

Hybrid Multicore Productivity Research (CHMPR)

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Quantum Learning - Machine Learning using D-Wave's Quantum Computer

In support of D-Wave Systems, a CHMPR member, and sponsored by a NASA grant to explore the potential viability of the D-Wave quantum annealing computer which is to be a future disruptive technology, CHMPR staff scientists implemented the largest known working Neural Net multi-hidden layer algorithm (called a Boltzmann Machine in the literature). The D-Wave 2X system is owned by Google and shared with NASA Ames.



D-Wave 1,000 qubit processor

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To design and test a Neural Net, many in the industry use MNIST, a well-known and freely available set of handwritten images of digits. In this breakthrough approach to machine learning, the computer program undergoes "supervised learning" wherein a "training set" is used to acquaint the computer program with what numbers look like. The program is "trained", and then a "test set" is used to see how well the computer program does.

While the set of all possible 28x28 MNIST images is an impossibly large set for a classical computer to explore, the D-Wave2X is able to explore such a vastly large set very quickly. The D-Wave2X is programmed using a set of biases and weights. The researchers set up an initial set of biases and weights, and then in subsequent runs of the computer program adjusts them to get closer and closer to representing the training digits with the model comprised of the biases and weights.

However, "single layer" machine learning computer programs that have one set of biases and weights, are not able to do well representing digits, because the representational power of a single set of biases and weights is small. Researchers then introduce multiple layers of biases and weights to model more complex relationships between different pixels (or the input data, or the labels). These layers are known as "hidden layers" in Boltzmann machines.

It may seem as though it is always a good idea to increase the representational power of a model. The drawback, however, is that the more parameters a model has, the harder it is to train the computer. The main thing is to have a model that has enough freedom to be able to represent the data. For natural data, having as many parameters as computationally possible seems to be the best approach (hence the success of deep learning which have many layers of nodes).

The UMBC research team first used a single layer on the D-Wave System, achieving 99% recognition of the digits trained on. Approximately 70% recognition was attained on digits not trained on. Then, two hidden layers were used, using a hybrid model with both the D-Wave system and a classical system. This approach enabled researchers to use connections both within and between the layers. Finally, a three-layer neural net was started using the D-Wave System for the hidden layers.

With advancements in computational systems environments promising exascale performance in the near future, the ability to solve large, multifarious scientific problems in various science and engineering fields has increased. The quantum hardware finds solutions to quadratic binary optimization problems (QUBOs), by drawing samples from a probability distribution. Using adiabatic quantum annealing with over one thousand qubits on the D-Wave 2X, UMBC researchers are using this breakthrough technology to construct powerful machine learning algorithms based on probabilistic frameworks.

Further, UMBC's implementation approach - using the D-Wave 2X with a classical computer in a hybrid manner - enables researchers to encode thousands of neurons, employing all the qubits for each of the hidden layers in the neural net. This construct expands the size of the problem set that can be solved with the current D-Wave quantum processor, enabling researchers to do Quantum Computing for large problems with real-world relevance.

In an interesting application, working with NASA researchers, UMBC will apply this neural net to remotely sensed CO₂ data from the NASA satellite OCO-2. This should allow them to improve upon the inability of current hydrological model predictions to more accurately predict the fraction of annual global carbon

uptake by surface vegetation of the anthropomorphic CO₂ atmospheric loading; which current estimate put at ~20%.

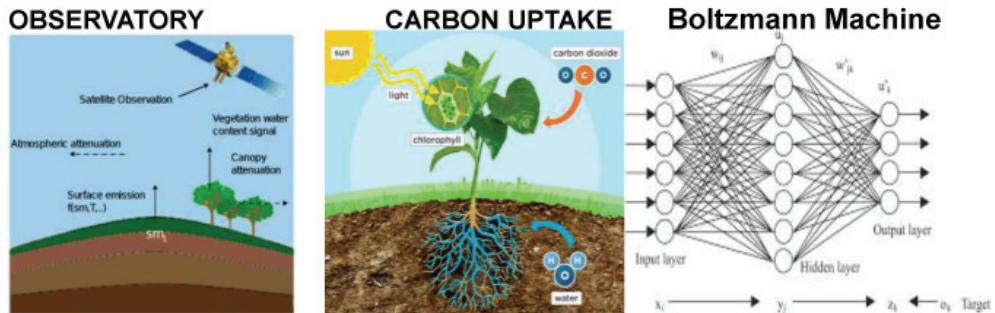
UMBC anticipates applications in further learning systems, including applications to improve software for binary classification, multi-label classification, image segmentation, and sparse image processing, leading to improved computer vision, natural language processing, and robot control. The end-user products and services that this enables are endless.

Economic impact: Improving time to insight using D-Wave quantum computing systems for deep learning will lead to other scientific breakthroughs. It will also increase revenue opportunities through new innovative products and services. It will also result in cost savings opportunities for commercial companies across industries.

The bottom line is that any application that is improved with advanced pattern recognition and predictive modeling, will benefit from this breakthrough. Personalized medicine, cancer drug discovery, and financial predictions are but a few areas with significant potentials to benefit society in major ways.

Calculating Annual Carbon Uptake from OCO-2 and Photosynthetic Modeling using D-Wave

ORBITING CARBON LAND SURFACE MODEL D-Wave Quantum Annealing



Measures surface CO₂ from space

Vegetation model needs Fluxes from Station Data

NN trains CO₂ to infer CO₂ fluxes

Calculating Carbon Uptake from OCO-2 and Photosynthetic Modeling Using D-Wave

