TENSOR-TRAIN UNSUPERVISED IMAGE SEGMENTATION

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ABSTRACT

We propose TT-Seg, an unsupervised image segmentation framework that employs Tensor Train (TT) decomposition and probabilistic tensor sampling to optimize Quadratic Unconstrained Binary Optimization (QUBO) problems. TT-Seg achieves segmentation performance comparable to classical solvers while offering enhanced scalability. Experimental results indicate that the TT-based approach performs effectively on small-scale problems, although for larger QUBO instances, leading solvers such as Gurobi and the D-Wave hybrid solver remain superior.

1 INTRODUCTION

Image segmentation, a core problem in computer vision, can be formulated as an NP-hard minimum cut problem via QUBO Heidari et al. (2024); Benkner et al. (2021); Choong et al. (2023). Although quantum annealing methods like Q-Seg Venkatesh et al. (2024) leverage D-Wave hardware to tackle these problems, practical limitations restrict their widespread use Salloum et al. (2024; 2025); Salloum et al.. In contrast, TT-Seg utilizes Tensor Train decomposition Oseledets (2011) to efficiently represent the solution space and employs probabilistic sampling to search for optimal segmentations without relying on specialized quantum hardware. This approach offers competitive performance in small-scale settings and highlights the potential of tensor networks—exemplified by methods such as PROTES—in addressing high-dimensional combinatorial optimization challenges Batsheva et al. (2023); Ryzhakov et al. (2024).

2 METHODS

2.1 GRAPH REPRESENTATION AND PROBLEM FORMULATION

Similar to Q-Seg, TT-Seg represents an image as a graph, where pixels correspond to nodes and edges encode similarity between adjacent pixels. The segmentation task is formulated as a minimum cut problem, which is then expressed in QUBO form:

$$\min_{x \in 0,1^n} x^T Q x, \tag{1}$$

where Q encodes pixel similarity weights.

2.2 TENSOR-TRAIN PROBABILISTIC OPTIMIZATION

TT-Seg replaces quantum annealing for QUBO problems with a tensor-based probabilistic method inspired by the PROTES algorithm Batsheva et al. (2023). Here, the $n \times n$ QUBO matrix is reshaped into a d-dimensional tensor $Q \in \mathbb{R}^{m_1 \times \cdots \times m_d}$ (with $d \ll n$) to capture hierarchical interactions. We employ TT decomposition to approximate the probability distribution:

$$P(\mathbf{x}) \approx \prod_{k=1}^{d} G_k(x_k), \quad G_k \in \mathbb{R}^{r_{k-1} \times m_k \times r_k}, \tag{2}$$

thereby reducing the parameter complexity from $O(m^d)$ to $O(dmr^2)$ and enabling efficient sequential sampling via conditional distributions.

The optimization process alternates between:

1. **Exploration**: Drawing samples through matrix product state traversal to identify high-probability regions.
2. **Exploitation**: Evaluating QUBO energies and updating TT cores via gradient ascent on the log-likelihood of the best samples.

This approach effectively balances global exploration and local refinement, offering enhanced scalability over both simulated and quantum annealing. The TT format's linear memory scaling permits high-resolution problem handling on standard GPUs, with efficient parallel tensor contractions.

3 Experimental Results and Analysis

We evaluate TT-Seg on synthetic datasets and real-world remote sensing images the same in the work Venkatesh et al. (2024), comparing its performance against classical solvers such as Gurobi. Key metrics include segmentation accuracy, runtime, and scalability. The results in Table 1 clearly demonstrate that Gurobi and Q-Seg outperform TT-Seg, particularly as the problem size increases. TT-Seg failed in large-scale instances. However, in small-scale instances, TT-Seg produced better solutions than the D-Wave solver and achieved results close to the optimal QUBO values.

Nodes	**TT-Seg**		**Gurobi**		**Q-Seg**	
	Time (s)	**Value**	**Time (s)**	**Value**	**Time (s)**	**Value**
5	2.56	**-0.79**	**0.06**	−0.78	4.29	−0.78
25	2.07	**-9.26**	**0.07**	**-9.26**	4.84	−9.18
100	2.57	−35.87	**0.51**	**-38.65**	4.68	**-38.65**
256	3.89	**-75.64**	**3.30**	−103.16	11.01	−101.54
361	**5.65**	−87.87	7.07	**-139.78**	7.95	−137.01
576	**10.07**	−103.93	25.54	**-228.82**	19.02	−221.02
841	**23.31**	−106.17	40.22	**-310.00**	23.96	−292.05
1089	43.90	−132.21	53.64	**-413.56**	**37.50**	−395.93
1521	**54.71**	−158.77	108.22	**-580.49**	132.82	−555.68
1681	69.45	−178.46	127.42	**-645.82**	**37.66**	−608.11
1936	125.44	−186.59	184.27	**-748.45**	**39.28**	−715.93

Table 1: Performance comparison between TT-Seg, Gurobi, and Annealer solver. TT-Seg maintains consistent solve times while Gurobi and Annealer behave similarly on larger instances. All times in seconds.

4 Conclusion

We introduced TT-Seg, an unsupervised image segmentation application that employs a probabilistic tensor-based sampling method to eliminate the reliance on quantum annealing. Although TT-Seg requires further improvements for scalability, our results indicate that while Gurobi and Q-Seg outperform TT-Seg in large-scale instances, TT-Seg achieves competitive performance in small-scale scenarios by surpassing the D-Wave solver and approaching optimal QUBO values.

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