Région

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Abstract

1. Learning on natural images

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B

Figure 1: **Role of homeostasis in learning sparse representations**: We show the results of Sparse Hebbian Learning using two different homeostasis algorithms at convergence (20000 learning steps). 324 filters of the same size as the image patches (16×16) are presented in a matrix (separated by a white border). Note that their position in the matrix is arbitrary as in ICA. (A) When switching off the cooperative homeostasis during learning, the corresponding Sparse Hebbian Learning algorithm converges to a set of filters that contains some less localized filters and some high-frequency Gabor functions that correspond to more "textural" features. One may wonder if these filters are inefficient and capturing noise or if they rather correspond to independent features of natural images in the LGM model. (B) Results with the same coding and learning algorithm but by enabling homeostasis.

2. Simulating a perturbation

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Figure 2: **Quantitative role of homeostasis in sparse coding**: We show the results of Sparse Coding using the two different homeostasis algorithms using surrogate data where each filter was equiprobable but for which we manipulated the first half of the coefficients to be artificially twice as big. (A) Such a situation replicates a situation arising during learning when a sub-group of filters is more active, e. g. because it learned more salient features. Here, we show the probability of the selection of the different filters (normalised to an average of 1) which shows a bias of the standard Matching Pursuit to select more often filters whose activity is higher. (B) Non-linear homeostatic functions learned using Hebbian learning. These functions were initialised as the cumulative distribution function of uniform random variables. Then they are used to modify choices in the Matching step of the Matching Pursuit algorithm. Progressively, the non-linear functions converge to the (hidden) cumulative distributions of the coefficients of the surrogate, clearly showing the group of filters with twice a big coefficients. (C) At convergence, the probability of choosing any filter is uniform. As a result, entropy is maximal, a property which is essential for the optimal representation of signals in distributed networks such as the brain.

3. Application to classification

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Figure 3: **Quantitative role of homeostasis in a classification network**: We used the generic MNIST protocol to assess the role of the homeostasis algorithm on classification. (A-C) 144 dictionaries learned from the MNIST database with a sparseness of 5 after 10000 iterations with (A) MP Algorithm ($\eta = 0.01$): No homeostasis regulation, only a small subset of dictionaries are selected with a high probability to describe the dataset. (B) SPARSENET Algorithm ($\eta = 0.01$, $\eta_h = 0.01$, $\alpha_h = 0.02$): The homeostasis regulation is made by normalizing the volatility. (C) MEUL Algorithm ($\eta = 0.01$, $\eta_h = 0.01$): All dictionaries are selected with the same probability to describe the dataset, leading to a cooperative learning. (D) Comparison of the reconstruction error (computed as the square root of the squared difference between the image and the residual) for the 3 algorithms (MEUL, SPARSENET, MP): The convergence velocity of MEUL is higher than SPARSENET and MP.

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