Introduction

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1) Given an over-complete dictionary $\mathbf{D} = \begin{bmatrix} \mathbf{d}_1 & \cdots \mathbf{d}_K \end{bmatrix} \in \mathbb{R}^{5 \times K}$ with K atoms, sparse coding seeks to representing a feature vector $\mathbf{y}_i$ using at most T_0 atoms:

$$\min_{\mathbf{x}_i \in \mathbb{R}^K} \left\| \mathbf{y}_i - \mathbf{D}\mathbf{x}_i \right\|_2, \qquad \text{s.t.} \quad \left\| \mathbf{x}_i \right\|_0 \leqslant T_0 [1] \tag{1}$$

2) From a robustness point of view, sparse vectors are desired to be stable against content-preserving manipulations. [1]
3) K-SVD [27] is one of the most effective algorithms for dictionary learning, in which approximation error is minimized by alternatively updating $\mathbf{X}$ and $\mathbf{D}$. However, it does not take the mutual coherence constraint into account. [1]
4) Denote the training set by $\mathbf{V} = [\mathbf{v}_1, \cdots, \mathbf{v}_S]$, then the objective of dictionary learning can be expressed as

$$\begin{array}{ll} \text{minimize} & \left\| \mathbf{V} - \mathbf{D}\mathbf{X} \right\|_2 \\ \text{subject to} & \mu(\mathbf{D}) \leqslant \mu_0; \quad \left\| \mathbf{x}_i \right\| \leqslant T_0, 1 \leqslant i \leqslant S \end{array} [1] \tag{2}$$

5) Algorithm 1 **outlines** the procedures of dictionary learning. [1]
6) **In contrast to** RVFL theories for semi-randomness, ELM theories show that
    a) Generally speaking, all the hidden node parameters can be randomly generated as long as the activation function is nonlinear piecewise continuous;
    b) all the hidden nodes can be not only independent from training samples but also **independent from** each other;
    c) ELM theories are valid for but not limited to sigmoid networks, RBF networks, threshold networks, trigonometric networks, fuzzy inference systems, fully complex neural networks, high-order networks, ridge polynomial networks, wavelet networks, Fourier series, and biological neurons whose modeling/shapes may be unknown, *etc.* [9], [10], [13].

    [2]

REFERENCES

[1] N. L. Yue, “Robust content fingerprinting algorithm based on sparse coding,” *IEEE Signal Processing Letters*, vol. 22, no. 9, pp. 1254–1258, 2015. 1
[2] G. B. Huang, Z. Bai, L. L. C. Kasun, and M. V. Chi, “Local receptive fields based extreme learning machine,” *IEEE Computational Intelligence Magazine*, vol. 10, no. 2, pp. 18–29, 2015. 1