

ЕВРОПЕЙСКИ СЪЮЗ ЕВРОПЕЙСКИ ФОНД ЗА РЕГИОНАЛНО РАЗВИТИЕ



оперативна програма НАУКА И ОБРАЗОВАНИЕ ЗА ИНТЕЛИГЕНТЕН РАСТЕЖ

Using machine learning for quantum annealing accuracy prediction

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ЦЕНТЪР ЗА ВЪРХОВИ ПОСТИЖЕНИЯ ПО ИНФОРМАТИКА И ИНФОРМАЦИОННИ И КОМУНИКАЦИОННИ ТЕХНОЛОГИИ

Problem statement

- Quantum annealing introduction
- Motivation and objectives
- Methods
 - Machine learning model
 - Implementation
- Results
 - Prediction accuracy analysis



Problem statement



Background: quantum annealing

Quantum annealing background

 Quantum annealing (QA) uses quantum effects to find good quality solutions to Ising (QUBO) problems of the type

minimize
$$Q(x_1, \dots, x_n) = \sum_{i=1}^n \sum_{j=i+1}^n J_{ij} x_i x_j + \sum_{i=1}^n h_i x_i, \quad x_i \in \{-1, 1\}$$

(or $x_i \in \{0, 1\}$),

by mapping them to the Quantum Processing Unit, which seeks a minimum-energy quantum state that corresponds to a minimum value of function Q.

- Many NP-hard problems can be easily formulated as QUBOs
 - Maximum clique, graph coloring, minimum vertex cover, maximum cut, knapsack, traveling salesman, graph partitioning, Boolean satisfiability (SAT), ...



D-Wave quantum annealers



- D-Wave is a commercially available quantum annealer that solves optimization problems using the following steps:
 - Original problem formulated as a QUBO (or Ising);
 - QUBO mapped to D-Wave's hardware;
 - D-Wave performs a number of anneals and measures the qubits;
 - Results retrieved from D-Wave and transformed into a <u>solution</u> of the original problem.

How good is such a solution?



- DW returns a solution with low value (energy), but not necessarily the best.
- Quality depends on the problem's coefficients, annealing parameters, and the current state of the machine.
- There is no known method that can be used to determine how hard a particular problem will be for DW.

Our goal: use machine learning to predict problem's difficulty.

- This may help to
 - Allocate more resources (time) for solving harder problems;
 - Choose a (re)formulation that makes the problem easier for DW.



Methods



- Training set consists of random graphs of various densities.
- Problem solved is the Maximum Clique problem: find a *clique* (a set of maximally connected vertices) of maximum size, an NP-hard problem.
- Features include graph density, vertex degrees, # of triangles, eigenvalues, and annealing parameters.
- Two types of objective:
 - Can the problem be solved to optimality?
 - What is the size of the clique returned by D-Wave?
- Machine learning package used: *scikit-learn*.



In a loop:

- Generate a random graph *G*;
- Compute QUBO coefficients matrix M for solving G;
- Get ML model <u>feature</u> vector *F*:
 - Get features using G, M, and D-Wave parameters;
- Get value *v* of ML target:
 - Use a classical solver to compute an optimal solution opt;
 - Send *M* to quantum annealer to get a solution *sol*;
 - Compare sol to opt to get v ∈ {yes, no}, for the classification version, or v = sol for the regression;
- Add features+target vector (F, v) to training/testing set.







Results: Is the problem solvable to optimality on DW?

Prediction results:

		Predicted	
		Not solvable	Solvable
Actual	Not solvable	3458	654
	Solvable	97	497

Accuracy: 0.84, Precision: 0.84, Recall (Sensitivity): 0.43

Decision tree for classification:



Results: What clique size is returned by DW?

Prediction results:





Summary

- Predicting the outcome of quantum annealing is hard.
- Can be useful for estimating what resources to allocate for a particular problem.
- Machine learning works reasonably well (for the case of the maximum clique problem).
- Future work may target other optimization problems.

More details can be found in the paper:

A. Barbosa, E. Pelofske, G. Hahn and H. Djidjev, "Using machine learning for quantum annealing accuracy prediction," *Algorithms*, 14 (6), 187, 2021.

