

Predictable Dual-View Hashing

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Integrate different modalities

- · High dimensional modalities
- Efficient data structure for search

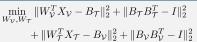
Previous approaches

- Domain specific [Farhadi et al. 2010]
- CCA-based [Gong et al. 2011, Sharma et al. 2012]

Optimization

 $\min_{W_{\mathcal{V}}, W_{\mathcal{T}}} \|\operatorname{sgn}(W_{\mathcal{V}}^T X_{\mathcal{V}}) - \operatorname{sgn}(W_{\mathcal{T}}^T X_{\mathcal{T}})\|_2^2$





$$B_{\mathcal{T}} = \operatorname{sgn}(W_{\mathcal{T}}^T X_{\mathcal{T}}),$$

$$B_{\mathcal{V}} = \operatorname{sgn}(W_{\mathcal{V}}^T X_{\mathcal{V}}).$$

Optimization is non-convex and combinatorial

$$\min_{W_{\mathcal{V}}, W_{\mathcal{T}}, \xi_{\mathcal{V}}, \xi_{\mathcal{T}}} \|B_{\mathcal{T}} B_{\mathcal{T}}^T - I\|_2^2 + \|B_{\mathcal{V}} B_{\mathcal{V}}^T - I\|_2^2 + \sum_{i=1}^{N} \|w_{\mathcal{V}i}\| + \sum_{i=1}^{N} \|w_{\mathcal{T}i}\| + C_1 \sum_{i=1}^{N} \xi_{\mathcal{V}} + C_2 \sum_{i=1}^{N} \xi_{\mathcal{T}}$$
s.t.

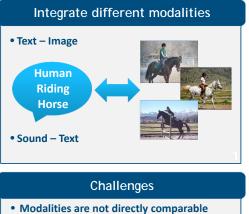
 $B_{\mathcal{T}} = \operatorname{sgn}(W_{\mathcal{T}}^T X_{\mathcal{T}}),$

 $B_{\mathcal{V}} = \operatorname{sgn}(W_{\mathcal{V}}^T X_{\mathcal{V}}),$

 $B_{\mathcal{T}}^{ij}(w_{\mathcal{V}i}^T X_{\mathcal{V}}^j) \ge 1 - \xi_{\mathcal{V}}^{ij} \quad \forall i, j,$

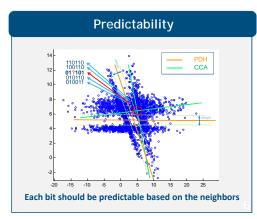
 $B_{\mathcal{V}}^{ij}(w_{\mathcal{T}i}^T X_{\mathcal{T}}^j) \ge 1 - \xi_{\mathcal{T}}^{ij} \quad \forall i, j.$ Using a block coordinate descent algorithm

How we do it



Dual-view hashing Textual Space Visual Space Human riding a horse Person laughing at restaurant Cow standing in a farm

Binary code assignment



Modality 1 **Modality 2** /••• 1010 1001 ■ label 1110 1110 0010

Algorithm

Algorithm 1 Predictable Dual-View Hashing

Input: $X_{\mathcal{V}}, X_{\mathcal{T}} \in \mathbb{R}^{d_* \times n}$

Input: $X_{\mathcal{V}}, X_{\mathcal{T}} \in \mathbb{R}^{d_w \times d_v}$. Output: $B_{\mathcal{V}}, B_{\mathcal{T}} \in \mathbb{B}^{d_w \times k}$. 1: $W_{\mathcal{V}}, W_{\mathcal{T}} \in \mathbb{R}^{d_w \times k} \leftarrow CCA(X_{\mathcal{V}}, X_{\mathcal{T}}, k)$

- 2: $B_{\mathcal{V}} \leftarrow \operatorname{sgn}(W_{\mathcal{V}}^T X_{\mathcal{V}})$ 3: $B_{\mathcal{T}} \leftarrow \operatorname{sgn}(W_{\mathcal{T}}^T X_{\mathcal{T}})$
- 4: repeat
- $W_{\mathcal{V}} \leftarrow \text{Weights of } k \text{ linear SVMs (for } i^{th} \text{ SVM: train-}$ ing features are columns of $X_{\mathcal{V}}$ and training labels are elements of i^{th} row of $B_{\mathcal{T}}$)
- $B_{\mathcal{V}} \leftarrow \operatorname{sgn}(W_{\mathcal{V}}^T X_{\mathcal{V}})$
- Update $B_{\mathcal{V}}$ using Eq. (5) $W_T \leftarrow \text{Weights of } k \text{ linear SVMs (for } i^{th} \text{ SVM: training features are columns of } X_T \text{ and training labels are}$
- elements of i^{th} row of $B_{\mathcal{V}}$) $B_{\mathcal{T}} \leftarrow \operatorname{sgn}(W_{\mathcal{T}}^T X_{\mathcal{T}})$ Update $B_{\mathcal{T}}$ using Eq. (5)

- 11: **until** convergence 12: $B_{\mathcal{V}} \leftarrow \operatorname{sgn}(W_{\mathcal{V}}^T X_{\mathcal{V}})$ 13: $B_{\mathcal{T}} \leftarrow \operatorname{sgn}(W_{\mathcal{T}}^T X_{\mathcal{T}})$

Optimization analysis

