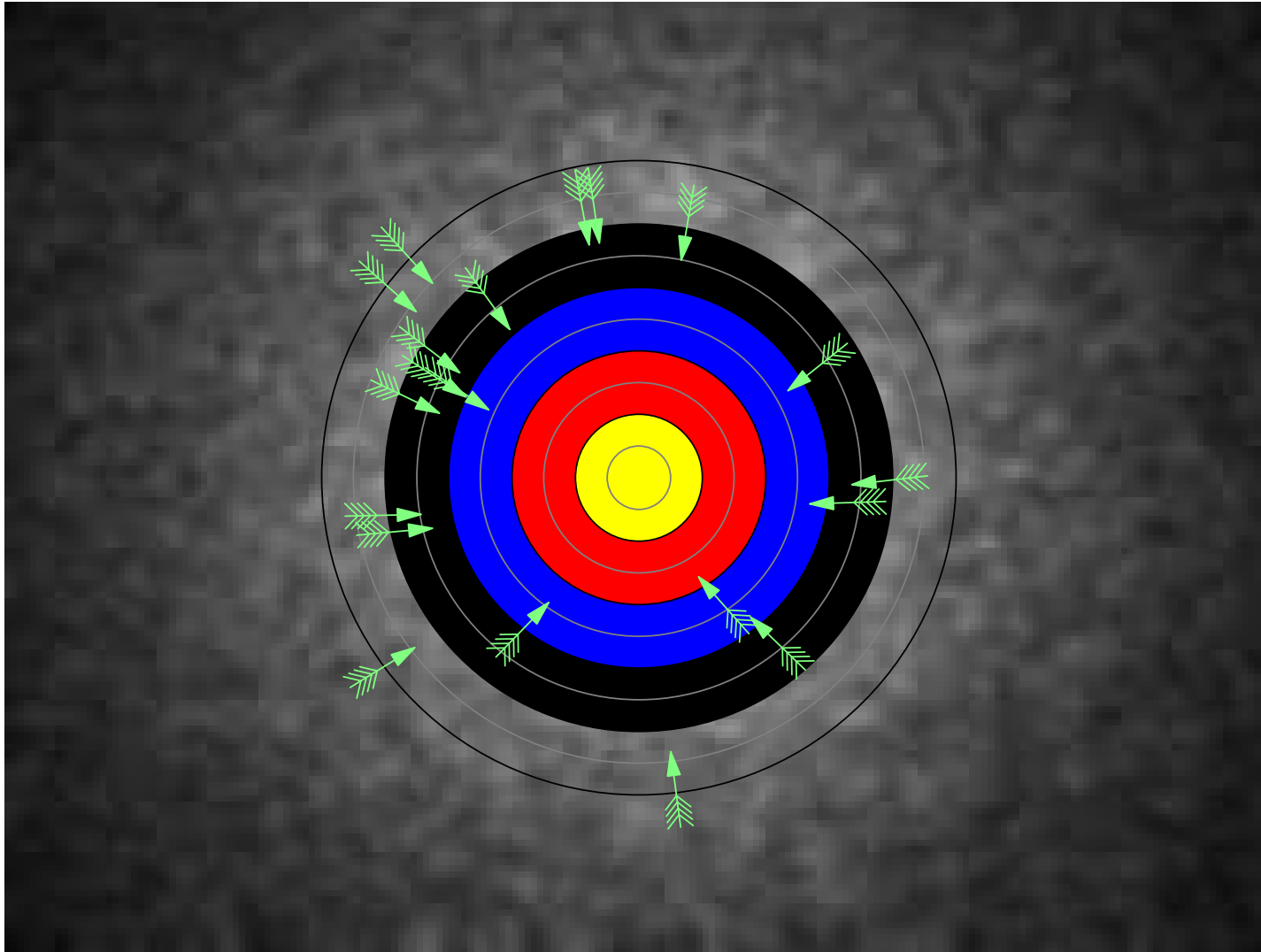
Getting More Out of Local Search



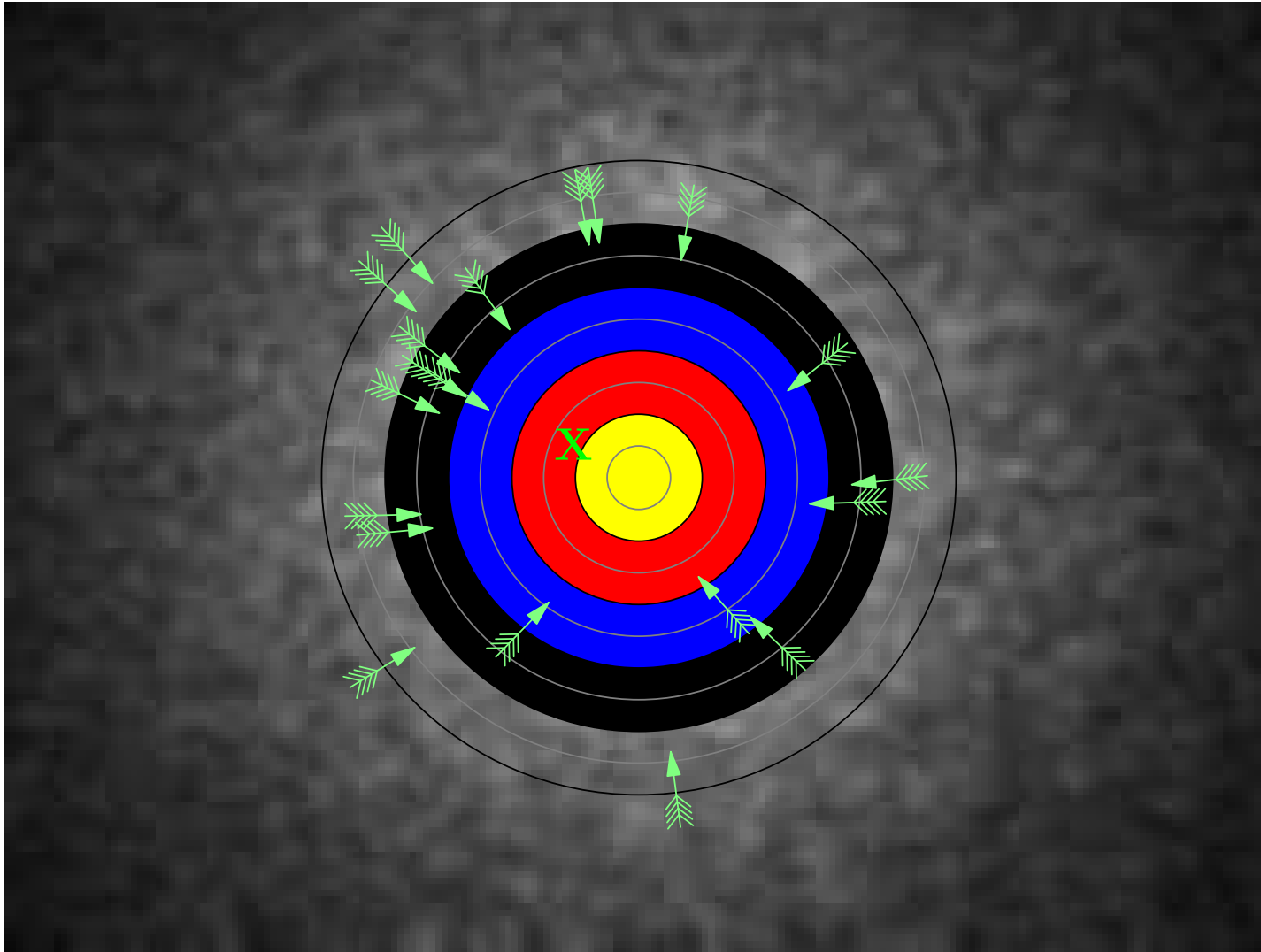
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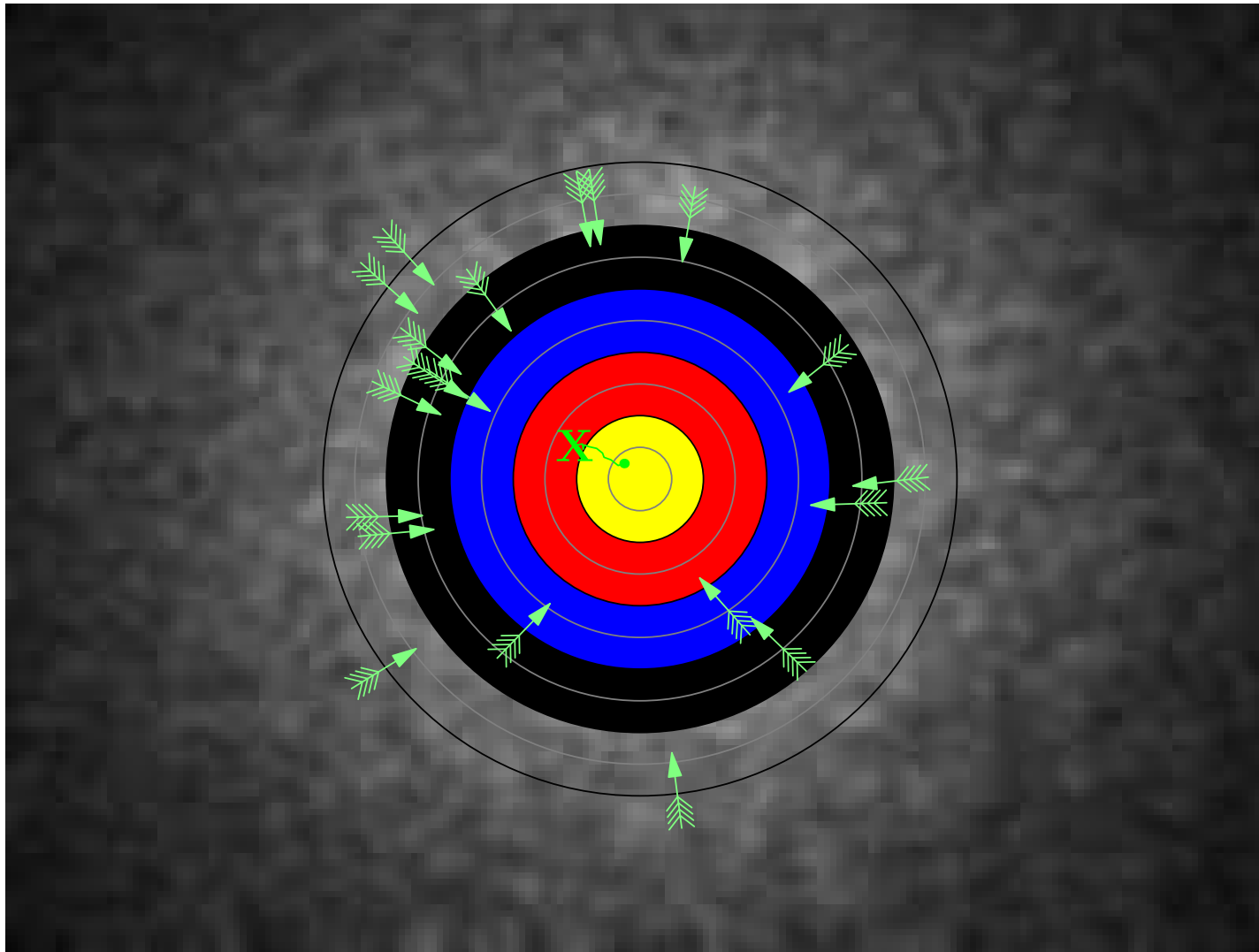
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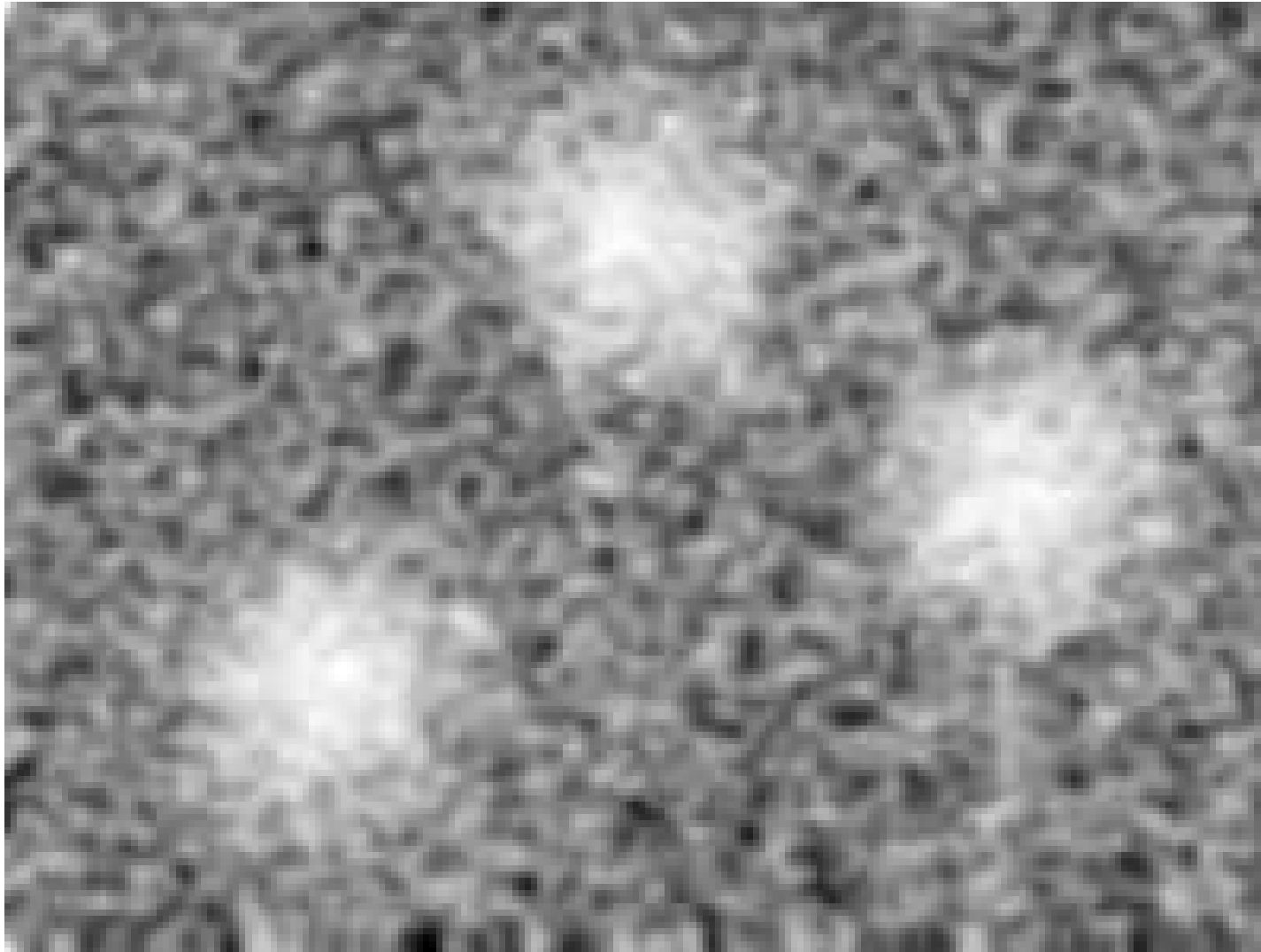
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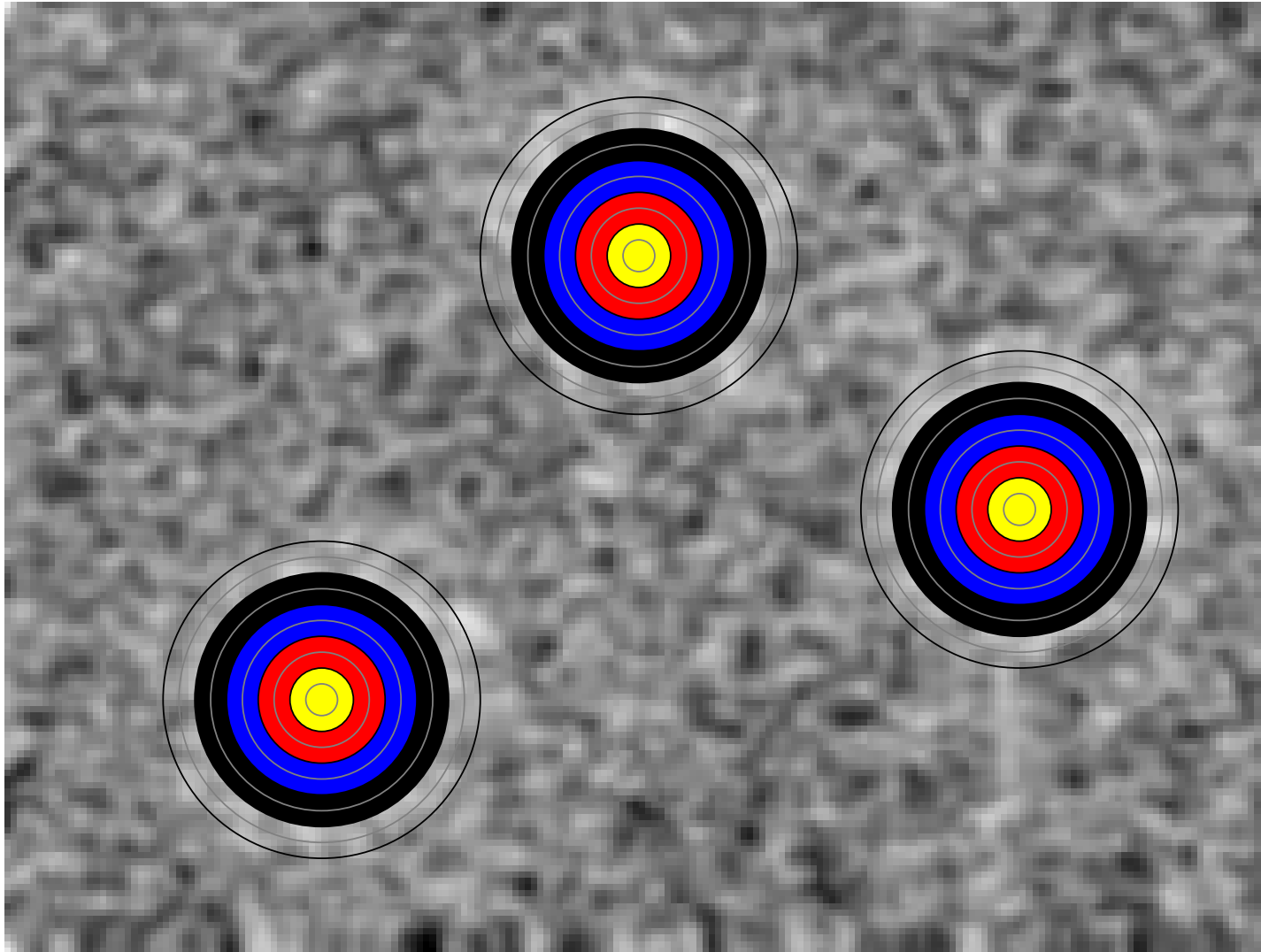
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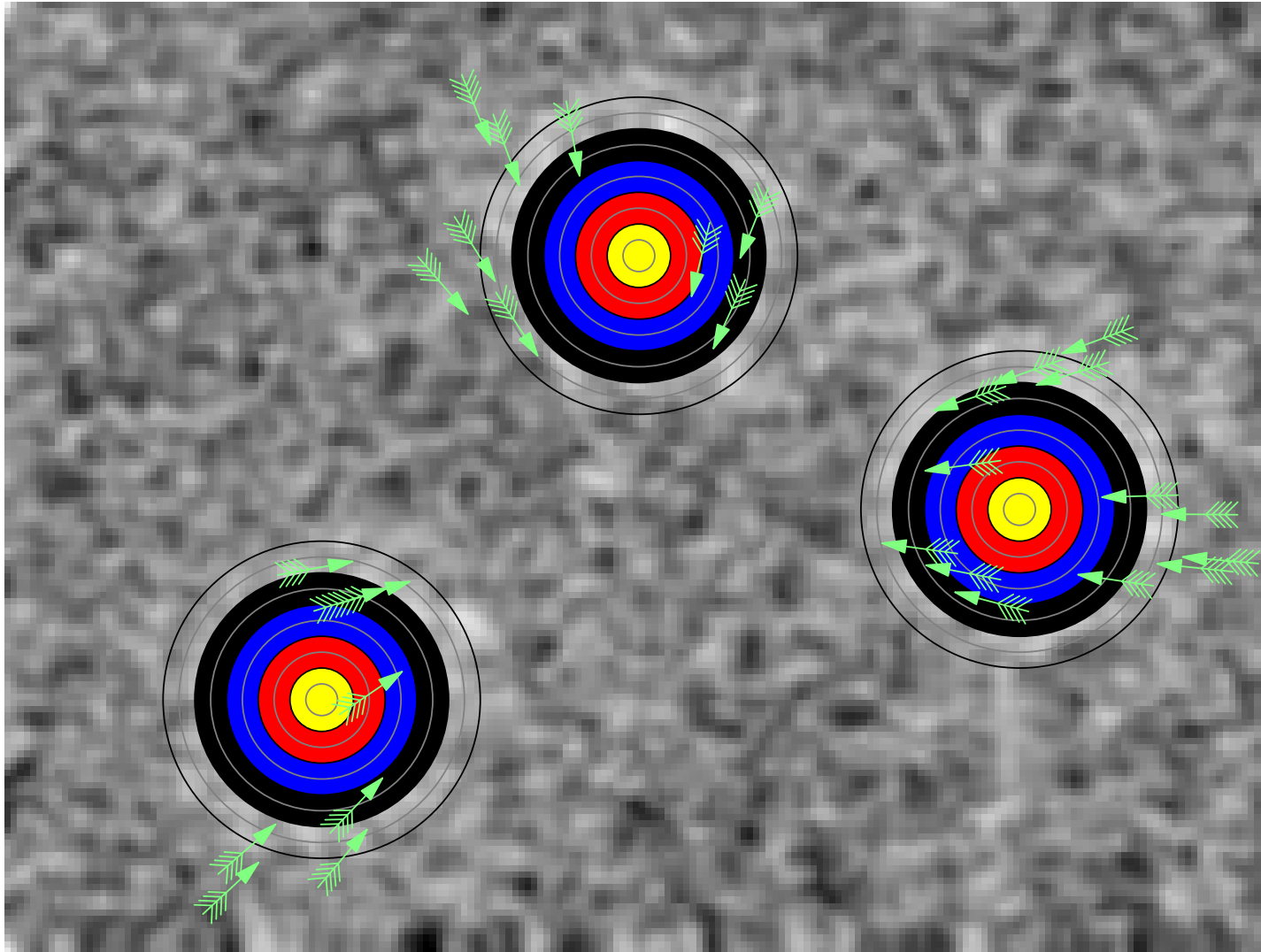
Clusters of Clusters



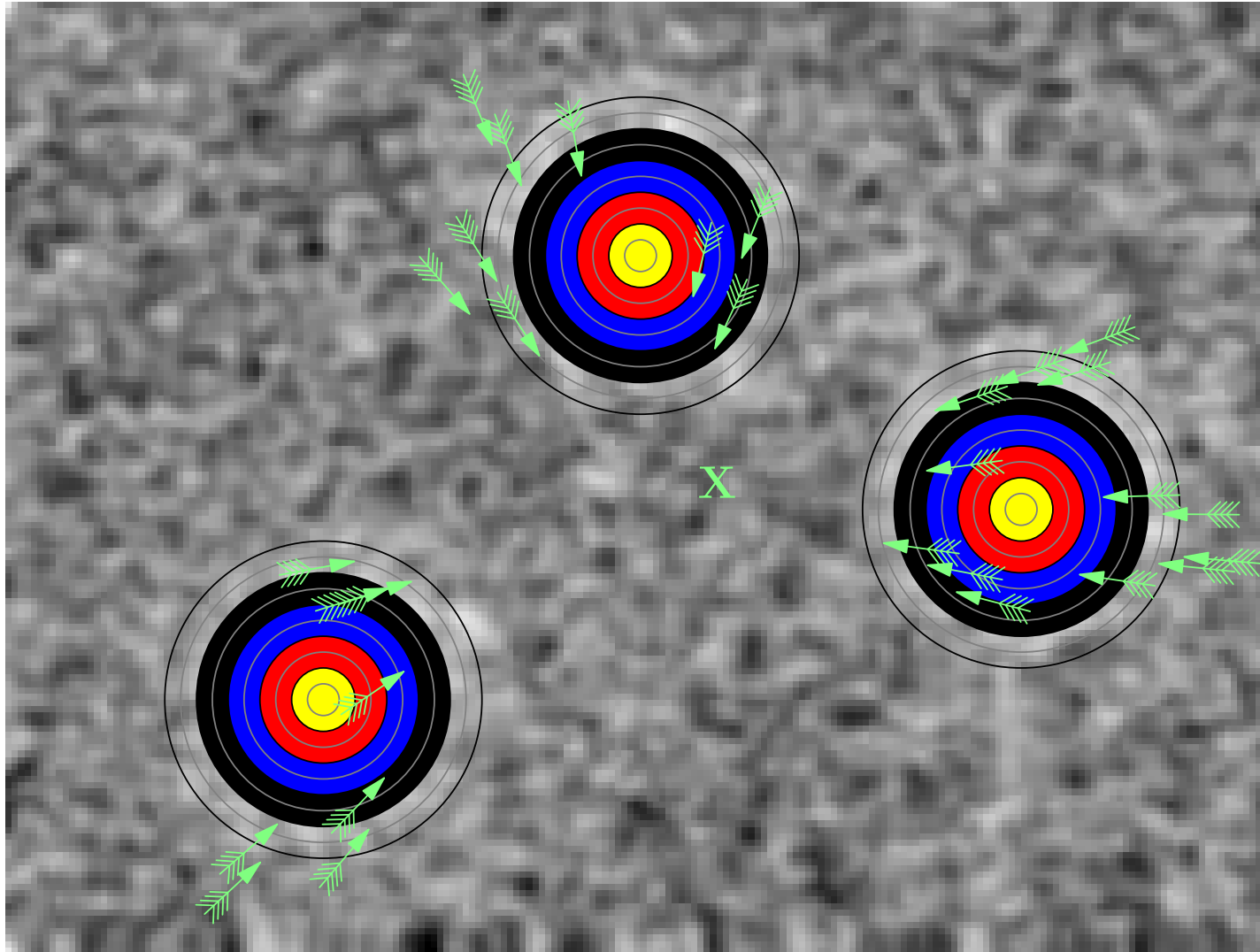
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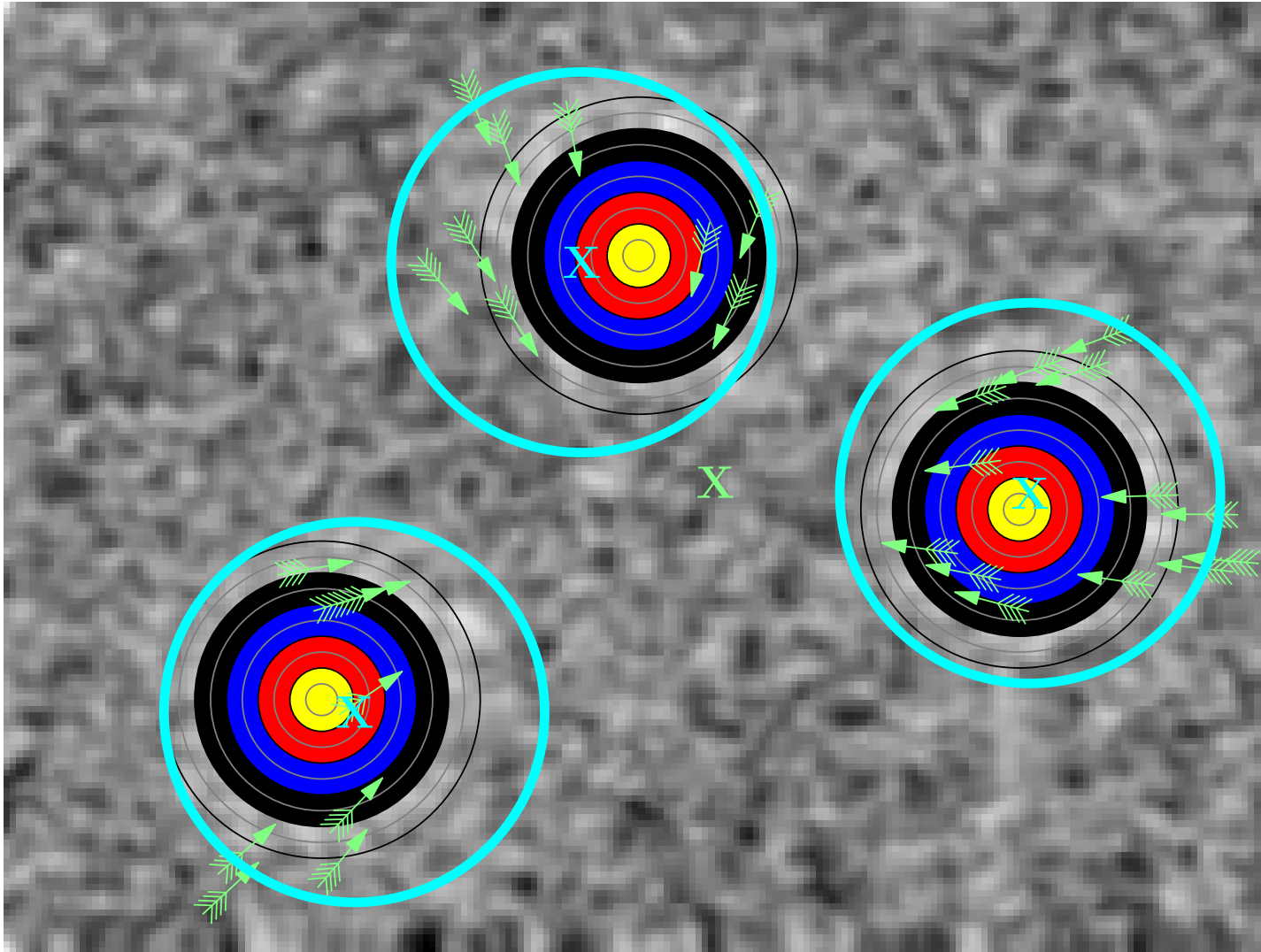
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Doing Better

- Preliminary results show that both averaging and clustering substantially outperforms standard techniques (GSAT and WALKSAT)
- For very large problems k -means clustering begins to outperform averaging alone
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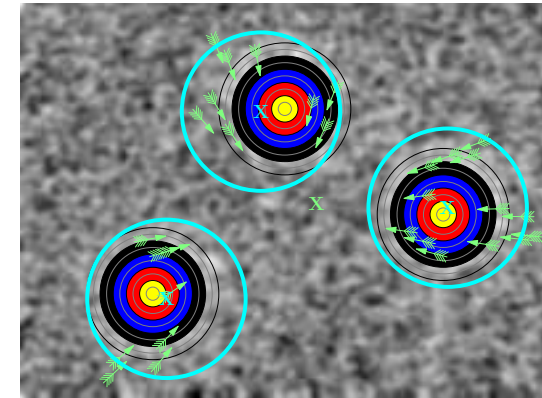
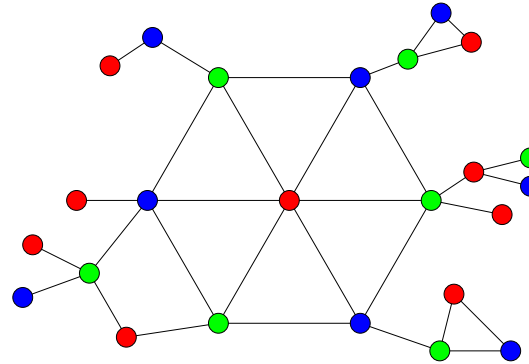
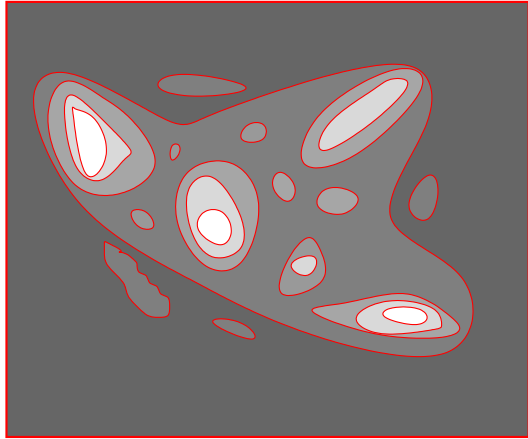
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- We've learnt how to construct such problems, but they have always seemed implausible as models that occur in practice
- A crazy thought is that maybe populations *really* can solve many real-world problems in a way that other heuristics can't

Any Questions?



Population after 50 hill-climbing steps

1	1	1	-1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	-1	-1	-1	-1	20
1	1	1	1	1	1	1	1	1	1	1	1	1	-1	-1	-1	-1	1	1	1	1	1	1	1	1	22
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	-1	-1	22
1	1	1	1	1	1	1	1	1	1	1	1	1	-1	-1	-1	-1	1	1	1	1	1	1	1	1	22
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	24
1	1	1	1	1	1	1	1	1	1	1	1	1	-1	-1	-1	-1	1	1	1	1	1	1	1	1	22
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	24
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	22
1	1	1	1	1	1	1	1	1	1	1	1	1	-1	-1	-1	-1	1	1	1	1	1	1	1	1	22
-1	-1	-1	-1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	18

Binary String

1 -1 1 1 1 1 -1 -1 -1 -1 -1 -1 -1 -1 1 1 1 1 1 1 -1 -1 -1 -1 -2

