Abstract

This network is a bipartite graph consisting of N pattern neurons and m, m-intraneurons. The un-clustered design: Intraneurons are connected to a random set of grid and place cells. The clustered design: Intraneurons are split into M distinct clusters of n intraneu- rons per cluster with each cluster connected to a distinct grid module. Intraneurons are connected randomly to pattern neurons chosen from a set consisting of every grid cell in the corresponding module, and every place cell.

Subspace learning

Before denoising is possible, this network must learn (i.e. adapt its weights) for the hybrid code.

Code subspace learning is complete when the intraneurons may be read to determine if the states of the pattern neurons map to a valid codeword, i.e. when the network has developed a connectivity matrix, W, whose rows are approximately perpendicular to the code space.

\[(\alpha)iHebbian learning update rule: \]
\[w \leftarrow w - \alpha g(x) = \sum_{i=1}^{n} w_i g_i \left( \theta_m - \theta_{m,j} - \sigma \right) \]

\[= \alpha g(x) = \sum_{i=1}^{n} w_i g_i \left( \theta_m - \theta_{m,j} - \sigma \right) \]

\[\theta_r \leftarrow \theta_r + \epsilon \] defines delta Hebbian learning update rule.

De-noising network

De-noising algorithms

**Goal**: Recover the correct pattern of activity, x, from the noisy state, x_n, where n is the noise pattern. \[x_n = x + \epsilon \]

\[s_n(x) \Rightarrow \text{Inconsistencies in } x_n \text{ that the de-noising algorithm seeks to correct in the feedback stage.} \]

\[\text{Chosen de-noising algorithm:} \]

\[\text{Algorithm 1: Sequential decoding:} \]

\[\text{Algorithm 2: Sequential decoding:} \]

\[\text{Algorithm 3: Median decoding:} \]

Coding theoretic results

**Define**: \(\mu_p\), a hybrid code configuration's spatial phase multiplicity (i.e. maximum number of grid cells with the same phase in the same module).

**Define**: \(d\), the code's orientation multiplicity.

**Define**: \(R = \frac{\text{number of places}}{\text{number of grid cells}}\), normalized rank of the code.

**Define**: \(e\), code rate (number of locations represented per neuron).

De-noising results

**Pattern error rate (rate of occurrence of incorrect code-words after de-noising)**: only clustered configurations with \(\mu_p > 1\) perform well here.

Discussion

**The grid code is dense.**

**Inclusion of place cells and in the future, other cell types (e.g. head direction cells, border cells, time cells) - this code could be made sparser.**

**Codes with any desired rank can be constructed by proper choice of population parameters.**

**Random choices of these parameters under the code too dense for effective de-noising.**

**Biological choices of orientation and phase produce readily de-nosizable codes for position.**

References


