Big Data Machine Learning
大数据机器学习

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Outline

1. Introduction
2. Learning to Hash
   - Isotropic Hashing
   - Supervised Hashing with Latent Factor Models
   - Supervised Multimodal Hashing with SCM
   - Multiple-Bit Quantization
3. Distributed Learning
   - Coupled Group Lasso for Web-Scale CTR Prediction
   - Distributed Power-Law Graph Computing
4. Stochastic Learning
   - Distributed Stochastic ADMM for Matrix Factorization
5. Conclusion

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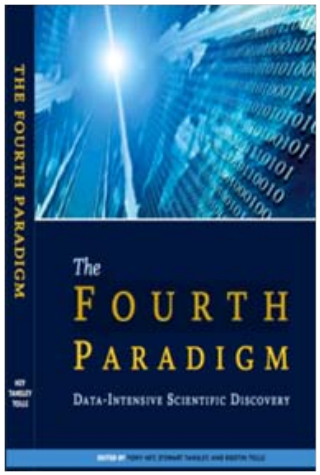
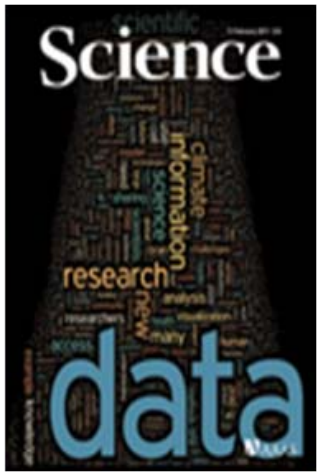
Big Data

Big data has attracted much attention from both academic and industry.

- Facebook: 750 Million users
- Flickr: 6 Billion photos
- Wal-Mart: 267 Million items/day; 4PB data warehouse
- Sloan Digital Sky Survey: New Mexico telescope captures 200 GB image data/day





Definition of Big Data

- Gartner (2012): "Big data is high volume, high velocity, and/or high variety information assets that require new forms of processing to enable enhanced decision making, insight discovery and process optimization." ("3Vs")
- International Data Corporation (IDC) (2011): "Big data technologies describe a new generation of technologies and architectures, designed to economically extract value from very large volumes of a wide variety of data, by enabling high-velocity capture, discovery, and/or analysis." ("4Vs")
- McKinsey Global Institute (MGI) (2011): "Big data refers to datasets whose size is beyond the ability of typical database software tools to capture, store, manage, and analyze."

Why not hot until recent years?

- Big data: 金矿
- Cloud computing: 采矿技术
- Big data machine learning: 冶金技术

Big Data Machine Learning

- Definition: perform machine learning from big data.
- Role: key for big data
  - Ultimate goal of big data processing is to mine value from data.
  - Machine learning provides fundamental theory and computational techniques for big data mining and analysis.

Challenge

- Storage: memory and disk
- Computation: CPU
- Communication: network

Our Contribution

- Learning to hash (哈希学习): memory/disk/cpu/communication
- Distributed learning (分布式学习): memory/disk/cpu;
  but increase communication cost
- Stochastic learning (随机学习): memory/disk/cpu

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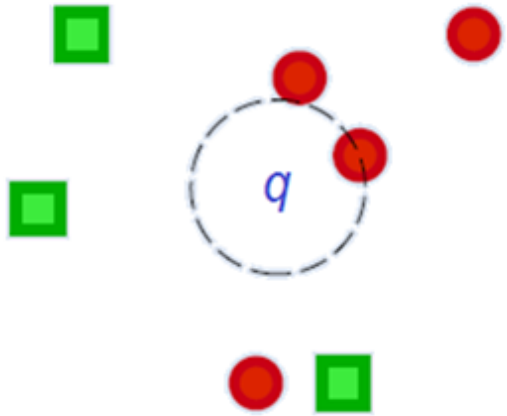
Nearest Neighbor Search (Retrieval)

- Given a query point q, return the points closest (similar) to q in the database(e.g. images).
- Underlying many machine learning, data mining, information retrieval problems



Challenge in Big Data Applications:

- Curse of dimensionality
- Storage cost
- Query speed

Similarity Preserving Hashing

h(Statue of Liberty) = 10001010

h (Napoléon) = 01100001

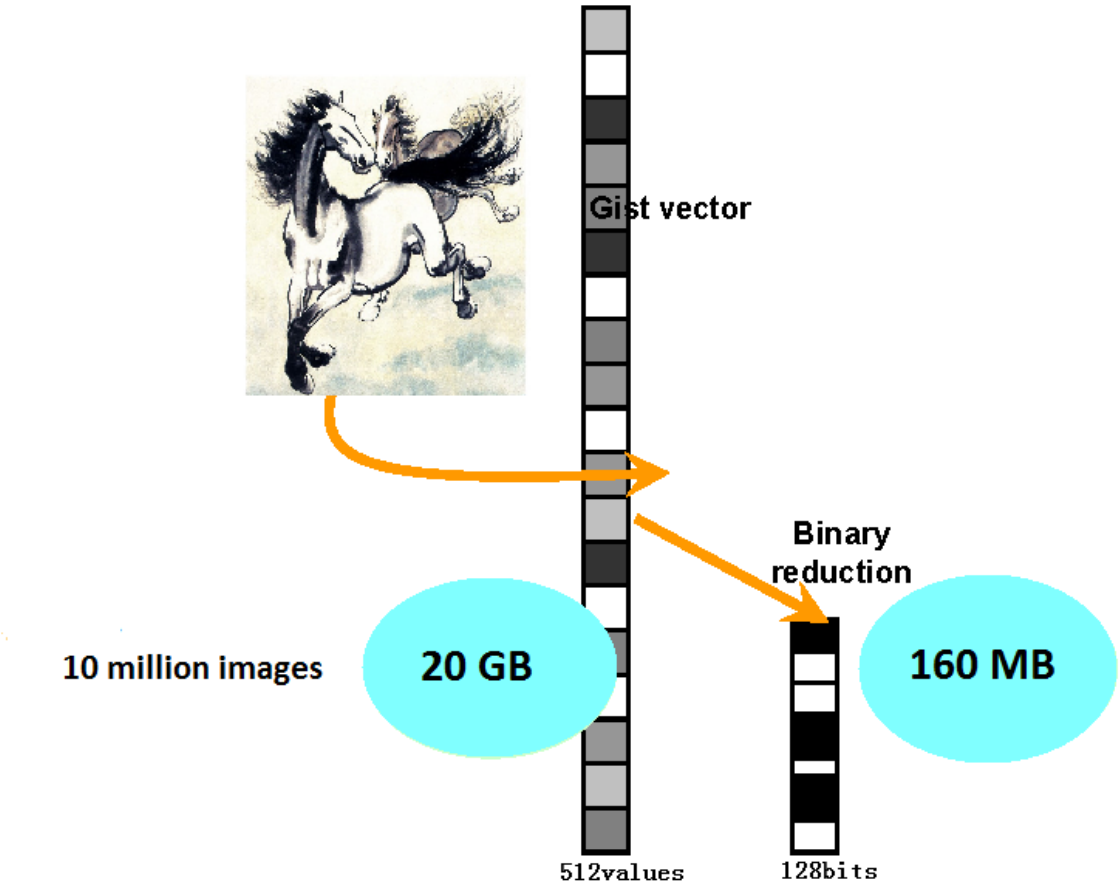
h (Napoléon) = 01100101

flipped bit

Should be very different

Should be similar

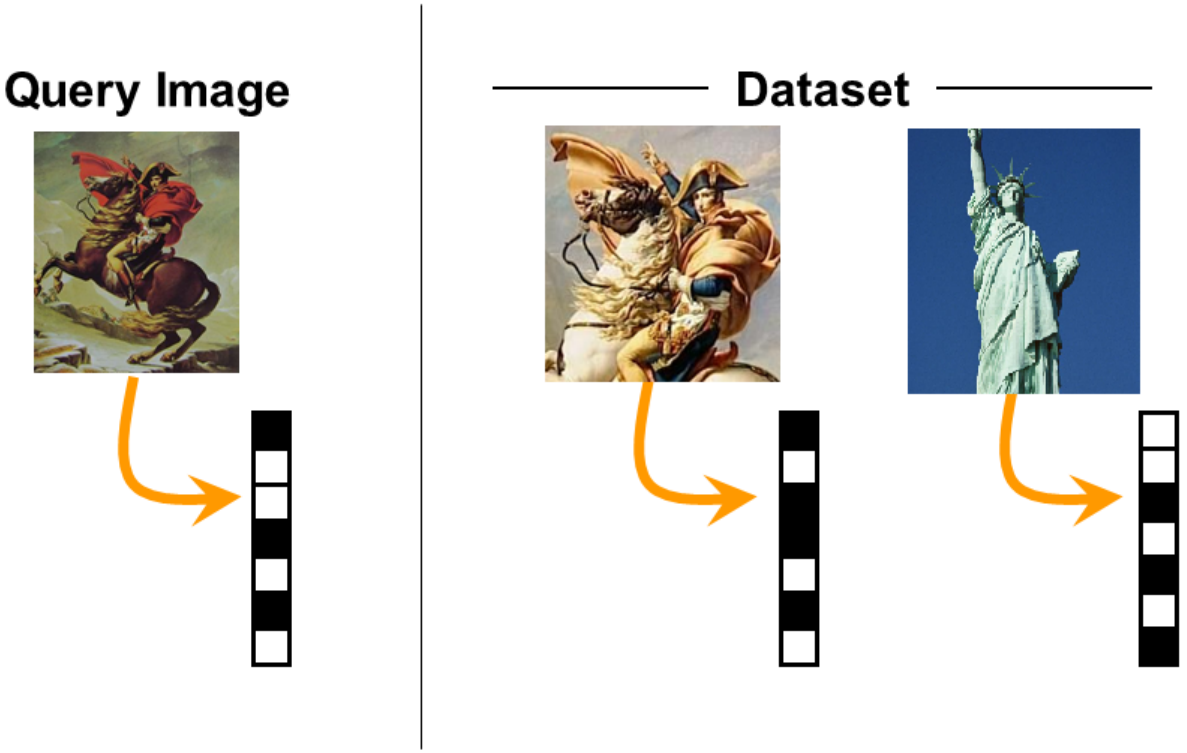
Reduce Dimensionality and Storage Cost



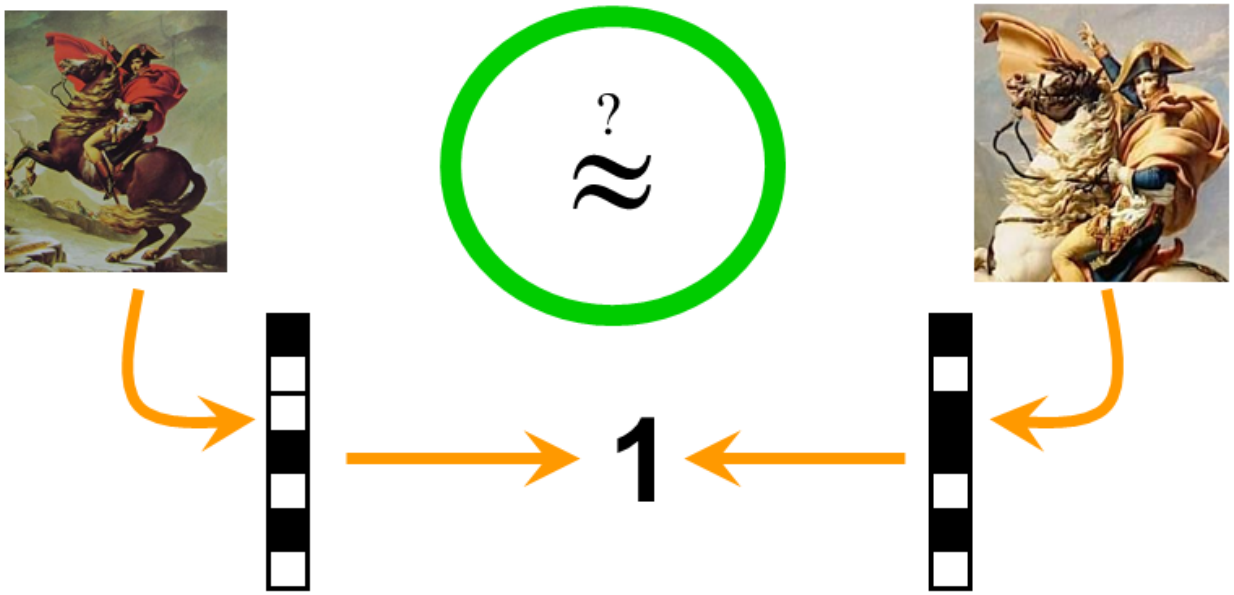
Querying

Hamming distance:

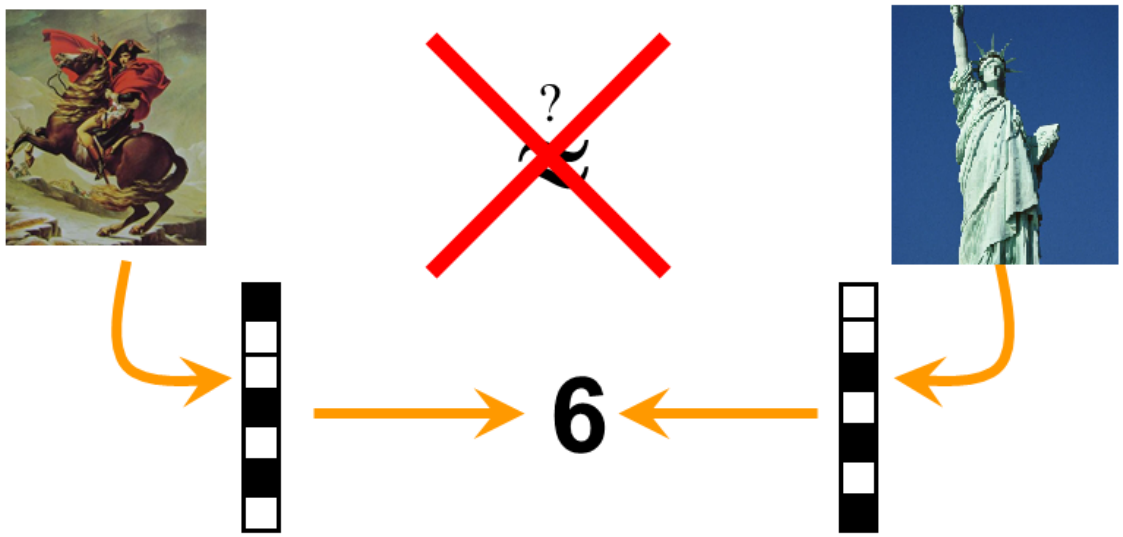
- $||01101110, 00101101||_H = 3$
- $||11011, 01011||_H = 1$



Querying



Querying



Fast Query Speed

- By using hashing scheme, we can achieve constant or sub-linear search time complexity.

- Exhaustive search is also acceptable because the distance calculation cost is cheap now.

Two Stages of Hash Function Learning

- Projection Stage (Dimension Reduction)
  - Projected with real-valued projection function
  - Given a point x, each projected dimension i will be associated with a real-valued projection function $f_i(x)$ (e.g. $f_i(x) = w_i^T x$)
- Quantization Stage
  - Turn real into binary

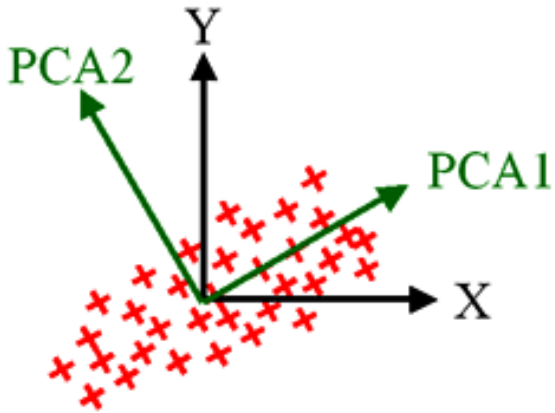
Our Contribution

- Unsupervised Hashing [NIPS 2012]:
  Isotropic hashing (IsoHash)
- Supervised Hashing [SIGIR 2014]:
  Supervised hashing with latent factor models
- Multimodal Hashing [AAAI 2014]:
  Large-scale supervised multimodal hashing with semantic correlation maximization
- Multiple-Bit Quantization:
  - Double-bit quantization (DBQ) [AAAI 2012]
  - Manhattan quantization (MQ) [SIGIR 2012]

Motivation

Problem:

All existing methods use the same number of bits for different projected dimensions with different variances.



Possible Solutions:

- Different number of bits for different dimensions (Unfortunately, have not found an effective way)
- Isotropic (equal) variances for all dimensions

PCA Hash

To generate a code of m bits, PCAH performs PCA on X, and then use the top m eigenvectors of the matrix XX^T as columns of the projection matrix $W \in \mathbb{R}^{d \times m}$. Here, top m eigenvectors are those corresponding to the m largest eigenvalues $\{\lambda_k\}_{k=1}^m$, generally arranged with the non-increasing order $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_m$. Let $\lambda = [\lambda_1, \lambda_2, \cdots, \lambda_m]^T$. Then

$$\Lambda = W^T X X^T W = \text{diag}(\lambda)$$

Define hash function

$$h(\mathbf{x}) = sgn(W^T \mathbf{x})$$

Idea of IsoHash

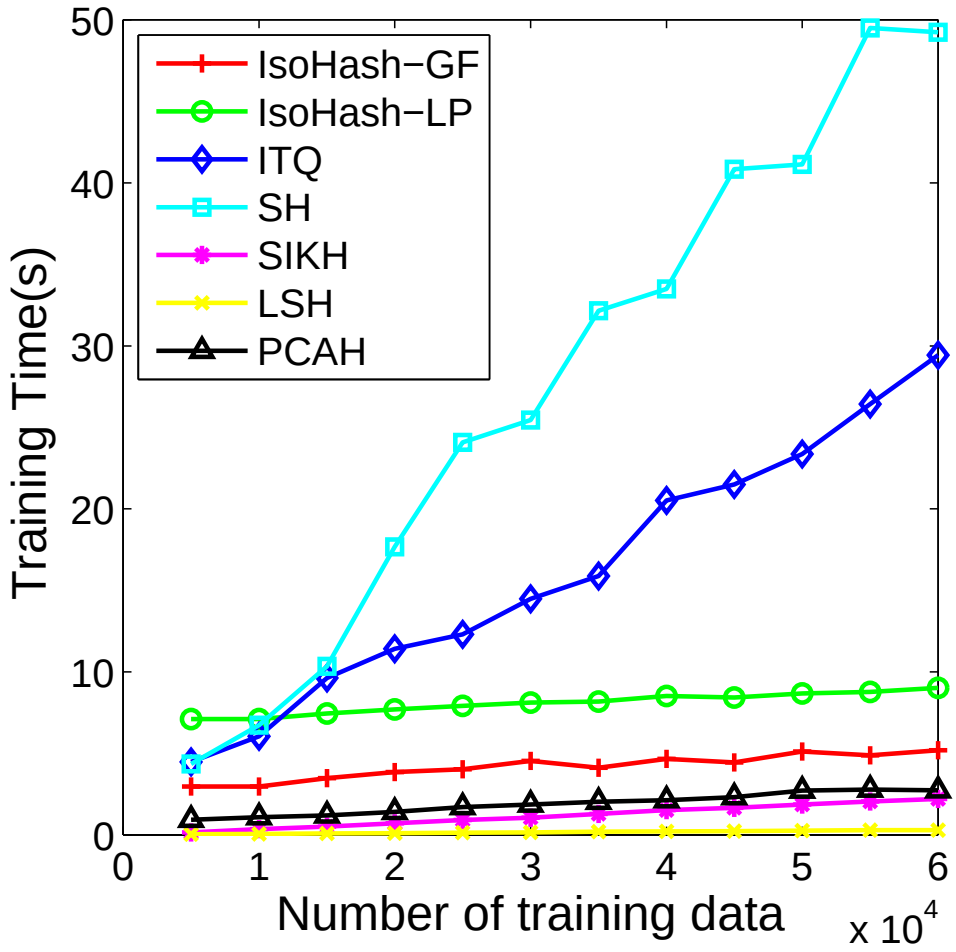
- Learn an orthogonal matrix $Q \in \mathbb{R}^{m \times m}$ which makes $Q^T W^T X X^T W Q$ become a matrix with equal diagonal values.

- Effect of Q: to make each projected dimension has the same variance while keeping the Euclidean distances between any two points unchanged.

Accuracy (mAP)

Method	CIFAR				
# bits	32	64	96	128	256
IsoHash	0.2249	0.2969	**0.3256**	**0.3357**	**0.3651**
PCAH	0.0319	0.0274	0.0241	0.0216	0.0168
ITQ	**0.2490**	**0.3051**	0.3238	0.3319	0.3436
SH	0.0510	0.0589	0.0802	0.1121	0.1535
SIKH	0.0353	0.0902	0.1245	0.1909	0.3614
LSH	0.1052	0.1907	0.2396	0.2776	0.3432

Training Time



Problem Definition

Input:

- Feature vectors: $\mathbf{x}_i \in \mathbb{R}^D, i = 1, \ldots, N$.
  (Compact form: $\mathbf{X} \in \mathbb{R}^{N \times D}$)
- Similarity labels: $s_{ij}, i, j = 1, \ldots, N$.
  (Compact form: $\mathcal{S} = \{s_{ij}\}$)
  - $s_{ij} = 1$ if points i and j belong to the same class.
  - $s_{ij} = 0$ if points i and j belong to different classes.

Output:

- Binary codes: $\mathbf{b}_i \in \{-1, 1\}^Q, i = 1, \ldots, N$.
  (Compact form: $\mathbf{B} \in \{-1, 1\}^{N \times Q}$)
  - When $s_{ij} = 1$, the Hamming distance between $\mathbf{b}_i$ and $\mathbf{b}_j$ should be low.
  - When $s_{ij} = 0$, the Hamming distance between $\mathbf{b}_i$ and $\mathbf{b}_j$ should be high.

Motivation

Existing supervised methods:

- High training complexity
- Semantic information is poorly utilized

Model

The likelihood on the observed similarity labels $\mathcal{S}$ is defined as:

$$p(\mathcal{S} \mid \mathbf{B}) = \prod_{s_{ij} \in \mathcal{S}} p(s_{ij} \mid \mathbf{B})$$

$$p(s_{ij} \mid \mathbf{B}) = \begin{cases} a_{ij}, & s_{ij} = 1 \\ 1 - a_{ij}, & s_{ij} = 0 \end{cases}$$

a_{ij} is defined as $a_{ij} = \sigma(\Theta_{ij})$ with:

$$\sigma(x) = \frac{1}{1 + e^{-x}}$$

$$\Theta_{ij} = \frac{1}{2}\mathbf{b}_i^T \mathbf{b}_j$$

Relationship between the Hamming distance and the inner product:

$$\text{dist}_H(\mathbf{b}_i, \mathbf{b}_j) = \frac{1}{2}(Q - \mathbf{b}_i^T \mathbf{b}_j) = \frac{1}{2}(Q - 2\Theta_{ij})$$

Relaxation

Re-defined Θ_{ij} as:

$$\Theta_{ij} = \frac{1}{2}\mathbf{U}_{i*}^T\mathbf{U}_{j*}$$

$p(\mathcal{S} \mid \mathbf{B})$, $p(\mathbf{B})$, $p(\mathbf{B} \mid \mathcal{S})$ become $p(\mathcal{S} \mid \mathbf{U})$, $p(\mathbf{U})$, $p(\mathbf{U} \mid \mathcal{S})$.
Define a normal distribution of $p(\mathbf{U})$ as:

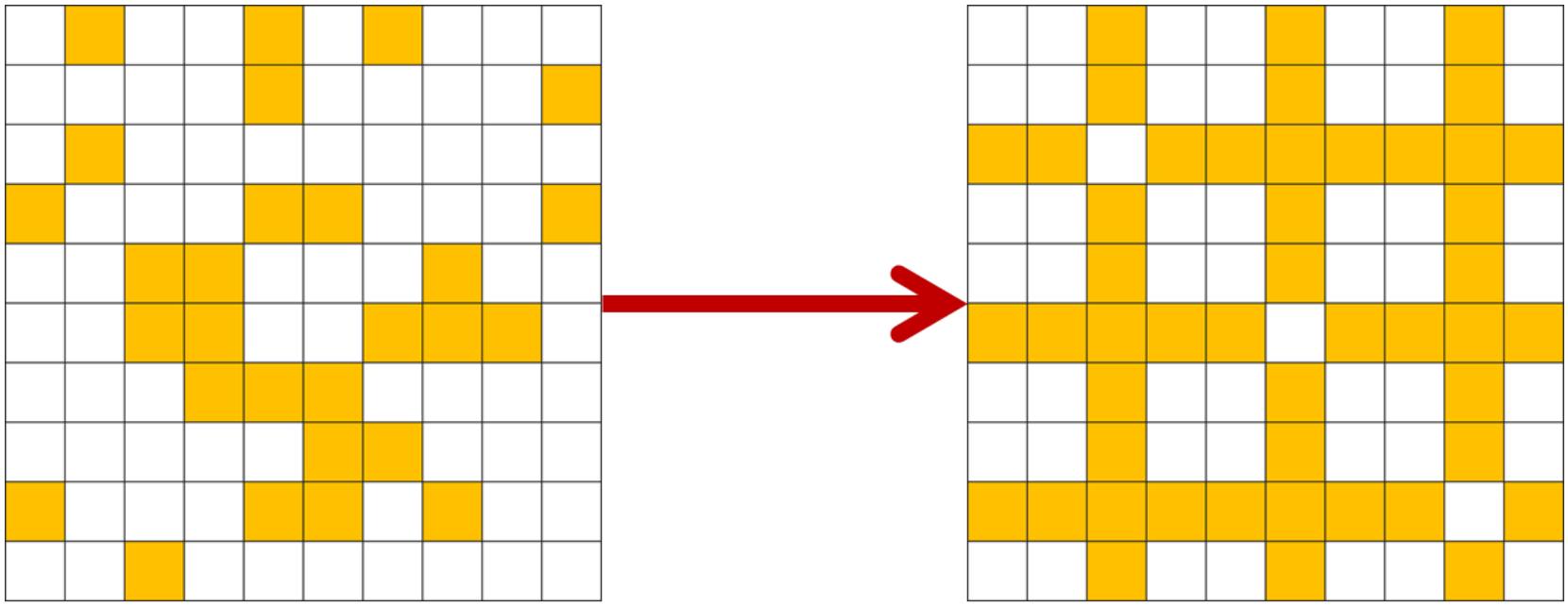
$$p(\mathbf{U}) = \prod_{d=1}^{Q} \mathcal{N}(\mathbf{U}_{*d} \mid \mathbf{0}, \beta\mathbf{I})$$

The log posteriori of $\mathbf{U}$ can be derived as:

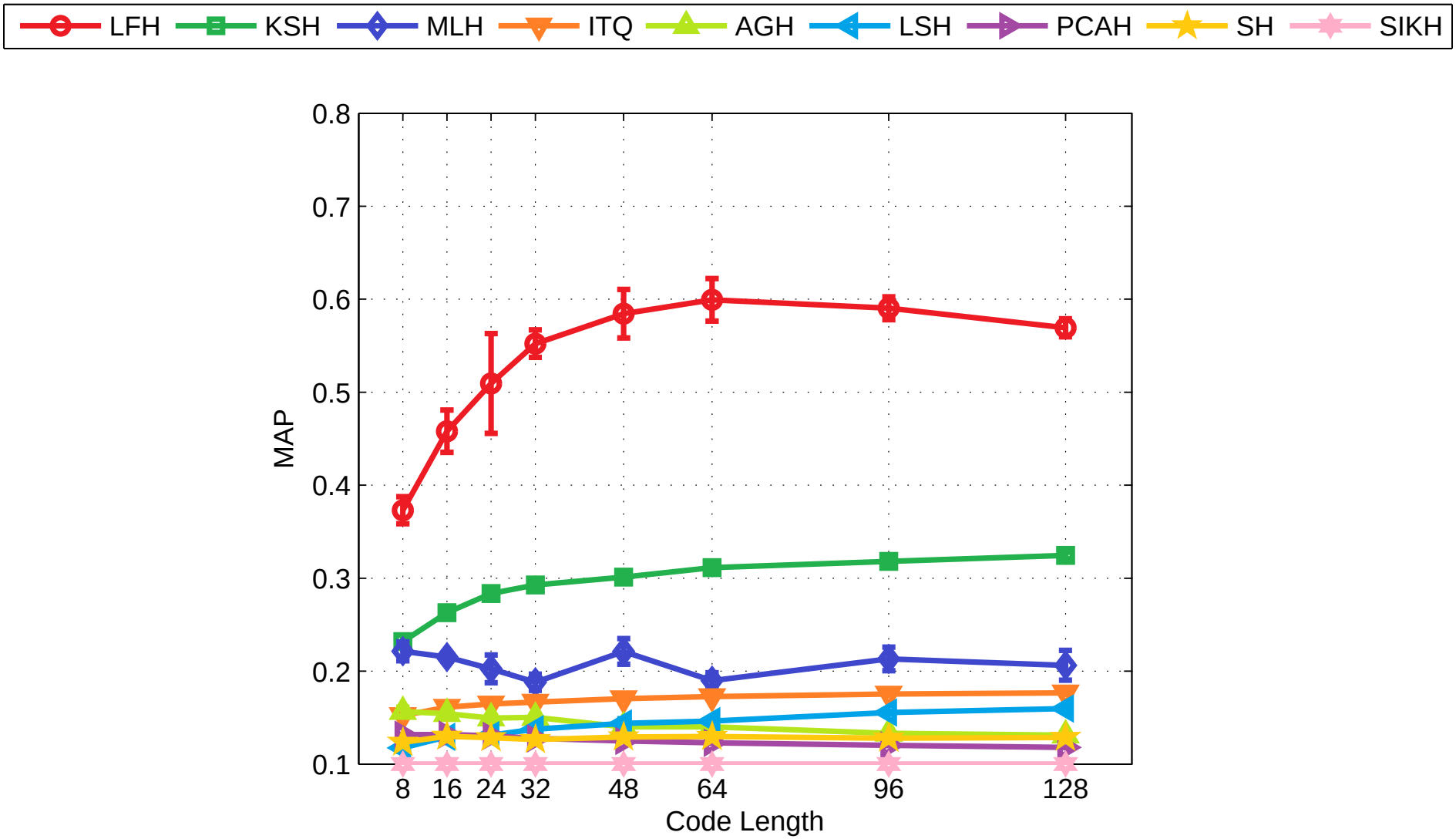
$$L = \log p(\mathbf{U} \mid \mathcal{S}) = \sum_{s_{ij} \in \mathcal{S}} (s_{ij}\Theta_{ij} - \log(1 + e^{\Theta_{ij}})) - \frac{1}{2\beta}\|\mathbf{U}\|_F^2 + c$$

Stochastic Learning

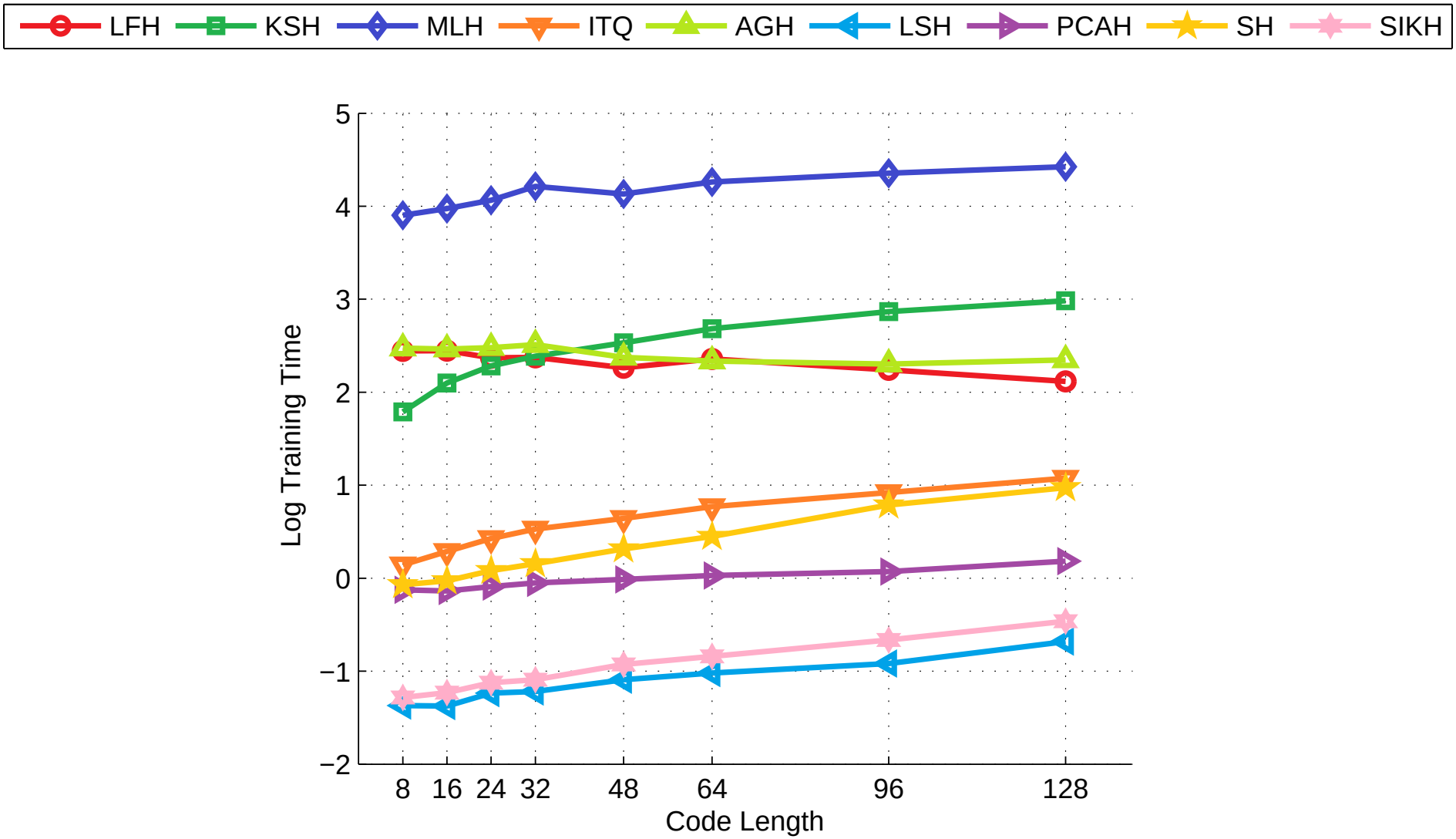
Furthermore, if we choose the subset of $\mathcal{S}$ by randomly selecting $\mathcal{O}(Q)$ of its columns and rows, we can further reduce the time cost to $\mathcal{O}(NQ^2)$ per iteration.



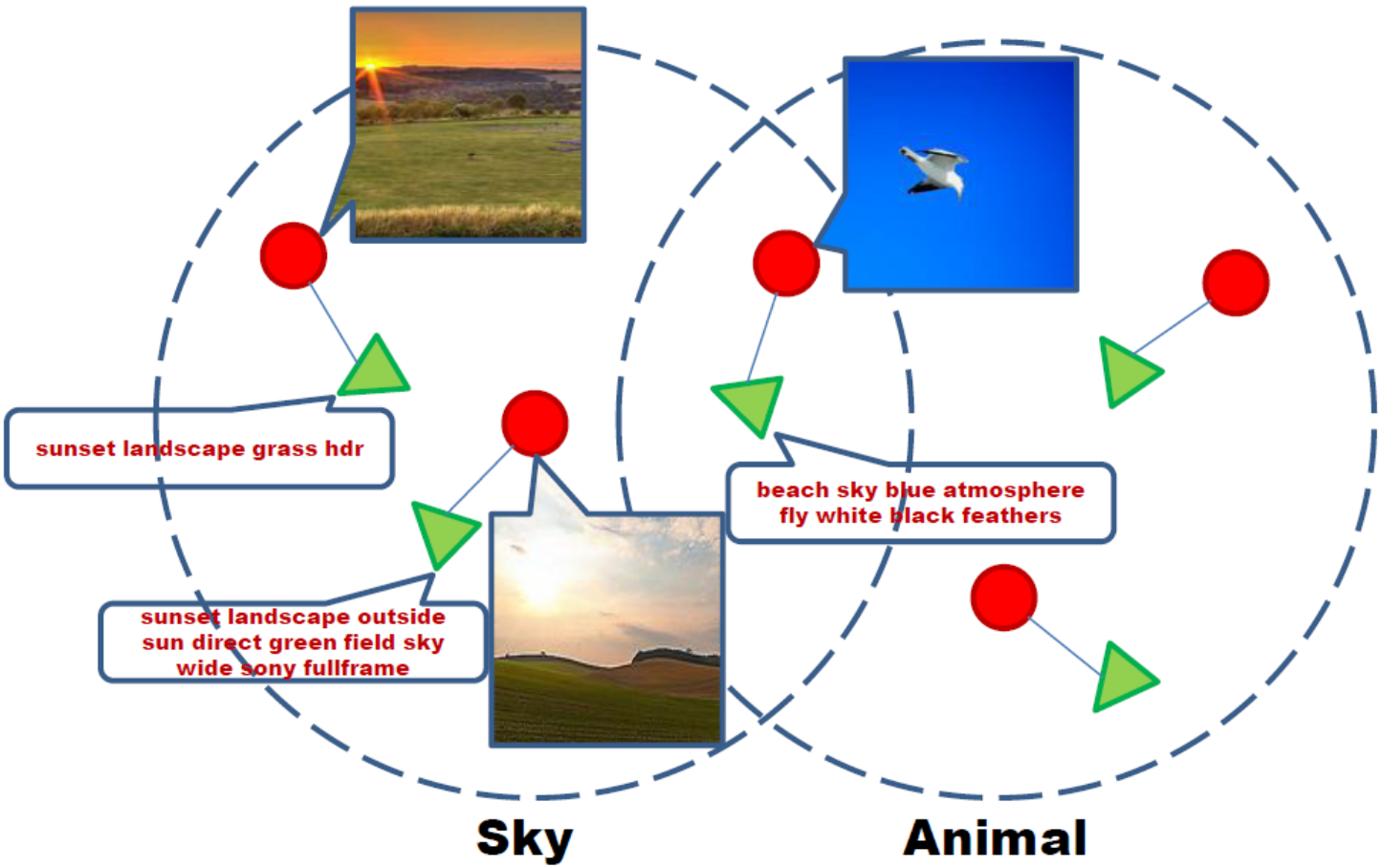
MAP (CIFAR-10)


LFH
KSH
MLH
ITQ
AGH
LSH
PCAH
SH
SIKH
MAP
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
8
16
24
32
48
64
96
128
Code Length

Training Time (CIFAR-10)



Supervised Multimodal Similarity Search



- Given a query of either image or text, return images or texts similar to it in both feature space and semantics (label information).

Motivation and Contribution

Motivation

- Existing supervised methods are not scalable

Contribution

- Avoiding explicitly computing the pairwise similarity matrix, linear-time complexity w.r.t. the size of training data.
- A sequential learning method with closed-form solution to each bit, no hyper-parameters and stopping conditions are needed.

In matrix form, we can rewrite the problem as follows

$$\begin{aligned} \min_{W_x, W_y} & \left\| sgn(XW_x) sgn(YW_y)^T - cS \right\|_F^2 \\ \text{s.t.} \ & sgn(XW_x)^T sgn(XW_x) = nI_c \\ & sgn(YW_y)^T sgn(YW_y) = nI_c. \end{aligned}$$

Sequential Strategy

Assuming that the projection vectors $w_x^{(1)}, ..., w_x^{(t-1)}$ and $w_y^{(1)}, ..., w_y^{(t-1)}$ have been learned, to learn the next projection vectors $w_x^{(t)}$ and $w_y^{(t)}$.

Define a residue matrix

$$R_t = cS - \sum_{k=1}^{t-1} sgn(Xw_x^{(k)})sgn(Yw_y^{(k)})^T.$$

Objective function can be written as

$$\min_{w_x^{(t)}, w_y^{(t)}} \left\| sgn(Xw_x^{(t)})sgn(Yw_y^{(t)})^T - R_t \right\|_F^2.$$

Algorithm 1 Learning Algorithm of SCM Hashing Method.

$C_{xy}^{(0)} \leftarrow 2(X^T\tilde{L})(Y^T\tilde{L})^T - (X^T\mathbf{1}_n)(Y^T\mathbf{1}_n)^T$;
$C_{xy}^{(1)} \leftarrow c \times C_{xy}^{(0)}$;
$C_{xx} \leftarrow X^TX + \gamma I_{d_x}$;
$C_{yy} \leftarrow Y^TY + \gamma I_{d_y}$;
for $t = 1 \rightarrow c$ **do**
  Solving the following generalized eigenvalue problem
  $C_{xy}^{(t)}C_{yy}^{-1}[C_{xy}^{(t)}]^T w_x = \lambda^2 C_{xx} w_x$,
  we can obtain the optimal solution $w_x^{(t)}$ corresponding to the largest eigenvalue λ_{max};
  $w_y^{(t)} \leftarrow \frac{C_{yy}^{-1}C_{xy}^T w_x^{(t)}}{\lambda_{max}}$;
  $h_x^{(t)} \leftarrow sgn(Xw_x^{(t)})$;
  $h_y^{(t)} \leftarrow sgn(Yw_y^{(t)})$;
  $C_{xy}^{(t+1)} \leftarrow C_{xy}^{(t)} - (X^T sgn(Xw_x^{(t)}))(Y^T sgn(Yw_y^{(t)}))^T$;
end for

Scalability

Table: Training time (in seconds) on NUS-WIDE dataset by varying the size of training set.

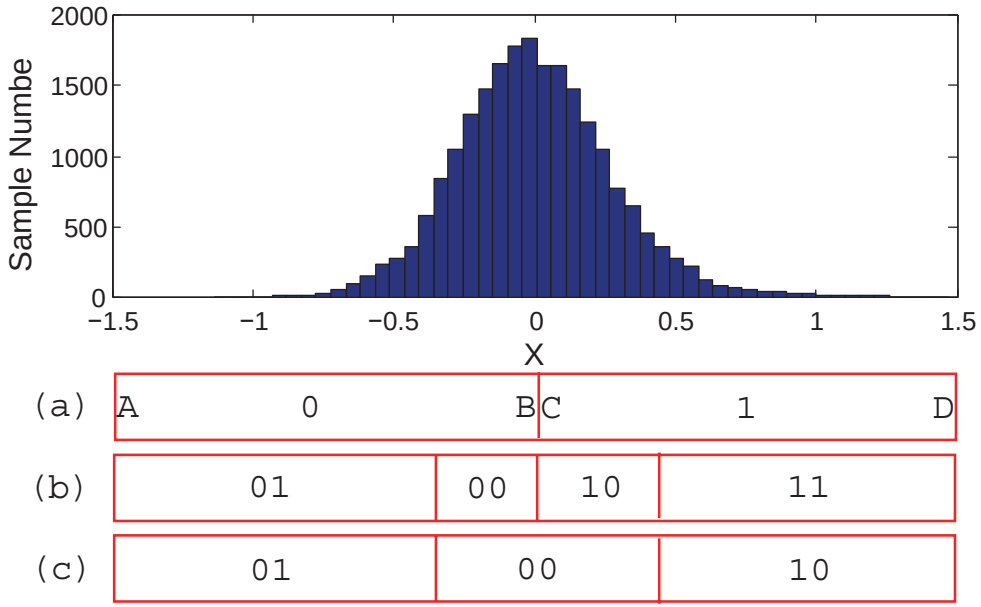
Method\Size of Training Set	500	1000	1500	2000	2500	3000	5000	10000	20000
SCM-Seq	276	249	303	222	236	260	248	228	230
SCM-Orth	36	80	85	77	83	76	110	87	102
CCA	25	20	23	22	25	22	28	38	44
CCA-3V	69	57	68	69	62	55	67	70	86
CVH	62	116	123	149	155	170	237	774	1630
CRH	68	253	312	515	760	1076	-	-	-
MLBE	67071	126431	-	-	-	-	-	-	-

Accuracy

Table: MAP results on NUS-WIDE. The best performance is shown in boldface.

Task	Method	Code Length		
		$c = 16$	$c = 24$	$c = 32$
Image Query v.s. Text Database	SCM-Seq	**0.4385**	**0.4397**	**0.4390**
	SCM-Orth	0.3804	0.3746	0.3662
	CCA	0.3625	0.3586	0.3565
	CCA-3V	0.3826	0.3741	0.3692
	CVH	0.3608	0.3575	0.3562
	CRH	0.3957	0.3965	0.3970
	MLBE	0.3697	0.3620	0.3540
Text Query v.s. Image Database	SCM-Seq	**0.4273**	**0.4265**	**0.4259**
	SCM-Orth	0.3757	0.3625	0.3581
	CCA	0.3619	0.3580	0.3560
	CCA-3V	0.3801	0.3721	0.3676
	CVH	0.3640	0.3596	0.3581
	CRH	0.3926	0.3910	0.3904
	MLBE	0.3877	0.3636	0.3551

Double Bit Quantization



Point distribution of the real values computed by PCA on *22K LabelMe* data set, and different coding results based on the distribution:

- (a) single-bit quantization (SBQ);
- (b) hierarchical hashing (HH);
- (c) double-bit quantization (DBQ).

Experiment

mAP on LabelMe data set

# bits	32			64		
	SBQ	HH	DBQ	SBQ	HH	DBQ
ITQ	0.2926	0.2592	**0.3079**	0.3413	0.3487	**0.4002**
SH	0.0859	0.1329	**0.1815**	0.1071	0.1768	**0.2649**
PCA	0.0535	0.1009	**0.1563**	0.0417	0.1034	**0.1822**
LSH	**0.1657**	0.105	0.12272	**0.2594**	0.2089	0.2577
SIKH	0.0590	0.0712	**0.0772**	0.1132	0.1514	**0.1737**

# bits	128			256		
	SBQ	HH	DBQ	SBQ	HH	DBQ
ITQ	0.3675	0.4032	**0.4650**	0.3846	0.4251	**0.4998**
SH	0.1730	0.2034	**0.3403**	0.2140	0.2468	**0.3468**
PCA	0.0323	0.1083	**0.1748**	0.0245	0.1103	**0.1499**
LSH	0.3579	0.3311	**0.4055**	0.4158	0.4359	**0.5154**
SIKH	0.2792	0.3147	**0.3436**	0.4759	0.5055	**0.5325**

Manhattan Quantization

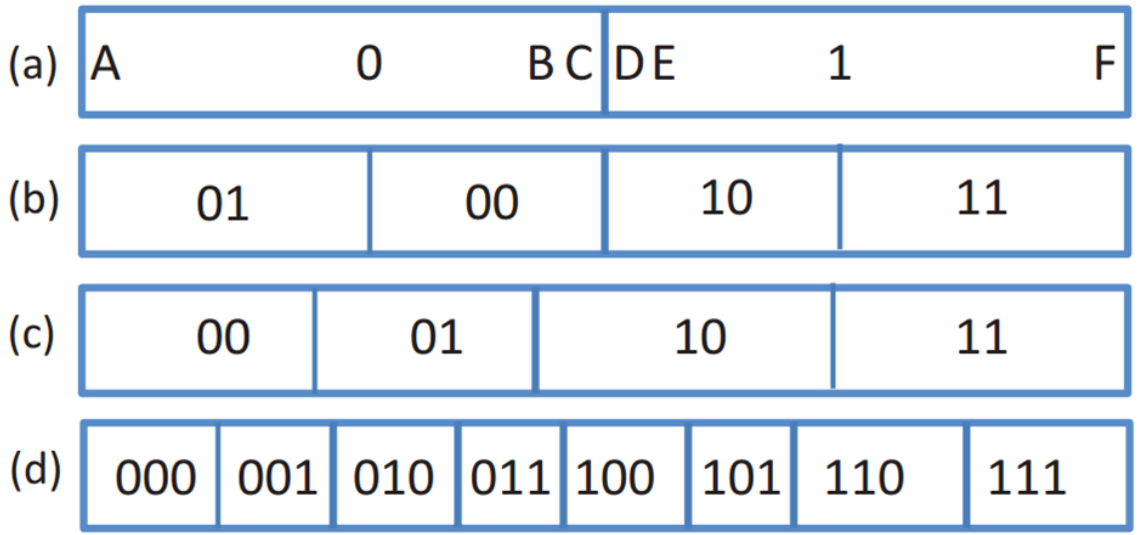


Figure 1: Different quantization methods: (a) single-bit quantization (SBQ); (b) hierarchical quantization (HQ); (c) 2-bit Manhattan quantization (2-MQ); (d) 3-bit Manhattan quantization (3-MQ).

Experiment

Table: mAP on ANN_SIFT1M data set. The best mAP among SBQ, HQ and 2-MQ under the same setting is shown in bold face.

# bits	32			64			96		
	SBQ	HQ	2-MQ	SBQ	HQ	2-MQ	SBQ	HQ	2-MH
ITQ	0.1657	0.2500	**0.2750**	0.4641	0.4745	**0.5087**	0.5424	0.5871	**0.6263**
SIKH	0.0394	0.0217	**0.0570**	0.2027	0.0822	**0.2356**	0.2263	0.1664	**0.2768**
LSH	0.1163	0.0961	**0.1173**	0.2340	0.2815	**0.3111**	0.3767	0.4541	**0.4599**
SH	0.0889	0.2482	**0.2771**	0.1828	0.3841	**0.4576**	0.2236	0.4911	**0.5929**
PCA	0.1087	0.2408	**0.2882**	0.1671	0.3956	**0.4683**	0.1625	0.4927	**0.5641**

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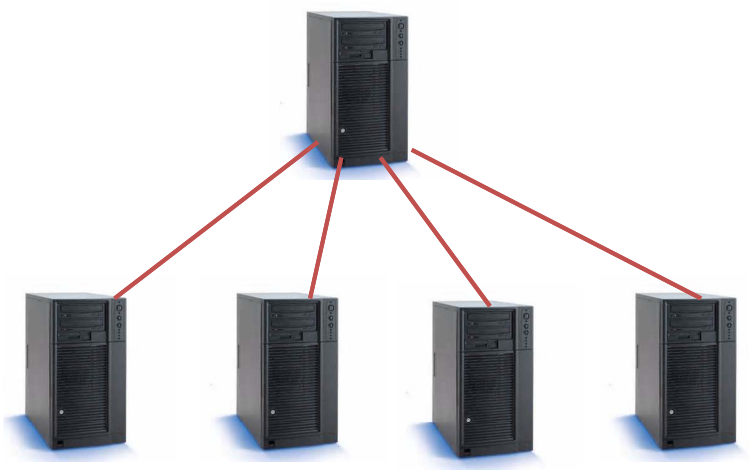
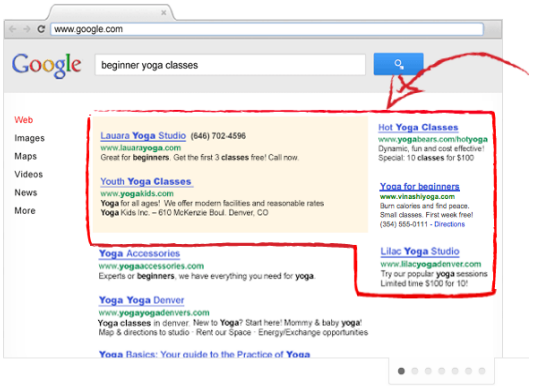
Definition

Perform machine learning on clusters with several machines (nodes).

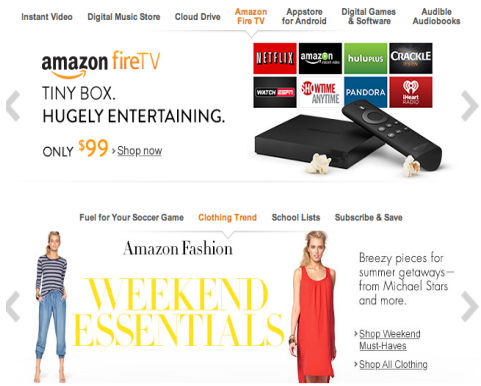


CTR Prediction for Online Advertising

- Multi-billion business on the web and accounts for the majority of the income for the major internet companies.
- Display advertising is a big part of online advertising.
- Click through rate (CTR) prediction is the problem of estimating the probability that an ad is clicked when displayed to a user in a specific context.



(a) Google

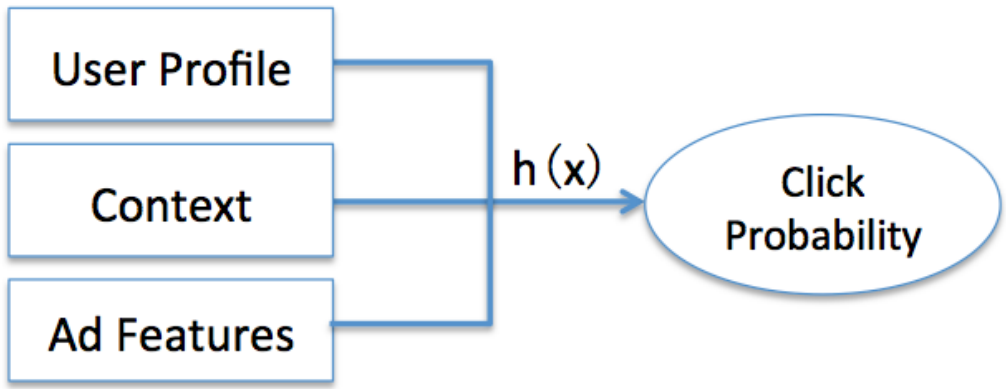


(b) Amazon

(c) Taobao

Notation

- Impression (instance): ad + user + context
- Training set $\{(\mathbf{x}^{(i)}, y^{(i)}) \mid i = 1, ..., N\}$
- $\mathbf{x}^T = (\mathbf{x}_u^T, \mathbf{x}_a^T, \mathbf{x}_o^T)$
- $y \in \{0, 1\}$ with $y = 1$ denoting *click* and $y = 0$ denoting *non-click*
- Learn $h(\mathbf{x}) = h(\mathbf{x}_u, \mathbf{x}_a, \mathbf{x}_o)$ to predict CTR



Coupled Group Lasso (CGL)

1. Likelihood

$$h(\mathbf{x}) = Pr(y = 1|\mathbf{x}, \mathbf{W}, \mathbf{V}, \mathbf{b}) = g\left((\mathbf{x}_u^T\mathbf{W})(\mathbf{x}_a^T\mathbf{V})^T + \mathbf{b}^T\mathbf{x}_o\right)$$

where

$$\mathbf{W} \in \mathbb{R}^{d_u \times k}, \mathbf{V} \in \mathbb{R}^{d_a \times k}, (\mathbf{x}_u^T\mathbf{W})(\mathbf{x}_a^T\mathbf{V})^T = \mathbf{x}_u^T(\mathbf{W}\mathbf{V}^T)\mathbf{x}_a$$

2. Objective function

$$\min_{\mathbf{W},\mathbf{V},\mathbf{b}} \sum_{i=1}^{N} \xi\left(\mathbf{W}, \mathbf{V}, \mathbf{b}; \mathbf{x}^{(i)}, y^{(i)}\right) + \lambda\Omega(\mathbf{W}, \mathbf{V}),$$

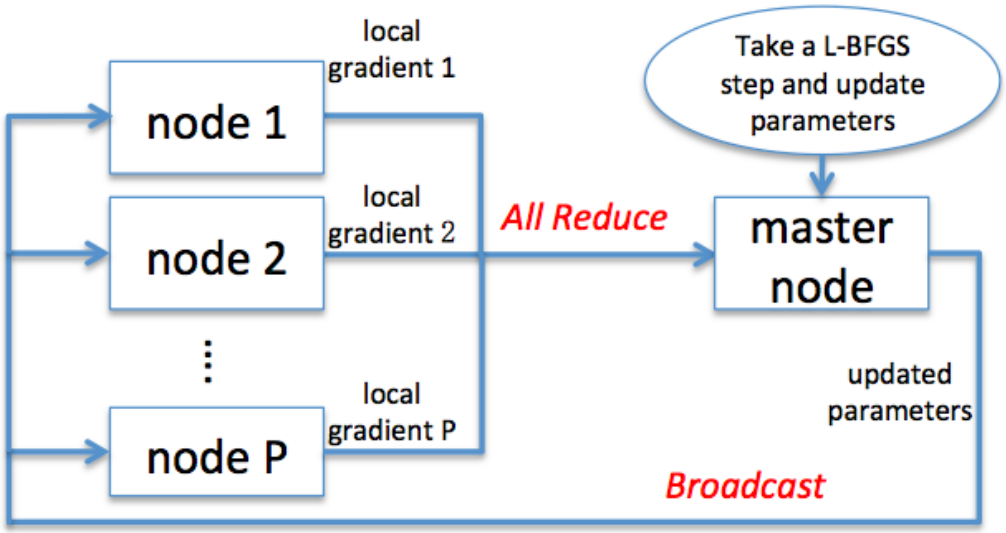
in which

$$\xi(\mathbf{W}, \mathbf{V}, \mathbf{b}; \mathbf{x}^{(i)}, y^{(i)}) = -\log\left((h(\mathbf{x}^{(i)}))^{y^{(i)}}(1 - h(\mathbf{x}^{(i)}))^{1-y^{(i)}}\right)$$

$$\Omega(\mathbf{W}, \mathbf{V}) = ||\mathbf{W}||_{2,1} + ||\mathbf{V}||_{2,1} = \sum_{i=1}^{d_u} ||\mathbf{W}_{i*}||_2 + \sum_{i=1}^{d_a} ||\mathbf{V}_{i*}||_2$$

Distributed Learning Framework

- Compute gradient $\mathbf{g}'_p$ locally on each node p *in parallel*.
- Compute gradient $\mathbf{g}' = \sum_{p=1}^{P} \mathbf{g}'_p$ with *AllReduce*.
- Add the gradient of the regularization term and take an L-BFGS step in the master node.
- *Broadcast* the updated parameters to each slaver node.



Experiment

Experiment Environment

- MPI-Cluster with hundreds of nodes, each of which is a 24-core server with 2.2GHz CPU and 96GB of RAM

Baseline and Evaluation Metric

- Baseline: LR (with L2-norm) [Chapelle et al., 2013]
- Evalution Metric (Discrimination)

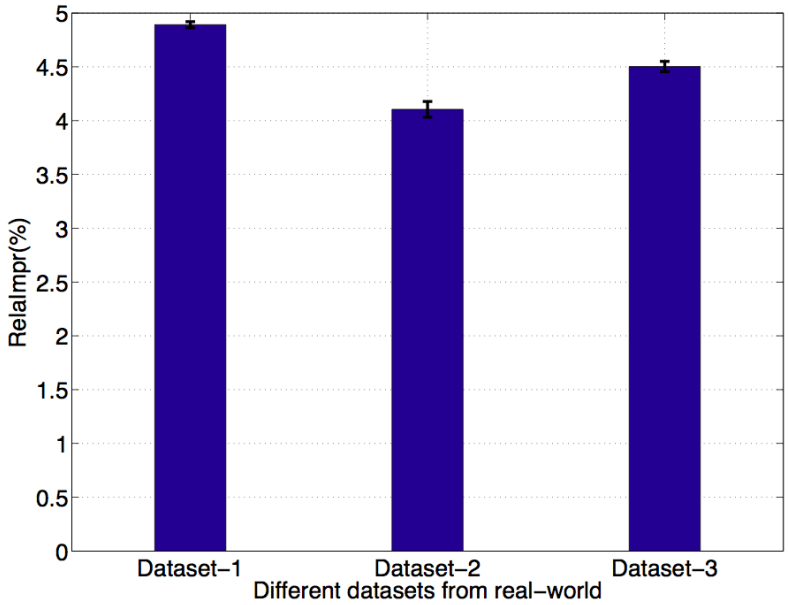
$$RelaImpr = \frac{AUC(model) - 0.5}{AUC(baseline) - 0.5} \times 100\%$$

Data Sets

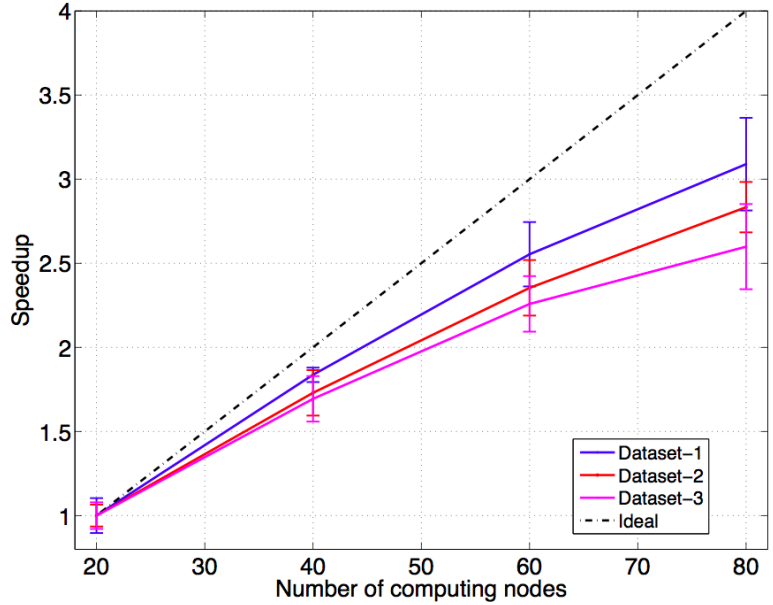
Data set	# Instances (Billion)	CTR (%)	# Ads	# Users (Million)	Storage (TB)
Train 1	1.011	1.62	21,318	874.7	1.895
Test 1	0.295	1.70	11,558	331.0	0.646
Train 2	1.184	1.61	21,620	958.6	2.203
Test 2	0.145	1.64	6,848	190.3	0.269
Train 3	1.491	1.75	33,538	1119.3	2.865
Test 3	0.126	1.70	9,437	183.7	0.233

Real-world data sets collected from *taobao* of Alibaba Group

Performance



(c) RelaImpr w.r.t. Baseline



(d) Speedup

Accuracy and Scalability

Feature Selection

.

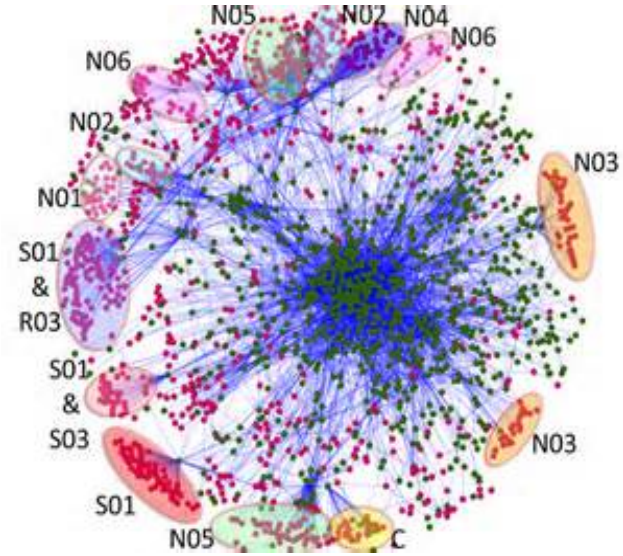
	Ad Part	User Part
Important Features	Women's clothes, Skirt, Dress,Children's wear, Shoes, Cellphone	Watch, Underwear, Fur clothing, Furniture
Useless Features	Movie, Act, Take-out, Food booking service	Stage Costume, Flooring, Pencil, Outdoor sock

Feature Selection Results

Graph-based Machine Learning

- Big graphs emerge in many real applications
- Graph-based machine learning is a hot research topic with wide applications: *relational learning*, *manifold learning*, *PageRank*, *community detection*, *etc*
- Distributed graph computing frameworks for big graphs

(a) Social Network



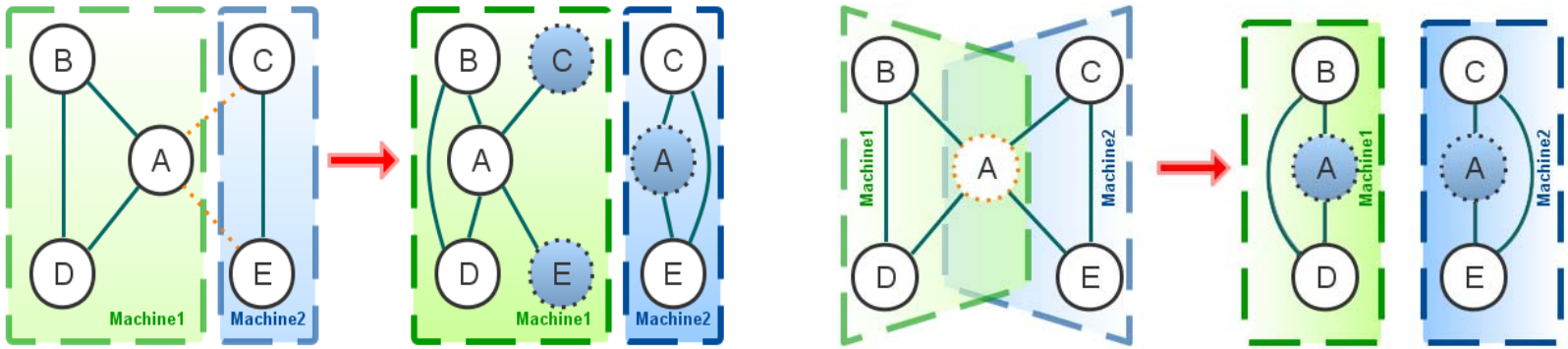
(b) Biological Network

Graph Partitioning

Graph partitioning (GP) plays a key role to affect the performance of distributed graph computing:

- Workload balance
- Communication cost

Two strategies for graph partitioning. Shaded vertices are ghosts and mirrors, respectively.

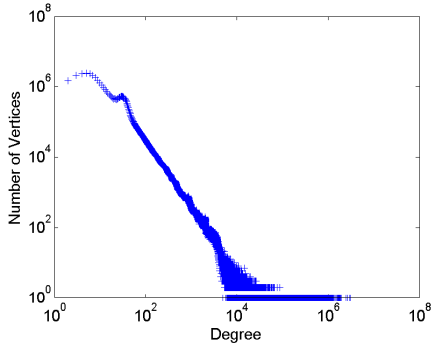


(a) Edge-Cut (b) Vertex-Cut

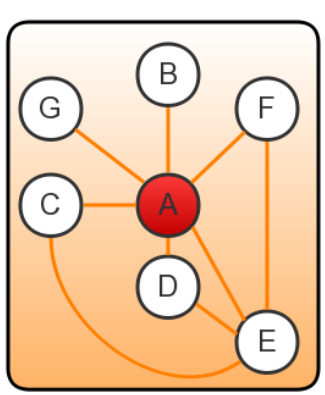
Theoretical and empirical results show vertex-cut is better than edge-cut.

Power-Law Graph Partitioning

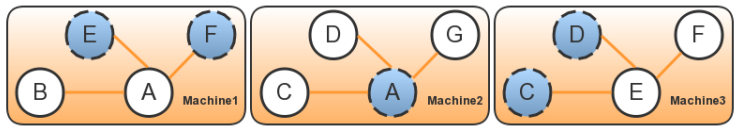
Natural graphs from real world typically follow skewed power-law degree distributions: $\Pr(d) \propto d^{-\alpha}$.



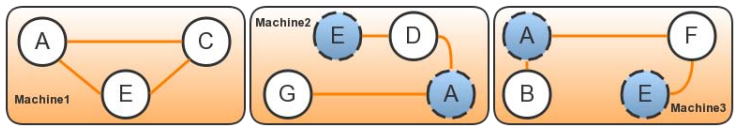
Different vertex-cut methods can result in different performance



(a) Sample



(b) Bad partitioning



(c) Good partitioning

Degree-based Hashing (DBH)

Existing GP methods, such as the Random in PowerGraph (Joseph E Gonzalez et al, 2012) and Grid in GraphBuilder (Nilesh Jain et al, 2013), do not make effective use of the power-law degree distribution.

We propose a novel GP method called degree-based hashing (DBH):

Algorithm 2 GP with DBH

Input: The set of edges E; the set of vertices V; number of machines p.
Output: The assignment $M(e) \in \{1, \ldots, p\}$ for each edge e.
Initialization: count the degree d_i for each vertex $i \in \{1, \ldots, n\}$ in parallel
for all $e = (v_i, v_j) \in E$ **do**
  Hash each edge in parallel:
  if $d_i < d_j$ **then**
    $M(e) \leftarrow vertex\_hash(v_i)$
  else
    $M(e) \leftarrow vertex\_hash(v_j)$
  end if
end for

Theoretical Analysis

We theoretically prove that our DBH method can outperform Random and Grid in terms of:

- reducing replication factor (communication and storage cost)
- keeping good edge-balance (workload balance)

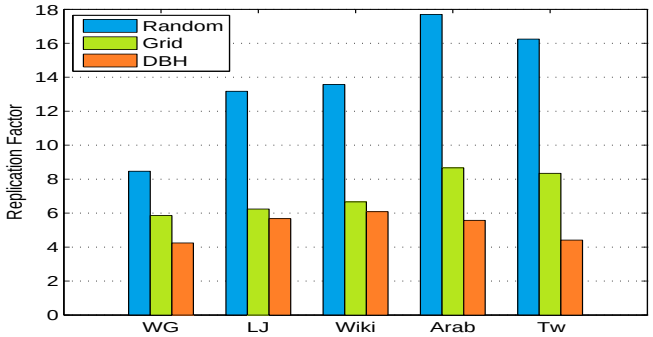
Nice property: Our DBH reduces more replication factor when the power-law graph is more skewed.

Data Set

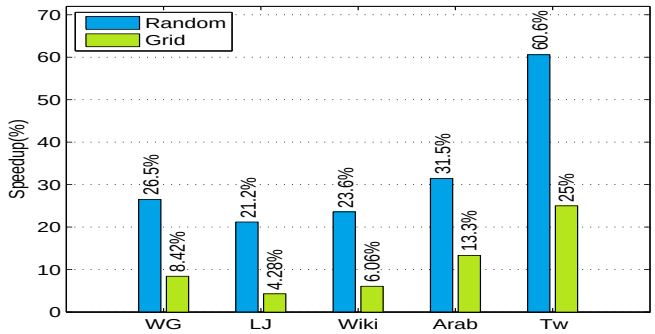
Table: Datasets

Alias	Graph	$\|V\|$	$\|E\|$
Tw	Twitter	42M	1.47B
Arab	Arabic-2005	22M	0.6B
Wiki	Wiki	5.7M	130M
LJ	LiveJournal	5.4M	79M
WG	WebGoogle	0.9M	5.1M

Empirical Results

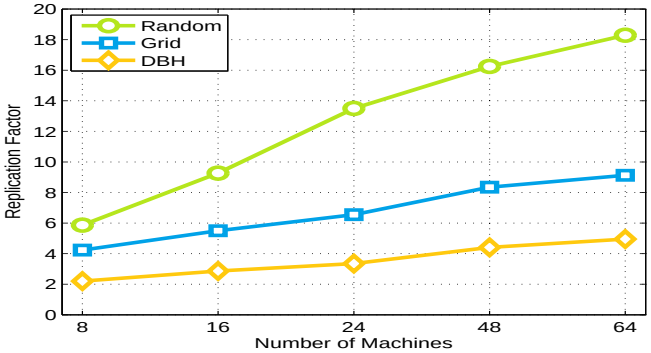


(d) Replication Factor

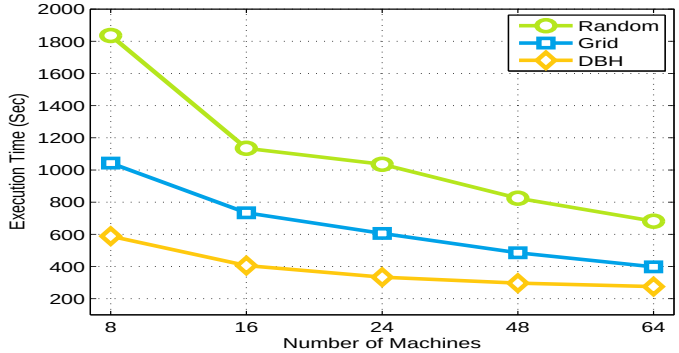


(e) Speedup relative to baselines

Figure: Experiments on real-world graphs. The number of machines is 48.



(a) Replication Factor



(b) Execution Time

Figure: The number of machines ranges from 8 to 64 on Twitter graph.

Outline

1. Introduction
2. Learning to Hash
   - Isotropic Hashing
   - Supervised Hashing with Latent Factor Models
   - Supervised Multimodal Hashing with SCM
   - Multiple-Bit Quantization
3. Distributed Learning
   - Coupled Group Lasso for Web-Scale CTR Prediction
   - Distributed Power-Law Graph Computing
4. Stochastic Learning
   - Distributed Stochastic ADMM for Matrix Factorization
5. Conclusion

Definition

Given a (large) set of training data $\{(\mathbf{x}_i, y_i)|i = 1, 2, \cdots, n\}$, each time we randomly sample one training instance for training.

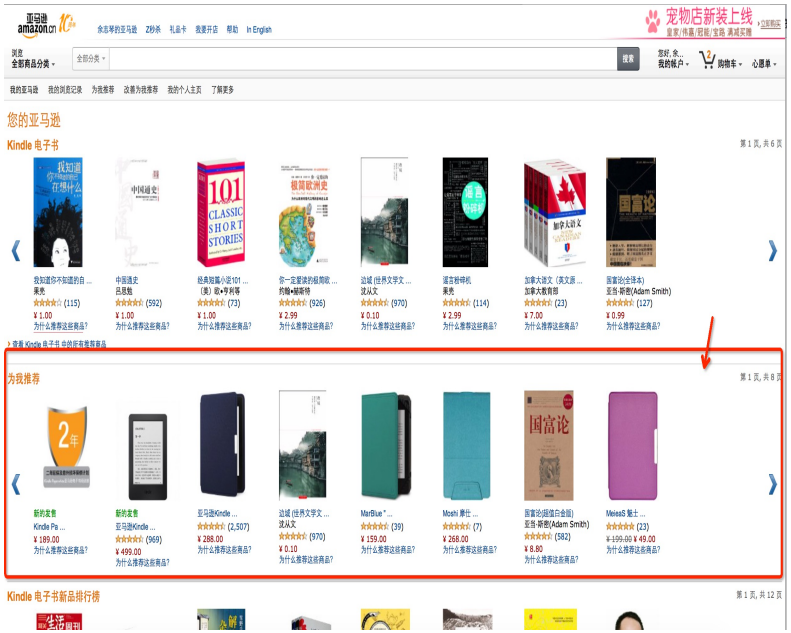
Many machine learning problems can be formulated as:

$$\underset{\mathbf{w}}{\operatorname{argmin}} L(\mathbf{w}) = \frac{1}{n} \sum_{i=1}^{n} f_i(\mathbf{w}|\mathbf{x}_i, y_i)$$

Hence, the computation cost can be greatly reduced by using stochastic learning.

Recommender System

- Recommend products (items) to customers (users) by utilizing the customers' historic preferences.

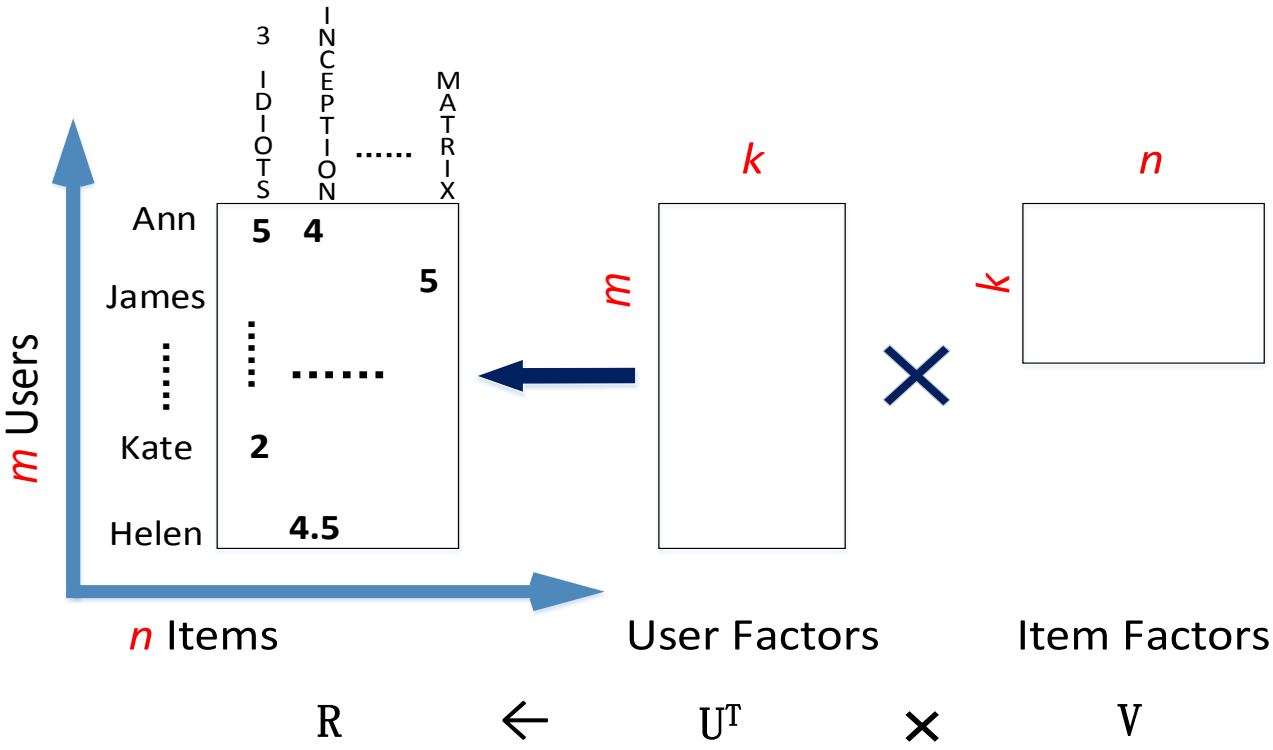


(a) Amazon

(b) Sina Weibo

Matrix Factorization

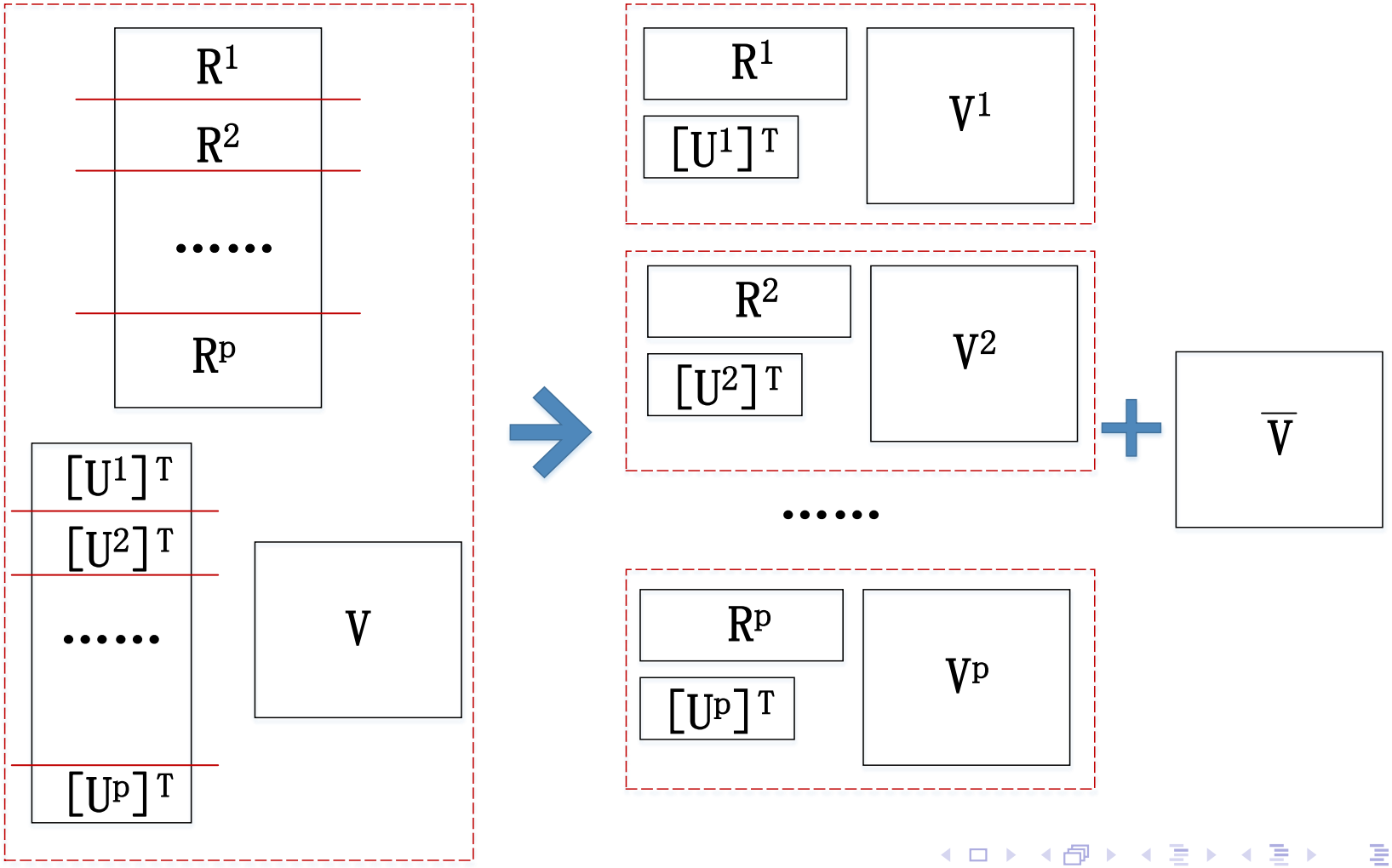
- Popular in recommender systems for its promising performance



$$\min_{\mathbf{U},\mathbf{V}} \frac{1}{2} \sum_{(i,j)\in\Omega} \left[(R_{i,j} - \mathbf{U}_{*i}^T \mathbf{V}_{*j})^2 + \lambda_1 \mathbf{U}_{*i}^T \mathbf{U}_{*i} + \lambda_2 \mathbf{V}_{*j}^T \mathbf{V}_{*j} \right]$$

Data Split Strategy

Decouple $\mathbf{U}$ and $\mathbf{V}$ as possible as we can:



Distributed ADMM

Reformulated MF problem :

$$\min_{\mathbf{U},\overline{\mathbf{V}},\mathcal{V}} \frac{1}{2}\sum_{p=1}^{P}\sum_{(i,j)\in\Omega^p}\left[(R_{i,j}-\mathbf{U}_{*i}^T\mathbf{V}_{*j}^p)^2+\lambda_1\mathbf{U}_{*i}^T\mathbf{U}_{*i}+\lambda_2[\mathbf{V}_{*j}^p]^T\mathbf{V}_{*j}^p\right]$$

$$s.t.: \quad \mathbf{V}^p-\overline{\mathbf{V}}=0; \quad \forall p\in\{1,2,...,P\}$$

where $\mathcal{V}=\{\mathbf{V}^p\}_{p=1}^P$, Ω^p denotes the (i,j) indices of the ratings located in node p

Distributed ADMM

Define:

$$\begin{aligned} L^p(\mathbf{U}, \mathbf{V}^p, \mathbf{\Theta}^p, \overline{\mathbf{V}}) &= f^p(\mathbf{U}, \mathbf{V}^p) + l^p(\mathbf{V}^p, \overline{\mathbf{V}}, \mathbf{\Theta}^p) \\ &= \sum_{(i,j)\in\Omega^p} \hat{f}_{i,j}(\mathbf{U}_{*i}, \mathbf{V}^p_{*j}) \\ &+ \left[\frac{\rho}{2}\|\mathbf{V}^p - \overline{\mathbf{V}}\|_F^2 + \mathrm{tr}\big([\mathbf{\Theta}^p]^T(\mathbf{V}^p - \overline{\mathbf{V}})\big)\right], \end{aligned}$$

we can get

$$L(\mathbf{U}, \mathcal{V}, \mathcal{O}, \overline{\mathbf{V}}) = \sum_{p=1}^{P} L^p(\mathbf{U}, \mathbf{V}^p, \mathbf{\Theta}^p, \overline{\mathbf{V}}).$$

Distributed ADMM

Get the solutions by repeating the following three steps:

$$\mathbf{U}_{t+1}, \mathbf{V}^p_{t+1} \leftarrow \operatorname*{argmin}_{\mathbf{U},\mathbf{V}^p} L^p(\mathbf{U}, \mathbf{V}^p, \mathbf{\Theta}^p_t, \overline{\mathbf{V}}_t), \forall p \in \{1, 2, ..., P\}$$

$$\overline{\mathbf{V}}_{t+1} \leftarrow \operatorname*{argmin}_{\overline{\mathbf{V}}} L(\mathbf{U}_{t+1}, \mathcal{V}_{t+1}, \mathcal{O}_t, \overline{\mathbf{V}}),$$

$$\mathbf{\Theta}^p_{t+1} \leftarrow \mathbf{\Theta}^p_t + \rho(\mathbf{V}^p_{t+1} - \overline{\mathbf{V}}_{t+1}), \forall p \in \{1, 2, ..., P\}.$$

The solution for $\overline{\mathbf{V}}_{t+1}$ is:

$$\overline{\mathbf{V}}_{t+1} = \frac{1}{P} \sum_{p=1}^{P} \mathbf{V}^p_{t+1}$$

which can be calculated efficiently.

The problem lies in getting $\mathbf{U}_{t+1}$,$\mathcal{V}_{t+1}$ efficiently

Stochastic Learning

Batch learning is still not very efficient:

$$\mathbf{U}_{t+1} = \mathbf{U}_t - \tau_t * \nabla^T_{\mathbf{U}} f^p(\mathbf{U}_t, \mathbf{V}^p_t),$$

$$\mathbf{V}^p_{t+1} = \frac{\tau_t}{1+\rho\tau_t}[\frac{\mathbf{V}^p_t}{\tau_t} + \rho\overline{\mathbf{V}}_t - \mathbf{\Theta}^p_t - \nabla^T_{\mathbf{V}^p} f^p(\mathbf{U}_t, \mathbf{V}^p_t)]$$

Stochastic Learning

$$(\mathbf{U}_{*i})_{t+1} = (\mathbf{U}_{*i})_t + \tau_t(\epsilon_{ij}(\mathbf{V}^p_{*j})_t - \lambda_1(\mathbf{U}_{*i})_t),$$

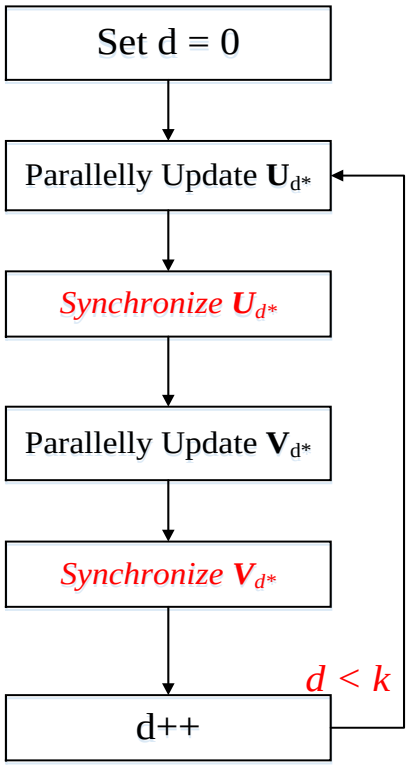
$$(\mathbf{V}^p_{*j})_{t+1} = \frac{\tau_t}{1+\rho\tau_t}[\frac{1-\lambda_2\tau_t}{\tau_t}(\mathbf{V}^p_{*j})_t + \epsilon_{ij}(\mathbf{U}_{*i})_t + \rho(\overline{\mathbf{V}}_{*j})_t - (\mathbf{\Theta}^p_{*j})_t],$$

where $\epsilon_{ij} = R_{ij} - [(\mathbf{U}_{*i})_t]^T(\mathbf{V}^p_{*j})_t$.

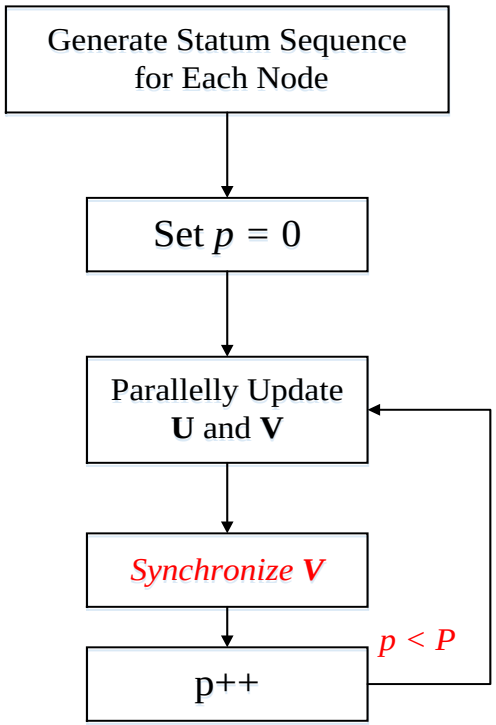
Scheduler Comparison

Baselines: CCD++ (H.-F Yu etc, ICDM'12); DSGD (R. Gemulla etc, KDD'11)

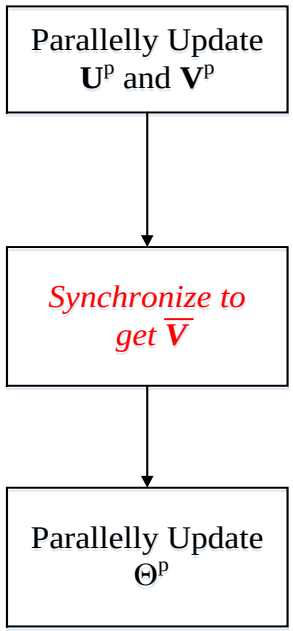
Number of synchronization for one iteration to fully scan all the ratings:



(a) CCD++, total synchronizes **k** times



(b) DSGD, totally synchronizes **P** times



(c) DS-ADMM, totally synchronizes **1** time

Experiment

- Experiment environment
  - MPI-Cluster with 20 nodes, each of which is a 24-core server with 2.2GHz CPU and 96GB of RAM;
  - One core and 10GB memory for each node are actually used.

- Baseline and evaluation metric
  - Baseline: CCD++, DSGD, DSGD-Bias
  - Evalution metric:

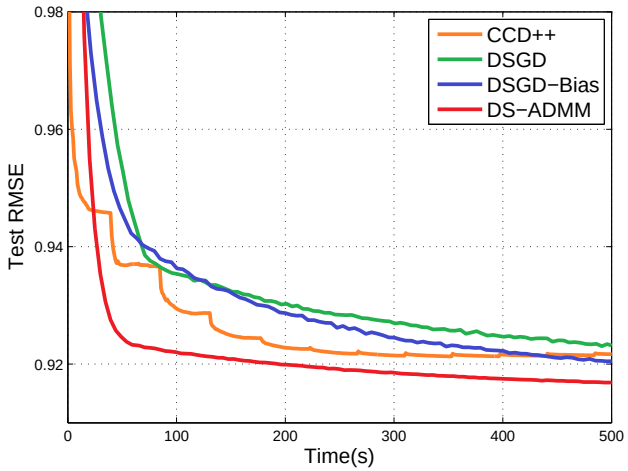
    test RMSE : $\frac{1}{Q}\sqrt{\sum (R_{i,j} - \mathbf{U}_{*i}^T \overline{\mathbf{V}}_{*j})^2}$

Data Sets

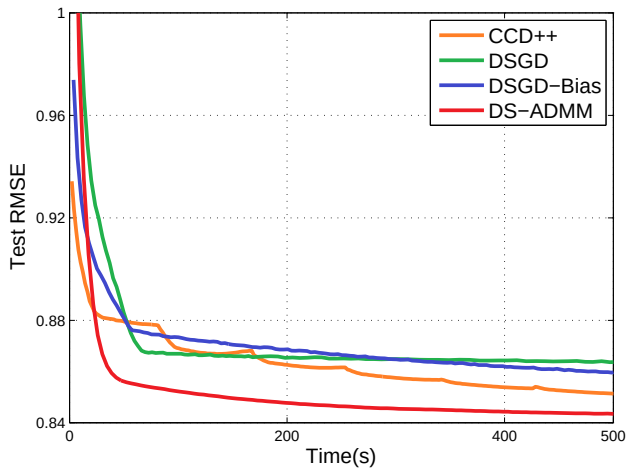
Table: Data sets and parameter settings

Data Set	Netflix	Yahoo! Music R1	Yahoo! Music R2
m	480,190	1,938,361	1,823,179
n	17,770	49,995	136,736
#Train	99,072,112	73,578,902	699,640,226
#Test	1,408,395	7,534,592	18,231,790
k	40	40	40
η_0/τ_0	0.1	0.1	0.1
λ_1/λ_2	0.05	0.05	0.05
ρ	0.05	0.05	0.1
α	0.002	0.002	0.006
β	0.7	0.7	0.7
P	8	10	20

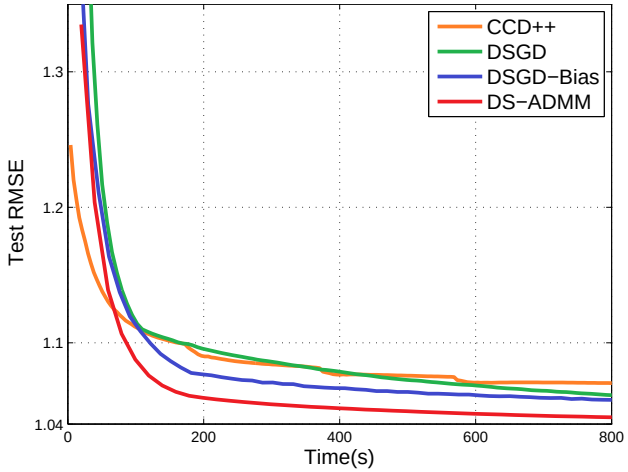
Accuracy and Efficiency



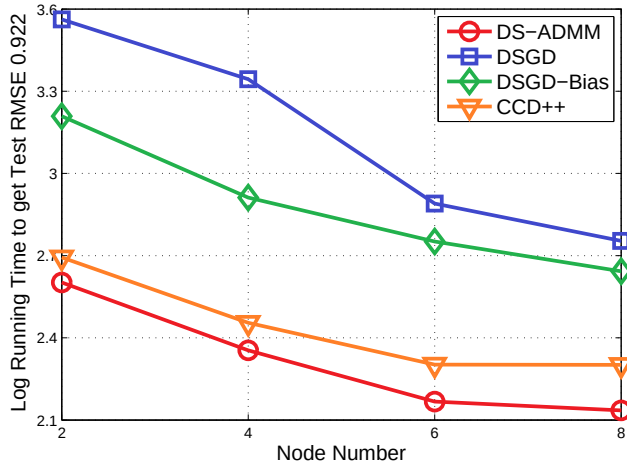
(a) Netflix



(b) Yahoo-Music-R1

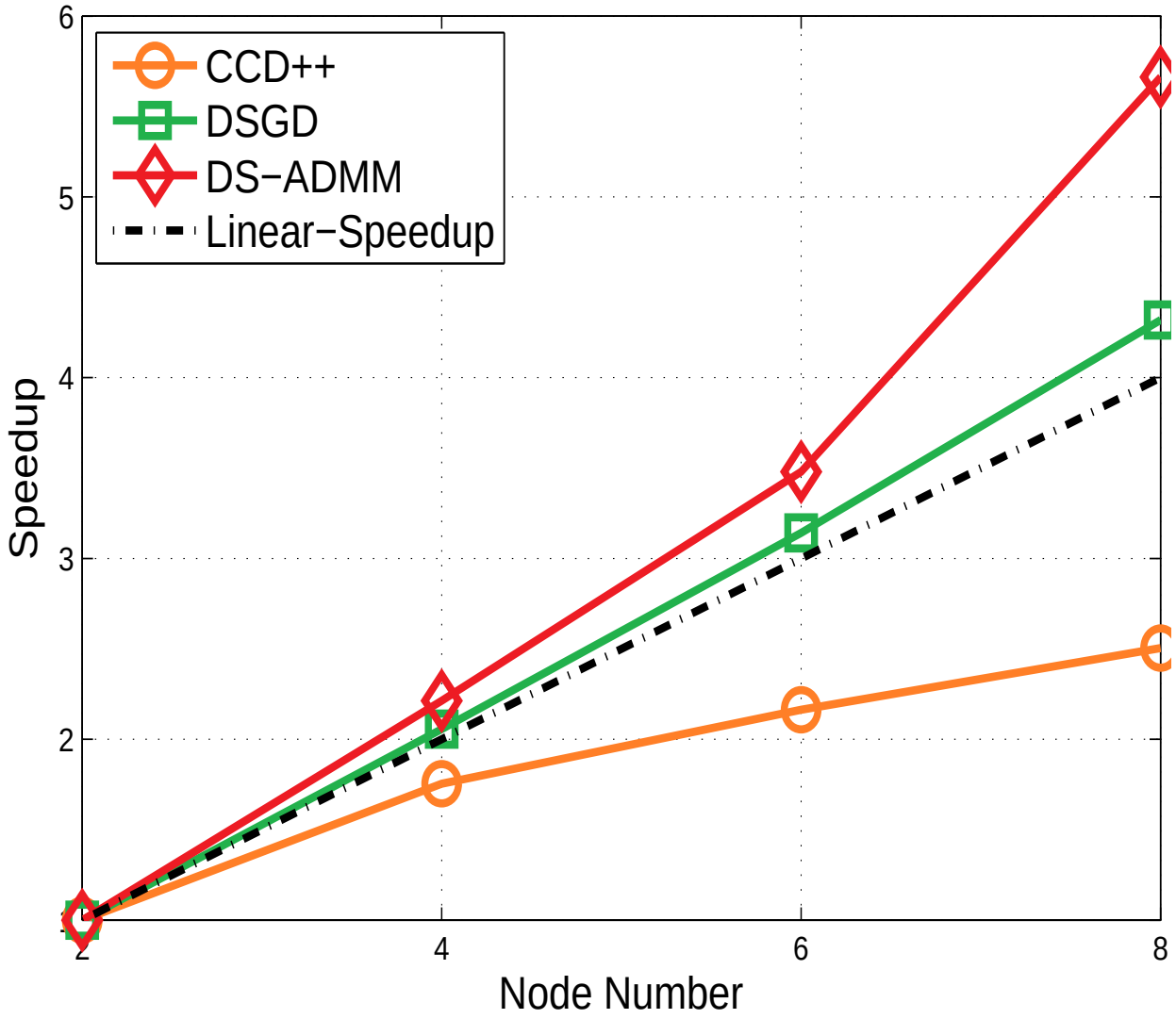


(c) Yahoo-Music-R2



(d) Time to fixed-RMSE (0.922)

Speedup


CCD++
DSGD
DS−ADMM
Linear−Speedup
Speedup
Node Number
2
4
6
8
2
3
4
5
6

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Our Contribution

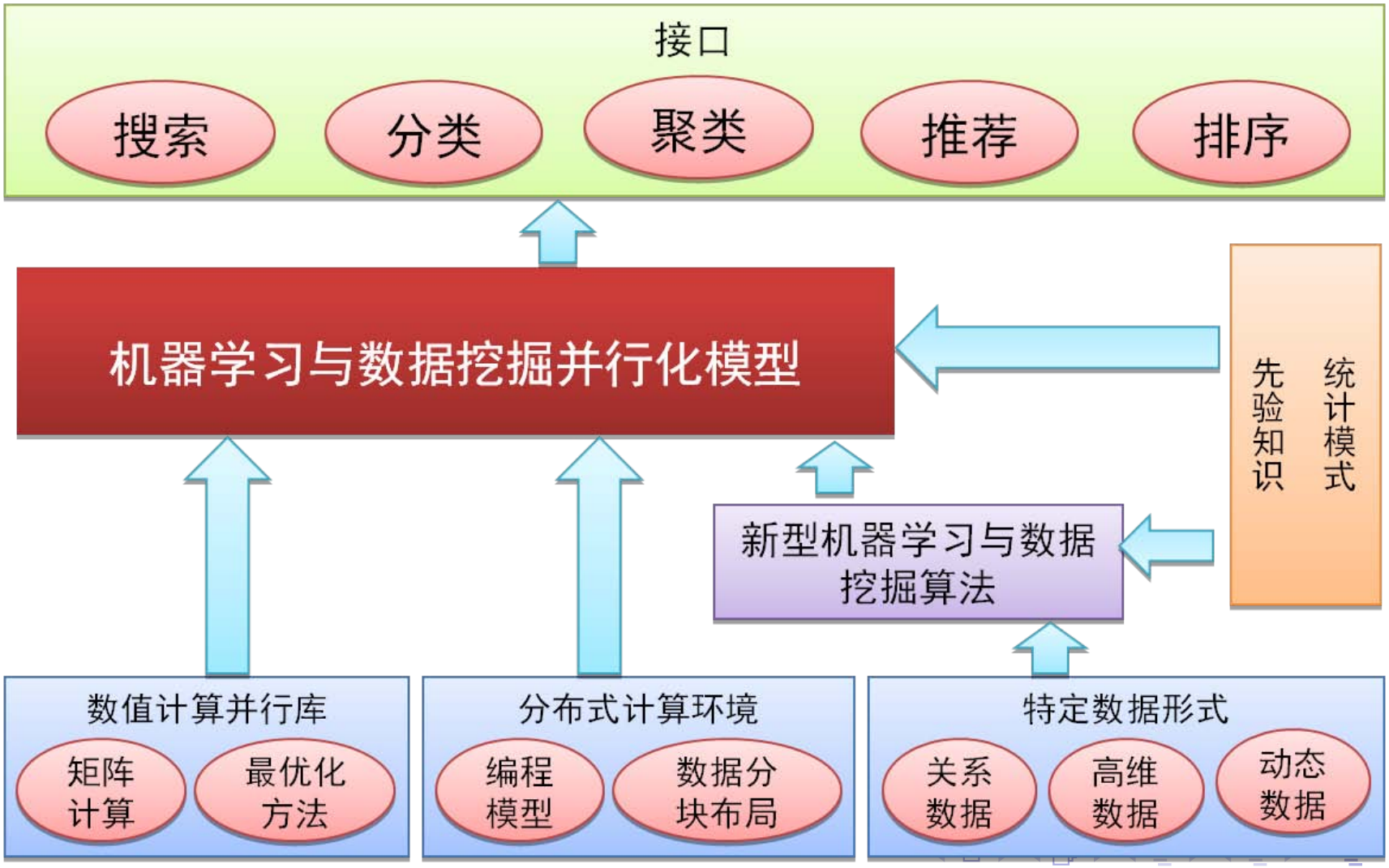
- Learning to hash (哈希学习): memory/disk/cpu/communication
- Distributed learning (分布式学习): memory/disk/cpu;
  but increase communication cost
- Stochastic learning (随机学习): memory/disk/cpu

Future Work

- Learning to hash for decreasing communication cost
- Distributed programming models and platforms for machine learning: *MPI (fault tolerance, asynchronous), GraphLab, Spark, Parameter Server, MapReduce, Storm, GPU, etc*
- Distributed stochastic learning: *communication modeling*

Future Work

Big data machine learning (big learning) framework



Related Publication (1/2)[*indicate my students]

- Ling Yan*, Wu-Jun Li, Gui-Rong Xue, Dingyi Han. Coupled Group Lasso for Web-Scale CTR Prediction in Display Advertising. *Proceedings of the 31st International Conference on Machine Learning (ICML), 2014.*
- Peichao Zhang*, Wei Zhang*, Wu-Jun Li, Minyi Guo. Supervised Hashing with Latent Factor Models. *Proceedings of the 37th International ACM SIGIR Conference on Research and Development in Information Retrieval (SIGIR), 2014.*
- Cong Xie*, Ling Yan*, Wu-Jun Li, Zhihua Zhang. Distributed Power-law Graph Computing: Theoretical and Empirical Analysis. *To Appear in Proceedings of the 28th Annual Conference on Neural Information Processing Systems (NIPS), 2014.*
- Zhi-Qin Yu*, Xing-Jian Shi*, Ling Yan*, Wu-Jun Li. Distributed Stochastic ADMM for Matrix Factorization. *To Appear in Proceedings of the 23rd ACM International Conference on Information and Knowledge Management (CIKM), 2014.*

Related Publication (2/2)[*indicate my students]

- Dongqing Zhang*, Wu-Jun Li. Large-Scale Supervised Multimodal Hashing with Semantic Correlation Maximization. *Proceedings of theTwenty-Eighth AAAI Conference on Artificial Intelligence (AAAI), 2014.*
- Weihao Kong*, Wu-Jun Li. Isotropic Hashing. *Proceedings of the 26th Annual Conference on Neural Information Processing Systems (NIPS), 2012.*
- Weihao Kong*, Wu-Jun Li, Minyi Guo. Manhattan Hashing for Large-Scale Image Retrieval. *Proceedings of the 35th International ACM SIGIR Conference on Research and Development in Information Retrieval (SIGIR), 2012.*
- Weihao Kong*, Wu-Jun Li. Double-Bit Quantization for Hashing. *Proceedings of the Twenty-Sixth AAAI Conference on Artificial Intelligence (AAAI), 2012.*

Q & A

Thanks!