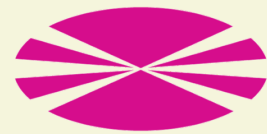


Hyperspectral Image Segmentation Using Quantum Annealing



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Classical Computing vs Quantum Computing

Unit of information

Bits

- Binary
- Deterministic
- Relatively stable
- Boolean logic
→ Logic Gates

Qubits

- Superposition
- Entanglement
- Decoherence / Extreme sensitivity
- Quantum measurement
→ Quantum Gates

Advantages & Limits

Classical Computing

- **Advantages :**
 - Reliability
 - Accuracy
 - Cost-effectiveness
- **Limits :**
 - Transistor density in Integrated Circuits (IC)
 - Moore's law
 - Exponential time complexity
 - NP-Hard problems
 - Simulation of large-scale quantum systems
 - Richard Feynman : "Nature isn't classical"

Quantum Computing

- **Advantages :**
 - Exponential speedup for certain problems
 - Shor's algorithm, Grover's algorithm
 - Large-scale memory capacity
 - Superposition of states represents large number of values simultaneously
 - Efficient simulation of real-world systems
 - Based on Quantum Mechanics
- **Limits :**
 - Decoherence
 - Error correction
 - Scalability

Quantum Annealers

Quantum

- Qubits
- Superposition
- Entanglement
- Interference

Annealing

- Probabilistic
- Randomness
- Exploration vs Exploitation
- Temperature schedule

Hyperspectral Image Segmentation

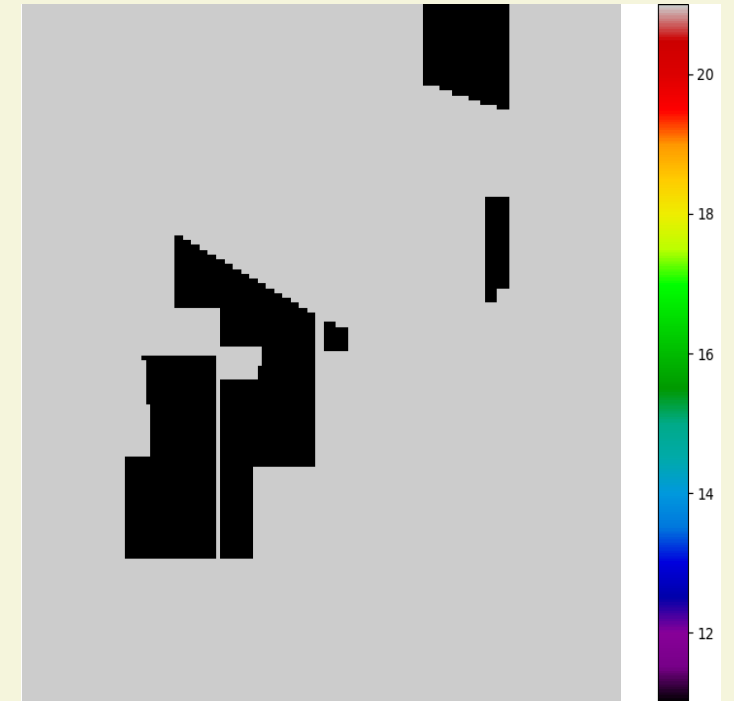
Using Quantum Annealing

Indian Pines Dataset

- 145*145 pixels.
- 200 spectral reflectance bands (for the corrected version).
- Wavelength range : 400nm - 2500nm.
- One-vs-Rest Classification Algorithm.



Indian pines Dataset : Sample



Ground state : Target Class N°11

Step 1

Choose a Classifier

Support Vector Machine SVM

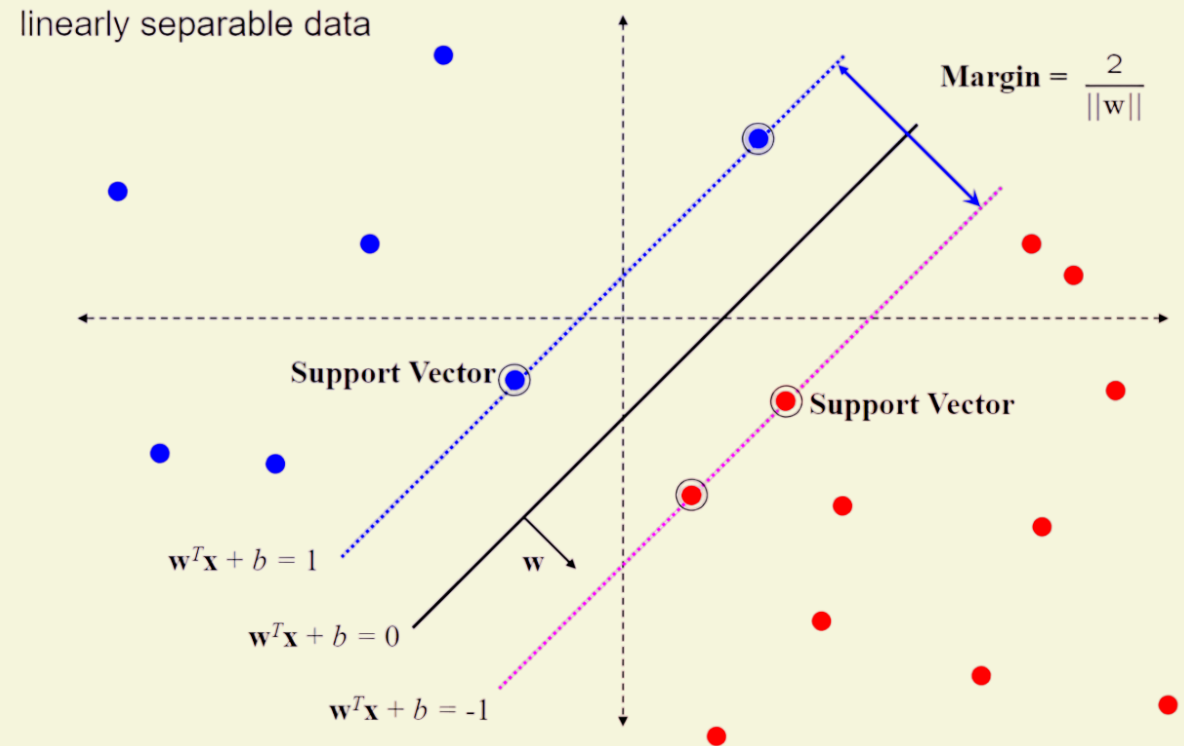
$$f(x) = w^T x + b$$

Given training data (x_i, y_i) for $i = 1 \dots N$, with
 $x_i \in \mathbb{R}^d$ and $y_i \in \{-1, 1\}$,
learn a classifier $f(x)$ such that :

$$f(x_i) = \begin{cases} \geq 0 & \text{if } y_i = +1 \\ < 0 & \text{if } y_i = -1 \end{cases}$$

i.e. $y_i f(x_i) > 0$ for a correct classification.

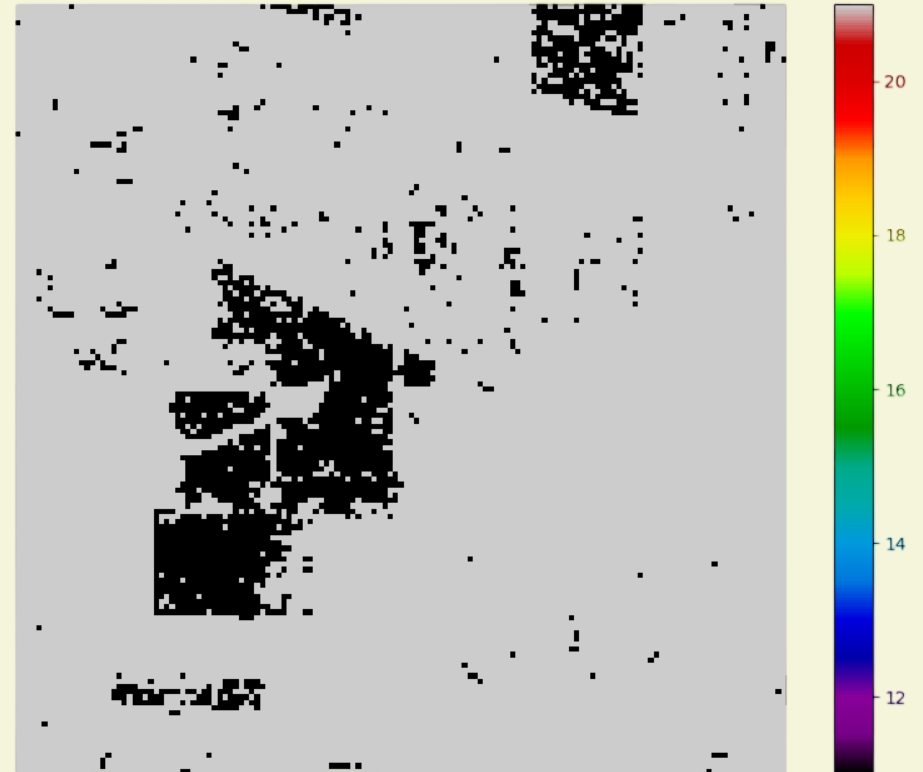
**Trade off between the margin and the number
of mistakes on the training data !**



Result

- SVM.
- Parameters (GridSearchCV):

```
SVC(C=100, cache_size=1024, kernel="poly", probability=True)
```

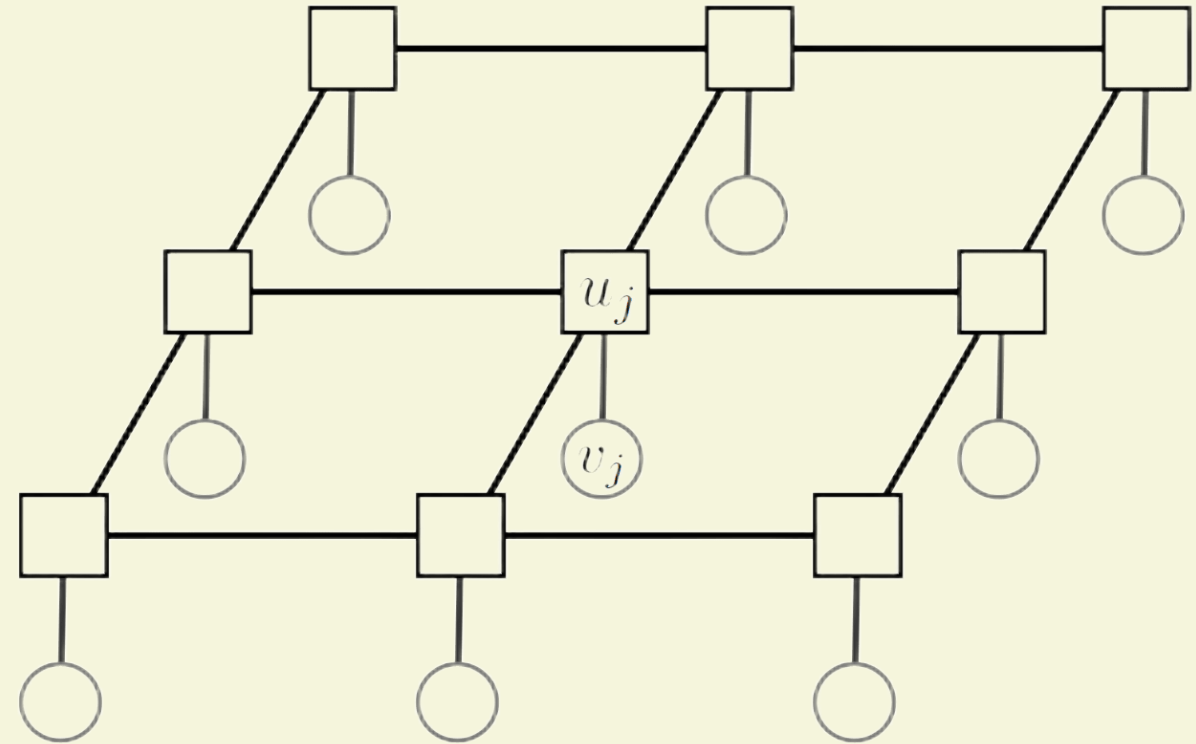


Step 2

Construct the adapted model for the problem formulation

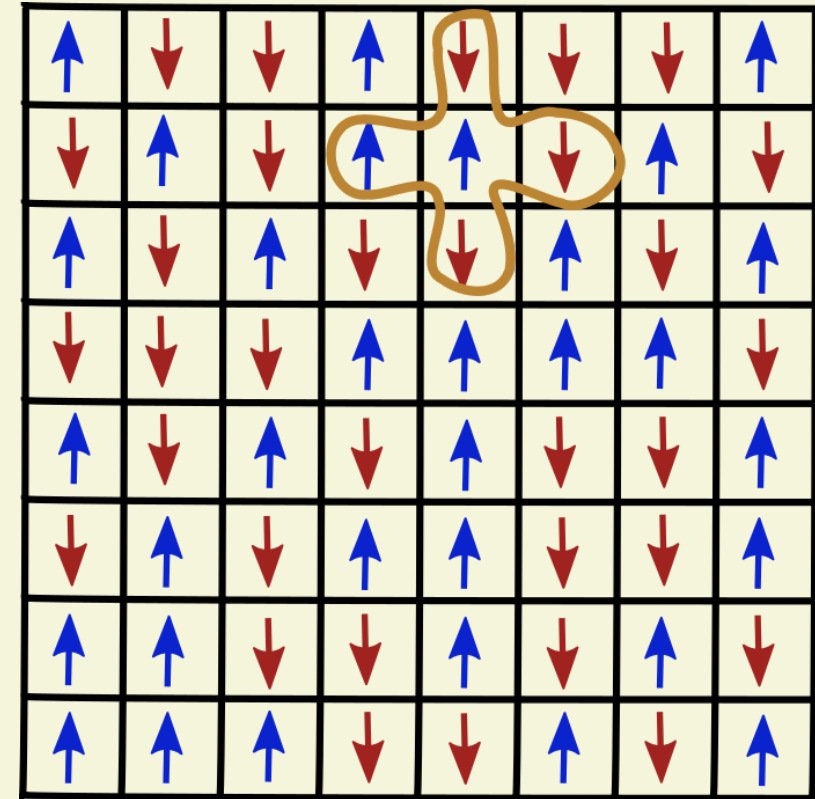
Markov Random Fields

- Undirected graph $G = (V, E)$.
- Nodes V :
 - Discrete or Gaussian Probability distribution of Random Variables RV : $\{u_j\}_{j \in V}$.
- Edges E :
 - Binary edges.
 - Strength of the dependence between both variables.
- Given N_i Markov blanket of Node i (Neighborhood) : $\forall i \in 1, 2, \dots, N$:
$$p(u_i | \{u_j\}_{j \in V - i}) = p(u_i | \{u_j\}_{j \in N_i})$$
- Energy expression :
$$E(u) = E_{data}(u) + E_{smoothness}(u)$$



Ising model

- Originated from Statistical Physics (Ferromagnetism).
- Hamiltonian :
$$\rightarrow H(s) = - \sum_i h_i * s_i - \beta \sum_{i \sim j} s_i * s_j$$
- Parameters :
 - s : Spin configuration.
 - s_i : Pixel index i of the image (as a 1D vector).
 - h_i : Likelihood / Energy of being in a particular class.
$$\rightarrow h_i = -1/4 \log(1/P_i(c) - 1)$$
 - β : How strongly its neighbors wants it to be in their class (magnetic moment).
$$\rightarrow \beta = 1$$



Result

- Classical Simulated Annealing.
- Metropolis-Hastings algorithm:
 - State transition probability : $e^{-\delta E / T}$
- Parameters:
 - temperature: $4 \rightarrow 0.5$
 - beta: 0.5

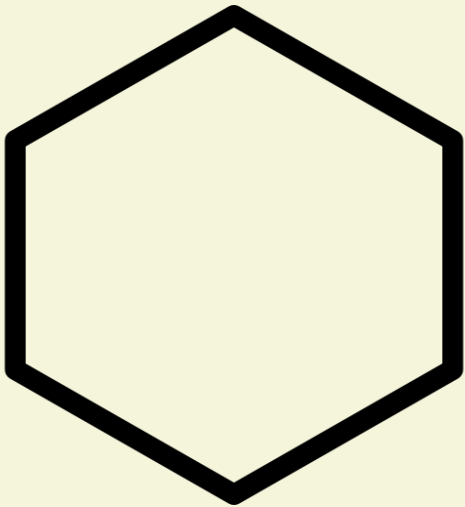


Step 3

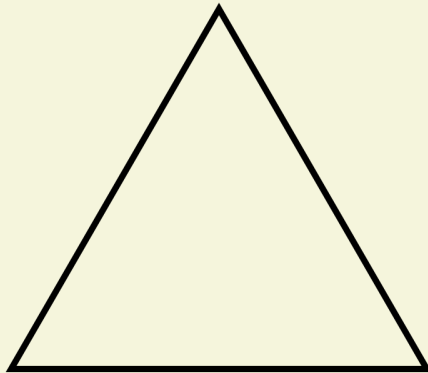
Embed the model into the Quantum Annealer

Embedding

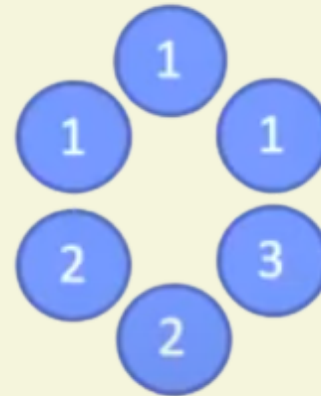
Host graph



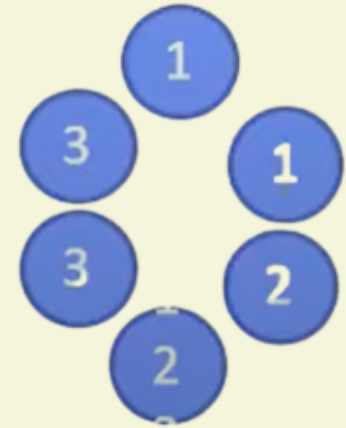
Problem graph



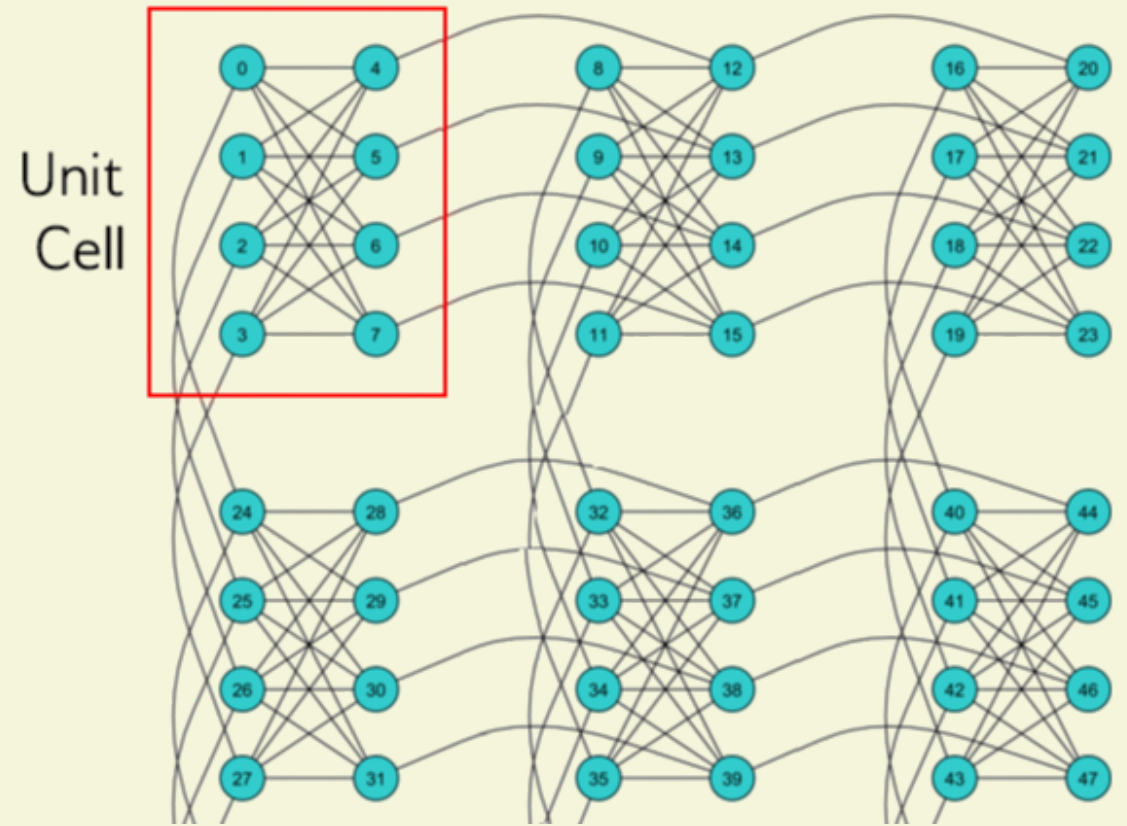
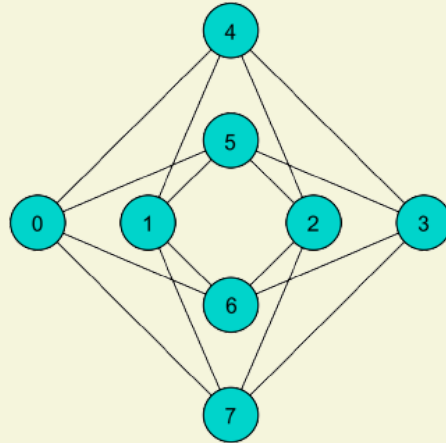
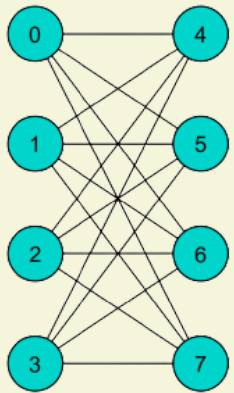
Embedding N°1



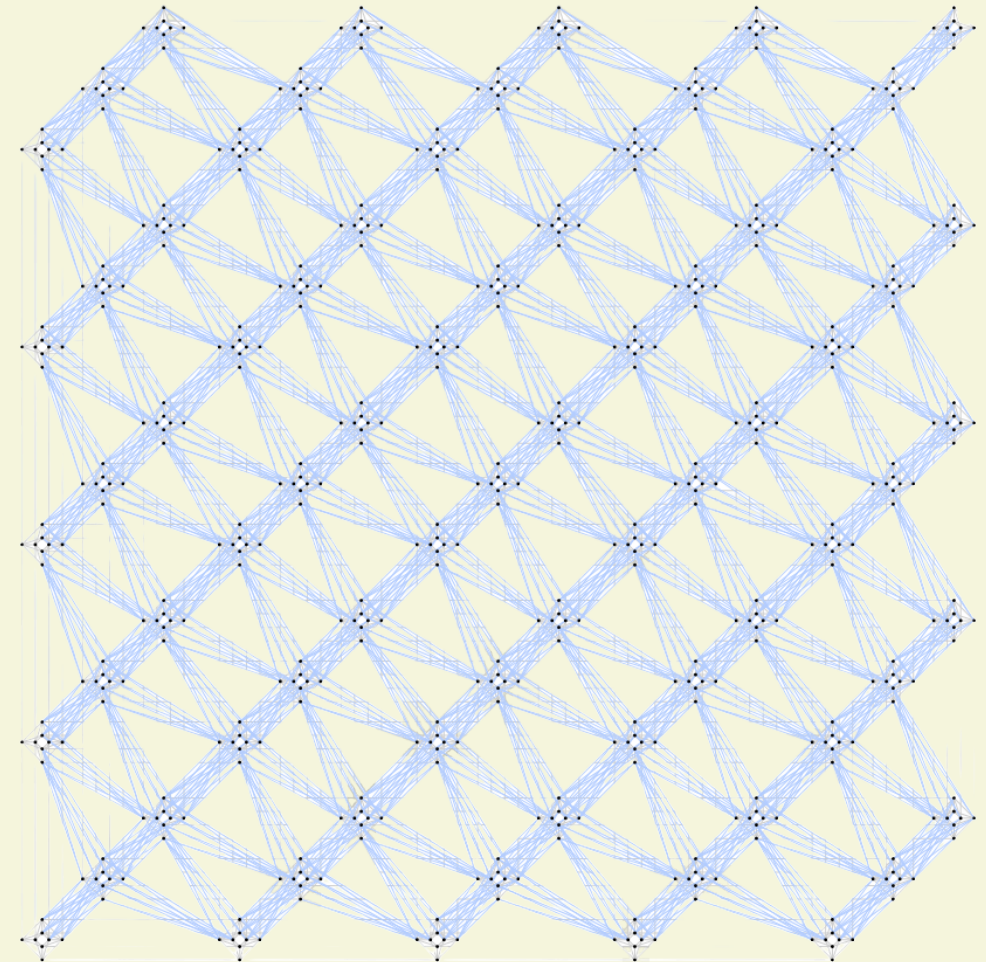
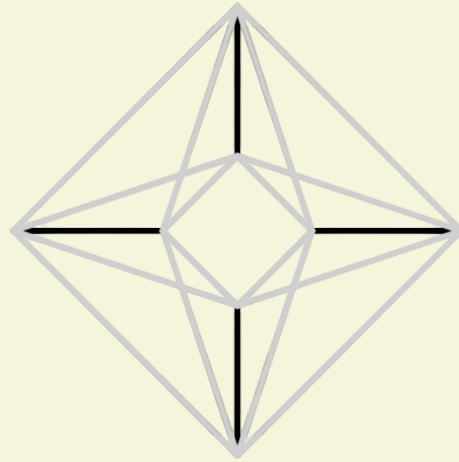
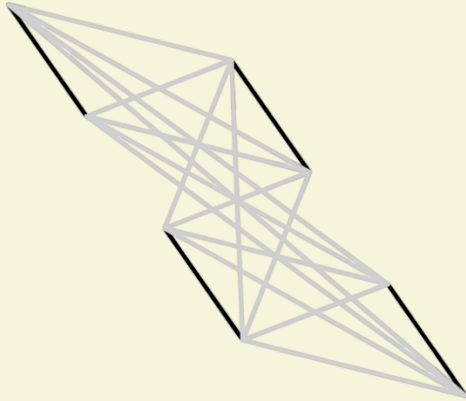
Embedding N°2



Chimera Graph

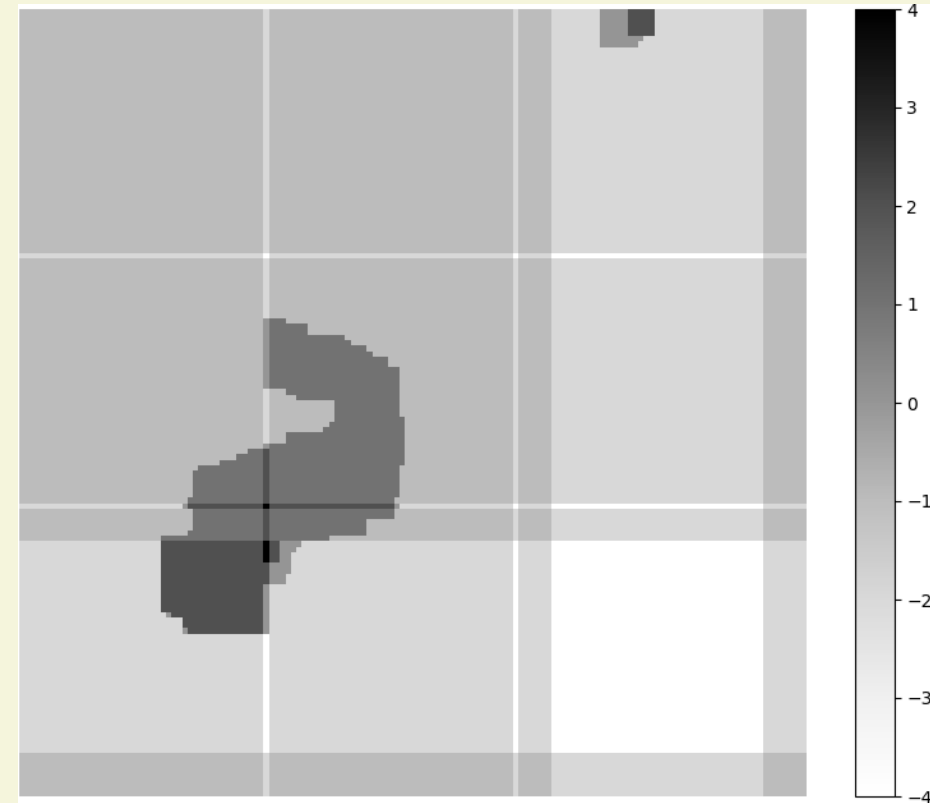


Pegasus Graph



Result

- Quantum Annealing
 - Patches: 16 * (47, 47, 2)
 - Default "minorminer" embedding algorithm.
- Parameters :
 - beta: 0.5
 - num_reads: 100



Thank you!

Appendix

One-vs-Rest Classification Algorithm

1. Normalize the data.
2. For each class $c \in C$:
 - 2.1 Split X_{train} into classes: $c, \neg c$ (not c).
 - 2.2 Train a binary SVM using X_{train} and y_{train} .
 - 2.3 Calculate probabilities $P_i(c), P_i(\neg c)$ of i -th pixel from X having/not having class c .
 - 2.4 Calculate **local energy**: $h_i = -1/4 \log(1/P_i(c) - 1)$.
 - 2.5 Build **Ising model**: $H(s) = -\sum_i h_i * s_i - \beta * \sum_{i \sim j} s_i * s_j$.
 - 2.6 Embed grid model into **chimera graph**.
 - 2.7 Sample $K = 10$ low energy states samples using DWave annealer.
 - 2.8 Unembed the model back to grid.
 - 2.9 For each pixel i : $P'_i(c) = \sum_{k=1}^K \frac{1}{\sum_{\xi=1}^K \exp(-H(s^{[\xi]})) + H(s^{[k]})} \times \delta(s_i^{[k]} = 1)$, where $s^{[k]}$ is a configuration and $H(s^{[k]})$ is energy of sample k .
3. For each pixel i assign class c_i^* : $c_i^* = \operatorname{argmax}_{c \in C} P'_i(c)$.