Compact Kernel Hashing with Multiple Features

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Background and Related Work

Background

- The explosive growth of the vision data motivates the recent studies on hashing based nearest neighbor search (ANN)
- Locality-Sensitive Hashing (LSH) gives the paradigm of hashing based ANN
- Various scenarios: unsupervised, supervised, kernelized, and multiple probes

Related Work

- Adaptively combining diverse complementary features can give improved performance
- Existing multiple feature hashing approaches either simply post-combine linear outputs of each feature type or equally pre-concatenate all features as one

Main Issues

- The correlation and importance of each feature type are still not fully exploited
- Computationally expensive in both training and searching

Multiple Feature Kernel Hashing

Notations

- a set of N training examples with M visual features
  - $X_n^{(m)} \in R^{d_m \times 1}$: the m-th feature (d_m dimension) of n-th sample
  - $X^{(m)} = \left[X_1^{(m)}, X_2^{(m)}, \dots, X_n^{(m)}\right]$: the m-th feature of all data

Key Idea

- Learn a kernel space incorporating multiple features, where the neighbor relationships can be well preserved.

Nonlinear feature mapping

- a series of embedding functions $\phi_m(\cdot)$ corresponding to each visual feature
- nonlinear mapping of i-th sample

$$\phi(X_i) = \left[\mu_1^{\frac{1}{2}}\phi_1^T\left(X_i^{(1)}\right), \dots, \mu_M^{\frac{1}{2}}\phi_M^T\left(X_i^{(M)}\right)\right]^T$$

- linear projection hashing

$$h_p(X_i) = sign\left(V_p^T\phi(X_i) + b_p\right),\quad p = 1,\dots,P.$$

Multiple kernel form

- V_p in kernel space can be represented as a combination of R landmarks Z_r

$$V_p = \sum_{r=1}^{R} W_{rp}\phi(Z_r), r = 1,\dots,R.$$

- let $K^{(m)}$ denote the kernel corresponding to $\phi_m(\cdot)$, then $\phi(\cdot)$ defines a kernel $K = \sum_{m=1}^{M}\mu_m K^{(m)}$
- kernel hashing

$$h_p(X_i) = sign\left(W_{\cdot p} K_i + b_p\right),\quad p = 1,\dots,P.$$

Optimization

Optimization

- Objective function similar to that of spectral hashing

$$\mathcal{L}(S, W, b, \mu) = \frac{1}{2}\boxed{\sum_{i,j=1}^{N} S_{ij}\|Y_i - Y_j\|^2} + \lambda\boxed{\|V\|_F^2}$$

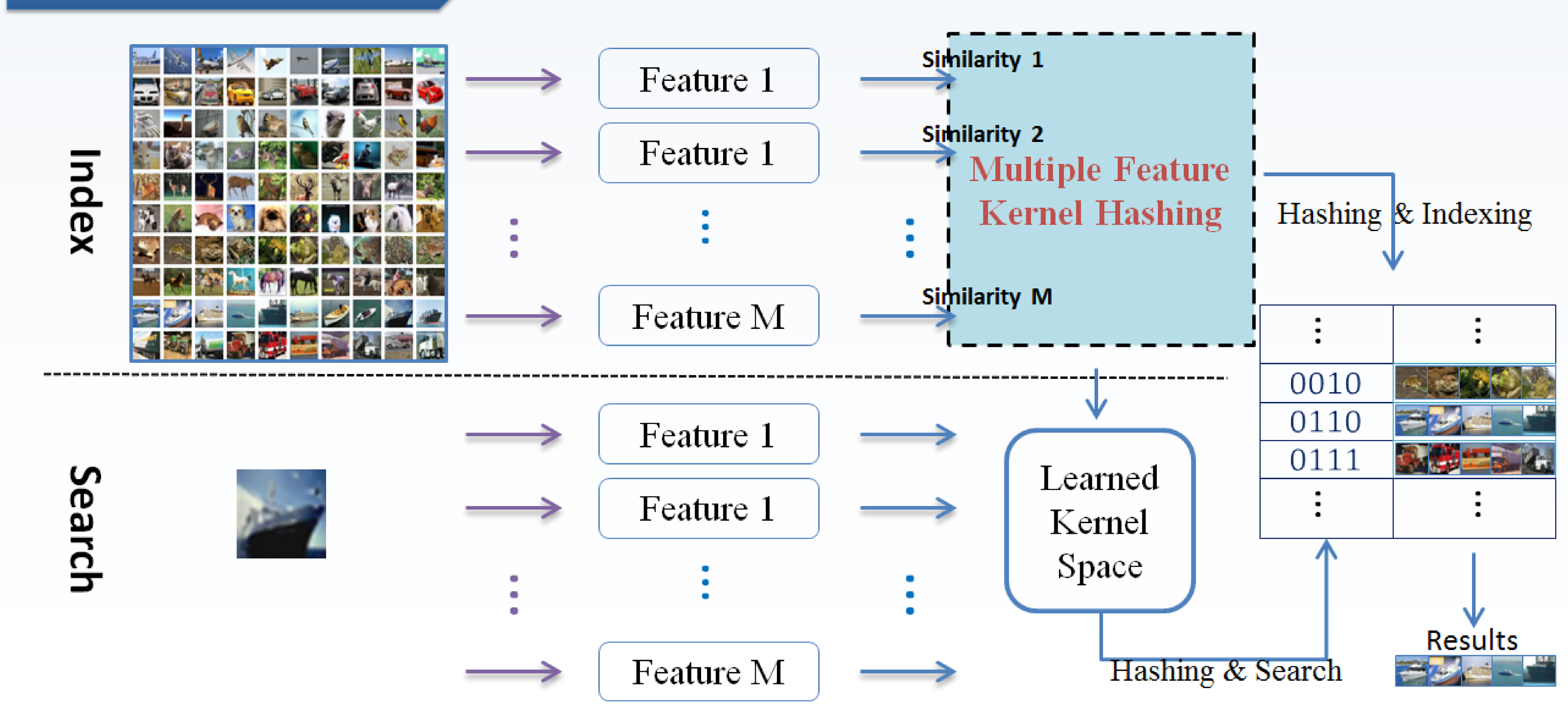
Spectral embedding loss regularization

- Alternating optimization
  - Update hashing parameters: (W, b)
  - Update linear combination coefficients: μ

methods	training	search
CHMS	$O(T(D^3 + D^2N + DN_s))$	$O(PD)$
MFH	$O(D^3 + D^2N + DN_s)$	$O(PD)$
Proposed	$O(T(LN_s + P^3))$	$O(PM + ML)$

[1] Here $P, M, T \ll D, N_s \ll N^2$ and $L < D$ ($D = \sum_{m=1}^{M} d_m$).

Framework

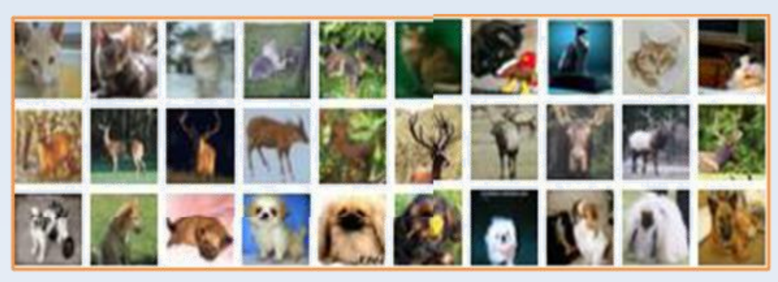


Experiments

Datasets

- CIFAR-10: 60K, 384D GIST + 300D SIFT BoW
- NUS-WIDE: 270K, 128D texture + 225D color

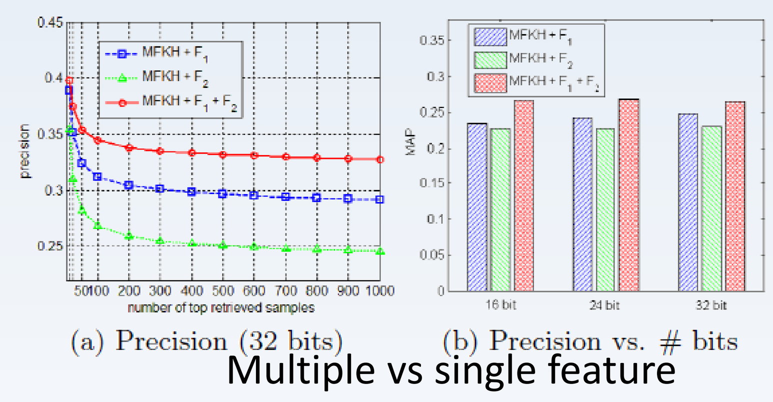
CIFAR-10



NUS-WIDE

Measurement

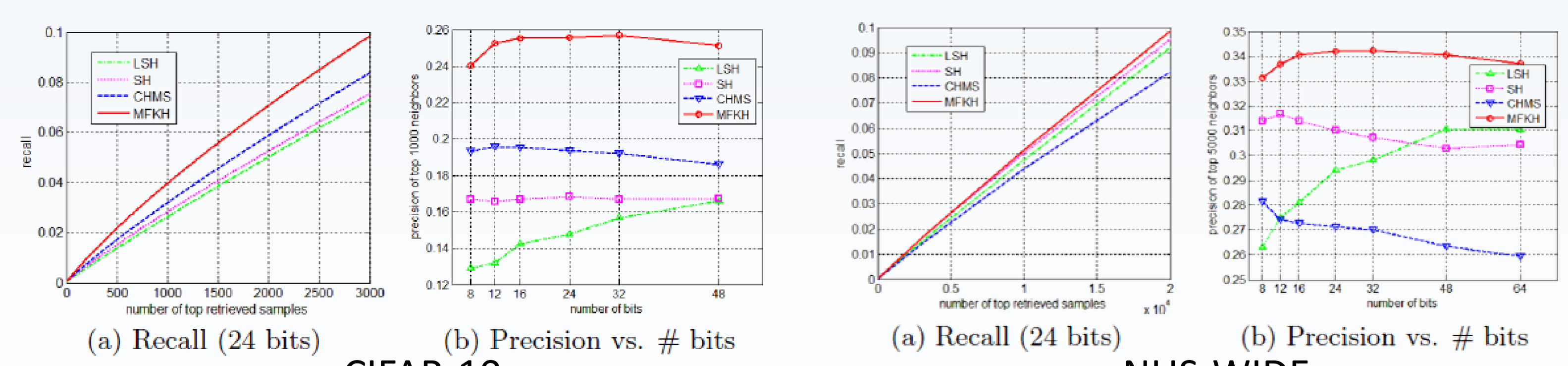
- MAP for Hamming ranking
- Recall, precision of top results



(a) Precision (32 bits) (b) Precision vs. # bits

Multiple vs single feature

Results



(a) Recall (24 bits) (b) Precision vs. # bits (a) Recall (24 bits) (b) Precision vs. # bits

CIFAR-10 NUS-WIDE

Conclusion

- Efficient multiple feature hashing.
  - similarity preserving hashing with linearly combined multiple kernels
  - efficient alternating optimizing way