# Bayesian Memory, a Possible Hardware Building Block for Intelligent Systems

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One of the problems with traditional AI and ANNs was that they did not scale well. But recently, the computational neuroscience community has started providing scalable algorithms (often loosely based on cortical models) that can be applied to large intelligent computing problems. These new algorithms, when combined with hybrid nanoelectronics, have the potential for “comparably scalable neuromorphic hardware”.

The goal of our research program is to investigate hardware building blocks for emulating neural models using both traditional CMOS and hybrid nanogrid technology, such as CMOL as proposed by Likharev. In the larger perspective, we are performing a “hardware design space exploration” and developing a methodology for architecting such hardware.

The cerebral cortex is the ultimate cognitive processor. It is remarkably uniform across all its constituent parts, and across almost all mammalian species. It is widely accepted that the cortex has a modular hierarchical structure. Other important characteristics include: sparse coding, over-complete representations, distributed representations, and probabilistic learning and inference. Some researchers have used the neurobiological concept of the cortical column as this basic module.

A very important point is that these structures mix the best of Bayesian Networks and hierarchical distributed representations to create exciting new algorithms for Intelligent Computing.

A number of recent models of the cortex are based on the probabilistic framework of Bayes’ theorem, as developed by Pearl. Based on these models, we have developed a building block, “Bayesian Memory” (BM). Figure 1 shows a generic BM. The term “memory” indicates the storage necessary for cluster centers or quantized vectors, and the probabilistic relationships between these vectors. The term “Bayesian” refers to the probabilistic message-passing framework that forms the core of the inference process.

A single BM consists of two functional parts. Part-A is largely involved in learning and consists of a set of quantized vectors, the Code Book (CB) of vectors. During learning, the CB captures and accumulates the data on the inputs that the modules sees. The conditional probability relations between these CB vectors are also captured during learning. These are then used for inference. Part-B is based on Pearl’s bidirectional Belief Propagation Algorithm (BPA). Figure 2 shows the details of Part-B.

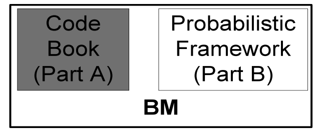


**Figure 1.** Bayesian memory module (BM) - Basic parts

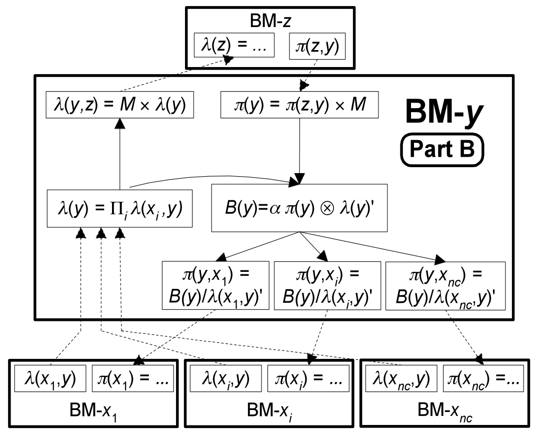


**Figure 2.** Detailed Part-B of a BM.

We are currently investigating a range of hardware implementations of the BM, from more traditional multi-core chips to more radical nano-grid associative memories.

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