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RBM Image Generation Using the D-Wave 2000Q

Jennifer Sleeman, Milton Halem, John Dorband
University of Maryland Baltimore County

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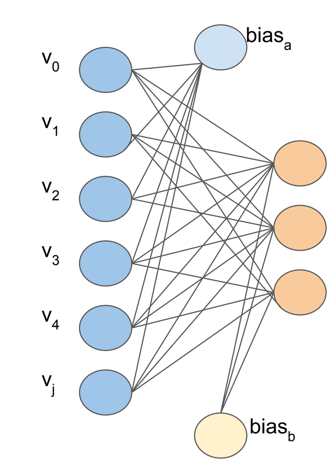
Introduction

We describe a hybrid approach that combines a deep convolutional neural network autoencoder and a quantum Restricted Boltzmann Machine (RBM) for image generation using the D-Wave 2000Q. We compare the quantum learned distribution with the classical learned distribution, and quantify the quantum effects on latent representations.

Background - RBM

- A simple neural network used to find stochastic representations of the input
- Probabilistic, graphical model
- One visible layer $v_0 \ldots v_j$
- One hidden layer $h_0 \ldots h_k$
- Bias vectors a and b
- Restricted: No connections between nodes within a layer
- D-Wave connectivity 2-D grid, can be constrained to be chimera graph
- Chimera graph can be partitioned to form bipartite graphs
- For image processing we formulate an embedding based on the number of pixels of the image (We use the MNIST dataset) using an RBM based on [15].



RBM Architecture

Represents a probability distribution over the visible (***v***) and hidden (***h***) units

Uses an energy-based function ***E*** for measuring quality of the model, minimizes:

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

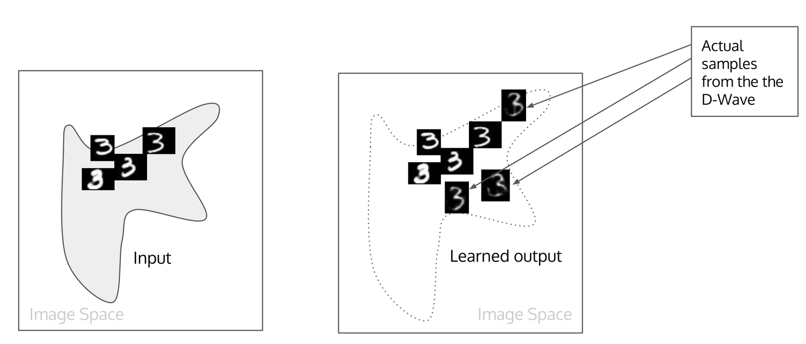
Joint probability mass function represented as:

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

- Gradient calculations of joint probability distribution are intractable
- Gibb's sampling is used to sample from the joint Boltzmann distribution using Markov Chain Monte Carlo (MCMC)

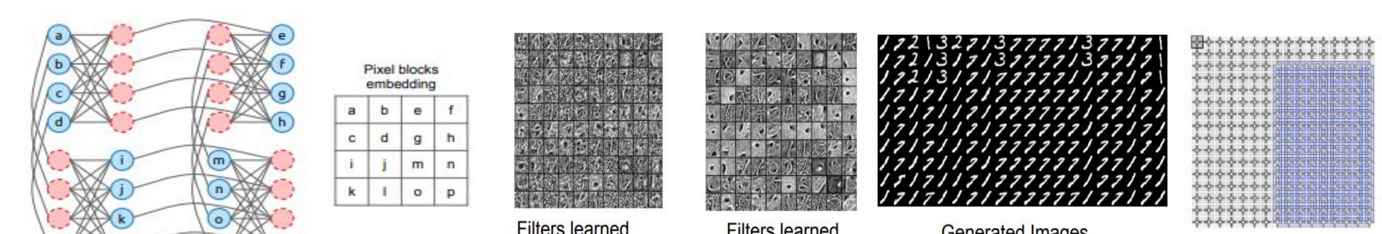
The Generative Properties of an RBM

RBMs learn a joint probability distribution *P(v,h)*
Where *v* represents the visible units and *h* represents the hidden units
Given *P(v,h)* , sampling from this distribution, *could* enable generated output that is not necessarily a replication of a sample from the input distribution



Original Space vs Learned Space

Related Work



In [11] - Chimera-RBM embedding - mapping of pixels to visible units

Based on previous work [10] - we used D-Wave for sampling

RBM based on CFRBM Quantum RBM for Collaborative Filtering [15]

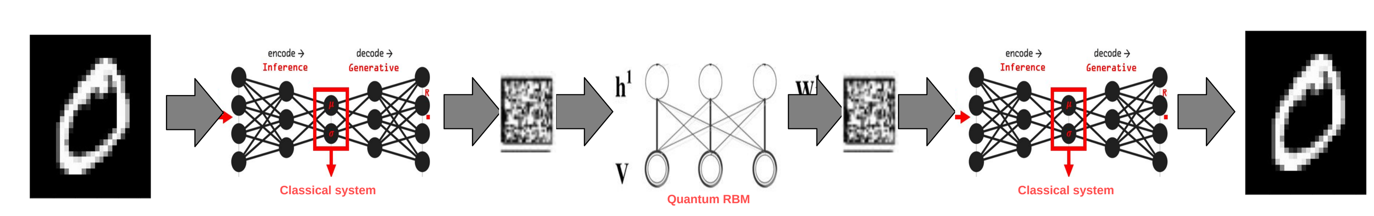
Approach

Using the D-Wave for RBM image sampling is challenged by three main issues:

- Qubit size limitations makes it harder to embed large problems
- Samples from the D-Wave are binary and need to be mapped to their floating point values
- Generative sampling using a similar approach for embedding the RBM in the past has yielded poor results [10]

To overcome these limitations,we mapped the original image space to a compressed image space.

- We compress MNIST digits from 28 x 28 to 7 x 7 and also 28 x 28 to 6 x 6
- We use the D-Wave API for working with the quantum annealer
- These experiments do not include the new D-Wave Hybrid API

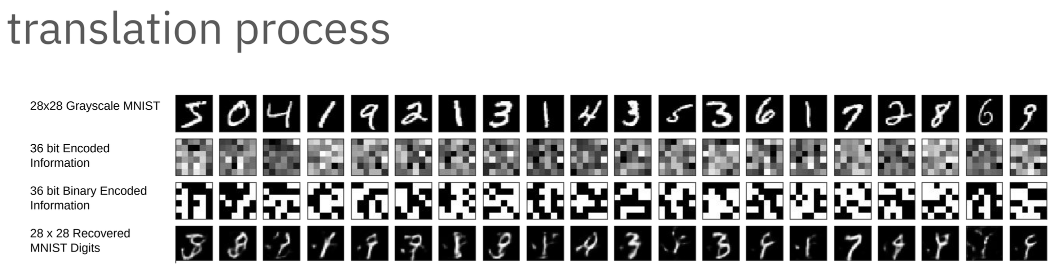


Our Approach uses a Custom-Built Deep Convolutional Autoencoder on the Classical System and A Restricted Boltzmann Machine that uses the D-Wave Sampler

Early Results

The original grayscale digits, even at a compression of 6 x 6 in size, is recoverable using our method when evaluating just the translation method in isolation

Shown are MNIST digits recovered after going through the translation process



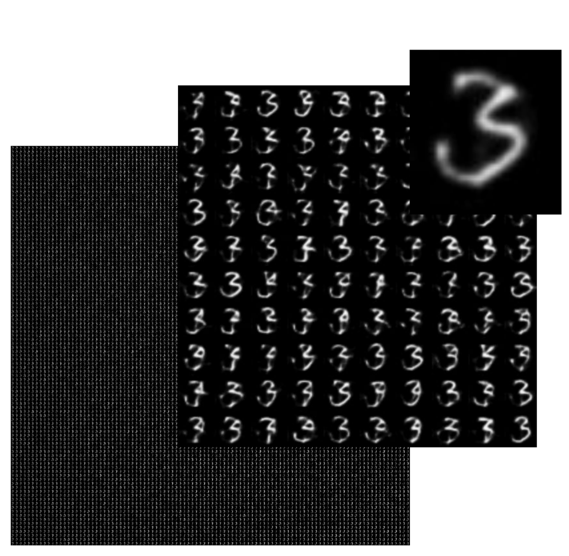
Translation from MNIST grayscale images, to encoded representation, to binary embedding to grayscale.

MNIST digits recovered after training the RBM using the D-Wave and going through the translation process after sampling digits 0-9

Samples from D-Wave After Translated Back to 28 x 28 Grayscale MNIST digits.

Using the MNIST digit *3* - we show a large sampling, of this digit after training the RBM using the D-Wave

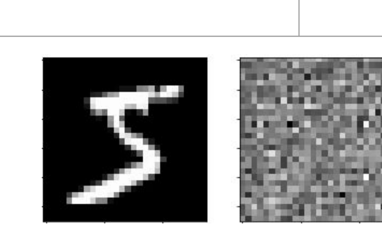
Using an RBM and the D-Wave as a generative sampler, we believe we can generate *NEW* variations of MNIST digits


Large Scale Sampling From the D-Wave - 3's.

Using a downstream process, we formulate a MNIST classification problem, whereby we use samples from our methods to train the MNIST classifier and compare the test results against an MNIST classifier with the original MNIST training data set. Training data consist of 60,000 samples, test set consist of 10,000 samples. Trained for 5 epoch only. Using a convolutional neural network.

	Accuracy On a Test set	***Validation Loss***
Training Data Variants		
Original MNIST 28 x 28 digits	0.9919	0.025
Sampled from Classical RBM MNIST 28 x 28 digits (no encodings)	0.9784	0.0912
Encoded/Decoded Binary Translated MNIST 28 x 28 digits (no RBM)	0.9717	0.232
Encoded/Decoded Binary MNIST 16 x 16 to translated to 28 x 28 digits (no RBM)	0.9534	0.195
Encoded/Decoded Binary MNIST 6 x 6 to translated to 28 x 28 digits (no RBM)	0.909	0.374
Encoded/Decoded Binary MNIST 6 x 6 to translated to 28 x 28 digits Sampled from the RBM D-Wave	0.6062	3.938

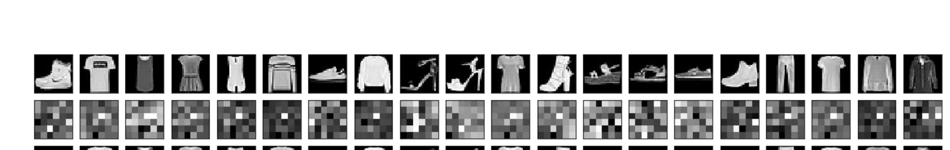
Note: Training with a classical RBM using both 28 x 28 and 6 x 6 binary encodings yielded results that could not be translated to a digit - ongoing.


Classical RBM Sample

Conclusions

This work puts forth a way to overcome qubit size limitations on the D-Wave by training on an embedded representation of images

By using a hybrid classical to quantum translation, we show promising results that indicate we may be able to use the D-Wave for image generation



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