

Label Embedding Online Hashing for Cross-Modal Retrieval

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CONTRIBUTIONS

- A novel supervised online cross-modal hashing framework is presented. It can not only fully exploit the semantic information by label embedding, but also consider the correlation between new and existing data.
- A discrete and efficient optimization algorithm is proposed for LEMON. The binary codes can be generated discretely without relaxation. And, it efficiently updates hash functions by keeping old hash codes unchangeable.
- Extensive experiential results demonstrate the superiority of LEMON.

PROPOSED METHOD

➤ Label Embedding

- binary codes should preserve the semantic similarity

$$\min_{\mathbf{B}^{(t)}} \|\mathbf{B}^{(t)\top} \mathbf{B}^{(t)} - r \mathbf{S}^{(t)}\|^2, \text{ s.t. } \mathbf{B}^{(t)} \in \{-1, 1\}^{r \times N_t},$$

- labels could be reconstructed from binary codes

$$\min_{\{\mathbf{B}, \mathbf{P}\}^{(t)}} \|\mathbf{L}^{(t)} - \mathbf{P}^{(t)} \mathbf{B}^{(t)}\|^2 + \gamma \|\mathbf{P}^{(t)}\|^2, \text{ s.t. } \mathbf{B}^{(t)} \in \{-1, 1\}^{r \times N_t},$$

- jointly considering above functions

$$\min_{\{\mathbf{B}, \mathbf{P}\}^{(t)}} \alpha \|\mathbf{B}^{(t)\top} \mathbf{B}^{(t)} - r \mathbf{S}^{(t)}\|^2 + \beta \|\mathbf{L}^{(t)} - \mathbf{P}^{(t)} \mathbf{B}^{(t)}\|^2 + \beta \gamma \|\mathbf{P}^{(t)}\|^2, \text{ s.t. } \mathbf{B}^{(t)} \in \{-1, 1\}^{r \times N_t},$$

➤ Efficient Discrete Optimization

- alternatively and iteratively update $\{\bar{\mathbf{B}}, \bar{\mathbf{V}}, \mathbf{P}, \mathbf{R}\}^{(t)}$

- auxiliary variables $\mathbf{C}_*^{(t-1)}$

E.g. $\mathbf{C}_1^{(t)} = \bar{\mathbf{L}}^{(t)} \bar{\mathbf{V}}^{(t)\top} + \mathbf{L}^{(t)} \mathbf{V}^{(t)\top}$

$\mathbf{C}_1^{(t-1)} \in \mathbb{R}^{c \times r}$ is calculated at the previous round.
 $\mathbf{C}_1^{(t)}$ is only relevant to new data, i.e., n_t .

$$\mathbf{C}_1^{(t)} = \bar{\mathbf{L}}^{(t)} \bar{\mathbf{V}}^{(t)\top} + \mathbf{C}_1^{(t-1)}$$

➤ Online Learning

- define a block similarity matrix $\mathbf{S}^{(t)} = \begin{bmatrix} \mathbf{S}_{oo}^{(t)} & \mathbf{S}_{oc}^{(t)} \\ \mathbf{S}_{co}^{(t)} & \mathbf{S}_{cc}^{(t)} \end{bmatrix}$, $\mathbf{S}^{(t)} = 2\mathbf{U}^{(t)\top} \mathbf{U}^{(t)} - \mathbf{1}\mathbf{1}^\top$,

- keep $\mathbf{B}^{(t)}$ unchanged and only update $\bar{\mathbf{B}}^{(t)}$

$$\min_{\{\bar{\mathbf{B}}, \mathbf{P}\}^{(t)}} \alpha \|\bar{\mathbf{B}}^{(t)\top} \bar{\mathbf{B}}^{(t)} - r \mathbf{S}^{(t)}\|^2 + \alpha \|\bar{\mathbf{B}}^{(t)} - r \mathbf{S}^{(t)}\|^2 + \alpha \|\bar{\mathbf{B}}^{(t)} - r \mathbf{S}^{(t)}\|^2 + \beta \|\bar{\mathbf{L}}^{(t)} - \mathbf{P}^{(t)} \bar{\mathbf{B}}^{(t)}\|^2 + \beta \gamma \|\mathbf{P}^{(t)}\|^2, \text{ s.t. } \bar{\mathbf{B}}^{(t)} \in \{-1, 1\}^{r \times N_t}.$$

- solve update-imbalance problem

$$\min_{\{\bar{\mathbf{B}}, \bar{\mathbf{V}}, \mathbf{P}, \mathbf{R}\}^{(t)}} \alpha \|\bar{\mathbf{B}}^{(t)\top} \bar{\mathbf{B}}^{(t)} - r \mathbf{S}^{(t)}\|^2 + \alpha \|\bar{\mathbf{B}}^{(t)} - r \mathbf{S}^{(t)}\|^2 + \alpha \|\bar{\mathbf{B}}^{(t)} - r \mathbf{S}^{(t)}\|^2 + \beta \|\bar{\mathbf{L}}^{(t)} - \mathbf{P}^{(t)} \bar{\mathbf{V}}^{(t)}\|^2 + \beta \|\bar{\mathbf{L}}^{(t)} - \mathbf{P}^{(t)} \bar{\mathbf{V}}^{(t)}\|^2 + \beta \gamma \|\mathbf{P}^{(t)}\|^2 + \|\bar{\mathbf{B}}^{(t)} - \mathbf{R}^{(t)} \bar{\mathbf{V}}^{(t)}\|^2 + \|\bar{\mathbf{B}}^{(t)} - \mathbf{R}^{(t)} \bar{\mathbf{V}}^{(t)}\|^2, \text{ s.t. } \bar{\mathbf{B}}^{(t)} \in \{-1, 1\}^{r \times N_t}, \mathbf{R}^{(t)} \mathbf{R}^{(t)\top} = \mathbf{I}, \bar{\mathbf{V}}^{(t)} \bar{\mathbf{V}}^{(t)\top} = n_t \mathbf{I}, \bar{\mathbf{V}}^{(t)} \mathbf{1} = \mathbf{0}.$$

➤ Out-of-Sample

- Hash Mapping: linear regression

$$\min_{\mathbf{W}_m^{(t)}} \|\mathbf{B}^{(t)} - \mathbf{W}_m^{(t)} \mathbf{X}_m^{(t)}\|^2 + \xi \|\mathbf{W}_m^{(t)}\|^2,$$

- Online Learning: $\mathbf{B}^{(t)} = [\mathbf{B}^{(t)}, \bar{\mathbf{B}}^{(t)}]$

$$\min_{\mathbf{W}_m} \|\mathbf{B}^{(t)} - \mathbf{W}_m^{(t)} \mathbf{X}_m^{(t)}\|^2 + \|\bar{\mathbf{B}}^{(t)} - \mathbf{W}_m^{(t)} \bar{\mathbf{X}}_m^{(t)}\|^2 + \xi \|\mathbf{W}_m^{(t)}\|^2.$$

- Efficient Optimization

- auxiliary variables $\mathbf{H}_*^{(t-1)}$ and $\mathbf{F}_*^{(t-1)}$

- Out-of-Sample $H_m^{(t)}(\mathbf{x}_m) = \text{sign}(\mathbf{W}_m^{(t)} \mathbf{x}_m)$.

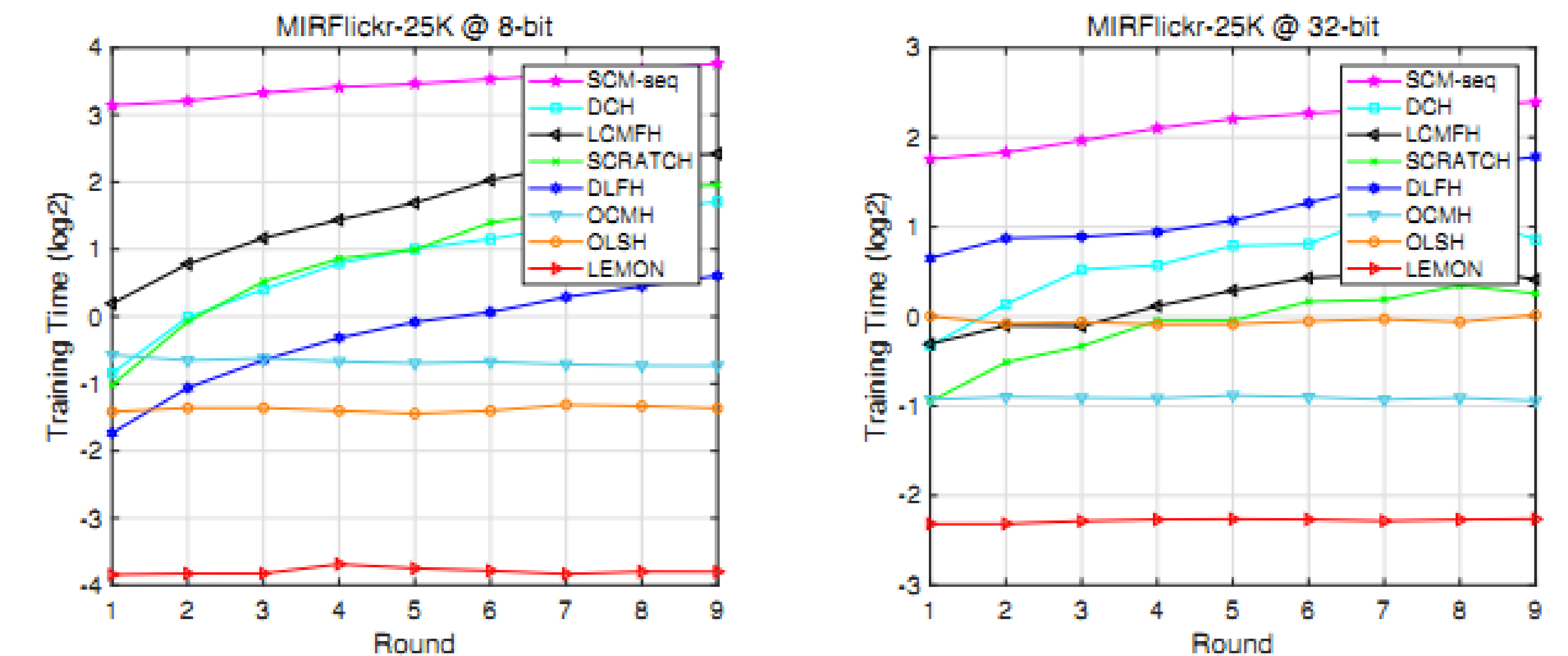
EXPERIMENTS

➤ MAP results on MIRFlickr-25K, and NUS-WIDE

Table 1: The MAP results of all methods on MIRFlickr-25K. Table 3: The MAP results of all methods on NUS-WIDE.

Task	Method	8-bit	16-bit	32-bit	64-bit	128-bit
$I \rightarrow T$	SCM-seq	0.6307	0.6457	0.6455	0.6629	0.6148
	DCH	0.6739	0.7093	0.6774	0.7219	0.7424
	LCMFH	0.6796	0.6750	0.6896	0.6898	0.7002
	SCRATCH	0.6870	0.7084	0.7136	0.7234	0.7256
	DLFH	0.7102	0.7076	0.7182	0.7188	0.7254
	OCMH	0.5484	0.5515	0.5578	0.5565	0.5536
	OLSH	0.5791	0.5778	0.6008	0.5971	0.5935
	LEMON	0.7272	0.7258	0.7476	0.7474	0.7485
$T \rightarrow I$	SCM-seq	0.6151	0.6257	0.6245	0.6512	0.6010
	DCH	0.7388	0.7649	0.7410	0.7786	0.8010
	LCMFH	0.7332	0.7293	0.7528	0.7627	0.7740
	SCRATCH	0.7446	0.7692	0.7727	0.7810	0.7877
	DLFH	0.7235	0.7836	0.8066	0.8225	0.8285
	OCMH	0.5500	0.5530	0.5547	0.5565	0.5533
	OLSH	0.5801	0.5829	0.6094	0.6038	0.6024
	LEMON	0.7924	0.8166	0.8238	0.8298	0.8327

➤ Training time-round curves on MIRFlickr-25K



CONTRACT

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