







"Challenge Problems"

- 1. Implement the Knapsack problem with the DQM solver
- 2. Implement the Nurse Scheduling Problem with the DQM solver
- 3. Implement the game "Star Battle/Two Not Touch" (Google it)
 - 4. Implement the puzzle "TetraVex" (Google it)
 - 5. Find the famous Andrew Lucas paper https://arxiv.org/abs/1302.5843. Implement one of the NP-hard problems. If you find a D-Wave example for it (for example, graph partitioning), implement it using the DQM solver

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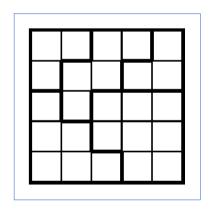


- Lots of fun to play
- Educate players on the power of Quantum Computing
 - □ → create interactive system

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What is Starbattle / Two Not Touch?



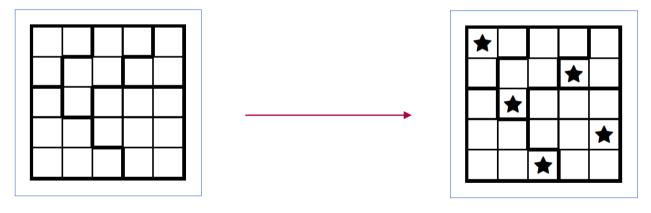


5x5/1★ Normal Star Battle Puzzle ID: 9,053,837

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What is Starbattle / Two Not Touch?





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Playing the game...



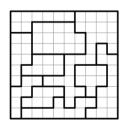
- ... is hard:
 - lots of constraints
 - lots of possiblities
 - advanced strategies limit the search space, but no one strategy

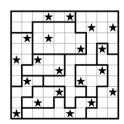


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Advanced Strategies for Two Not Touch Puzzles

A tutorial by Krazydad





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Deciding on a model



- Choice between
 - Binary Quadratic Model (BQM)
 - Discrete Quadratic Model (DQM)

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Deciding on a model



- Choice between
 - Binary Quadratic Model (BQM)
 - Discrete Quadratic Model (DQM)
- Every cell of the board is a boolean variable:
 - 0 = no star
 - $_{\square}$ 1 = star
- → Quadratic Unconstrained Binary Optimization (QUBO)

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Penalize adjacent stars:

x_i	x_j	$E(x_i, x_j)$
0	0	0
0	1	0
1	0	0
1	1	1

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Penalize adjacent stars:

x_i	x_j	$E(x_i, x_j)$
0	0	0
0	1	0
1	0	0
1	1	1

- AND function
- $ax_i + bx_j + cx_ix_j + d = x_ix_j$
- c could be any other positive value \rightarrow 1 is a good value

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Modelling the constraints (2)



- k stars per...
 - 1. ...row
 - 2. ...column
 - 3. ...block
- \rightarrow exactly k of the cells to be chosen

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Let *R* be the set of qubit indices of the selected row, column or block

- \rightarrow QUBO: $(\sum_{i \in R} x_i k)^2$

$$= (\sum_{i \in R} x_i)^2 - 2k(\sum_{i \in R} x_i) + k^2$$

$$= \sum_{i \in R} x_i + \sum_{i,j \in R, i < j} 2x_i x_j - 2k(\sum_{i \in R} x_i) + k^2$$

$$= (1 - 2k) \sum_{i \in R} x_i + \sum_{i,j \in R, i < j} 2x_i x_j + k^2$$

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Implementing the BQM (1)



```
bqm = BinaryQuadraticModel({}, {}, 0.0, BINARY)
# constraint 1: n stars per row
for y, row in enumerate(cells):
    row coords = [(y,x) \text{ for } x, \text{ in enumerate}(row)]
    row bqm = combinations(row coords, num stars)
    bqm.update(row bqm)
```

. . .

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Implementing the BQM (2)



 \bullet n choose k constraints:

dimod.generators.constraints.combinations

 $\textbf{combinations}(n, k, strength=1, vartype=<Vartype.BINARY: frozenset(\{0, 1\})>) \qquad [source]$

Generate a bqm that is minimized when k of n variables are selected.

More fully, we wish to generate a binary quadratic model which is minimized for each of the k-combinations of its variables.

The energy for the binary quadratic model is given by $(\sum_i x_i - k)^2$.

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Implementing the BQM (3)



Coupling between adjacent qubits:

dimod.BinaryQuadraticModel.add_interaction

BinaryQuadraticModel.add_interaction(u, v, bias, vartype=None) [source]

Add an interaction and/or quadratic bias to a binary quadratic model.

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We tried lots of samplers, but LeapHybridSampler performed the best

LeapHybridSampler

class LeapHybridSampler(solver=None, connection_close=True, **config) [source]

A class for using Leap's cloud-based hybrid BQM solvers.

Leap's quantum-classical hybrid BQM solvers are intended to solve arbitrary application problems formulated as binary quadratic models (BQM).

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Sampling the BQM (2)



- 3 puzzle categories (KrazyDad):
 - Easy (8x8, 1☆)
 - Medium (10x10, 2☆)
 - Hard (14x14, 3☆)
- 100% valid samples on Easy & Medium
- Samples on Hard are not always valid

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Sampling the BQM (2)



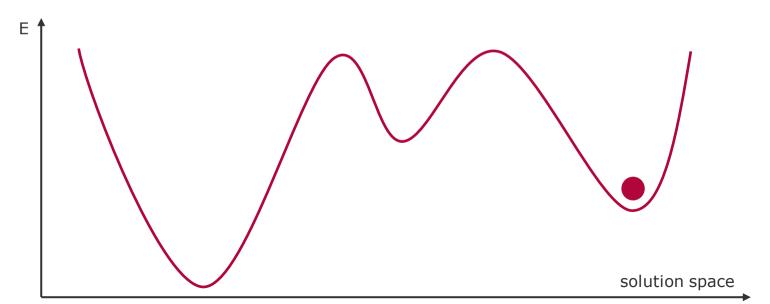
- 3 puzzle categories (KrazyDad):
 - Easy (8x8, 1☆)
 - Medium (10x10, 2☆)
 - □ Hard (14x14, 3☆)
- 100% valid samples on Easy & Medium
- Samples on Hard are not always valid
 - □ ~ 90% of samples are valid

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- Why might the BQM be inaccurate on big problems?
 - > Lots of local minima that are far away from the optimal solution
- Energy landscape:



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User Interface: game files (1)



Puzzles are stored in text files, repository contains examples

1

0 0 0 1 2 2 2 2

00012222

00011222

1 1 1 1 1 2 3 2

4 1 1 1 3 2 3 2

4 4 4 1 3 3 3 5

4 4 4 1 3 6 6 6

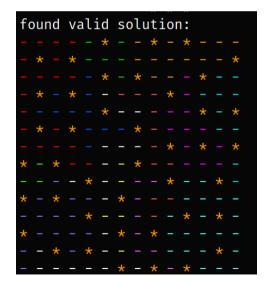
4 7 7 3 3 3 6 6

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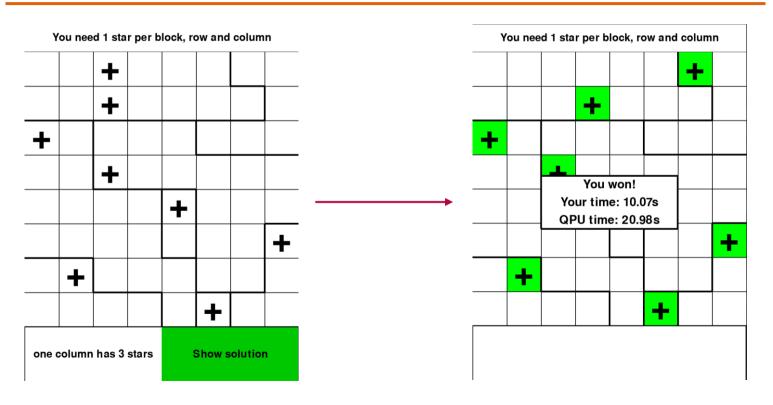
```
$ python main.py solve games/hard/hard-1.txt
puzzle (3☆):
```



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User Interface: play (3)





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Live Demo



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