Context-guided denoising

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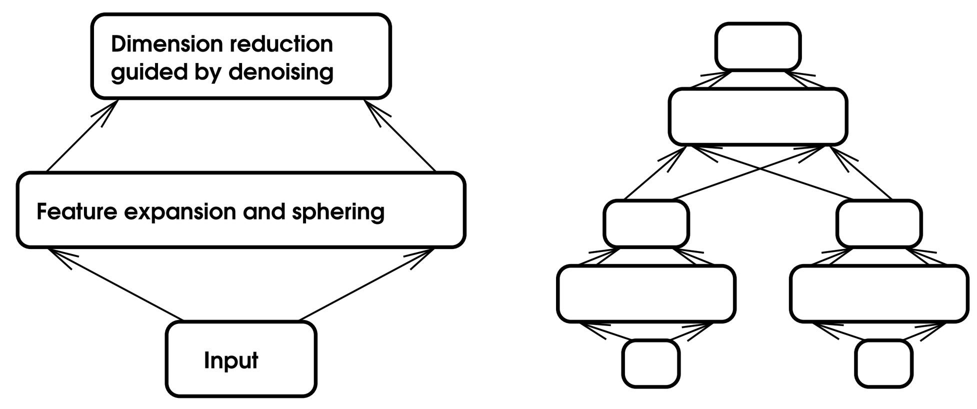
Hierarchical nonlinear models

Slow feature analysis (SFA,[9]) provides an example of how hierarchical nonlinear models can be learned using local criteria. Each unit integrates inputs coming from a set of lower-level units and extracts features which are increasingly invariant.

In SFA, one unit has two parts: nonlinear feature expansion and dimension reduction guided by slowness. The upper part is equivalent to denoising source separation (DSS, [6]) where low-pass filtering is used in denoising. Thus, SFA can be described as follows:
SFA = nonlinear feature expansion + DSS.

From images, it learns features baring similarity to those found at the early stages of visual system.

Figure shows the structure of SFA. On the left: one unit; on the right: hierarchy on units.



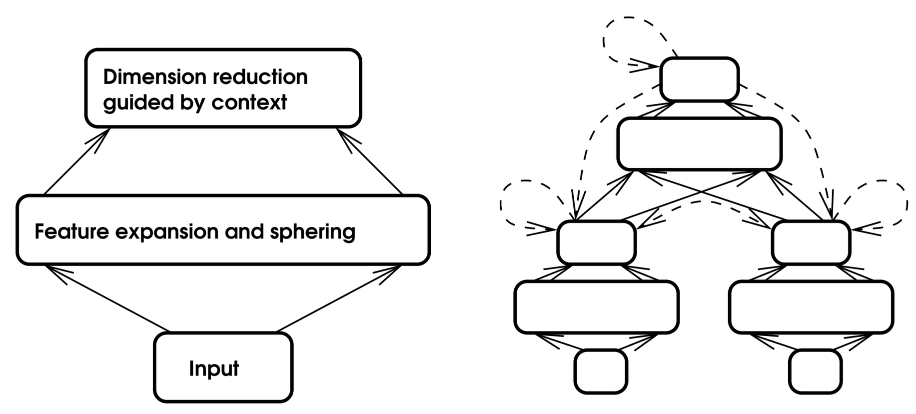
Context-guided denoising

Context can guide feature extraction more generally than slowness.

In the figure below, the visual stimuli from '12 13' is exactly the same as the visual stimuli 'RB'. Depending on the context, the percept is completely different. This contextual effect can be interpreted as denoising which can guide feature extraction.

A special case of context is temporal context which is closely related to slowness-principle in SFA. More generally, context-guided denoising (CGD) can also include lateral and top-down connections. CGD can be implemented by augmenting the sphered bottom-up inputs by the context.

In the figure, the contextual input (top-down, lateral and temporal) is shown in dashed arrow-lines.



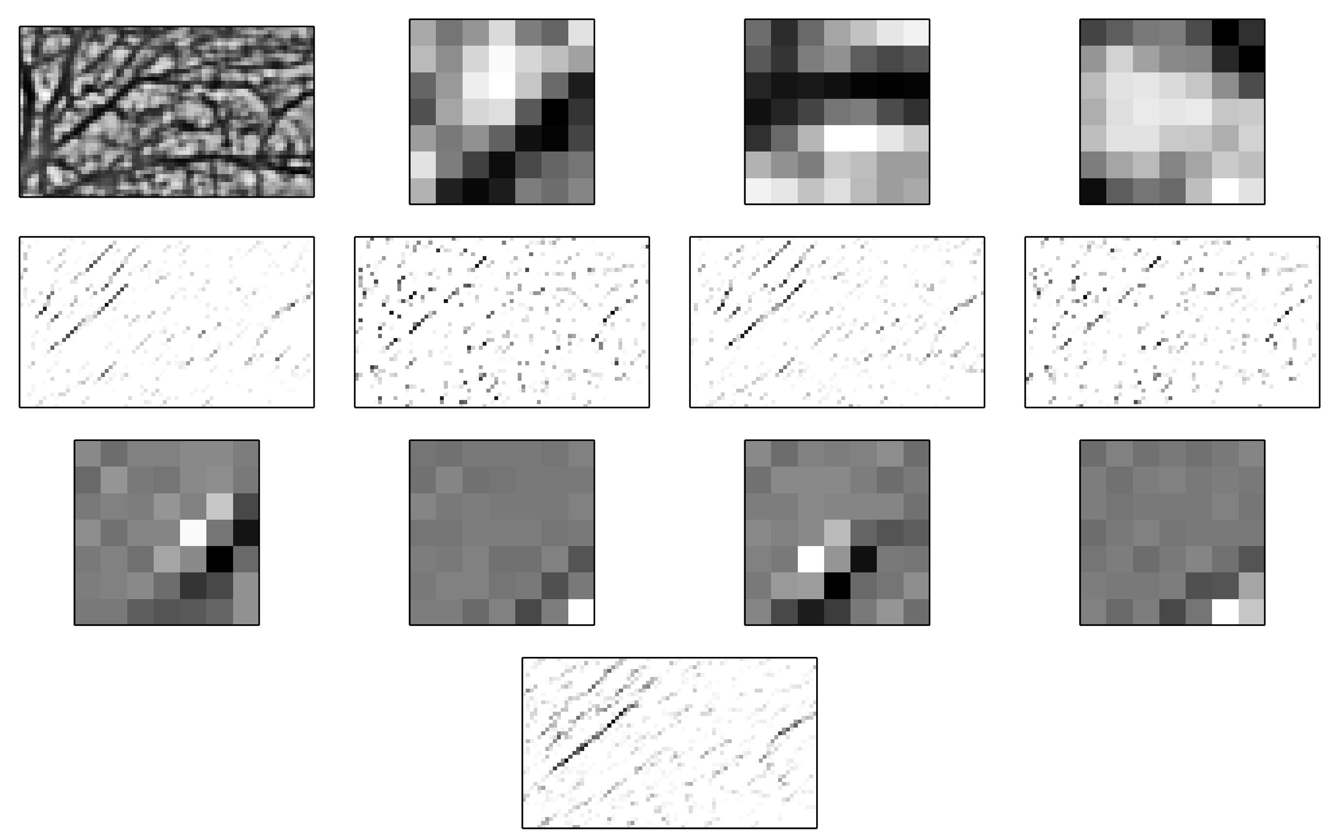
Experiments

Here we show that spacial context alone is sufficient for developing invariant features (in SFA and related models temporal context has been used). In this experiment, we used 9 units laterally connected on one layer. 10% share of weights was assigned to the lateral contextual inputs.

Top row from the left: the edge-enhanced natural image and three 7×7 sample patches from it. There were a total of 5,220 patches in the data set.

Second row: activations of four out of 100 nonlinear features at the feature expansion level of one unit when scanning over the entire image. Third row: corresponding 7×7 receptive fields.

Last row: activations of a feature developed on the output layer under spatial contextual guidance. The strongest bottom-up connections were made to the four features shown on the previous rows. This feature is more invariant than any of the more elementary features.



Relation to attention

Contextual, predominantly top-down, biasing of local lateral competition has been proposed as a model of covert attention in humans [3]. In simulations, such models have replicated many of the phenomena found in neurophysiological experiments (see, e.g., [1,2,4,5,7]). Attention can thus be seen as a dynamic process emerging from an interplay between long-range excitatory and local inhibitory connections. Different strengths of excitation and inhibition have been shown to give rise to several distinct functional regimes, covert attention being one of them [9]. We propose that sphering-like normalisation allows weaker top-down modulation to give rise to attention.

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