

Deep Hashing with Active Pairwise Supervision

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Supplementary

A. Proof of (5)

According to (4), we obtain the following inequality for the empirical risk:

$$\mathbb{E}_M(J) \leq \hat{\mathbb{E}}_M(J) + \Phi \quad (1)$$

Where $\Phi = 2R_c(\Omega) + \sqrt{\frac{\ln 1/\delta}{c}}$ means the model complexity. Using the true risk $E(J)$ to minus the above inequality, we can obtain (5).

B. Proof of Three Properties of the Distance Defined in (10)

We define the distance between binary code pairs as follows:

$$\begin{aligned} d(\mathcal{H}(\mathbf{x}), \mathcal{H}(\mathbf{t})) \\ = \min(\|\mathcal{H}(\mathbf{x}_a) - \mathcal{H}(\mathbf{t}_a)\|_F + \|\mathcal{H}(\mathbf{x}_b) - \mathcal{H}(\mathbf{t}_b)\|_F, \\ \|\mathcal{H}(\mathbf{x}_b) - \mathcal{H}(\mathbf{t}_a)\|_F + \|\mathcal{H}(\mathbf{x}_a) - \mathcal{H}(\mathbf{t}_b)\|_F) \end{aligned}$$

Generally, the distance in the Hamming space has three fundamental mathematical properties: non-negativity, symmetry and triangle inequality. We show that the defined distance satisfies the above three properties in the following.

Non-negativity and Symmetry:

These two properties are obvious according to the non-negativity and symmetry of the Frobenius norm.

Triangle Inequality:

The triangle inequality means that for any sample pairs $\mathbf{x}, \mathbf{t}, \mathbf{s}$, we have

$$d(\mathcal{H}(\mathbf{x}), \mathcal{H}(\mathbf{t})) + d(\mathcal{H}(\mathbf{t}), \mathcal{H}(\mathbf{s})) \geq d(\mathcal{H}(\mathbf{x}), \mathcal{H}(\mathbf{s}))$$

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We prove it in the following:

$$\begin{aligned}
& d(\mathcal{H}(\mathbf{x}), \mathcal{H}(\mathbf{t})) + d(\mathcal{H}(\mathbf{t}), \mathcal{H}(\mathbf{s})) \\
&= \min \left\{ \|\mathcal{H}(\mathbf{x}_a) - \mathcal{H}(\mathbf{t}_a)\|_F + \|\mathcal{H}(\mathbf{x}_b) - \mathcal{H}(\mathbf{t}_b)\|_F, \right. \\
&\quad \left. \|\mathcal{H}(\mathbf{x}_b) - \mathcal{H}(\mathbf{t}_a)\|_F + \|\mathcal{H}(\mathbf{x}_a) - \mathcal{H}(\mathbf{t}_b)\|_F \right\} + \\
&\quad \min \left\{ \|\mathcal{H}(\mathbf{t}_a) - \mathcal{H}(\mathbf{s}_a)\|_F + \|\mathcal{H}(\mathbf{t}_b) - \mathcal{H}(\mathbf{s}_b)\|_F, \right. \\
&\quad \left. \|\mathcal{H}(\mathbf{t}_b) - \mathcal{H}(\mathbf{s}_a)\|_F + \|\mathcal{H}(\mathbf{t}_a) - \mathcal{H}(\mathbf{s}_b)\|_F \right\} \\
&= \min \left\{ A, B \right\} + \min \left\{ C, D \right\} \\
&= \min \left\{ A + C, B + C, A + D, B + D \right\}
\end{aligned}$$

Where

$$\begin{aligned}
& A + C \\
&= \left\{ \|\mathcal{H}(\mathbf{x}_a) - \mathcal{H}(\mathbf{t}_a)\|_F + \|\mathcal{H}(\mathbf{x}_b) - \mathcal{H}(\mathbf{t}_b)\|_F \right\} + \\
&\quad \left\{ \|\mathcal{H}(\mathbf{t}_a) - \mathcal{H}(\mathbf{s}_a)\|_F + \|\mathcal{H}(\mathbf{t}_b) - \mathcal{H}(\mathbf{s}_b)\|_F \right\} \\
&= \left\{ \|\mathcal{H}(\mathbf{x}_a) - \mathcal{H}(\mathbf{t}_a)\|_F + \|\mathcal{H}(\mathbf{t}_a) - \mathcal{H}(\mathbf{s}_a)\|_F \right\} + \\
&\quad \left\{ \|\mathcal{H}(\mathbf{x}_b) - \mathcal{H}(\mathbf{t}_b)\|_F + \|\mathcal{H}(\mathbf{t}_b) - \mathcal{H}(\mathbf{s}_b)\|_F \right\} \\
&\geq \|\mathcal{H}(\mathbf{x}_a) - \mathcal{H}(\mathbf{s}_a)\|_F + \|\mathcal{H}(\mathbf{x}_b) - \mathcal{H}(\mathbf{s}_b)\|_F \\
&\geq \min \left\{ \|\mathcal{H}(\mathbf{x}_a) - \mathcal{H}(\mathbf{s}_a)\|_F + \|\mathcal{H}(\mathbf{x}_b) - \mathcal{H}(\mathbf{s}_b)\|_F, \right. \\
&\quad \left. \|\mathcal{H}(\mathbf{x}_b) - \mathcal{H}(\mathbf{s}_a)\|_F + \|\mathcal{H}(\mathbf{x}_a) - \mathcal{H}(\mathbf{s}_b)\|_F \right\} \\
&= d(\mathcal{H}(\mathbf{x}), \mathcal{H}(\mathbf{s}))
\end{aligned}$$

Similarly, we have

$$B + C, A + D, B + D \geq d(\mathcal{H}(\mathbf{x}), \mathcal{H}(\mathbf{s}))$$

Thus,

$$\begin{aligned}
& d(\mathcal{H}(\mathbf{x}), \mathcal{H}(\mathbf{t})) + d(\mathcal{H}(\mathbf{t}), \mathcal{H}(\mathbf{s})) \\
&= \min \left\{ A + C, B + C, A + D, B + D \right\} \\
&\geq d(\mathcal{H}(\mathbf{x}), \mathcal{H}(\mathbf{s}))
\end{aligned}$$

Q.E.D.

C. Proof of (11)

Similar to [1], we hope to minimize the MMD objective:

$$\begin{aligned} \text{MMD}[\mathcal{L} \cup \mathcal{Q}, \mathcal{U} \setminus \mathcal{Q}] &= \inf_{\mathbf{k}_1, \mathbf{k}_2} \left\| \frac{1}{l+q} \sum_{i=1}^{l+q} \mathcal{T}_{k_{1,i}}(\mathcal{H}(\mathbf{x}_{1,i})) \right. \\ &\quad \left. - \frac{1}{u-q} \sum_{i=1}^{u-q} \mathcal{T}_{k_{2,i}}(\mathcal{H}(\mathbf{x}_{2,i})) \right\|_F^2 \end{aligned} \quad (2)$$

where $\mathbf{x}_{1,i} \in \mathcal{L} \cup \mathcal{Q}$ is the i_{th} pair sampled from the labeled and query sets, and $\mathbf{x}_{2,i} \in \mathcal{U} \setminus \mathcal{Q}$ is the i_{th} pair sampled from the unlabeled excluding query instances. $k_{1,i}$ and $k_{2,i}$ is the i_{th} element of the permutation indicator $\mathbf{k}_1 \in \{0, 1\}^{l+q}$ and $\mathbf{k}_2 \in \{0, 1\}^{u-q}$.

Next we define a binary vector $\boldsymbol{\alpha}$ of size u to demonstrate the sample selection. Thus the problem reduces to finding $\boldsymbol{\alpha}$ that minimize the MMD objective:

$$\begin{aligned} \min_{\boldsymbol{\alpha}} &\left\| \frac{1}{l+q} \left(\sum_{i=1}^l \mathcal{T}_{k_{L,i}}(\mathcal{H}(\mathbf{x}_{L,i})) + \sum_{j=1}^u \alpha_j \mathcal{T}_{k_{U,j}}(\mathcal{H}(\mathbf{x}_{U,j})) \right) \right. \\ &\quad \left. - \frac{1}{u-q} \sum_{j=1}^u (1 - \alpha_j) \mathcal{T}_{k_{U,j}}(\mathcal{H}(\mathbf{x}_{U,j})) \right\|_F^2 \\ \text{s.t. } &\boldsymbol{\alpha} \in \{0, 1\}^u, \|\boldsymbol{\alpha}\|_1 = q \end{aligned} \quad (3)$$

where we define $\mathbf{x}_{U,i}$ and $\mathbf{x}_{L,i}$ as the i_{th} pair sampled from the unlabeled and labeled sets. $k_L \in \{0, 1\}^l$ and $k_U \in \{0, 1\}^u$ as the corresponding permutation indicator, whose j_{th} elements are denoted as $k_{L,j}$ and $k_{U,j}$ respectively. α_j represents for the j_{th} element of $\boldsymbol{\alpha}$.

We can rewrite (2) as:

$$\begin{aligned} \min_{\boldsymbol{\alpha}} &\left\| \sum_{i=1}^l \mathcal{T}_{k_{L,i}}(\mathcal{H}(\mathbf{x}_{L,i})) + \frac{n}{u-q} \sum_{j=1}^u \alpha_j \mathcal{T}_{k_{U,j}}(\mathcal{H}(\mathbf{x}_{U,j})) \right. \\ &\quad \left. - \frac{l+q}{u-q} \sum_{j=1}^u \mathcal{T}_{k_{U,j}}(\mathcal{H}(\mathbf{x}_{U,j})) \right\|_F^2 \end{aligned}$$

This is equivalent to:

$$\begin{aligned} \min_{\boldsymbol{\alpha}} &\left\| \sum_{j=1}^u \alpha_j \mathcal{T}_{k_{U,j}}(\mathcal{H}(\mathbf{x}_{U,j})) + \frac{u-q}{n} \sum_{i=1}^l \mathcal{T}_{k_{L,i}}(\mathcal{H}(\mathbf{x}_{L,i})) \right. \\ &\quad \left. - \frac{l+q}{n} \sum_{j=1}^u \mathcal{T}_{k_{U,j}}(\mathcal{H}(\mathbf{x}_{U,j})) \right\|_F^2 \end{aligned}$$

Finally we rewrite the above equation and obtain the learning objective:

$$\begin{aligned} \min_{\boldsymbol{\alpha}} \quad & \frac{1}{2} \boldsymbol{\alpha}^T \mathbf{K}_{UU} \boldsymbol{\alpha} + \frac{u-q}{n} \mathbf{1}^l \mathbf{K}_{LU} \boldsymbol{\alpha} - \frac{l+q}{n} \mathbf{1}^u \mathbf{K}_{UU} \boldsymbol{\alpha} \\ \text{s.t.} \quad & \boldsymbol{\alpha} \in \{0, 1\}^u, \|\boldsymbol{\alpha}\|_1 = q \end{aligned} \quad (4)$$

where the element in the i_{th} row and j_{th} column of \mathbf{K}_{UU} and \mathbf{K}_{LU} is denoted as $K_{UU,ij}$ and $K_{LU,ij}$ respectively:

$$\begin{aligned} K_{UU,ij} &= \inf_k \mathcal{H}(\mathbf{x}_{U,i})^T \mathcal{T}_k(\mathcal{H}(\mathbf{x}_{U,j})) \\ K_{LU,ij} &= \inf_k \mathcal{H}(\mathbf{x}_{L,i})^T \mathcal{T}_k(\mathcal{H}(\mathbf{x}_{U,j})) \end{aligned}$$

References

1. Chattopadhyay, R., Wang, Z., Fan, W., Davidson, I., Panchanathan, S., Ye, J.: Batch mode active sampling based on marginal probability distribution matching. TKDD **7**(3), 13 (2013)