Quantum-Classical Sentiment Analysis

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Goal

Testing the effectiveness of quantum computation on machine learning tasks

Using the QPU extensively while avoiding the closed source alternatives of D-Wave

Quantum Annealing

QA is an optimization process for finding the global minimum of a given objective function over a given set of candidate solutions.

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Sentiment Analysis
SA is the use of natural language processing to systematically identify, extract, quantify, and study affective states and subjective information.

Applying Quantum Annealing to Sentiment Analysis

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Goal of Machine Learning
Minimizing a loss function.

Using Quantum Annealing for Sentiment Analysis

From Machine Learning to Quantum Annealing

Model Selection

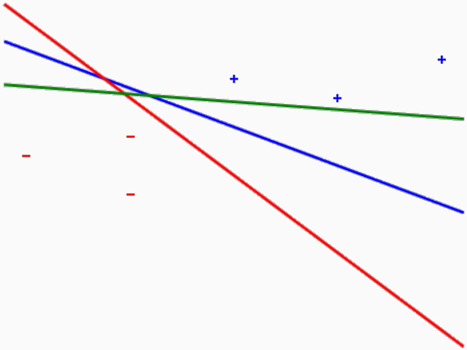
↓

Reduction to Minimization of Quadratic Programming

↓

Solve with D-Wave Hybrid Solver

Support Vector Machine

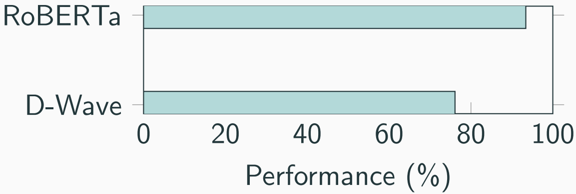


Why using SVM?

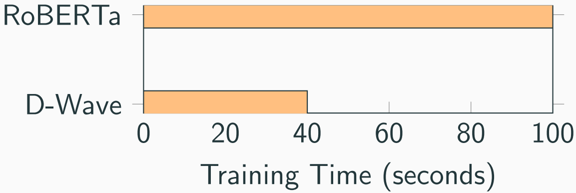
- Machine learning model for binary classification
- Native formulation as quadratic programming problem

Binary Sentiment Analysis Results

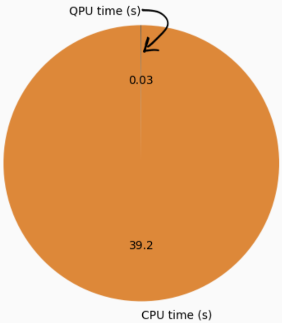
D-Wave is worse than RoBERTa



D-Wave converges in only 40s



Usage of QPU to Obtain the Above BSA



- Only 0.08% of the time is spent on the QPU
- The performance boost should comes from quantum annealing
- Is it possible to increase the QPU usage?
- Is it possible to avoid the closed-source procedures of D-Wave?

Increase QPU usage

From Quadratic Programming to QUBO

Quadratic Programming Problem

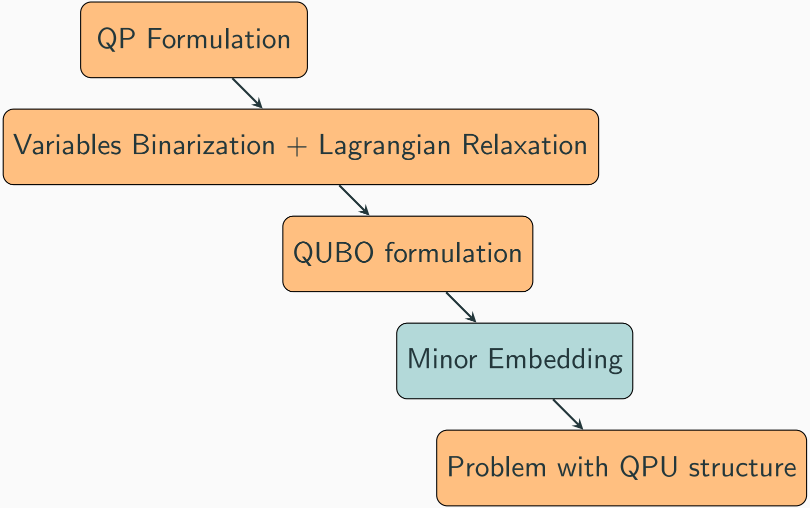
$$
\begin{aligned}
\min_{x} \quad & \frac{1}{2} x^T Q x + c^T x \\
\text{s.t.} \quad & Ax \preceq b \\
& x_i \in \mathbb{R}, \forall i
\end{aligned}
$$

$$\Longrightarrow$$

QUBO Problem

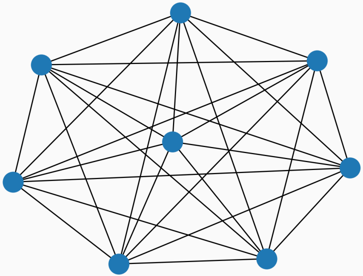
$$
\begin{aligned}
\min_{x} \quad & x^T Q x \\
& x_i \in \{0, 1\}, \forall i
\end{aligned}
$$

From Quadratic Problem to QPU

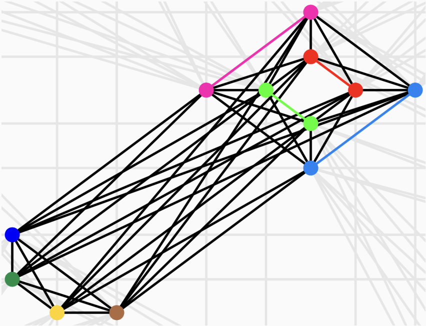


From Quadratic Problem to QPU

SVM graph for 8 variables $\Longrightarrow$ Mapped problem on Pegasus QPU

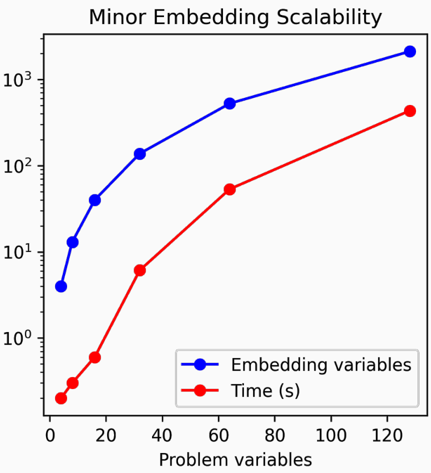


$\Longrightarrow$



Pegasus QPU is not enough

For SVMs with 128 binary variables, the QPU is almost completely used



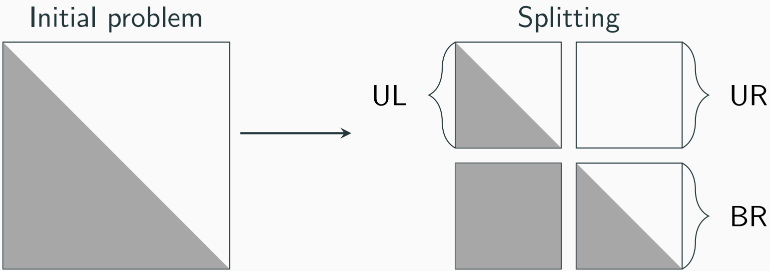
QUBO Formulation

The QPU process directly problems in QUBO form:

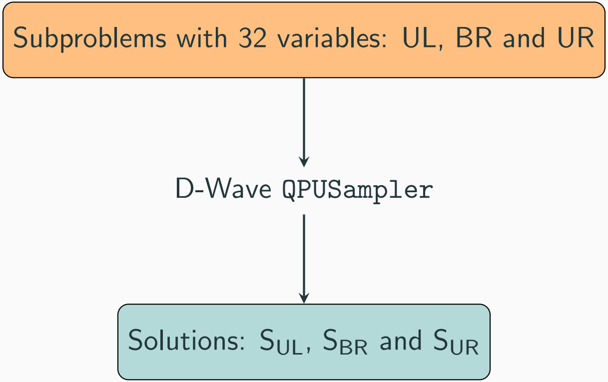
$$\min_{x} \quad x^T Q x$$
$$x_i \in \{0, 1\}, \forall i$$

Example with 4 binary variables:

$$\begin{bmatrix} x_1 & x_2 & x_3 & x_4 \end{bmatrix} \begin{bmatrix} -3 & 5 & 1 & -7 \\ 0 & 1 & 0 & 8 \\ 0 & 0 & 9 & -4 \\ 0 & 0 & 0 & -2 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix}$$

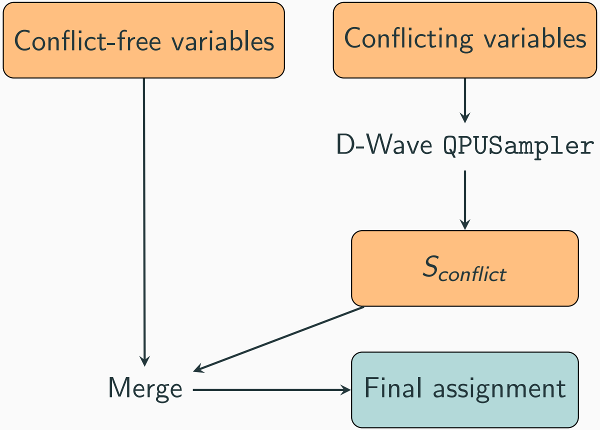

Initial problem
Splitting
UL
UR
BR

QSplitSampler - Solving Subproblems



QSplitSampler - **Aggregate Solutions**

Aggregating S_{UL}, S_{BR} and S_{UR} gives two sets of variables



QSplitSampler Results

	QSplitSampler		QPUSampler	
Cut Dim	Classical time	QPU time	Classical time	QPU time
2	470.71	0.45	142.54	0.02
4	223	0.35	116.02	0.02
8	94.97	0.25	271.36	0.02
16	68.33	0.17	190.29	0.02
32	48.46	0.1	207.86	0.02

Table 1: Results for randomly generated QUBO problems with 128 variables

Conclusion

Using only the **free version** of the D-Wave solvers, we showed:

- How hybrid solvers can be used for real problems
- How closed source infrastructure can be avoided
- How the use of QPU can be increased

Thanks for your attention