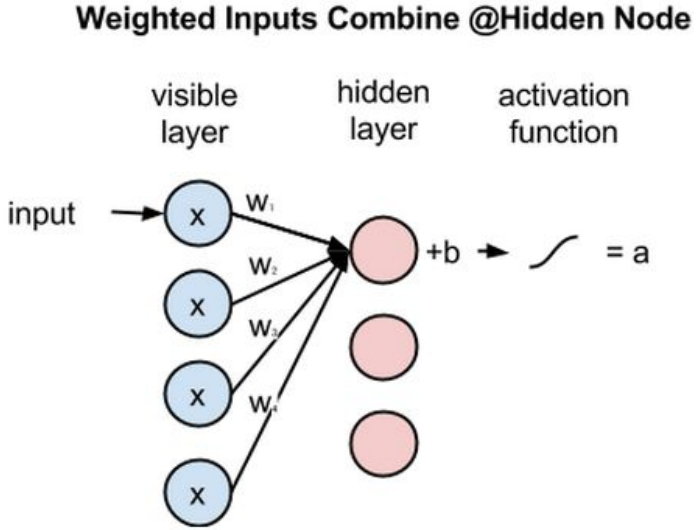
Real data

Quantum enhanced data generation

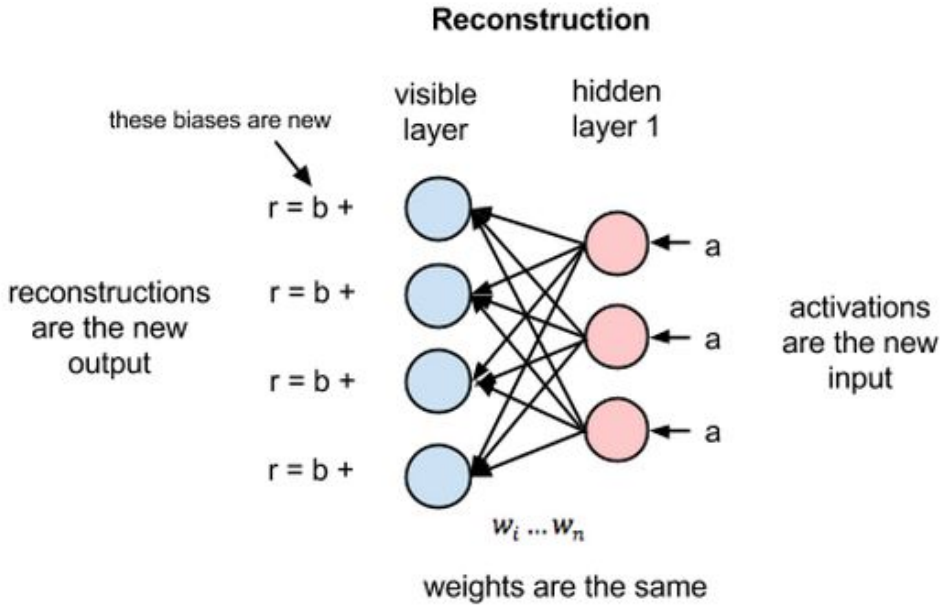
1. Boltzmann Machines. QRBM

Artificial data

0. Restricted Boltzmann machines



0. Restricted Boltzmann machines



0. Restricted Boltzmann machines training

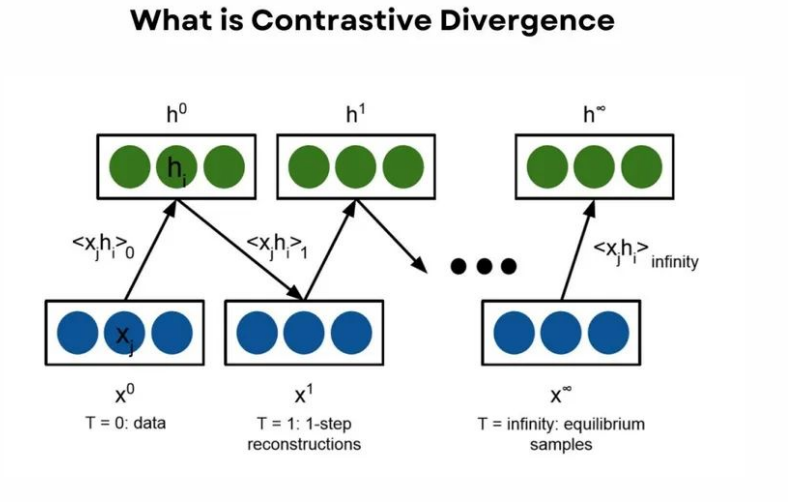
“RBMs are usually trained using the **contrastive divergence learning procedure”.**

- Hinton, G. E. (2012). A practical guide to training restricted boltzmann machines. Lecture Notes in Computer Science, 599–619. https://doi.org/10.1007/978-3-642-35289-8_32

See a summary of this guide:
RBM implementation

Another explanation of Contrastive Divergence:
What is Contrastive Divergence

- Markov chain Monte Carlo (MCMC) algorithm used for parameter estimation in probabilistic models.



0. RBMs efficient enough for practical applications

- **Recommender systems:** Salakhutdinov, R., Mnih, A., & Hinton, G. (2007). Restricted boltzmann machines for collaborative filtering. *Proceedings of the 24th International Conference on Machine Learning*, 791–798. https://doi.org/10.1145/1273496.1273596
- **MNIST Image classification:** Larochelle, H., & Bengio, Y. (2008). Classification using discriminative restricted boltzmann machines. *Proceedings of the 25th International Conference on Machine Learning - ICML ’08*, 536–543. https://doi.org/10.1145/1390156.1390224
- **RBM for Drug discovery:** Wang, Y., & Zeng, J. (2013). Predicting drug-target interactions using restricted Boltzmann machines. Bioinformatics, 29, i126 - i134.

Excerpt from: Generative model that won 2024 nobel prize.

1. Applying a Quantum Annealing Based Restricted Boltzmann Machine for MNIST Handwritten Digit Classification

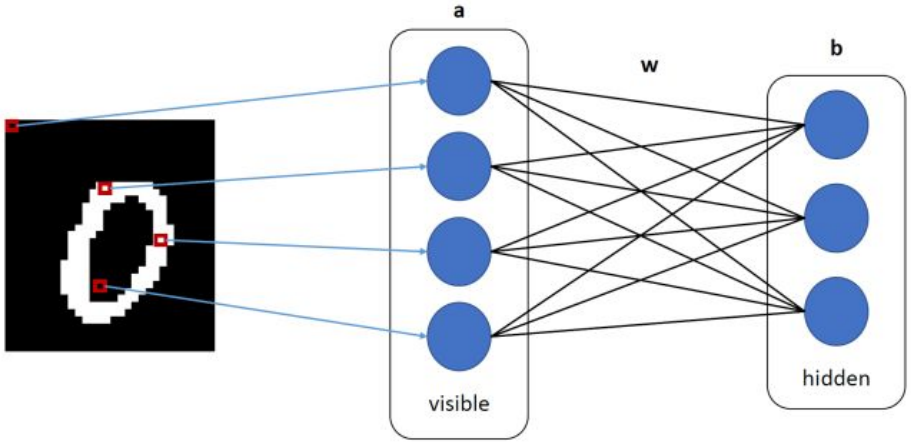
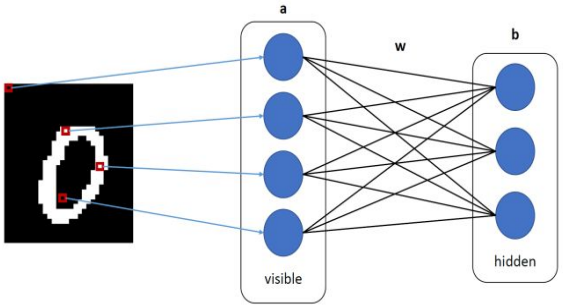


Fig. 1. The schematic representation of a Restircted Boltzman Machine

Quantum Annealing Based RBM for MNIST



RBM is an energy based model with an energy function described in Eq. (1). The D-wave's Quantum Annealing algorithm provides an efficient way to solve such a function. In order to do that, a QUBO (Quadratic Unconstrained Binary Optimization) Eq. (11) needs to be constructed:

$$f(x) = \sum_i Q_{i,i} x_i + \sum_{i<j} Q_{i,j} x_i x_j \ . \qquad (11)$$

In the next step, the QUBO representation is transformed into a *Binary Quadratic Model* which can be used by D-wave's quantum sampler in order to obtain samples from the model's actual probability distribution.

$$E(v,h) = -\sum_i a_i v_i - \sum_j b_j h_j - \sum_{i,j} v_i h_j w_{ij} \ . \qquad (1)$$

Probability value for a given state (v, h) is described as:

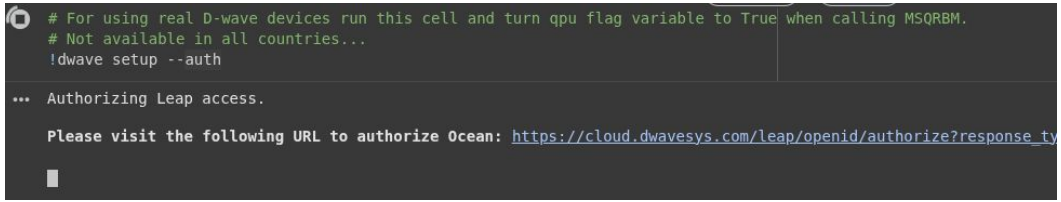
$$p(v,h) = \frac{1}{Z} e^{-E(v,h)} \ , \qquad (2)$$

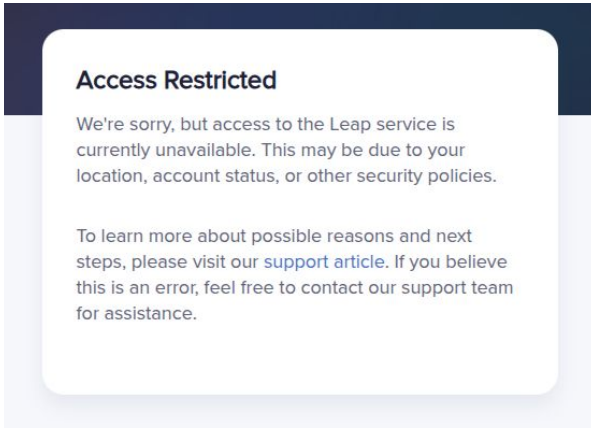
where Z is a partition function which serves as a normalization factor and is generally difficult to compute

$$Z = \sum_{v,h} e^{-E(v,h)} \ . \qquad (3)$$

D-Wave Leap

https://cloud.dwavesys.com/leap/signup/ Restricted in Colombia. D-waveSetup



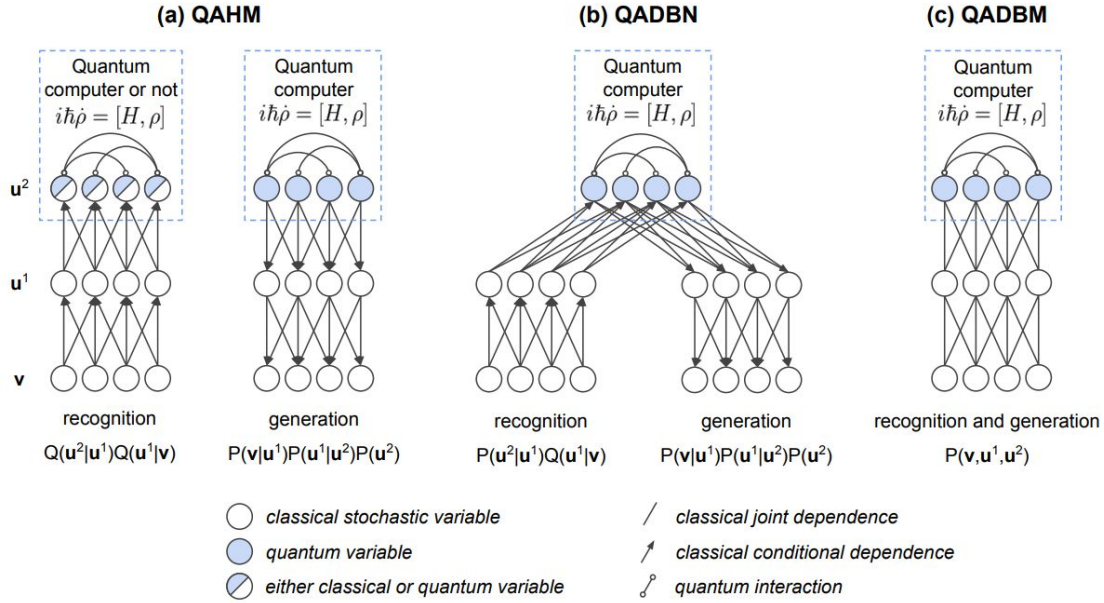


Note: find other options (IBM).

2. MNIST data generation using D-wave 2000Q

The authors demonstrated how a D-Wave 2000Q device can be used for the generation of artificial images. For this task, they used a sub-sampled 16 × 16 pixels version of the standard handwritten digit dataset MNIST.

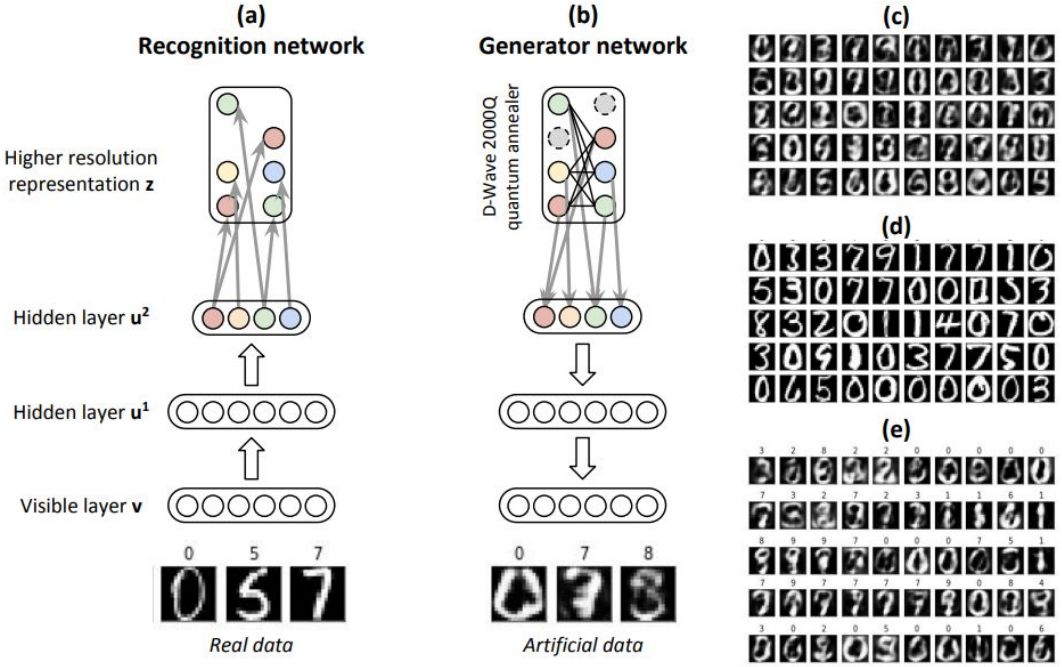
M. Benedetti, J. Realpe-Gomez, A. Perdomo-Ortiz, Quantum-assisted helmholtz machines: a quantum-classical deeplearning framework for industrial datasets in near-term devices, arXiv: 1708.09784 (2017). quantum-assisted Helmholtz machine, deep belief network and deep Boltzmann machine



MNIST data generation using D-wave 2000Q

Scheme for the experimental implementation of the QAHM on the D-Wave 2000Q quantum annealer for the sub-sampled MNIST dataset.

- visible layer: 256 continuous variables v that encode the gray-scale pixels of 16 × 16 images and 10 binary variables that encode the class.



Related articles

- **Generative quantum advantage for classical and quantum problems (2025):** Introduce families of generative quantum models that are hard to simulate classically, are efficiently trainable, exhibit no barren plateaus or proliferating local minima, and can learn to generate distributions beyond the reach of classical computers.

Google Quantum AI

- **Train on classical, deploy on quantum: scaling generative quantum machine learning to a thousand qubits:** We propose an approach to generative quantum machine learning that overcomes the fundamental scaling issues of variational quantum circuits.

  The core idea is to use a class of generative models based on instantaneous quantum polynomial circuits, which we show can be trained efficiently on classical hardware.

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