Deep Learning of Binary Hash Codes for Fast Image Retrieval

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Large-scale Image Search

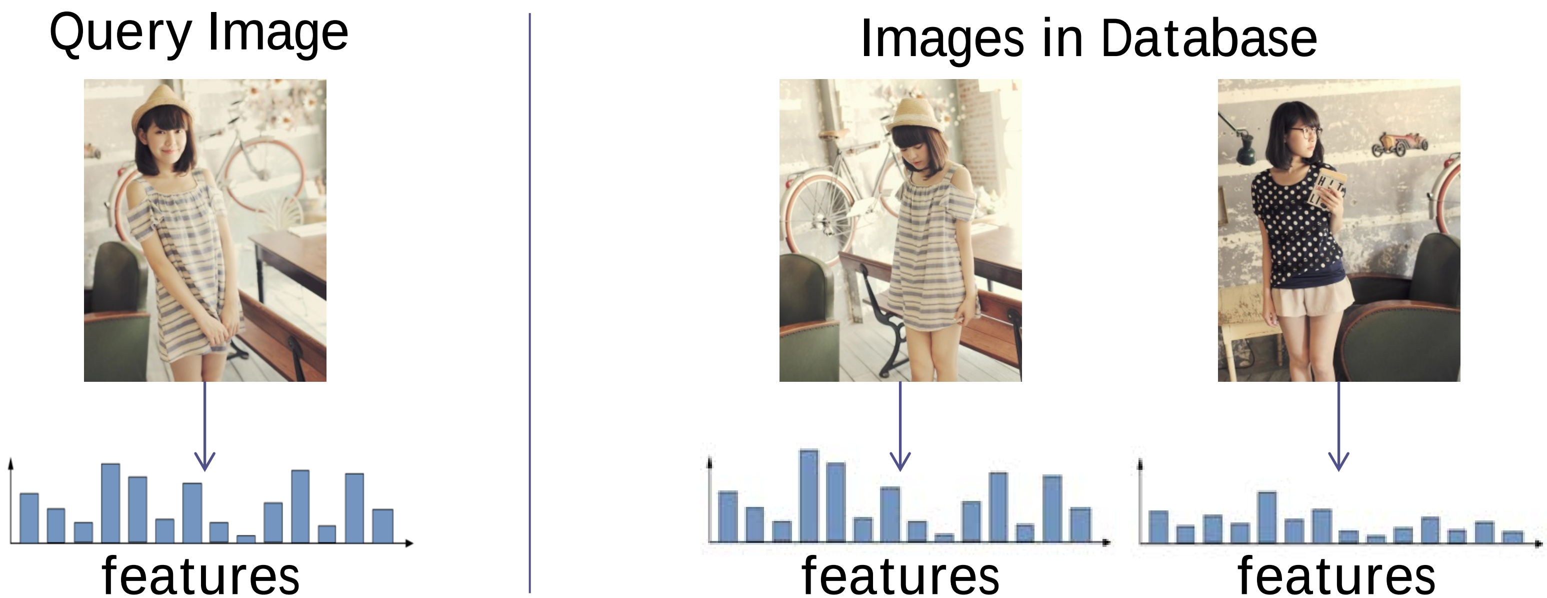
Query

Database

Top Retrieved Image

Search Strategy

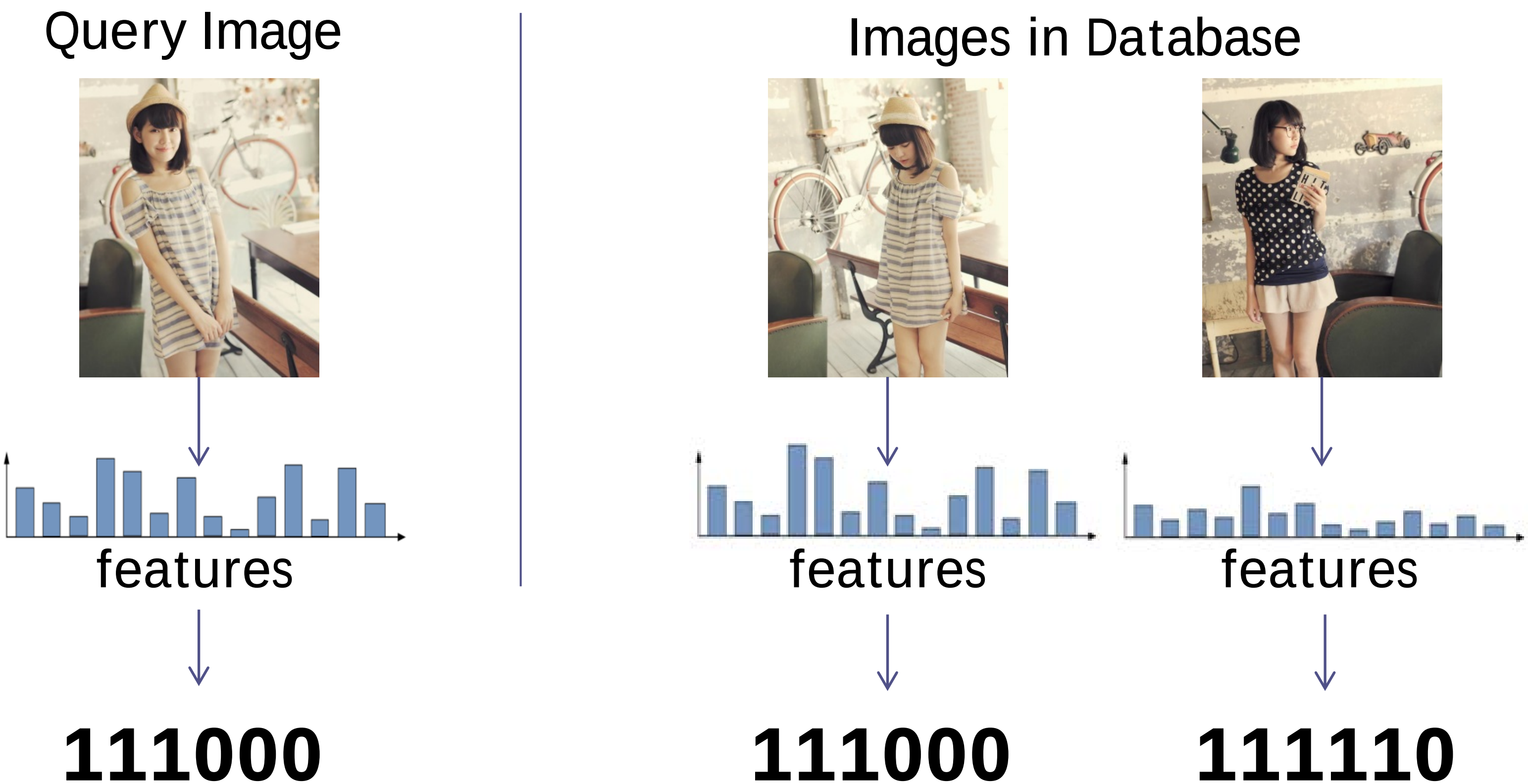
- Images are represented by features.



- Nearest neighbor search: neighbors of a point are determined by Euclidean distance.
- Challenge: How to efficiently search over millions or billions of images?

Solution: Binary Codes

- Images are represented by **binary codes**.



- Fast search can be carried out via Hamming distance measurement. (XOR operation)

Related works: Learning Binary Codes (1/2)

- Unsupervised learning
  - Use only training data, no label info.
  - Locality-Sensitive Hashing (LSH) [1]
  - Iterative quantization (ITQ) [2]
- Supervised learning
  - Use supervised info. (labels, pairwise similarities, …)
  - Binary reconstructive embedding (BRE) [3]
  - Minimal loss hashing (MLH) [4]

[1] A. Andoni and P. Indyk, "Near-optimal hashing algorithms for approximate nearest neighbor in high dimensions," in Proc. FOCS, 2006.

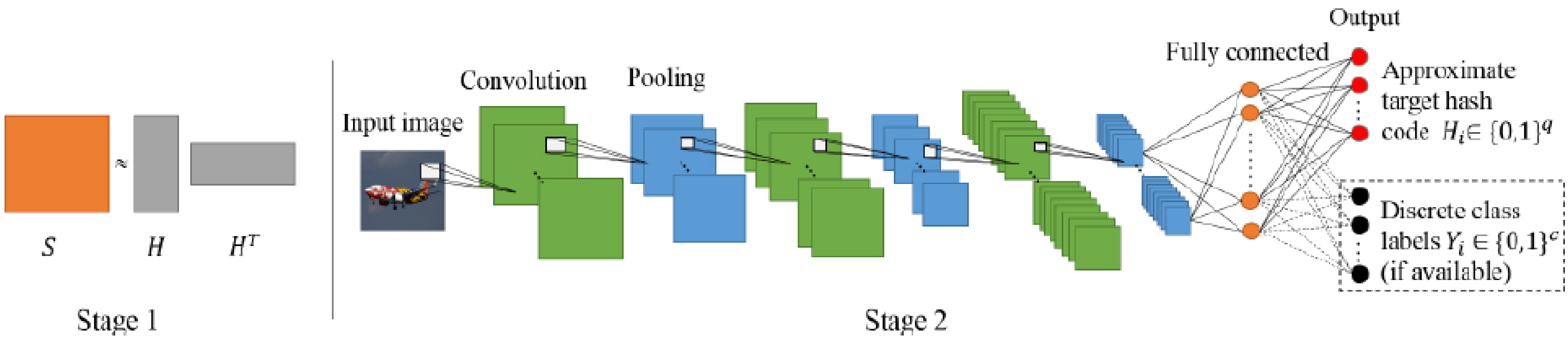
[2] Y. Gong, S. Lazebnik, A. Gordo, and F. Perronnin, "Iterative quantization: A procrustean approach to learning binary codes for large-scale image retrieval," IEEE Trans. Pattern Anal. Mach. Intell., vol. 35, no. 12, pp. 2916–2929, 2013.

[3] B. Kulis and T. Darrell, "Learning to hash with binary reconstructive embeddings," in Proc. NIPS, 2009.

[4] M. Norouzi and D. J. Fleet, "Minimal loss hashing for compact binary codes," in Proc. ICML, 2011.

Related works: Learning Binary Codes (2/2)

- Supervised deep Learning
  - Take advantage of deep neural network
  - Convolutional Neural Network Hashing (CNNH) [5]
  - Deep Neural Network Hashing (DNNH) [6]



[5] R. Xia, Y. Pan, H. Lai, C. Liu, and S. Yan. Supervised hashing for image retrieval via image representation learning. In Proc. AAAI Conference on Artificial Intelligence (AAAI), 2014.
[6] H. Lai, Y. Pan, Y. Liu, and S. Yan. Simultaneous feature learning and hash coding with deep neural networks. In Proc. IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2015.

Goal

- Can we take the advantage of deep CNN to achieve hashing?
- Can we generate the binary compact codes directly from the deep CNN?
- Solution: Supervised Semantic-preserving Deep Hashing (SSDH)

Approach

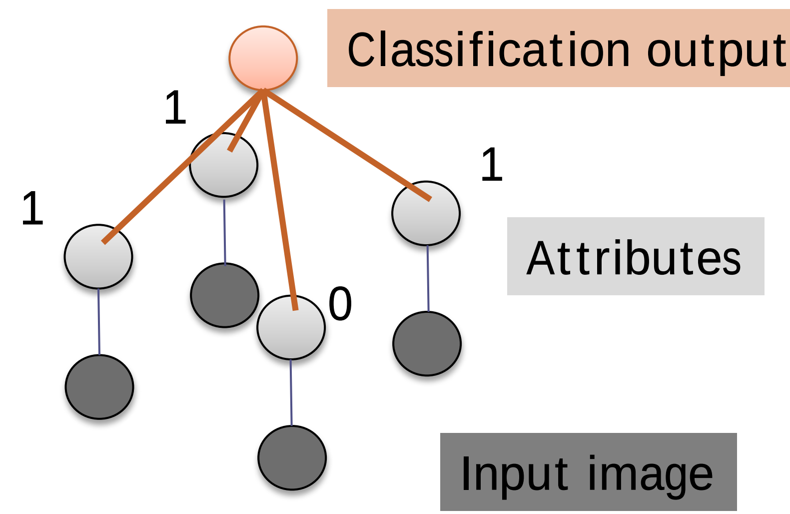
- Assume the classification outputs rely on a set of hidden attributes ***on*** and ***off***.

Bird

"furry"	0
"feather"	1
⋮	
"has head"	1
"has leg"	1

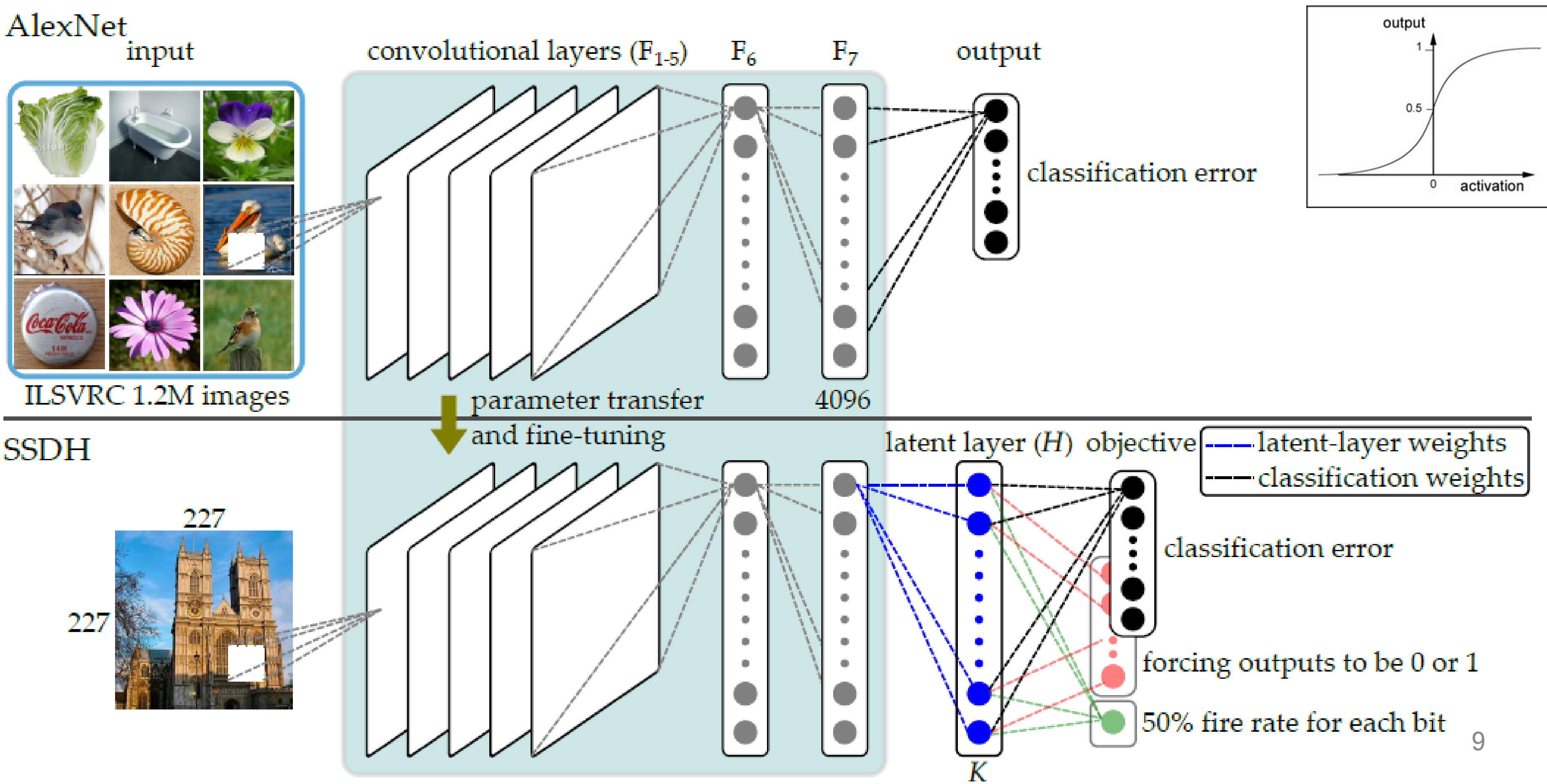
Cow

"furry"	1
"feather"	0
⋮	
"has head"	1
"has leg"	1

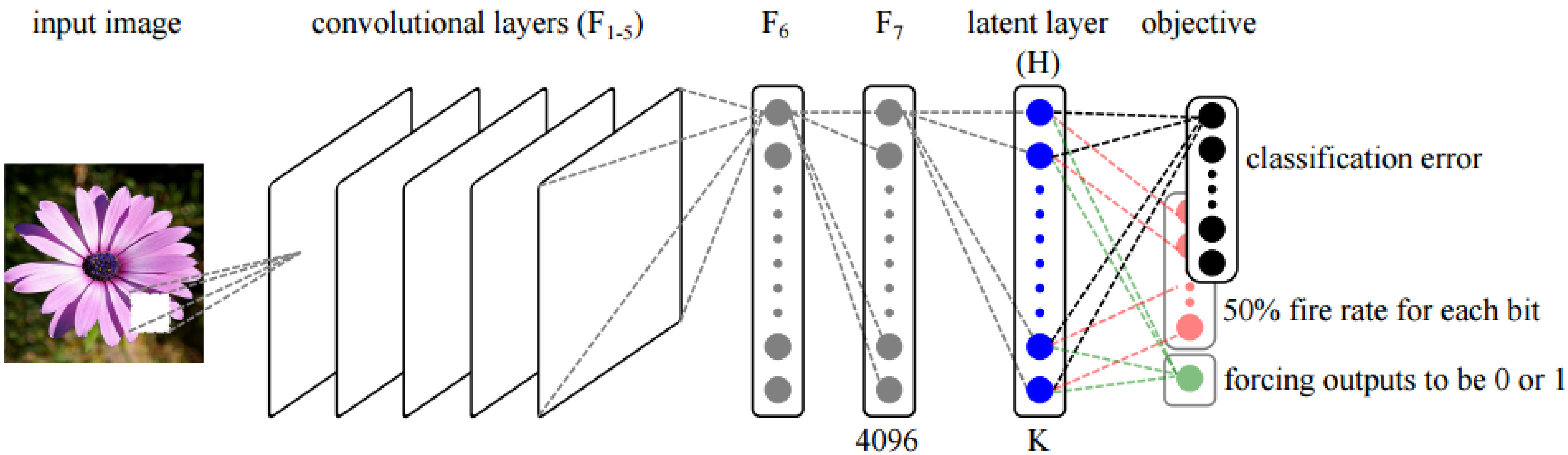


Approach

- We add the fully connected ***latent layer H*** between ***F7*** and ***F8***.
- The neurons in ***H*** are activated by sigmoid functions.



Approach

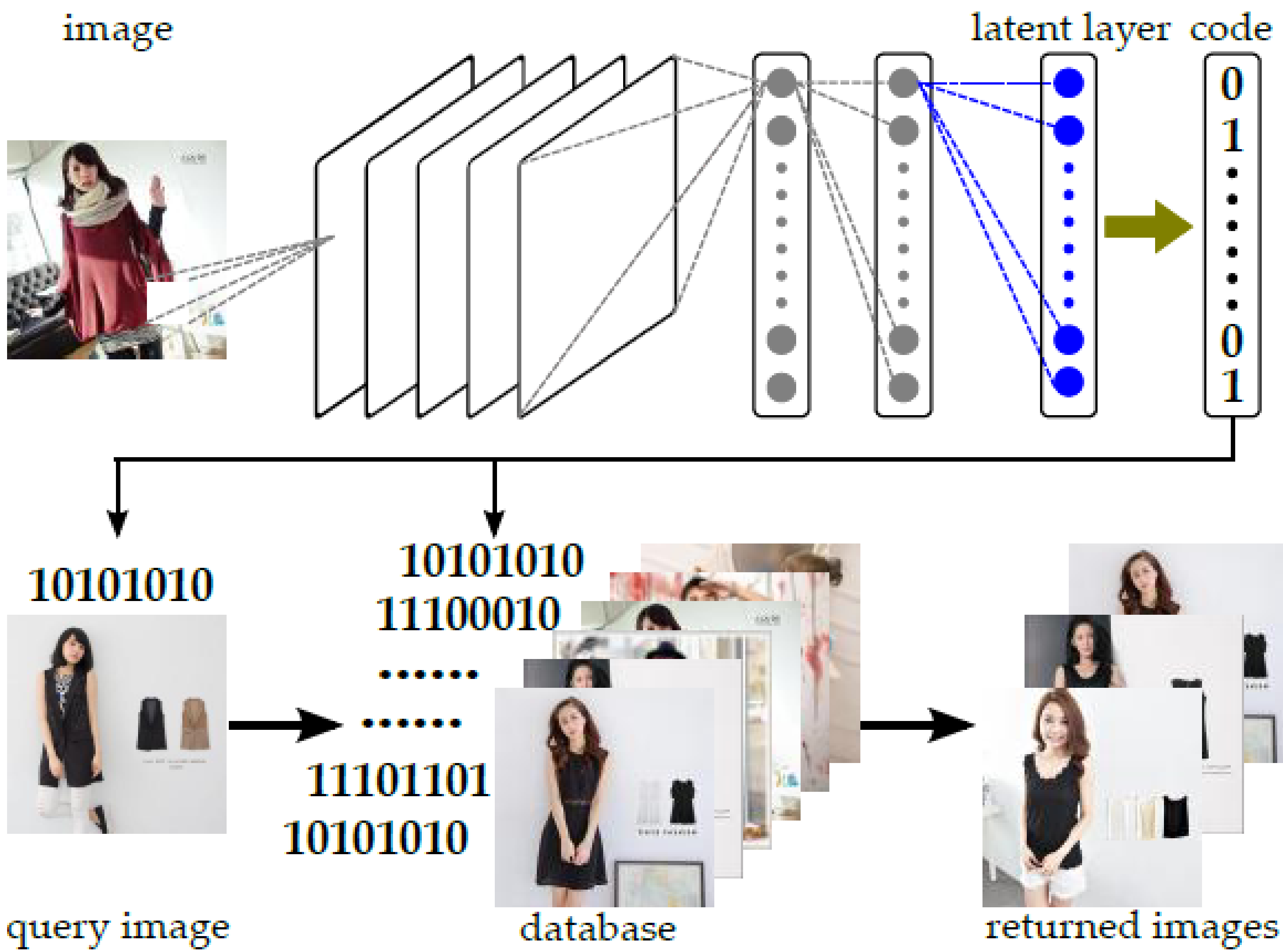


- Overall learning objective

$$\arg\min_{W} \quad \alpha \sum_{n=1}^{N} L(y_n, \hat{y}_n) + \lambda ||W||^2$$
$$- \beta \frac{1}{K} \sum_{n=1}^{N} ||a_n^H - 0.5\mathbf{e}||^2$$
$$+ \gamma \sum_{n=1}^{N} (\text{mean}(a_n^H) - 0.5)^2$$

Approach

- Compute binary codes for fast image retrieval

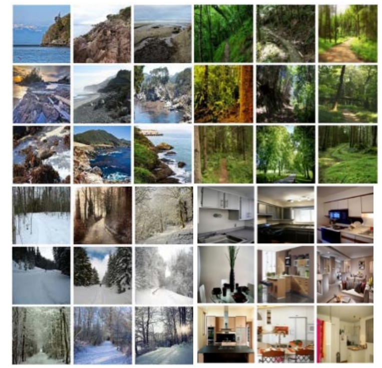


Experiments

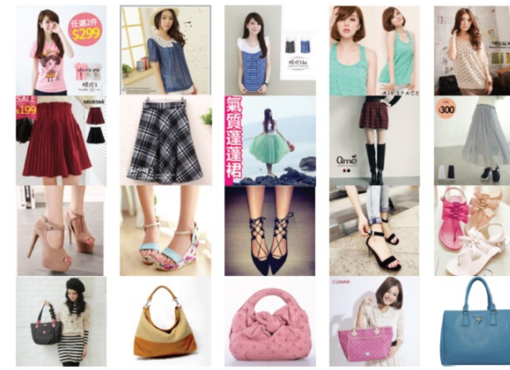
- Datasets

CIFAR10

MNIST



SUN397



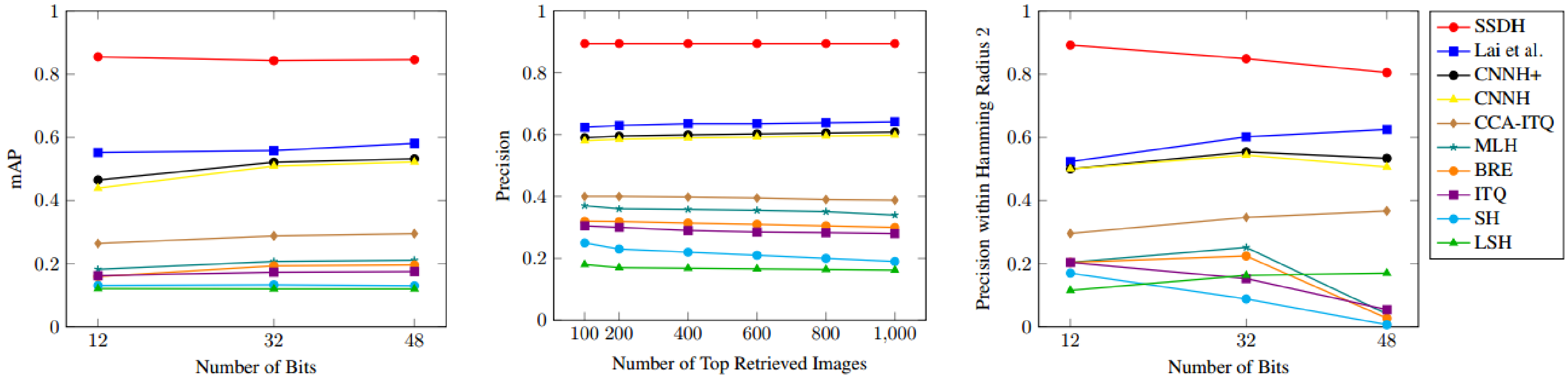
Yahoo-1M

TABLE
Statistics of datasets used in the experiments.

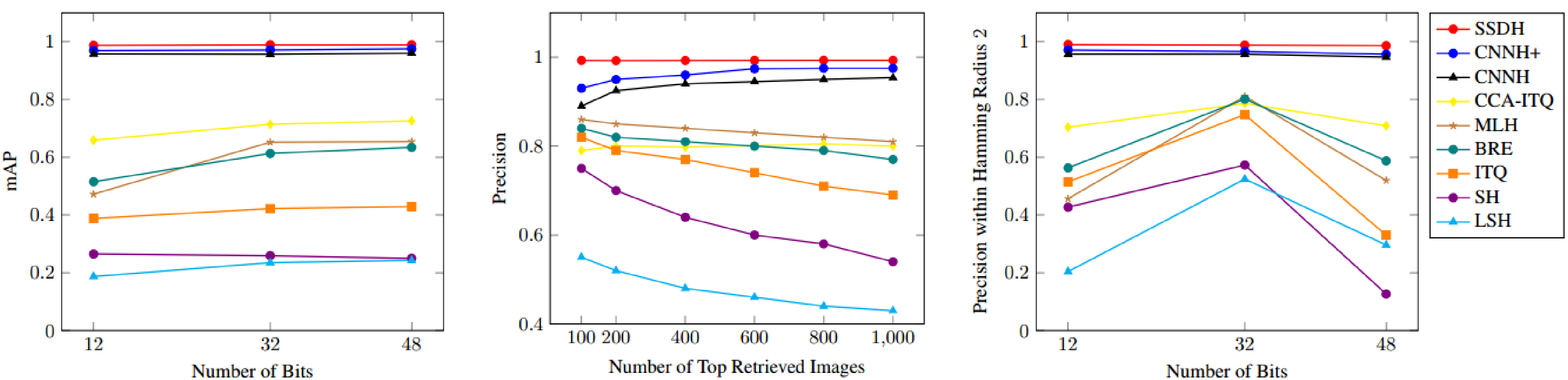
Dataset	# Labels	Training Set	Test Set
CIFAR-10	10	50,000	1,000
MNIST	10	60,000	10,000
SUN397	397	100,754	8,000
Yahoo-1M	116	1,011,723	112,363

Experiments

- CIFAR10



- MNIST



Experiments

Figure: Top 10 retrieved images from CIFAR-10 by varying the code length. Images with appearance more similar to the query are returned when the code length increases.

Experiments

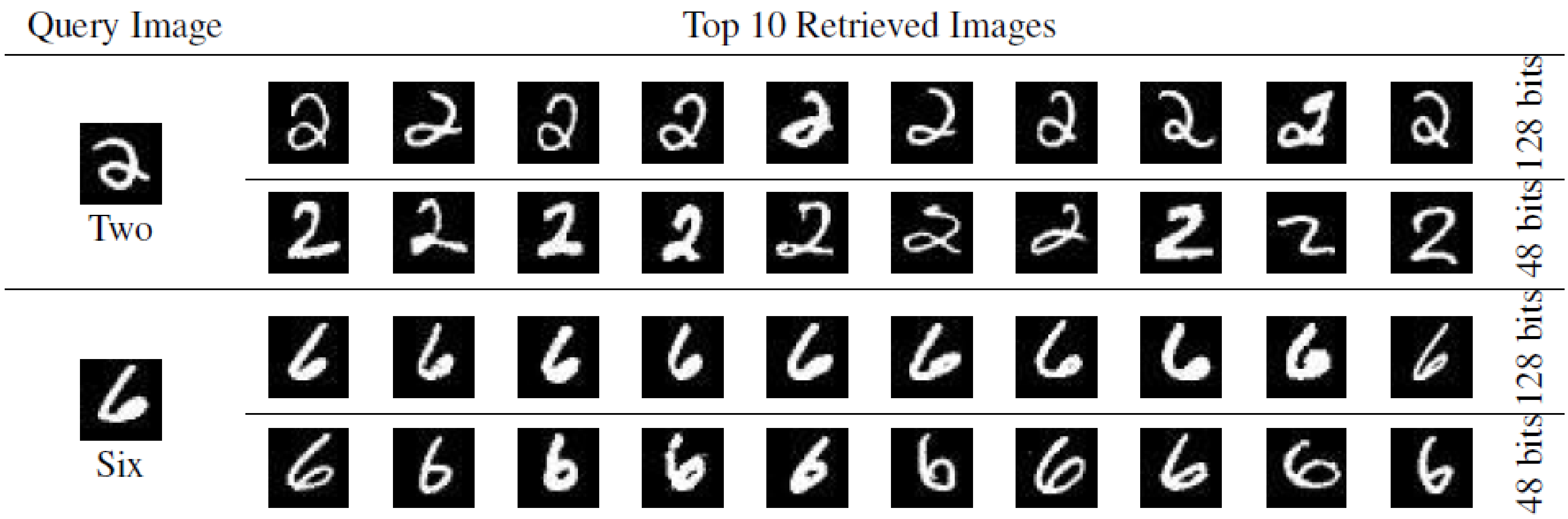


Figure: Top 10 retrieved images from MNIST by varying the code length. Images with appearance more similar to the query are returned when the code length increases.

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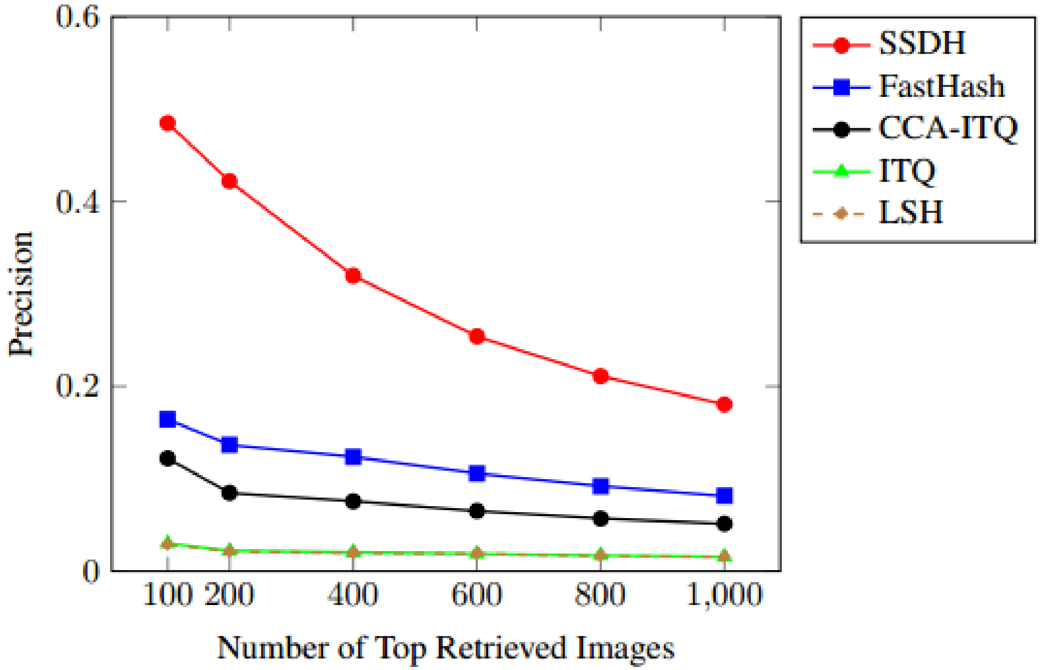
- SUN397



[7]
[8]
[8]
[9]

Fig. 5. Precision curves with respect to different number of top retrieved samples on the SUN397 dataset when the 1024-bit hash codes are used in the evaluation.

[7] G. Lin, C. Shen, Q. Shi, A. van den Hengel, and D. Suter, “Fast supervised hashing with decision trees for high-dimensional data,” in Proc. CVPR, 2014
[8] Y. Gong, S. Lazebnik, A. Gordo, and F. Perronnin, “Iterative quantization: A procrustean approach to learning binary codes for large-scale image retrieval,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 35, no. 12, pp. 2916–2929, 2013.
[9] A. Andoni and P. Indyk, “Near-optimal hashing algorithms for approximate nearest neighbor in high dimensions,” in Proc. FOCS, 2006

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- Yahoo-1M

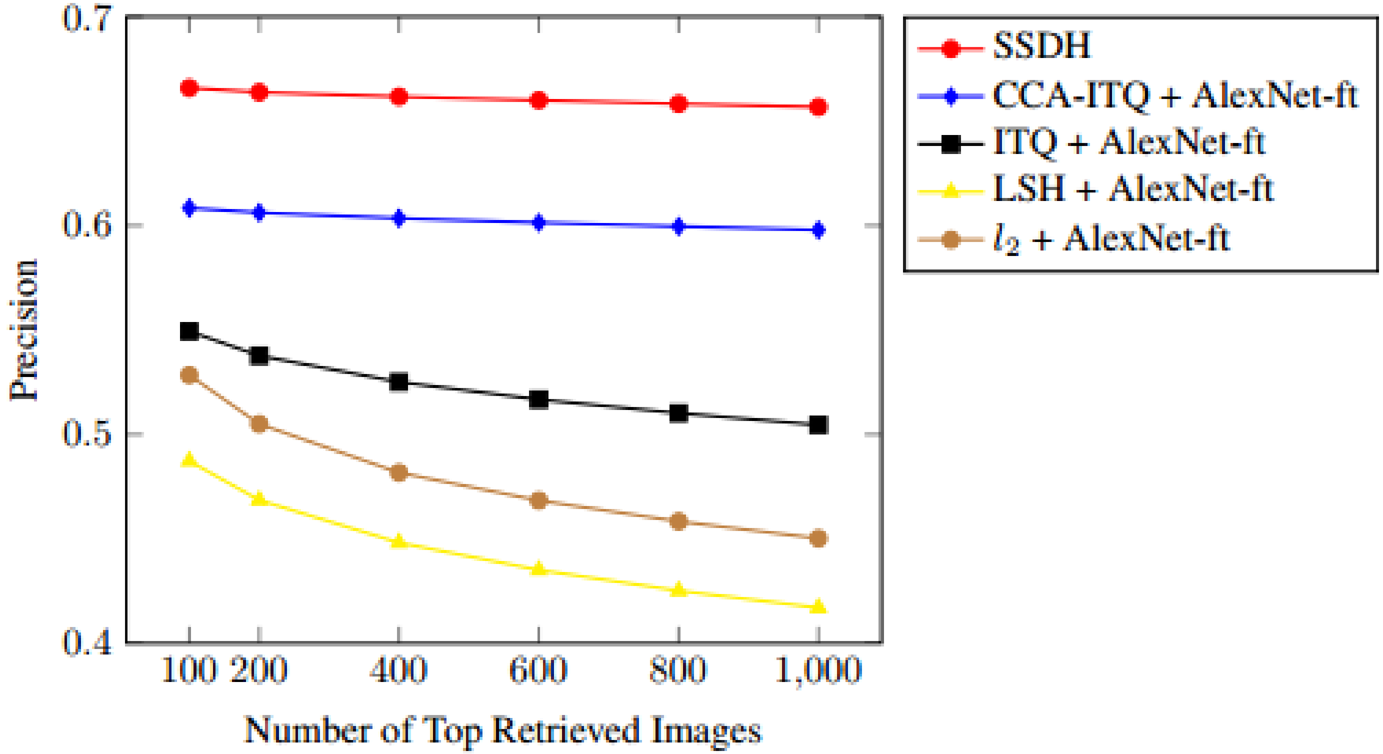


Fig. 6. Precision curves with respect to different number of top retrieved samples on the Yahoo-1M dataset when the 128-bit hash codes are used in the evaluation. AlexNet-ft denotes that the features from layer F_7 of AlexNet fine-tuned on Yahoo-1M are used in learning hash codes.

Experiments

Query	Top 5 Retrieved Image

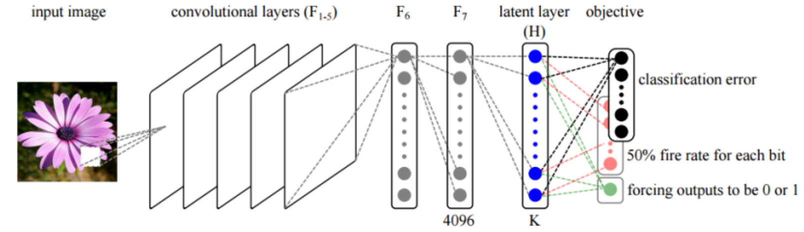
Ours

AlexNet

Ours

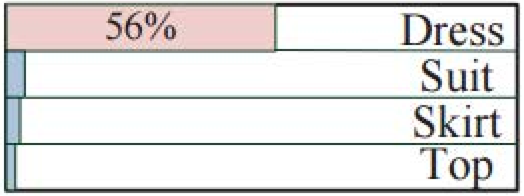
AlexNet

Experiments

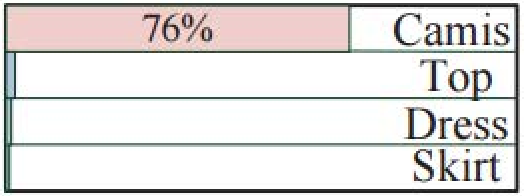


- Image classification results

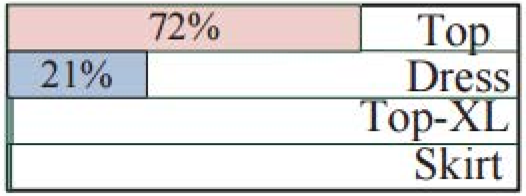
Dress



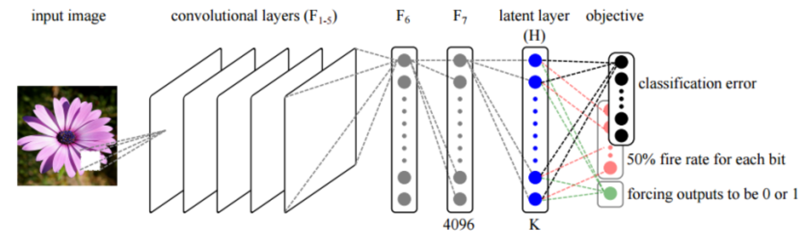
Camis



Top



Experiments



- Image classification results

Experiments

- Image classification results

TABLE 3
Classification accuracy of various methods on CIFAR-10.

Method	Accuracy (%)
Stochastic Pooling [64]	84.87
CNN + Spearmint [65]	85.02
AlexNet + Fine-tuning	88.31
NIN + Dropout [66]	89.59
NIN + Dropout + Augmentation [66]	91.19
SSDH w/ 12-bit codes	88.75
SSDH w/ 32-bit codes	89.50
SSDH w/ 48-bit codes	89.59

TABLE 4
Classification accuracy of various methods on MNIST.

Method	Accuracy (%)
Stochastic Pooling [64]	99.53
AlexNet + Fine-tuning	99.16
NIN + Dropout [66]	99.53
SSDH w/ 12-bit codes	99.25
SSDH w/ 32-bit codes	99.09
SSDH w/ 48-bit codes	99.16

TABLE 5
Classification accuracy of various methods on SUN397.

Method	Accuracy (%)
AlexNet + Fine-tuning	47.94
Cascade fine-tuned CNN [67]	46.87
MOC-CNN [68]	51.98
SSDH w/ 48-bit codes	46.16
SSDH w/ 128-bit codes	49.13
SSDH w/ 1024-bit codes	49.03

TABLE 6
Classification accuracy of various methods on Yahoo-1M.

Method	Accuracy (%)
AlexNet + Fine-tuning	71.28
SSDH w/ 128-bit codes	72.38

[64] M. D. Zeiler and R. Fergus, "Stochastic pooling for regularization of deep convolutional neural networks," in Proc. ICLR, 2013.
[65] J. Snoek, H. Larochelle, and R. P. Adams, "Practical bayesian optimization of machine learning algorithms," in Proc. NIPS, 2012.
[66] M. Lin, Q. Chen, and S. Yan, "Network in network," in Proc. ICLR, 2014.
[67] Z. Jie and S. Yan, "Robust scene classification with cross-level LLC coding on CNN features," in Proc. ACCV, 2014
[68] Y. Gong, L. Wang, R. Guo, and S. Lazebnik, "Multi-scale orderless pooling of deep convolutional activation features," in Proc. ECCV, 2014.

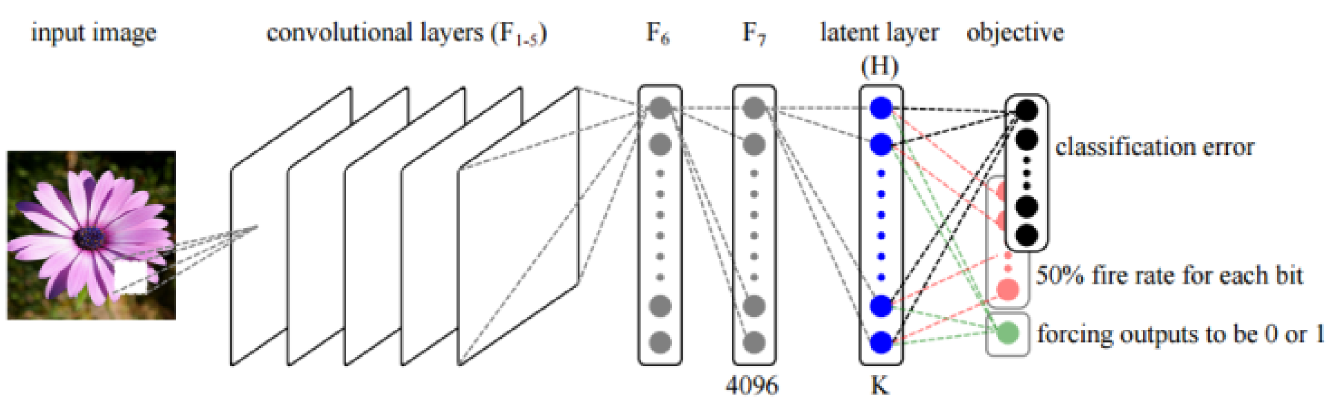
Experiments

Descriptor	Measurement	Time
CNN-fc7-4096	Euclidean distance	22.6 µs
SSDH-64	Hamming distance	23.0 ps

- Search with 64-bit codes is approximately ~982,600x faster than traditional exhaustive search with 4096-dimensional deep features.

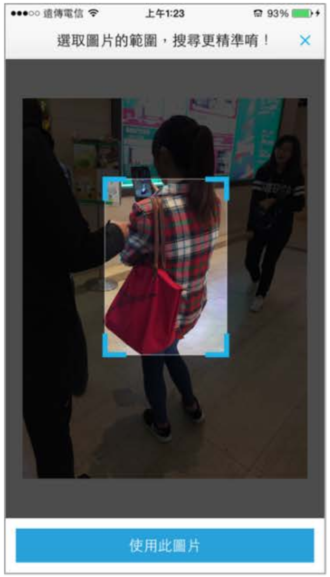
Conclusion

- SSDH constructs hash functions as a latent layer between the feature layer and classification layer in a network.
- SSDH jointly learn binary codes, features, and classification by optimizing the parameters of the network with the proposed objective function.
- SSDH is scalable to large scale search.



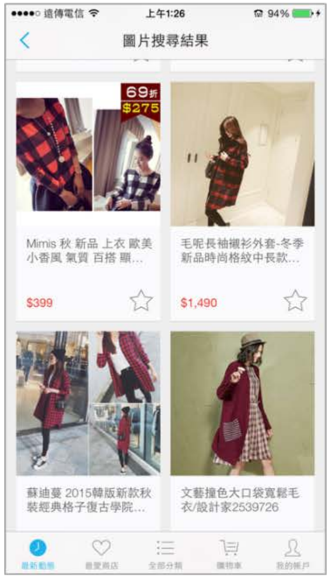
Application: Mobile clothing search

- The technology has been integrated in YAHOO!奇摩超級商城



Take photo

Select category



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Download our codes and models at

https://github.com/kevinlin311tw/caffe-cvprw15

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