Desirable Features of a Neocortically-Inspired Ab Initio Model of Associative Memory

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Using characterization via "information-bearing signal", such similarity becomes more manageable to establish.

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Simple memories encoded at lower levels can be combined to make more complex memories at higher levels. This is reminiscent of sequences of sequences.

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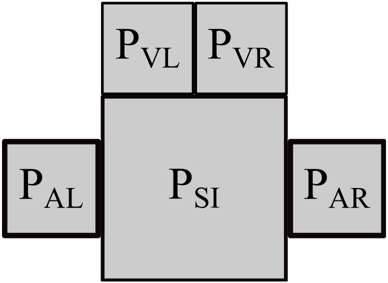

Figure: **Basic Diagram of Signal Transduction Model (Layer 1)**. Each pair of populations sharing a border will have neurons connected to one another. Those that do not share a border will *not* have neurons that share a synapse.

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