

# Support Vector Guided Dictionary Learning

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## Appendix A: Proof of Lemma 1

**Lemma 1.** Denote by  $\bar{z}_c$  and  $\bar{z}$  the mean vectors of  $Z_c$  and  $Z$ , respectively, where  $Z_c$  is the set of coding vectors of samples from class  $c$ . Then  $\mathcal{L}(Z)$  in FDDL is equivalent to the weighted sum of the squared distances of pairs of coding vectors:

$$\mathcal{L}(Z) = \sum_{c=1}^C \left( \sum_{y_i=c, y_j=c} \left( \frac{1}{n_c} - \frac{1}{2n} \right) \|z_i - z_j\|_2^2 + \sum_{y_i=c, y_j \neq c} \left( -\frac{1}{2n} \right) \|z_i - z_j\|_2^2 \right).$$

**Proof:** The Fisher discrimination criterion  $\mathcal{L}(Z)$  adopted in FDDL [18] can be formulated into the following equivalent form:

$$\begin{aligned} \mathcal{L}(Z) &= \text{tr}(S_W(Z)) - \text{tr}(S_B(Z)) \\ &= \sum_{c=1}^C \sum_{y_i=c} \|z_i - \bar{z}_c\|_2^2 - \sum_{c=1}^C n_c \|\bar{z}_c - \bar{z}\|_2^2 \\ &= \sum_{c=1}^C \sum_{y_i=c} (\|z_i\|_2^2 - 2z_i^T \bar{z}_c + \|\bar{z}_c\|_2^2) - \sum_{c=1}^C n_c (\|\bar{z}_c\|_2^2 - 2\bar{z}_c^T \bar{z} + \|\bar{z}\|_2^2) \\ &= \sum_{c=1}^C \left( \sum_{y_i=c} \|z_i\|_2^2 - 2(\sum_{y_i=c} z_i)^T \bar{z}_c + n_c \|\bar{z}_c\|_2^2 \right) - \left( \sum_{c=1}^C n_c \|\bar{z}_c\|_2^2 - 2(\sum_{c=1}^C n_c \bar{z}_c)^T \bar{z} + n \|\bar{z}\|_2^2 \right) \\ &= \sum_{c=1}^C \left( \sum_{y_i=c} \|z_i\|_2^2 - n_c \|\bar{z}_c\|_2^2 \right) - \left( \sum_{c=1}^C n_c \|\bar{z}_c\|_2^2 - n \|\bar{z}\|_2^2 \right) \\ &= 2 \sum_{c=1}^C \left( \sum_{y_i=c} \|z_i\|_2^2 - n_c \|\bar{z}_c\|_2^2 \right) - \left( \sum_{c=1}^C \sum_{y_i=c} \|z_i\|_2^2 - n \|\bar{z}\|_2^2 \right) \\ &= 2 \sum_{c=1}^C \left( \sum_{y_i=c} \|z_i\|_2^2 - n_c \|\bar{z}_c\|_2^2 \right) - \left( \sum_i \|z_i\|_2^2 - n \|\bar{z}\|_2^2 \right). \end{aligned}$$

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It is easy to see that:

$$\begin{aligned}
\sum_{i,j} \frac{1}{2n} \|z_i - z_j\|_2^2 &= \frac{1}{2n} \sum_{i,j} (\|z_i\|_2^2 - 2z_i^T z_j + \|z_j\|_2^2) \\
&= \frac{1}{2n} (2n \sum_i \|z_i\|_2^2 - 2(\sum_i z_i)^T (\sum_j z_j)) \\
&= \frac{1}{2n} (2n \sum_i \|z_i\|_2^2 - 2n^2 \|\bar{z}\|_2^2) \\
&= \sum_i \|z_i\|_2^2 - n \|\bar{z}\|_2^2.
\end{aligned}$$

The above equation can also be applied to each class  $c$ , i.e.,

$$\sum_{y_i=c, y_j=c} \frac{1}{2n_c} \|z_i - z_j\|_2^2 = \sum_{y_i=c} \|z_i\|_2^2 - n_c \|\bar{z}_c\|_2^2.$$

Finally, the Fisher discrimination criterion  $\mathcal{L}(Z)$  can be written as:

$$\begin{aligned}
\mathcal{L}(Z) &= \sum_{c=1}^C \sum_{y_i=c, y_j=c} \frac{1}{n_c} \|z_i - z_j\|_2^2 - \sum_{i,j} \frac{1}{2n} \|z_i - z_j\|_2^2 \\
&= \sum_{c=1}^C \left( \sum_{y_i=c, y_j=c} \left( \frac{1}{n_c} - \frac{1}{2n} \right) \|z_i - z_j\|_2^2 + \sum_{y_i=c, y_j \neq c} \left( -\frac{1}{2n} \right) \|z_i - z_j\|_2^2 \right).
\end{aligned}$$

The proof is completed.

## Appendix B: Proof of Lemma 2

**Lemma 2.** Let  $w_{ij}(\beta) = y_i y_j \beta_i \beta_j$ . If  $\sum_{j=1}^n y_j \beta_j = 0$ , then the discrimination term  $\mathcal{L}(Z)$  can be written as:

$$\mathcal{L}(Z, w_{ij}(\beta)) = -2 \sum_{i,j} y_i y_j \beta_i \beta_j z_i^T z_j = \beta^T K \beta,$$

where  $K$  is the negative semidefinite matrix.

**Proof:**  $w_{ij}(\beta) = y_i y_j \beta_i \beta_j$  is a specific parameterization of  $w_{ij}$ . To satisfy the balance property, we let  $\sum_{j=1}^n y_j \beta_j = 0$ , which leads to:

$$\begin{aligned}
\mathcal{L}(Z, w_{ij}(\beta)) &= \sum_{i,j} \|z_i - z_j\|_2^2 w_{ij}(\beta) \\
&= \sum_{i,j} y_i y_j \beta_i \beta_j (\|z_i\|_2^2 + \|z_j\|_2^2 - 2z_i^T z_j) \\
&= -2 \sum_{i,j} y_i y_j \beta_i \beta_j z_i^T z_j \\
&= \beta^T K \beta,
\end{aligned}$$

where  $K = -2(Z * \text{diag}(y))^T(Z * \text{diag}(y))$  and  $\text{diag}(y)$  is the diagonalization of class label vector  $y = [y_1, y_2, \dots, y_n]$ . According to the Cholesky decomposition, we can see that  $K$  is a negative semidefinite matrix, leading the conclusion of **Lemma 2**.