CEREBELLUM-LIKE MEMORY for COMPUTING with HIGH-DIMENSIONAL VECTORS

Cerebellum Figures and Facts

Cerebellum as part of vertebrate brains.

Cerebellum cell types in 3D .

3D organization of the "main" circuit.

Side view: parallel fibers and Purkinje cells

Cerebellum Facts and Figures

- . 200 million Mossy Fibers: external input
- . 40 billion Granule Cells, the most numerous
- . 15 million Purkinje Cells (PC): sole output
- . Climbing Fibers: internal input
	- -- 1/PC, shared by approx. 10 PCs

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100,000 synapses/PC
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. 1.5 trillion synapses overall

How big is 1.5 trillion?

 1.5 trillion synapses @ 1 bit/synapse $= 360,000$ books, 400 pages each = 4 miles of shelf space

THE CEREBELLUM CHALLENGE

Traditional theories--logic, rule-based AI, artificial neural nets, connectionism, parallel distributed processing, deep learning—-leave too much **unexplained** and **unexplored**.

For example, **why the cerebellum, when**

- . it has 40 billion neurons vs. 16 billion in the rest of the brain
- . its organization is simple and highly regular

The cerebellum must fulfill some essential function that computational theories and models of the brain cannot afford to ignore !!

TRADITIONAL (VON NEUMANN) MODEL FOR COMPUTING WITH NUMBERS

Random-Access Memory (RAM) for Storing Numbers

- . Millions of addressable memory **locations:** the **mega**bytes
- . Each capable of storing a **number**
- . **Address-decoder circuit** selects the addressed location for storing or retrieving a number

. The **circuit area** of the RAM is much larger than of the rest of the computer (CPU)

Random-Access Memory (RAM)

ASSOCIATIVE MEMORY MODELS OF THE CEREBELLUM

First mathematical models of a major neural circuit

. still today the most comprehensive and credible

Marr D (1969). A theory of cerebellar cortex. Journal of Physiology (London) 202:437-470.

Albus JS (1971). A theory of cerebellar function. Mathematical Biosciences $10(1/2)$:25-61.

Kanerva P (1984/1988). Sparse Distributed Memory. MIT Press.

Sparse Distributed Memory (SDM) as a neural-net associative memory for high-dimensional vectors

Left: Six vectors with 20% noise are stored, seventh retrieves a nearly noiseless vector in two iterations. **Right**: Sequence of six vectors is stored. Noisy third vector initiates the retrieval of noise-free sequence. **High-dimensional representation** (e.g., 10,000-bit vectors) **is subtle and counterintuitive**

Nearly all pairs of vectors are **dissimilar**

- . pairs of random vectors are approximately orthogonal
	- -- makes representation noise-tolerant, **robust**

Distant concepts have **similar neighbors**

```
 man ≉ lake
man ≈ fisherman ≈ fish ≈ lake
man ≈ plumber ≈ water ≈ lake
plumber ≉ fish
```
Small cues bring forth complete memories: "The name begins with T--oh yes, Steven"

Can explain the *tip-of-the-tongue phenomenon*

Binomial distribution, $N = 15$ and $N = 10,000$

VON NEUMANN-LIKE ARCHITECTURE FOR COMPUTING WITH HIGH-D VECTORS

The architecture is familiar from traditional (von Neumann) computing

. except that the operations and memory are for high-dimensional vectors

Sparse Distributed Memory (SDM)

Sparse Distributed Memory organized as a random-access memory. The first selected location is shown by shading. Correspondence to the vectormatrix picture of a feed-forward ANN is immediate.

Address space, hard locations, and the set of locations activated by input pattern x. H is (Hamming) radius of activation.

Activation overlaps as weights for stored words. Writing W_t at X_t stores one copy of W_t in each location activated by X_t . Reading at X_t pools the contents of all locations activated by X_7 . The pool S_7 will have 2 copies of W_t .

Each read and write **Each read and write** activates **one** activates **multiple** storage locations storage locations

1,000 bits

SDM AS A NEURAL NET MORPHING INTO THE CEREBELLUM

SDM as a feed-forward Artificial Neural Net

Three depictions of Sparse Distributed Memory

1,000-bit input is randomly projected to a milliondimensional, *sparsely* activated hidden layer for computing a 1,000-bit output

From SDM to the Cerebellum

Math, engineering, and neuroscience depictions of modifiable synapses of three Purkinje cells

Telltale Details

Each Purkinje cell receives input from a **single climbing fiber** ...

... as would be expected of a **training signal**

Granule cells--their **parallel fibers**--represent **memory locations**

Firing of a granule cell activates the location and allows its contents to be read out

The contents are updated when also the climbing fiber fires

- . Spike-timing-dependent plasticity
- . **Perceptron learning rule**

Agrees with models of human memory in **experimental psychology**: Atkinson-Shiffrin Memory Model (Wikipedia)

- . Short-term working memory
- . Long-term data store
- . Encoding specificity

A climbing fiber paired with a Purkinje cell

LEGEND

Ba = Basket cell $C1 = C1$ imbing fiber Go = Golgi cell **Gr = Granule cell Mo = Mossy fiber Pa = Parallel fiber Pu = Purkinje cell** St = Stellate cell

Feed-forward circuit in bold Axons in italics Golgi, basket and stellate cells are cerebellar interneurons

Sketch of the cerebellar circuit

Cerebellar interconnect diagram (Loebner, 1989) Figure 2. Cerebellar Interconnect Diagram

THEnd

Pentti Kanerva [<pkanerva@berkeley.edu>](mailto:pkanerva@berkeley.edu) at Bruno's VS265: Computational Neuroscience 3:10-5 PM on November 13, 2024

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