Sparse coding in V1

Based on
Olshausen & Field (2004)

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V1 simple cells

- Receptive fields are:
  - Spatially localized
  - Selective by orientation
  - Selective by spatial frequency

...they are equivalent to basis functions of wavelet transforms
Previous simulations

• Using unsupervised learning:
  – PCA discovers coefficients on image data that are pairwise decorrelated
  – These are not spatially localized (they span large regions of variance in the image)
    – and do not resemble any known cortical receptive fields
• Good for images that are already gaussian and where pairwise correlations matter
• Complex lines and edges out
A new approach

- Sparseness
- Learn a set of coefficients $a$ with a cost
  function for the number of coefficients used
- Inspired by minimum-entropy codes
  (Barlow 1989)
  - Lower the individual entropies ($a$’s) by
    using fewer of them at once
- Conjecture: Natural images have sparse
  structure
A new approach

- Optimize:

\[ E = \text{mean square error} \quad \text{-- sparseness of } a_i \]

- Q: Is this the same as thresholding the low values to be lower and the high values higher?
A new approach

- Learned image features ($\Phi$s) evolve by gradient descent on $E$
- Seeking a set of $\Phi$s such that $a_i$s can tolerate sparsification
Results

- algorithm discovered sparse structure in the data
- successfully recovered the sparse components from which the images were composed (even non-orthogonal components)
- entropy decreased
Learned image feature descriptors
Sparsity

- 'Recording' from the $a_s$ shows more tolerance for sparsification (wider tails; solid line) as compared to initial random values (dashed line)
Conclusion

- Penalizing inefficient encoding / maximizing efficient encoding yields units with V1-like properties:
  - Spatially localizable
  - Orientation selectivity
  - Spatial frequency selectivity