RANDOM FORESTS CAN HASH

Qiang Qiu, Guillermo Sapiro, and Alex Bronstein
Duke University and Tel Aviv University
{qiang.qiu, guillermo.sapiro}@duke.edu; bron@eng.tau.ac.il

ABSTRACT
Hash codes are a very efficient data representation needed to be able to cope with the ever growing amounts of data. We introduce a random forest semantic hashing scheme with information-theoretic code aggregation, showing for the first time how random forest, a technique that together with deep learning have shown spectacular results in classification, can also be extended to large-scale retrieval. Traditional random forest fails to enforce the consistency of hashes generated from each tree for the same class data, i.e., to preserve the underlying similarity, and it also lacks a principled way for code aggregation across trees. We start with a simple hashing scheme, where independently trained random trees in a forest are acting as hashing functions. We propose a subspace model as the splitting function, and show that it enforces the hash consistency in a tree for data from the same class. We also introduce an information-theoretic approach for aggregating codes of individual trees into a single hash code, producing a near-optimal unique hash for each class. Experiments on large-scale public datasets are presented, showing that the proposed approach significantly outperforms state-of-the-art hashing methods for retrieval tasks.

1 INTRODUCTION
In view of the recent huge interest in image classification and object recognition problems and the spectacular success of deep learning and random forests in these tasks, it seems astonishing that much less efforts are being invested into related, and often more difficult, problems of image content-based retrieval, and, more generally, similarity assessment in large-scale databases. These problems, arising as primitives in many computer vision tasks, are becoming increasingly important in the era of exponentially increasing information. Semantic and similarity-preserving hashing methods have recently received considerable attentions to address such a need, in part due to their memory and computational advantage over other representations. These methods learn to embed data points into a space of binary strings; thus producing compact representations with constant or sub-linear search time. Such an embedding can be considered as a hashing function on the data, which translates the underlying similarity into the collision probability of the hash or, more generally, into the similarity of the codes under the Hamming metric. Examples of recent similarity-preserving hashing methods include Gionis et al. (1999), Kulis & Grauman (2009), Weiss et al. (2009), Masci et al. (2014a), Liu et al. (2012), Liu et al. (2011), Li et al. (2011), and Zhang et al. (2010).

Due to the conceptual similarity between the problems of semantic hashing and that of binary classification, numerous classification techniques have been adapted to the former task. For example, state-of-the-art supervised hashing techniques like Masci et al. (2014a), Masci et al. (2014b), and Norouzi et al. (2012) are based on deep learning methodologies. Random forest (Breiman 2001; Criminisi & Shotton 2013) is another popular classification technique. Random forests have not been so far used to construct semantic hashing schemes. This is mainly because acting as a hashing function, a random forest fails to preserve the underlying similarity due to the inconsistency of hash codes generated in each tree for the same class data; it also lacks a principled way of aggregating hash codes produced by individual trees into a single longer code.

This work is the first construction of a semantic hashing scheme based on a random forest. We first introduce a transformation learner model for random forest enforcing the hash consistency in a tree, thereby preserving similarity. Then, we propose an information-theoretic approach for aggregating hash codes in a forest, encouraging a unique code for each class. Using challenging large-scale examples, we demonstrate significantly more consistent and unique hashes for data from the same semantic class, when compared to other state-of-the-art hashing schemes.
2 Forest Hashing

Random forest [Breiman, 2001; Criminisi & Shotton, 2013] is an ensemble of binary decision trees. Following the random forest literature, in this paper, we specify a maximum tree depth $d$ and also avoid post-training operations such as tree pruning. Thus, a tree of depth $d$ consists of $2^d - 2$ tree nodes, excluding the root node, indexed in the breadth-first order. During the training, we introduce randomness into the forest through a combination of random set sampling and randomized node optimization, thereby avoiding duplicate trees. As discussed in [Breiman, 2001] and [Criminisi & Shotton, 2013], training each tree with a different randomly selected set decreases the risk of overfitting, improves the generalization of classification forests, and significantly reduces the training time. When given more than two classes, we randomly partition the classes arriving at each binary split node into two categories for node randomness.

A pedagogic hashing scheme is constructed as follows: Each data point is pushed through a tree until reaching the corresponding leaf node. We simply set ‘1’ for nodes visited, and ‘0’ for the rest. By ordering those bits in a predefined node order, e.g., the breadth-first order, we obtain a $(2^d - 2)$-bit sparse hash code, always containing exactly $d - 1$ ones. In a random forest consisting of $M$ trees of the depth $d$, each point is simultaneously pushed through all trees to obtain $M$ $(2^d - 2)$-bit hash codes. Both the training and the hashing processes can be done in parallel to achieve high computational efficiency on modern parallel CPU or GPU hardware.

In classification, for which the forest was originally designed, an ensemble posterior is obtained by averaging from a large number of trees, thus boosting the classification accuracy [Breiman, 2001], and no confident class posteriors are required for individual trees. However, due to the lack of confident class posteriors for individual trees, we obtain highly inconsistent hashes from an individual tree for the same class data. It is also not obvious how to combine hashes from different trees given a target code length. The inconsistency of the hash codes prevents standard random forest from being directly adopted for hashing, being such codes critical for large-scale retrieval.

To address these problems we first propose a transformation as the learner model for the random forest [Qiu & Sapiro, 2014a; b], where each tree enforces consistent codes for similar points. Though a class may not be assigned a unique code in each tree due to limited leaf availability, each class shares code with different classes in different trees due to the underlying node randomness models.

We further propose an information-theoretic approach to aggregate hashes across trees into a unique code for each data class. Consider a random forest consisting of $M$ trees of depth $d$; the hash codes obtained for $N$ training samples are denoted as $B = \{B_i\}_{i=1}^M$, with the $B_i \in \{0, 1\}^{(2^d - 2) \times N}$ being the codes generated from the $i$-th tree, henceforth denoted as code blocks. Given the target hash code length $L$, our objective is to select $k$ code blocks $B^*, k \leq L/(2^d - 2)$, maximizing the mutual information between the selected and the remaining codes, $B^* = \arg \max_{B:B_i=\cdots=B^*_i} I(B; C_i(B))$. When the class labels $C$ are available for a subset of training samples, semi-supervised aggregation is performed as $B^* = \arg \max_{B:B_i=\cdots=B^*_i} I(B; C) + \lambda I(B; C)$. The two terms here can be evaluated using different samples to exploit all labeled and unlabeled data. Note that the code aggregation step is only learned once during training, no cost at testing.

3 Experimental Evaluation

We present an experimental evaluation of ForestHash on retrieval tasks using standard public benchmarks. Hashing methods compared include supervised methods FastHash [Lin et al., 2014], TSH [Lin et al., 2013], HDML [Norouzi et al., 2012], KSH [Liu et al., 2012], LDAHash [Strecha et al., 2012], and unsupervised methods SH [Weiss et al., 2009], KLSH [Kulis & Grauman, 2009], AGH [Liu et al., 2011]. All software was provided by the authors.

We adopt the same setup as in [Norouzi et al., 2012] for the image retrieval experiments on MNIST. We trained a forest of 64 trees of depth 3. Table I summarizes the retrieval performance of various methods at Hamming radius 0. Here HDML is a deep learning based hashing method, and FastHash is a boosted trees based method. We denote the proposed method as ForestHash. Due to our subspace-based learner models, which are known to be robust for small training samples [Bengio et al., 2013], and our semi-supervised code aggregation that exploits both labeled and unlabeled data, ForestHash significantly outperforms state-of-the-art methods for reduced training cases.
We adopt a challenging setup as in Liu et al. (2012); Masci et al. (2014a) for the image retrieval experiments on CIFAR10 (Krizhevsky, 2009). Table 2 summarizes the retrieval performance of various methods for Hamming radius 0 and 2. ForestHash-base is the pedagogic random forest hashing scheme in Section 2, where the decision stump learner model is used and a random subset of trained trees are selected. It is surprising that this simple pedagogic scheme outperforms all compared supervised methods at radius 0 with orders of magnitude speedup, and the recall is significantly improved with the proposed code aggregation (aggr.). ForestHash using the transformation learner dramatically improves the precision over the pedagogic scheme, significantly outperforms all compared methods at radius 0, and reports comparable precision and significantly higher recall at radius 2. Figure 1a presents image query examples in the CIFAR-10 dataset.

Results reported in Table 3 refer to an experiment on the Pubfig face dataset (Kumar et al., 2009), in which we construct the hashing forest using 30 training faces per subject (5,992 faces from 200 subjects), and search among their 37,007 unseen faces. As subspace methods are robust for small training samples problems (Bengio et al., 2013) and extraordinarily effective in representing faces (Wright et al., 2009), ForestHash shows significantly higher precision and recall compared to all state-of-the-art methods. Figure 1b presents several examples of face queries.

### 4 Conclusion

Considering the importance of compact and computationally efficient codes, we introduced a random forest semantic hashing scheme, which, to the best of our knowledge, is the first instance of using random forests for hashing, extending the use of it beyond classification for large-scale retrieval.
Table 3: 36-bit retrieval performance (%) on the Pubfig face dataset (rejection radius 0), 5,992
queries (200 known subjects) over 37,007 unseen faces of query subjects.

| Method     | Test time (µs) | Precision | Recall |
|------------|----------------|-----------|--------|
| SH         | 8              | 9.23      | 0.21   |
| KLSH       | 15             | 22.09     | 4.05   |
| AGH1       | 10             | 33.37     | 54.17  |
| AGH2       | 16             | 25.85     | 58.10  |
| LDAHash    | 2              | 30.05     | 1.28   |
| FastHash   | 97             | 58.95     | 3.47   |
| TSH        | 693            | 17.41     | 0.22   |
| ForestHash | 28             | 97.72     | 85.12  |

The proposed scheme consists of a forest with transformation learners, and an information-theoretic
code aggregation scheme. The proposed framework combines in a fundamental fashion feature
learning, random forests, and similarity-preserving hashing, and can be straightforwardly extended
to retrieval of incommensurable multi-modal data. Our method shows exceptional effectiveness
in preserving similarity in hashes, and outperforms state-of-the-art hashing methods in large-scale
retrieval tasks.

REFERENCES

Bengio, Y., Courville, A., and Vincent, P. Representation learning: A review and new perspectives.
IEEE Trans. on Patt. Anal. and Mach. Intell., 35(8):1798–1828, 2013.

Breiman, L. Random forests. Machine Learning, 45(1):5–32, 2001.

Criminisi, A. and Shotton, J. Decision Forests for Computer Vision and Medical Image Analysis.
Springer, 2013.

Gionis, A., Indyk, P., and Motwani, R. Similarity search in high dimensions via hashing. In Proc.
of International Conference on Very Large Data Bases, 1999.

Krizhevsky, Alex. Learning multiple layers of features from tiny images. Technical report, 2009.

Kulis, B. and Grauman, K. Kernelized locality-sensitive hashing for scalable image search. In Proc.
International Conference on Computer vision, 2009.

Kumar, N., Berg, A. C., Belhumeur, P. N., and Nayar, S. K. Attribute and simile classifiers for face
verification. In Proc. International Conference on Computer vision, Oct 2009.

Li, Z., Ning, H., Cao, L., Zhang, T., Gong, Y., and Huang, T. S. Learning to search efficiently in
high dimensions. In Advances in Neural Information Processing Systems. 2011.

Lin, G., Shen, C., Suter, D., and van den Hengel, A. A general two-step approach to learning-based
hashing. In Proc. International Conference on Computer Vision, 2013.

Lin, G., Shen, C., Shi, Q., van den Hengel, A., and Suter, D. Fast supervised hashing with decision
trees for high-dimensional data. In Proc. IEEE Computer Society Conf. on Computer Vision and
Patt. Recn., 2014.

Liu, W., Wang, J., and Chang, S. Hashing with graphs. In International Conference on Machine
Learning, 2011.

Liu, W., Wang, J., Li, R., Jiang, Y., and Chang, S. Supervised hashing with kernels. In Proc. IEEE
Computer Society Conf. on Computer Vision and Patt. Recn., June 2012.

Masci, J., Bronstein, A. M., Bronstein, M. M., Sprechmann, P., and Sapiro, G. Sparse similarity-
preserving hashing. In International Conference on Learning Representations, Banff, Canada,
2014a.

Masci, J., Bronstein, M. M., Bronstein, A. M., and Schmidhuber, J. Multimodal similarity-
preserving hashing. IEEE Trans. on Patt. Anal. and Mach. Intell., 36(4):824–830, 2014b.
Norouzi, M., Fleet, D. J., and Salakhutdinov, R. Hamming distance metric learning. In *Advances in Neural Information Processing Systems*, 2012.

Qiu, Q. and Sapiro, G. Learning transformations for classification forests. In *International Conference on Learning Representations*, Banff, Canada, 2014a.

Qiu, Q. and Sapiro, G. Learning transformations for clustering and classification. *JMLR (to appear)*, 2014b.

Strecha, C., Bronstein, A.M., Bronstein, M.M., and Fua, P. Ldahash: Improved matching with smaller descriptors. *IEEE Trans. on Patt. Anal. and Mach. Intell.*, 34(1):66–78, Jan 2012.

Weiss, Y., Torralba, A., and Fergus, R. Spectral hashing. In *Advances in Neural Information Processing Systems*, 2009.

Wright, J., Yang, M., Ganesh, A., Sastry, S., and Ma, Y. Robust face recognition via sparse representation. *IEEE Trans. on Patt. Anal. and Mach. Intell.*, 31(2):210–227, 2009.

Zhang, D., Wang, J., Cai, D., and Lu, J. Self-taught hashing for fast similarity search. In *Proc. of International Conference on Research and Development in Information Retrieval*, 2010.