## EE6367: Topics in Data Storage and Communications

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## 8.1 Vector Quantization Using Shared Randomness

Suppose that  $\mathbf{X} \sim \operatorname{iid} (\mathcal{N}(\mathbf{0}, \beta^2))$ . Then,

$$\mathbb{E}\left[\|\mathbf{X}\|^{2}\right] = \mathbb{E}\left[\sum_{i=1}^{d} X_{i}^{2}\right]$$

$$= d\beta^{2}.$$
(8.1)

Further, we note that

$$\Pr\left(\|\mathbf{X}\|^2 \geqslant d\beta^2 \left(1 + \delta\right)\right) \leqslant e^{-\theta(d)} \tag{8.3}$$

Consider a class of algorithms where the input vector is rotated using a uniformly chosen rotation matrix  $\mathbf{R} \in \mathbb{M}^{d \times d}$  before encoding and then rotated back after decoding by applying  $\mathbf{R}^{-1}$ . Clearly,  $\mathbf{R}\mathbf{R}^{\top} = \mathbf{I}$ , and for an encoded vector  $\mathbf{x}$ ,  $\mathbf{y} \triangleq \mathbf{R}\mathbf{x}$  is also similarly distributed to  $\mathbf{x}$ . Since  $\mathbf{x}$  is isotropically distributed, that is, depends on its 2-norm, it follows that

$$\frac{\mathbf{X}}{\|\mathbf{X}\|} \sim \text{Unif}\left(\mathbb{S}\left(\mathbf{0},1\right)\right).$$
 (8.4)

For these schemes, a careful analysis shows

$$Cost \le \theta \left( \frac{\|\mathbf{x}\|^2 \log d}{2^{\alpha}} \right). \tag{8.5}$$

However, a small tweak to the above scheme can lead to better performance. Assume that  $k = d(1 + \mathcal{O}1)$ . The encoder takes a random rotation vector  $\mathbf{R}$  and computes  $\mathbf{y} = \mathbf{R}\mathbf{x}$ , and the vector  $\mathbf{c}$  is transmitted, where

$$c_i \triangleq \text{sign}(y_i) = \begin{cases} 1 & y_i \ge 0\\ -1 & \text{otherwise} \end{cases}$$
 (8.6)

Along with  $\mathbf{c}$ , a scale factor  $s \in \mathbb{R}$  is also transmitted.

Given  $\mathbf{c}$  and s, the decoder computes

$$\hat{\mathbf{X}} \triangleq s\mathbf{R}^{\mathsf{T}}\mathbf{c}.\tag{8.7}$$

The most computationally intensive part is that of multiplication at the encoder, which gives an overall time compelxity of  $\mathcal{O}(d^2)$ .

The squared error of this scheme is given by

$$\left\|\mathbf{x} - \hat{\mathbf{X}}\right\|_{2}^{2} = \left\|\mathbf{R}\left(\mathbf{x} - \hat{\mathbf{X}}\right)\right\|_{2}^{2} \tag{8.8}$$

$$= \|\mathbf{R}\mathbf{x}\|_{2}^{2} + \|\mathbf{R}\hat{\mathbf{X}}\|_{2}^{2} - 2 < \mathbf{R}\mathbf{x}, \mathbf{R}\hat{\mathbf{X}} >$$

$$= \|\mathbf{x}\|_{2}^{2} + s^{2} \|\mathbf{c}\|_{2}^{2} - 2 < \mathbf{R}\mathbf{x}, s\mathbf{c} >$$
(8.9)

$$= \|\mathbf{x}\|_{2}^{2} + s^{2} \|\mathbf{c}\|_{2}^{2} - 2 < \mathbf{R}\mathbf{x}, s\mathbf{c} >$$
(8.10)

$$= \|\mathbf{x}\|_{2}^{2} + s^{2}d - 2s\sum_{i=1}^{d} |\mathbf{R}\mathbf{x}_{i}|$$
(8.11)

$$= \|\mathbf{x}\|_{2}^{2} + s^{2}d - 2s \|\mathbf{R}\mathbf{x}\|_{1}$$
(8.12)

$$\geq \|\mathbf{x}\|_{2}^{2} - \frac{\|\mathbf{R}\mathbf{x}\|_{1}^{2}}{d} = \theta \|\mathbf{x}\|_{2}^{2}$$
(8.13)

where the minimum is achieved at  $s_{\min} = \frac{\|\mathbf{R}\mathbf{x}\|_1}{d}$ .