The Importance of Encoding v.s. Training With Sparse Coding and Vector Quantization

In this paper by Coates et al., the main goal is to understand why sparse-coding has been successful in e.g. improving the performance of visual recognition problems. First, we need to understand sparse-coding.

sparse-coding is a method of unsupervised learning where input data is projected onto an overly complete basis efficiently (that is, only a few of the coordinates of the data representing in the overly complete basis are non-zero). Again, put another way, we wish to map $x \in \mathbb{R}^n$ to $s \in \mathbb{R}^k$ where $k > n$. Sparse-coding training and encoding uses the following optimization:

$$\min_{D,s(i)} \sum_i ||Ds^{(i)} - x^{(i)}||_2^2 + \lambda||s^{(i)}||_1$$
$$subject\ to\ ||D^{(j)}||_2^2 = 1\ \forall j$$

During training, the matrix D and corresponding mappings s are learned. During encoding, given a new input x, a previously learned dictionary D is used to minimize the term in the sum to map x to s (other things are done but this is an abridged and simplified explanation).

The question Coates asks is this: is the learned dictionary using sparse-coding the source of success, or is the encoding the source of success? Coates et al. found, which I believe to be the most surprising part of the paper, that it was almost solely the latter. One could use a randomized dictionary and if sparse-coding based encoding is used, performance will still be good. On the CIFAR data set, with a randomized dictionary and sparse-coding encoding, 74% accuracy was achieved, while a sparse-coding learned dictionary and sparse-coding encoding, 78.5% accuracy was achieved.

The impact of this discovery is two fold. First, it meant that a lot of training time can be saved because minimizing the sparse-coding equation for D is very computationally expensive. Secondly, it "sheds light" on why sparse-coding is successful, namely, that it is a "successful encoding scheme" and not because it excels in finding an effective bases.

The paper's primary weakness is that it skirts by the question, "why is sparse-coding a successful encoding scheme" and "why is it nearly no better at finding a good bases than random." The paper does not answer the second question, and for the first question, simply says that sparse-coding is a good encoding scheme for "non-linear features."

Human Level Control Through Deep Reinforcement Learning

This overview assumes the reader is familiar with basic reinforcement learning.

In this paper, Mnih et al. use deep-Q learning where a neural network is used to approximate the Q-value function to play classic atari games by providing only the pixels on the screen and the score as the reward function (the action space is also known apriori). Amazingly, the deep-Q network was able to learn long-term strategies to maximize the score, even surpassing professional human players. I believe the core contribution of this paper wasn't theoretical, but a demonstrative, insofar as the strength of neural networks to learn long-term optimal policies in an unfeasibly (in terms of memory storage) large $\mathbb{S} \times \mathbb{A}$ space where most configurations would not have been seen.

Deep reinforcement learning of Q functions was known to be susceptive to getting stuck in local minimums due to high correlations between observations. This paper uses two techniques to overcome this:

- First, it randomizes the training data thereby removing correlation in the sequence of observations. More precisely, batches from training samples are assembled by drawing from the pool of samples uniformly at random. This is called "experience replay" and it is apparently biologically inspired.
- Second, NN weights of the target Q function are only periodically updated which reduces correlation of the NN with the target network.

I think for what I perceive to be the purpose of this paper, it largely has no weaknesses. It has a lot of result data from training and playing multiple Atari games and conclusively demonstrated the feasibility of deep reinforcement learning to learn very long term policies.

The only weakness of the paper is it omitted the biological inspiration for some of their techniques and claims, although one could simply follow their references.