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Reciprocal Hash Tables for Nearest Neighbor Search

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Abstract

Recent years have witnessed the success of hashing techniques in approximate nearest neighbor search. In practice, multiple hash tables are usually employed to retrieve more desired results from all hit buckets of each table. However, there are rare works studying the unified approach to constructing multiple informative hash tables except the widely used random way. In this paper, we regard the table construction as a selection problem over a set of candidate hash functions. With the graph representation of the function set, we propose an efficient solution that sequentially applies normalized dominant set to finding the most informative and independent hash functions for each table. To further reduce the redundancy between tables, we explore the reciprocal hash tables in a boosting manner, where the hash function graph is updated with high weights emphasized on the misclassified neighbor pairs of previous hash tables. The construction method is general and compatible with different types of hashing algorithms using different feature spaces and/or parameter settings. Extensive experiments on two large-scale benchmarks demonstrate that the proposed method outperforms both naive construction method and state-of-the-art hashing algorithms, with up to 65.93% accuracy gains.

Introduction

The rapid growth of the vision data has posed great challenges on nearest neighbor search (ANN) in many applications like content-based image retrieval, large-scale classification, pose estimation, etc. Hashing-based approximate ANN achieves attractive performance than traditional tree based approaches. The idea of Locality-Sensitive Hashing (LSH) was first proposed in (Indyk and Motwani 1998), following which the hashing paradigm based on random projections was established for cosine (Charikar 2002) and l_p-norm ($p \in (0, 2]$) (Datar et al. 2004) similarity metric. It produces similar binary codes in Hamming space for close points in the original space. The binary coding not only reduces the indexing memory, but also achieves fast search in a constant or sub-linear time. However, since their hash functions are independently and randomly generated, usually long hash codes are desired to reach a satisfactory performance. To pursue compact, yet informative binary codes, various types of hashing algorithms have been proposed following LSH, including linear (Gong and Lazebnik 2011; Joly and Buisson 2011; Wang, Kumar, and Chang 2012), nonlinear (Kulis and Grauman 2009; Liu et al. 2011), non-metric (Mu and Yan 2010), multiple features (Zhang, Wang, and Si 2011; Kumar and Udupa 2011; Zhen and Yeung 2012), multiple bits (Liu et al. 2011; Kong and Li 2012), etc.

Most of state-of-the-art hashing algorithms concentrate on how to generate hash functions for a single hash table, where each data point is encoded into one hash code. In practice, to improve the search performance, one successful technique is building multiple hash tables and returning points in multiple probed buckets (Gionis, Indyk, and Motwani 1999; Lv et al. 2007; Norouzi, Punjani, and Fleet 2012). Xu et al. simultaneously take both hash function learning and hash table construction into consideration, and attain promising performance (Xu et al. 2011). However, there are very few works studying the general strategy for multiple hash table construction, which is strongly required to support various types of hashing algorithms, different data sets and scenarios, etc. (He, Kumar, and Chang 2012). Random selection as the most widely-used and general strategy faithfully improves the search performance (Lv et al. 2007; Norouzi, Punjani, and Fleet 2012), but usually it needs a large number of hash tables without utilizing the informativeness of hash functions and their independence.

Motivated by the well-studied feature selection problem (Zhao, Wang, and Liu 2010), we formulate the multiple table construction as a hash function selection problem. In the formulation, hash functions generated by existing hashing algorithms serve as a function pool, from which the most desired ones are selected for each hash table. Different from conventional research attempting to learn hash functions, our construction method puts emphasis on the selection over the learned hash functions. Based on hash function selection, the table construction is compatible with any hashing algorithm using different parameter settings or feature types.

To solve the function selection problem, we first represent the pooled hash functions as a graph, whose vertex and edge weights correspond to the important selection criteria: similarity preservation and mutual independence of hash

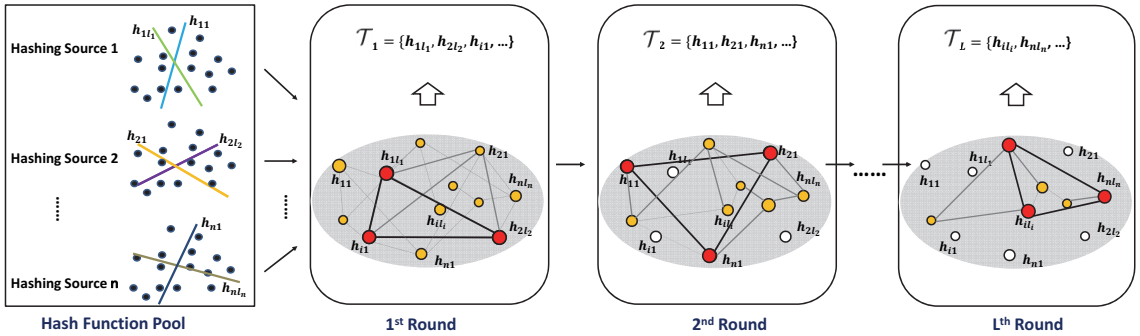


Figure 1: The proposed boosting framework for reciprocal hash table construction using dominant hash functions. See the formal description in Algorithm 2 and discussions in Reciprocal Hash Tables section.

functions. Then the hash function selection turns into a dominant subset discovery problem on the graph. For each hash table, the most desired functions that preserve neighbour relationships with small redundancy (named dominant hash functions) can be efficiently found using the technique of normalized dominant set. Since hash tables complementing each other guarantee a high probability that the nearest neighbors can be discovered from at least one of them (Xu et al. 2011; He et al. 2011), we propose a boosting-like approach that sequentially exploits the reciprocal relationships between hash tables, by selecting dominant hash functions that well preserve the previous mis-separated neighbors.

The main contribution of this paper is the reciprocal hash table construction based on hash function selection. To make each table informative enough, it selects the dominant hash functions according to both the quality of each individual hash function and the independence between all hash functions. To further increase the overall performance using less hash tables, the boosting manner is applied to discovering the complementary relationships among tables. The proposed method serves as a unified solution, supporting different types of hashing algorithms (using different feature spaces, parameter settings, etc) and various complex, yet practical scenarios (*e.g.*, multiple hashing algorithms, multiple bit hashing algorithms, hashing with multiple features, etc.). To our best knowledge, it is the first work that uniformly addresses multiple hash table construction by simultaneously considering both informativeness of each table and complementary relationships among them.

Figure 1 demonstrates the proposed table construction method that reciprocally selects dominant hashing functions in a boosting manner. Our empirical study on several large-scale benchmarks highlights the benefits of our method, with significant performance gains over the popular random selection and several state-of-the-art hashing algorithms.

Problem Definition

Notations

Suppose we have a pool of B hash functions $\mathcal{H} = \{h_1(\cdot), \ldots, h_B(\cdot)\}$ with the index set $\mathcal{V} = \{1, \ldots, B\}$, each of which is a binary mapping $h_i(\cdot) : \mathbb{R}^d \rightarrow \{-1, 1\}$. These hash functions can be generated by different types of hashing algorithms (linear/nonlinear, random/optimized, etc.) with different features, parameter settings, etc.

Given the training data set $\mathbf{X} = [\mathbf{x}_1, \ldots, \mathbf{x}_N] \in \mathbb{R}^{d \times N}$ (d is the feature dimension, and N the size of training data), each point $\mathbf{x}_i$ is encoded by the B hash functions. Then we have $\mathbf{Y}_i = h_i(\mathbf{X}) = [h_i(\mathbf{x}_1), \ldots, h_i(\mathbf{x}_N)] \in \{-1, 1\}^N$, $i = 1, \ldots, B$ as the bits generated by i-th function for all N points. If we define y as a B-dimension random binary vector, and $y_i = h_i(\cdot)$, $i = 1, \ldots, B$ as the i-th dimension of y, then $\mathbf{Y}_i$ can be viewed as N samples of y_i.

Our goal is to construct multiple reciprocal hash tables using hash function selection on the training set. Formally, given the B hash functions $\mathcal{H}$, we want to build L tables $\{\mathcal{T}_l, l = 1, \ldots, L\}$, each of which consists of K hash functions from $\mathcal{H}$: $\mathcal{T}_l = \{h_{l_1}, \ldots, h_{l_K}, \{l_1, \ldots, l_K\} \subset \mathcal{V}\}$.

Graph Representation

Motivated by recent research on modelling correlations based on graph (Pavan and Pelillo 2007; Liu and Yan 2010), we first represent the pooled hash functions $\mathcal{H}$ as a vertex-weighted and undirected edge-weighted graph:

$$G = (\mathcal{V}, \mathcal{E}, \mathbf{A}, \pi). \tag{1}$$

$\mathcal{V} = \{1, \ldots, B\}$ is the vertex set corresponding to the B hash functions in $\mathcal{H}$ with weights $\pi = [\pi_1, \ldots, \pi_B]^T$. $\mathcal{E} \subseteq \mathcal{V} \times \mathcal{V}$ is the edge set with weights $\mathbf{A} = (a_{ij})$, whose entry $a_{ij} : (i, j) \in \mathcal{E} \rightarrow \mathbb{R}_*$ is a non-negative weight corresponding to the edge between vertex i and j.

The vertex weights characterize the quality of each hash function, while the edge weights describe the pairwise relationships between hash functions (in practice it is difficult to compute higher-order correlations among more than two hash functions). Prior hashing research has proved that **similarity preservation** of each hash function and **independence** among them are two satisfying, yet non-redundant criteria for compact hash code generation in a single hash table (Weiss, Torralba, and Fergus 2008; Wang, Kumar, and Chang 2012). Therefore, we respectively adopt them as the vertex and edge weights in graph G.

Vertex Weights To obtain good hash codes guaranteeing search accuracy, hash functions should preserve similarities between data points, namely, neighbor points are supposed to have similar hash codes (Weiss, Torralba, and Fergus 2008), and non-neighbor pairs should be separated with a large margin (Wang, Kumar, and Chang 2012). To assess such capability of each hash function, a reasonable criteria

is the empirical accuracy (Wang, Kumar, and Chang 2012), the difference between the numbers of correctly and wrongly classified neighbors by each hash function. It relies on two types of neighbor sets: homogenous neighbors $\mathcal{M}$ and heterogeneous neighbors $\mathcal{C}$ (Yan et al. 2007). If i-th and j-th samples are either nearest neighbors in a metric space or share common labels, then $(i,j) \in \mathcal{M}$. Similarly, if they are far away or have different labels, then $(i,j) \in \mathcal{C}$. The similarity matrix $\mathbf{S}$ will be

$$\mathbf{S}_{ij} = \begin{cases} 1, & \text{if } (i,j) \in \mathcal{M} \\ -1, & \text{if } (i,j) \in \mathcal{C} \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

Based on the predefined similarity matrix S, we define the vertex weight of the i-th hash function in terms of the similarity preservation, with a $\gamma > 0$:

$$\pi_i = \exp\left(\gamma \mathbf{Y}_i \mathbf{S} \mathbf{Y}_i^T\right). \tag{3}$$

Edge Weights Previous research shows that the independent hash functions are desired to generate compact binary codes (Weiss, Torralba, and Fergus 2008). Mutual information among their bit variables serves as a good independence criterion (He et al. 2011). Following (Heo et al. 2012), we approximate it by considering the pairwise case .

Given the bit distribution for i-th hash function $p(y_i), y_i \in \{-1, 1\}$, and the joint bit distribution for i-th and j-th functions $p(y_i, y_j)$, the independence a_{ij} between any i-th and j-th bits based on their mutual information forms the edge weights $\mathbf{A} = (a_{ij})$, and each a_{ij} is defined with a $\lambda > 0$:

$$a_{ij} = \exp\left[-\lambda \sum_{y_i, y_j} p(y_i, y_j) \log \frac{p(y_i, y_j)}{p(y_i)p(y_j)}\right]. \tag{4}$$

Here $a_{ii} = 0$, because each function is self-dependent.

Informative Hash Table

Similarity preservation measures each hash function's capability of retaining neighbor relationships, while their independence results in short, yet discriminative hash codes by reducing the redundancy among them. To achieve high performance, the hash functions that are not only capable of preserving neighbor relationships but also mutually independent should be selected for an informative hash table. This intuition indicates that the most desired subset of hash functions should possess high vertex and edge weights inside, and thus can be regarded as the dominant set on the graph G (Pavan and Pelillo 2007; Liu and Yan 2010).

In the dominant set, each element is associated with a discriminative score induced from both vertex and edge weights. Therefore, the most desired K hash functions (named dominant hash functions) from the candidate set $\mathcal{H}$ are equivalent to the elements with largest scores in the dominant set of graph G. We establish the following theorem that explores the efficient solution to the dominant set (Liu et al. 2013):

Algorithm 1 Hash Table Construction using **D**ominant **H**ash **F**unctions (DHF).

Input: data $\mathbf{X}$, hash function set $\mathcal{H}$, similarity $\mathbf{S}$;
Initialize: $\mathbf{Y}_i \leftarrow h_i(\mathbf{X}), i = 1, \ldots, B$;
Compute weights π and $\mathbf{A}$ by Eq. (3) and Eq. (4);
for l = 1 to L **do**
  Optimize $\mathbf{z}^*$ of problem (5) with respect to $\mathcal{H}$;
  Set $\sigma \leftarrow \text{topK}(\mathbf{z}^*)$ and $\mathcal{V} \leftarrow \{1, \ldots, |\mathcal{H}|\} \setminus \sigma$;
  Set $\mathcal{T}_l \leftarrow \{h_i : h_{i \in \sigma} \in \mathcal{H}\}$;
  Update $\mathcal{H} \leftarrow \mathcal{H} \setminus \mathcal{T}_l$ and $\mathbf{A} \leftarrow \mathbf{A}_{\mathcal{V}}$;
end for
Output: hash tables $\mathcal{T}_l, l = 1, \ldots, L$.

Theorem 1 *If $\mathbf{z}^*$ is a strict local solution of the program*

$$\begin{array}{ll} \max & \frac{1}{2}\mathbf{z}^T \hat{\mathbf{A}} \mathbf{z} \\ s.t. & \mathbf{z} \geq 0, \mathbf{1}^T \mathbf{z} = 1 \end{array} \tag{5}$$

where $\hat{\mathbf{A}} = \mathbf{\Pi A \Pi}$, and $\mathbf{\Pi} = diag(\pi)$, then its support $\sigma(\mathbf{z}^*) = \{i \in \mathcal{V} : z_i^* \neq 0\}$ is the normalized dominant set of graph $G = (\mathcal{V}, \mathcal{E}, \mathbf{A}, \pi)$.

Theorem 1 indicates that the dominant set can be found efficiently by solving the quadratic programming problem in (5), whose strict and stable solution with respect to the nonnegative and symmetric $\hat{A}$ can be optimized using the replicator dynamics (Pavan and Pelillo 2007; Liu and Yan 2010) with the following iterations:

$$\mathbf{z}_i(t+1) = \mathbf{z}_i(t) \frac{(\hat{A}\mathbf{z}(t))_i}{\mathbf{z}(t)^T \hat{A} \mathbf{z}(t)}, \; i = 1, \ldots, L. \tag{6}$$

The objective function $\frac{1}{2}\mathbf{z}^T \hat{\mathbf{A}} \mathbf{z}$ of program (5) reflects the cohesiveness among functions, incorporating both proposed selection criteria. The solution $\mathbf{z}^*$ naturally scores each function, and its nonzero elements correspond to the dominant set in G. Then, our dominant hash functions are the K functions indexed by $\text{topK}(\mathbf{z}^*)$ with highest scores in $\mathcal{H}$, which directly constitutes an informative hash table.

Based on the idea of dominant hash functions, our straightforward strategy for hash table construction is to iteratively solve similar problems in (5), with respect to the remaining unselected hash functions (those already selected in previous tables are removed from $\mathcal{H}$). Algorithm 1 (named DHF for short) outlines the detailed table construction procedure using dominant hash functions, where $\mathbf{A}_{\mathcal{V}}$ denotes the submatrix of $\mathbf{A}$ with the rows and the columns indexed by the elements of $\mathcal{V}$. The algorithm is feasible for large-scale problems, since $\mathbf{A}$ can be sparse, and efficient optimization methods like graph shift (Liu and Yan 2010) can be adopted for fast computation.

Reciprocal Hash Tables

Although Algorithm 1 selects the most independent and informative functions for each hash table, it still ignores the redundancy among tables. In practice, it is critical that the multiple tables can be complementary to each other (Xu et al. 2011; He et al. 2011), so that the nearest neighbors can be

found in at least one of them. To take the factor into account, we construct reciprocal hash tables in a boosting manner, which sequentially selects the dominant hash functions that well separate the previous misclassified neighbor pairs.

In the boosting framework, we consider the neighbor prediction of multiple hash tables with respect to the two types of neighbors. Let's define the prediction of the current l hash tables on the neighbor pair $\mathbf{x}_i$ and $\mathbf{x}_j$ as

$$\mathbf{p}_{ij} = \mathbf{d}_{ij}^l - \mu, \tag{7}$$

where $\mathbf{d}_{ij}^l$ is the hamming distance contributed from l hash tables (let $\mathbf{d}_{ij}^0 = 0$):

$$\mathbf{d}_{ij}^l = \min_{i=1,\dots,l} \sum_{h \in \mathcal{T}_i} \|h(\mathbf{x}_i) - h(\mathbf{x}_j)\|^2, \tag{8}$$

and μ is the average hamming distance of all neighbors.

In each round, a new hash table is constructed by selecting the hash functions that can correct the prediction errors of previous tables. Therefore, the weights on the misclassified neighbor pairs will be amplified to incur greater penalty, while those on the correctly classified ones will be shrunk. Specifically, in the l-th round the weights ω are updated based on the prediction p of previous $(l-1)$ tables:

$$\omega_{ij} = \begin{cases} \exp(-\alpha \mathbf{p}_{ij}), & \text{if } (i,j) \in \mathcal{M} \\ \exp(\alpha \mathbf{p}_{ij}), & \text{if } (i,j) \in \mathcal{C} \\ 0, & \text{otherwise} \end{cases} \tag{9}$$

where $\alpha = \ln \frac{\sum_{ij} I(\mathbf{p}_{ij}\mathbf{S}_{ij} < 0)}{\sum_{ij} I(\mathbf{p}_{ij}\mathbf{S}_{ij} \geq 0)}$, measuring the total error rate of all $(l-1)$ hash tables, and $I(\cdot)$ is the indicator function.

The weight updating takes account of both the neighbor prediction on each pair and the overall prediction error of previous tables. Then, a typical way to update the similarity matrix $\mathbf{S}$ will be

$$\mathbf{S}_{ij} = \mathbf{S}_{ij}\omega_{ij}. \tag{10}$$

The updating scheme enlarges the similarity magnitudes of incorrectly predicted neighbor pairs compared to others. Based on S, the hash functions that well preserve the misclassified neighbors will gain large vertex weights updated using (3). Therefore, they possess high priority to be selected as the dominant hash function for the new hash table.

In Algorithm 2 (RDHF) we give our construction approach to reciprocal hash tables using dominant hash functions (See the illustration of the constructing procedure in Figure 1). Compared with DHF, RDHF requires to update the similarity matrix in each round, however, the extra computation is actually very small because of its sparsity.

Algorithm 2 **R**eciprocal Hash Table Construction using **D**ominant **H**ash **F**unctions (RDHF).

Input: data $\mathbf{X}$, hash function set $\mathcal{H}$, similarity $\mathbf{S}$;
Initialize: $\mathbf{Y}_i \leftarrow h_i(\mathbf{X}), i = 1, \dots, B$;
Compute edge weights $\mathbf{A}$ by Eq. (4);
for l = 1 to L **do**
  Update ω_{ij} and $\mathbf{S}_{ij}$ by Eq. (9) and Eq. (10);
  Compute vertex weights π by Eq. (3);
  Optimize $\mathbf{z}^*$ of problem (5) with respect to $\mathcal{H}$;
  Set $\sigma \leftarrow \text{topK}(\mathbf{z}^*)$ and $\mathcal{V} \leftarrow \{1, \dots, |\mathcal{H}|\} \setminus \sigma$;
  Set $\mathcal{T}_l \leftarrow \{h_i : h_{i \in \sigma} \in \mathcal{H}\}$;
  Update $\mathcal{H} \leftarrow \mathcal{H} \setminus \mathcal{T}_l$ and $\mathbf{A} \leftarrow \mathbf{A}_{\mathcal{V}}$;
end for
Output: hash tables $\mathcal{T}_l, l = 1, \dots, L$.

Experiments

In this section we will evaluate multiple table construction methods for two useful scenarios, that the hash functions are generated using *basic hashing algorithms* and *multiple multi-bit hashing algorithms* respectively. The proposed method based on dominant hash functions (**DHF**) and its reciprocal version (**RDHF**) will be compared with the random selection (**RAND**, the only general construction method in the literature) on several datasets. It should be noted that the performance of all these methods relies on the source hashing algorithms that generate the pooled hash functions.

Data Sets and Protocols

We conduct experiments on two widely-used large data sets in hashing research: **SIFT-1M** and **GIST-1M**, consisting of one million 128-D SIFT and 960-D GIST features respectively (Jegou, Douze, and Schmid 2011). For each data set, we construct a training set of 10,000 random samples and a test query set of 1,000 ones. We consider metric neighbors in the similarity matrix, where 100 homogenous neighbors and 200 heterogenous neighbors are calculated for each training sample (Yan et al. 2007). The groundtruth for each query is defined as the top ‰5 nearest neighbors computed by the exhaustive linear scan based on Euclidean distances.

Two common search methods are adopted in the evaluation, including Hamming ranking and hash lookup. The former ranks all points in the database according to their Hamming distances (Equation 8) from the query, while the later retrieves all points falling in the buckets of all tables within certain Hamming radius (usually 2) from the query codes.

All experiments are conducted on a workstation with Intel Xeon CPU E5645@2.40GHz and 24GB memory, and the results reported in this paper are averaged over 10 runs. For parameter (γ and λ) sensitivity, we observe that the proposed method is relatively robust to them. Thus, we roughly fix $\gamma = 0.2$ and $\lambda = 4$ in all experiments.

Over Basic Hashing Algorithms

The proposed table construction methods as well as the random way can support any types of hashing algorithms (*e.g.*, linear/nonlinear, random/optimized). Next, we comprehensively evaluate them over several basic hashing algorithms in terms of both hash lookup and Hamming ranking.

Hash Lookup Evaluation Hash For fast computation, state-of-the-art hashing algorithms usually build several hash tables and lookup multiple buckets (Lv et al. 2007; Norouzi, Punjani, and Fleet 2012) to retrieve more desired points, which however sharply reduces the search accuracy due to a large portion of irrelevant points contained in them (see an example in Table 1, where using 1 table and 8 tables the recall performance increases from 7.03% to 31.94%, but the precision decreases from 21.91% to

Table 1: PH2 (%) of multiple LSH hash tables on SIFT-1M.

# TABLES→	1	4	8	12	16
RAND	21.91	18.29	16.20	14.42	13.15
DHF	26.29	28.87	26.88	23.24	16.22
RDHF	**26.29**	**29.25**	**27.60**	**23.80**	**16.44**

16.20%). By contrast, our method relieves the degeneration by complementarily constructing multiple hash tables using the most informative and independent hash functions. On the one hand, each hash table is discriminative enough to find parts of the true neighbors; on the other hand, reciprocal hash tables together are able to widely cover all parts of neighbors.

Table 1 lists the hash lookup results (precision within hamming radius less than 2 (PH2)) comparing our methods (DHF and RDHF) with conventional random way (RAND). We build a function pool containing 500 ***Locality Sensitive Hashing*** (LSH) (Datar et al. 2004) functions on SIFT-1M. Using each construction method, we respectively construct a different number of hash tables, each of which consists of 24 (close to the optimal value $\log_2 n$ for $n = 10^6$ points) hash functions (Norouzi, Punjani, and Fleet 2012; Slaney, Lifshits, and He 2012). It is obvious that the precision of RAND deceases dramatically with more hash tables, while (R)DHF increase their performance first and attain significant performance gains over RAND in all cases.

In addition to LSH (linear, random), we also investigate the performance using other basic hashing algorithms including ***Kernelized LSH*** (KLSH) (Kulis and Grauman 2009) (non-linear,random) and ***Random Maximum Margin Hashing*** (RMMH) (Joly and Buisson 2011) (linear, optimized). Table 2 shows their PH2 performance using 8, 12, and 16 hash tables on SIFT-1M and GIST-1M. From the table, we first observe that DHF consistently outperforms RAND using different hashing algorithms, with large performance margins (*e.g.*, 65.93%, 56.10%, and 22.48% using 8 LSH, KLSH, and RMMH hash tables respectively on SIFT-1M). Moreover, owing to the complementary relationships among the hash tables, RDHF is slightly better than DHF in most cases, especially using more hash tables. It should be noted that PH2 performance of both DHF and RDHF drops faster than RAND when using more hash tables. This is because that DHF and RDHF construct hash tables by sequentially selecting the most informative functions, and thus the quality of their tables will decrease slightly. Even so, in all cases both methods faithfully improve the performance over RAND in terms of hash lookup.

Hamming Ranking Evaluation Hamming ranking usually achieves efficient implementation using the fast binary operations, and thus has been widely employed in hashing based ANN search (Liu et al. 2011; Xu et al. 2011; Wang, Kumar, and Chang 2012). We study the Hamming ranking performance of all three construction methods, and plot the precision curves in Figure 2. Here RAND is actually equivalent to multi-index hashing (**MIH**) (Norouzi, Punjani, and Fleet 2012), since these basic hashing algorithms generate their hashing functions disorderly and independently.

From Figure 2, it can be easily observed that DHF and RDHF, considering similarity preservation and mutual

Table 3: Performance (%) of hash lookup within Hamming radius 2 using multiple hashing tables on GIST-1M.

	PRECISION			RECALL		
	8	12	16	8	12	16
PCARDB	8.42	8.41	8.31	4.90	5.79	6.74
ITQDB	8.93	8.72	8.60	5.24	6.50	7.57
RAND	9.34	9.26	9.10	5.82	7.01	8.19
DHF	7.36	7.13	6.98	1.11	2.12	3.37
RDHF	**11.32**	**10.82**	**10.44**	**6.89**	**9.40**	**10.88**

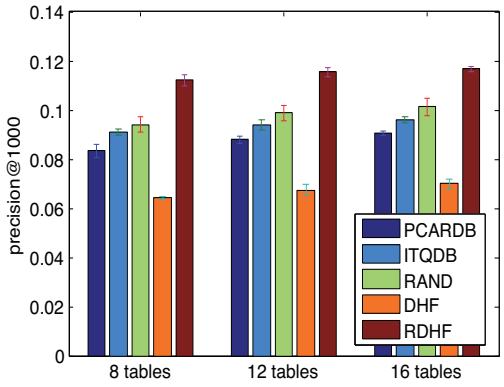


Figure 3: Hamming ranking precisions using multiple double bit hashing algorithms on GIST-1M.

independence of hash functions, consistently achieve the best performance over LSH, KLSH and RMMH in most cases (*e.g.*, on SIFT-1M, DFH using 12 tables gets 18.73%, 11.86%, and 7.58% precision@1,000 gains over RAND), and RDHF gains significant performance improvements over DHF by exploiting the mutual benefits between tables. Moreover, we can conclude that both methods can increase their performance using more hash tables (*e.g.*, for RDHF on GIST-1M, the precision@1,000 gain is up to 9.00%), while RAND improves very little, due to its aimless selection.

Over Multiple Hashing Algorithms

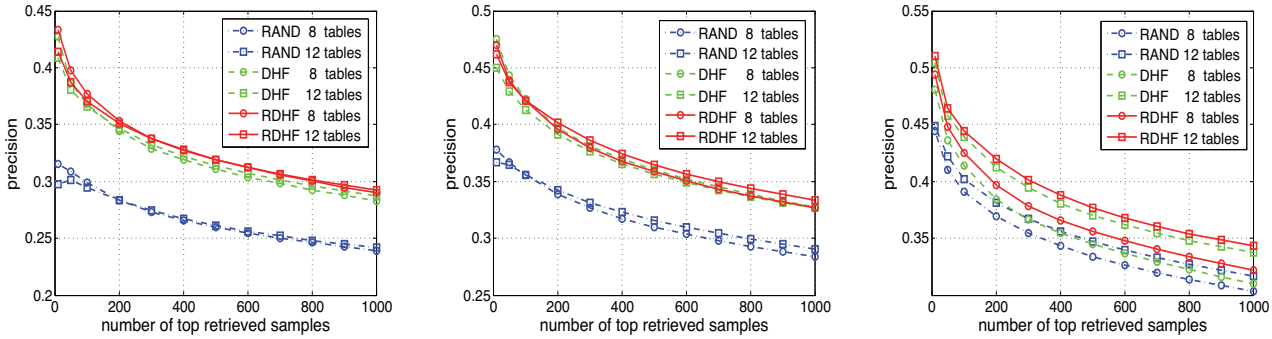
As mentioned earlier, there exist various situations that we need build multiple hash tables using different hashing algorithms with different settings. Besides the simple scenario in the last section, here we verify that our construction method can also work well with more complex scenarios, *e.g.*, construction using multiple double-bit hashing algorithms.

In practice, many hashing algorithms are prevented from being directly used to construct multiple tables, due to the upper limit of the hash function number, stemming from the dimension of data representation (*e.g.*, *Iterative Quantization* (Gong and Lazebnik 2011) can generate no more than 128 functions using SIFT feature). Table construction using multiple double-bit hashing algorithms can tackle this problem using double bit hashing algorithms like (Liu et al. 2011) and (Kong and Li 2012), which generate multiple hash functions along a single projection. However, the quality of these functions varies in a wide range, especially using hierarchical quantization (Liu et al. 2011).

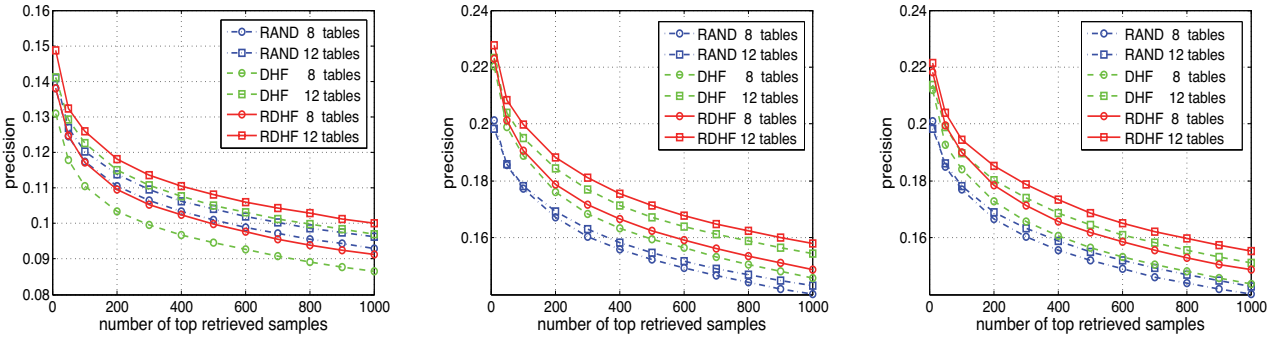
We evaluate our method in this scenario to demonstrate that how it efficiently picks the high quality hash functions for table construction. In this experiment, a 1,000 hash func-

Table 2: PH2 (%) of multiple hashing tables over LSH, KLSH, and RMMH on GIST-1M and SIFT-1M.

	ALGORITHMS →	LSH			KLSH			RMMH		
	# TABLES →	8	12	16	8	12	16	8	12	16
SIFT-1M	RAND	16.20	14.42	13.15	19.20	17.46	16.09	26.02	24.87	23.73
	DFH	26.88	23.24	16.22	**29.97**	25.34	18.86	**31.87**	30.62	28.63
	RDFH	**27.60**	**23.80**	**16.44**	29.40	**26.00**	**19.45**	31.23	**30.95**	**29.16**
GIST-1M	RAND	8.80	8.51	8.24	11.83	11.20	10.73	11.58	10.96	10.58
	DFH	9.21	9.30	8.72	**14.37**	13.63	11.88	13.28	12.68	11.59
	RDFH	**9.68**	**9.67**	**8.99**	14.27	**14.00**	**12.31**	**13.45**	**13.03**	**12.04**



(a) Precision of LSH on SIFT-1M (b) Precision of KLSH on SIFT-1M (c) Precision of RMMH on SIFT-1M



(d) Precision of LSH on GIST-1M (e) Precision of KLSH on GIST-1M (f) Precision of RMMH on GIST-1M

Figure 2: Hamming ranking performance of multiple table methods over basic hashing algorithms on SIFT-1M and GIST-1M.

tion pool is equally generated on GIST-1M by double bit (DB) quantization (Liu et al. 2011) on ***PCA-based Random Rotation Hashing*** (**PCARDB**) and ***Iterative Quantization*** (**ITQDB**) (Gong and Lazebnik 2011). Table 3 reports both precision and recall performance of all construction methods using hash lookup. Compared with the basic DB methods, RAND gives a balanced performance between them. But our RDFH, filtering poor quality functions out, significantly boosts the performance over these baselines with more than 14.73% precision and 18.38% recall gains. We also show their Hamming ranking performance in Figure 3, where we obtain the same conclusion that RDFH significantly outperforms others using a varying number of hash tables.

Note that DHF fails to compete with the baselines. According to our observations, this is because the hashing functions of DFH mostly come from the second functions of each projection, which individually lower the quantization loss (Kong and Li 2012), but break the neighbor relationships as a table. On the contrary, for each table RDHF adaptively prefers the high-quality hash functions that work well on the misclassified neighbors, and thus achieves the best performance.

Conclusion

We proposed a unified strategy for hash table construction supporting different hashing algorithms and various scenarios. For each table, its hash functions correspond to the dominant set in a vertex- and edge-weighted graph representing all pooled hash functions. These dominant hash functions are mutually uncorrelated, and preserve data similarities well. To reduce the redundancy between hash tables, we presented a reciprocal strategy based on dominant hash functions. It sequentially explores a new hash table to compensate the mistakes of pervious tables in a boosting manner. Comprehensive evaluation on large-scale benchmarks shows the strong practicability and the encouraging performances.

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